Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 5- Issue 2, Paper 42 August 2022

Modeling of biogas production from anaerobic biogas plant using adaptive neuro fuzzy inference system

Ravindra Bhardwaj, G.S. Sailesh Babu ,
Ajay Kumar Saxena Ashok Jangid,
Department of Electrical Engineering
Faculty of Engineering
Dayalbagh Educational Institute (Deemed University)
Agra, UP-282005, India

Abstract— ***The Adaptive Neuro Fuzzy Inference System (ANFIS) is used to model the parameters of anaerobic processes in order to predict the rate at which biogas will be made. The model is made with an ANFIS that includes four fuzzy input variables like pH value, temperature, Chemical Oxygen Demand (COD), and volatile fatty acid concentration (VFA). The parameters that were measured during the experiment are fed into the ANFIS model as input variables. For fuzzy subsets, Gaussian membership functions with three levels are used. In ANFIS, there are 193 nodes used, and 81 rules are made to put them all together. The imp method and the defuzzification method are the product (prod) method and the "Wtaver" method, respectively. The results of the experiments are used to train and test the ANFIS and make sure that its predictions are correct. The ANFIS model has a determination coefficient of 1.787e+004, an adjusted R2 of 0.9857, and a root mean square error of 1.324. The results showed that the ANFIS model was better at predicting biogas production and had fewer deviations, with satisfactory determination coefficients over 0.98. There is a close match between the experimental and predicted results, which shows that the ANFIS model can be used as an alternative tool for predicting and optimising anaerobic process parameters to get biogas yield from cow dung as a feedstock.***

Keywords- Adaptive Neuro Fuzzy Inference System (ANFIS), Modeling, Regression, Biogas, and Cow Dung

I. INTRODUCTION

Biogas is a renewable source of energy that can be made by breaking down organic waste without oxygen. The process of anaerobic digestion has been used for a long time to make biogas. The process takes place without oxygen to keep the organic matter stable. Biogas production is affected by many operational factors, such as pH, C/N ratio, chemical oxygen demand, temperature, total solid content, stirring process, hydraulic retention time, co-digestion of two or more substrates, etc. For this process, different types of biomass can be used. The various ratios of manure to water were examined to determine the optimal solid concentration for producing biogas from cow manure[1]. Their results show that the most biogas was made when the ratio of manure to water was 1:3 (TS 7.015 percent). various researchers showed that temperature, pH, chemical oxygen demand (COD), volatile fatty acid (VFA), alkalinity, volatile solids (VS), and biogas/methane flow are the most common process variables used to feed models [2],[3],[4],[5]. The effects of these process variables can be seen in the Advanced Controlling Technique of Anaerobic Digestion Using Hierarchical Neural Networks and Optimization of Biogas Production from a Waste digester Using Artificial Neural Network and Genetic Algorithm. This is a widely used model that was developed recently to better calibrate nonlinear relationships and predict variables in complex structures in the Adaptive Neural-Fuzzy Inference System (ANFIS). This method combines the best parts of fuzzy systems and neural networks. It is based on the ability of neural networks to learn on their own and the linguistic transparency of fuzzy inference. The ANFIS model is better than traditional modelling techniques because it can adapt to different system configurations, is easier to make, and takes less time to compute [6]. The ANFIS as a way to predict how fast biogas will be made from kitchen waste. For the training sets, the correlation between the data predicted by the ANFIS model and the actual experimental data showed a correlation coefficient (R2) and an adjusted correlation coefficient (adjusted R2) of 0.9946 and 0.9927, respectively. This showed that the ANFIS model was accurate because the R2 value matched the experimental data [7]. The fuzzy model was developed to predict the rate of biogas production in full-scale landfill bioreactors based on eleven fixed 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 was built and tested on seven lab-scale scenarios. It predicted 90.3% of the total biogas production rate, which suggests that 9.7% of the waste volume behaved differently than the selected control volume of landfill due to its heterogeneities [8]. There are a lot of reports about how ANFIS-based modelling has been used successfully to predict environmental problems[9],[10].

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 5- Issue 2, Paper 42 August 2022

II. THE MATERIALS AND PROCEDURES

The following is a list of the components that were utilised in the procedure of the experiment:

A. Cow manure and water that has been desalinated are the sources of the feed material. Cow manure was taken from a dairy farm on the grounds of the Dayalbagh Educational Institute in Dayalbagh, Agra, India, for this controlled experiment.

B. Apparatus consists of the following components: a feedstock mixture tank, a bio-digester, a gas membrane roof, ball valves, a slurry storage tank, a pH metre, a temperature gauge, an over/under pressure valve, and an enclosed biogas storage balloon.

C. Experimental Set-up of the Biogas plant

Figure 1 is an illustration of the experimental set-up. It comprises of an underground bio-digester (20 feet diameter and 20 feet deep) equipped with the following features:

i. Mixing tank: It is used to make sure that the feed materials are all the same (water and cow dung).
ii. Gas membrane roof: The digester's gas is stored in a gas holder with a membrane roof.
iii. Slurry storage tank: It has enough space for digested slurry to be stored.
iv. Control valves: They are at the entrance and exit to control how much substrate goes in and out.
v. Pressure gauge: It was used to measure how much gas was under pressure.
vi. Thermometer: This device measures how hot the organic waste is as it breaks down inside the bio-digester.
vii. pH metre: it measures the pH of the substrate before and after digestion.
viii. Biogas Storage Balloon with Enclosure: It is made of UV-resistant double-sided PVC coated or similar material and has a roof with all the necessary pipes and connections.

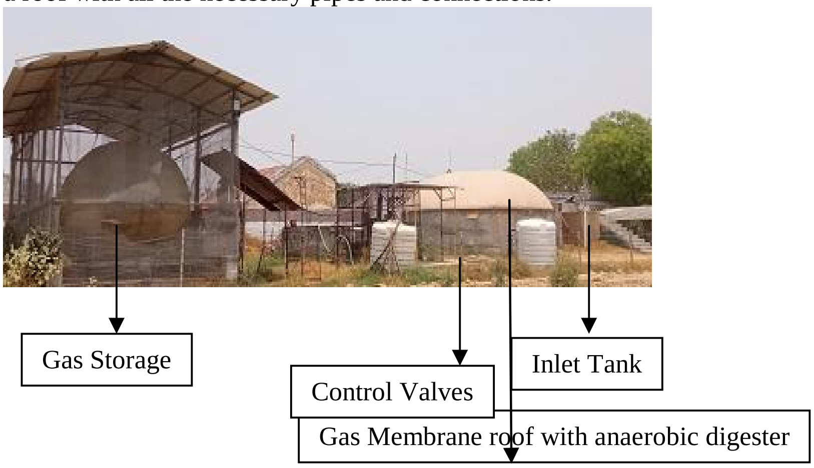

Fig 1 Photographic view of Biogas Plant for Experiment

D. Operation of Biogas Plant

The operation of the biogas plant setup included a bio-digester with ball valves at the inlet and outlet, a slurry circulation pump, a digested slurry storage tank, a thermometer, a three-phase control panel based on an Arduino, and a biogas storage balloon. Mixing the feed with water makes a homogeneous mixture that is easy for bacteria to digest. A mixer made in the area is used to mix the ingredients. The feed material is cleaned and made free of large pieces. It is fed into the digester through the inlet, and the substrate is taken out of the digester through the outlet. The substrate feeding is controlled by the ball valves at the inlet and outlet. The gas storage balloon got its gas from the digester through a hose that pulled the gas out of the digester. The biogas is stored in a balloon that can hold more than 150 m3 and is attached to the other end of the gas extraction pipe.

E. Methods

The digester is filled with cow manure and water in a 1:1 ratio when the biogas plant is first turned on.
Here are the steps that need to be taken when the biogas plant is running:
i. The total amount of cow dung in each batch is measured with a weighing balance.
ii. The cow dung is then mixed with distilled water, and each set of substrates is thoroughly mixed for 25–30 minutes, until the mixture becomes uniform.
iii. The bio-digester was filled with the mix of distilled water and substrates (through the inlet and after which, the digester inlet valve was closed).

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)
Volume 5- Issue 2, Paper 42 August 2022

iv. The gauge pressure is set to 0 bar and written down.
v. A digital pH metre is used to check the pH of the substrate before and after the digestion process.
vi. A thermometer in the bio-digester keeps track of the temperature of the anaerobic digestion process.
vii. The biogas that is made is put into a biogas balloon and measured with a biogas flow metre to find out how much biogas is made at each gas evacuation time.
viii. The same process is used for every 15-day batch.

III. Fuzzy Logic Modelling

Fuzzy logic controller system (FLCS) can be described as a non-linear mapping of an input data set to a scalar output data. It is designed to model for biogas production from the biodegradation of cow dung. Process diagram for fuzzy logic as shown in fig 2The typical elements of the FLC structure include: (i) inputs (ii) fuzzification unit (iii) database (iv) rule base (v) fuzzy inference engine (vi) defuzzification unit and (vii) output

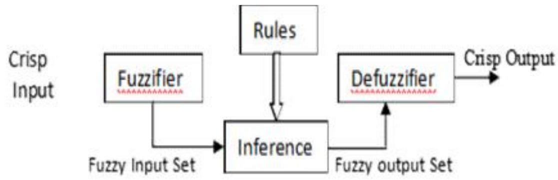

Fig 2 Process Diagram for Fuzzy Logic

The processes involved in fuzzy logic modelling are highlighted as follows:

1. Define the inputs and output (linguistic variables) and terms (initialization).
2. Convert the crisp variable to fuzzy sets (fuzzification)
3. Create a membership function (initialization)
4. Construct the rule base (initialization)
5. Convert the output data to non-fuzzy values (defuzzification)

In this study, the ANFIS model was developed to predict biogas yield.

A. Variable Input and Output

Bio-digester input variables are temperature, pH value, chemical oxygen demand (COD), and volatile fatty acid (VFA). The output variable is biogas.The crisp values of the input variables were obtained during the conducted experimental study.

B. Fuzzification

In this strategy, numerical inputs and output variables are converted into linguistic terms or adjectives (such as low, high, big, small, etc.). It involves the following steps: The fuzzification process necessitates a thorough understanding of all variables in order to (i) acquire the crisp values of the four input variables and (ii) map the crisp values of the input variables into the fuzzy membership functions. (iii) Converting the mapped data into suitable linguistic terms to make it a compatible fuzzy set representation is challenging.

C. Selection of Linguistic Variables

In the anaerobic digestion process, bio-digester temperature, pH value, chemical oxygen demand (COD), and volatile fatty acid (VFA) were selected as the linguistic variables to determine biogas generation. For all input parameters, linguistic terms (minimum, optimum, and maximum) were used as obtained from the experimental procedure. In real life, the output variable was used as: Biogas yield (minimum, best, and most).The linguistic variables and their range of values, which were selected from the experiment, are given as follows:

- Temperature of the bio-digester: 30-45 °C
- substrate pH value- 4-10
- COD (chemical oxygen demand): 25-80 (mg/L) 10^3
- Volatile fatty acid (VFA)-0-30%
- Biogas Generation: 50-90 m^3/D

D. System of fuzzy inference

The model was suggested to convert the crisp variables (actual experimental data) into fuzzy sets and also explain how the fuzzy inference system generate by ANFIS [11]. ANFIS is a hybrid intelligent model consisting of a fuzzy interface system

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)
Volume 5- Issue 2, Paper 42 August 2022

(FIS) and a neural network, with the advantages of both the models containing excellent approximation functions and superior learning algorithms. As shown in Fig. 3a, the raw experimental data were chosen as input variables in the ANFIS edit toolbox in order to make the FIS morphology. The ANFIS model consists of five layers. In the first layer (fuzzy system input), the crisp data is sent to adaptive neurofuzzy for possible conversion into fuzzy sets, since fuzzy sets do not accept the crisp data. The grid partition method is employed to generate the fuzzy inference system while the FIS button is clicked to initiate the process. The outputs of the first layer become inputs to the second layer. The second layer contains prior values of MFs. The ANFIS structure as shown in fig 3b contains membership functions (MFs) as shown in fig 3c and is improved through the capability of ANNs and fuzzy if-then rules as shown in fig 3d under a FIS. Membership functions are used to map the non-fuzzy input values to quantified linguistic terms and vice versa. For this problem, three membership functions were selected for each input variable, and the gaussian membership function was used. The fuzzy rules are determined with the nodes on them and then sent to the next layer with a related activity degree. In the third layer, the activity degree is normalised for all rules. The function and nodes are adopted in the fourth layer, and the first model through which derived parameters are provided and then sent to the output. In this step, defuzzification takes place. Typically, it involves weighting and incorporating a number of fuzzy sets into the calculation. In this phase, linguistic results obtained from the fuzzy inference are translated into crisp values for the output. 'Wtaver' methods are employed as defuzzification methods.In the fifth layer, which is the last layer, there is only one output node, and all the signals that come in are added together at the output.

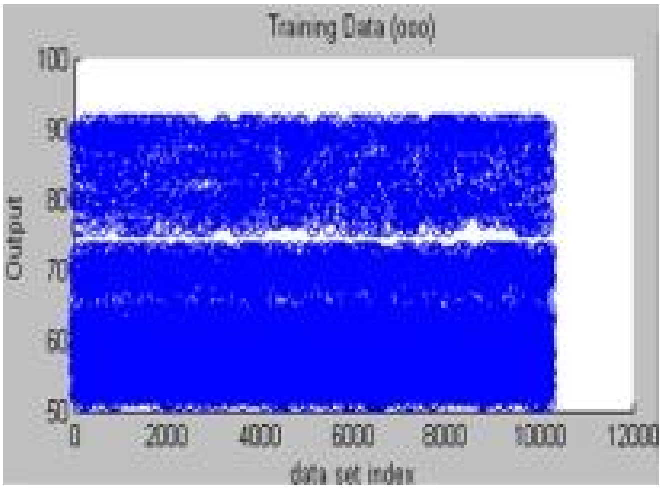

Fig 3a ANFIS tool box showing the crisp data

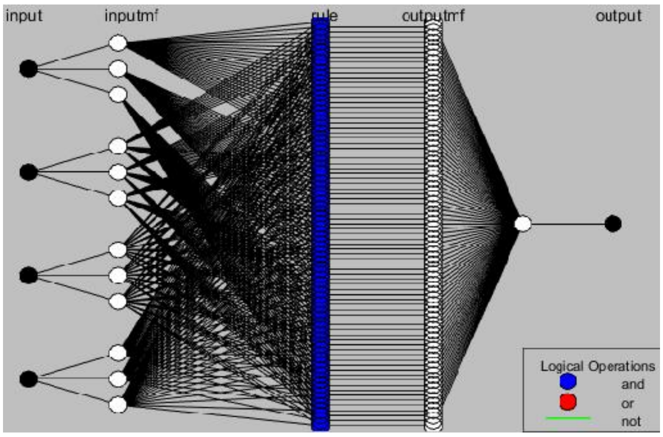

Fig 3b ANFIS Structure

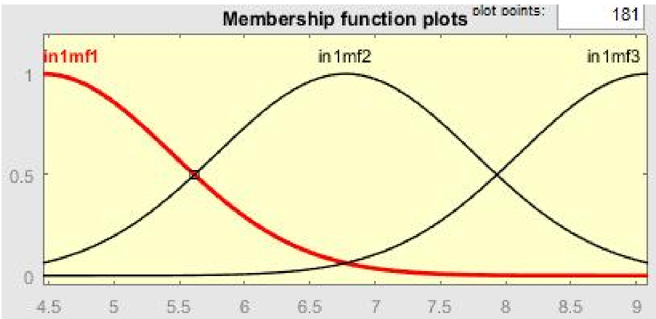

Fig 3c Membership function

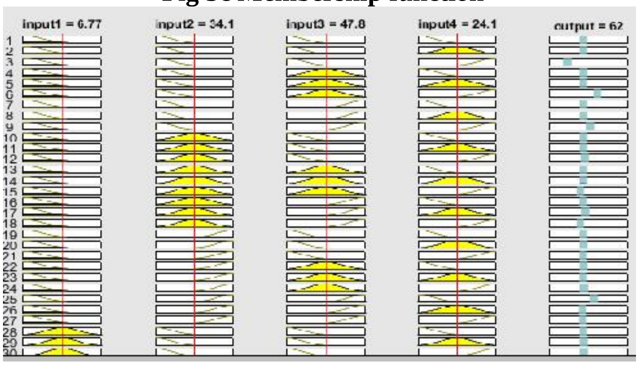

Fig 3d Rule viewer - Fuzzy if-then rules

IV. RESULT AND DISCUSSION

The inputs to the ANN model were selected to be four operational parameters, namely temperature, chemical oxygen demand, volatile fatty acid, and pH, while the output was the production of biogas from the anaerobic digester. The programs written in MATLAB are implemented. The results of the random run of the ANFIS program showed that biogas prediction is not affected by the different arrangements of input variables, and all groups of input parameters showed the same results. 70% of all data is randomly used as training datasets, and 15% for testing, and 15% for validation datasets. According to the results shown in Table 5, the MFs number for each input is 3,3,3,3, and the number of epochs is set at 10. A study by Khoshnevisan B et al. shows that the hybrid learning method used for ANFIS training gives the best results. Previous studies have also shown that this learning algorithm is very accurate.

TABLE 1 SHOWS THE OUTCOME OF THE REGRESSION VARIABLE

SSE:	R-square:	Adjusted R-square:	RMSE:	Data Type
1.787e+004	0.9857	0.9857	1.324	Training
3832	0.9855	0.9855	1.324	Validation
3539	0.9871	0.9871	1.273	Testing

SSE: Sum of Squared estimate of errors, RMSE: *Root Mean Square Error*

Table1 shows the R2 (value of determination coefficients) between the observed and predicted data for the training dataset and testing dataset (R2 = 0.9857 and 0.9871). This indicates that only 1.43% and 1.29% of the total variations are not explained by the ANFIS in prediction of biogas. It has confirmed the good performance of the ANFIS model obtained from observed and predicted biogas production as shown in Figures 4 for overall dataset. Adjusted R2 between the observed and predicted data for the training dataset and testing dataset (R^2 = 0.9857 and 0.9871) indicated a better fit. The Root Mean Square Error, RMSE, between the observed and predicted data for the training dataset and testing dataset is 1.324 and 1.273, respectively. The low value indicates a fit that is more useful for prediction.

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)
Volume 5- Issue 2, Paper 42 August 2022

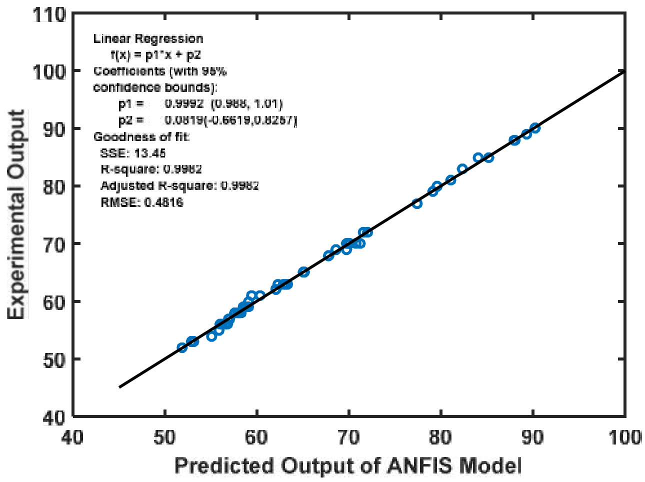

Fig 4 Comparison of Biogas between predicted and Experimental Data

Figures 5a ,5b and 5c show the linear regression between Biogas as predicted values by developed ANFIS models and experimental outputs at training testing and validation datasets with their residuals respectively. This shows that the predicted Biogas output dataset by developed ANFIS models agreed with the Biogas output experimental dataset.

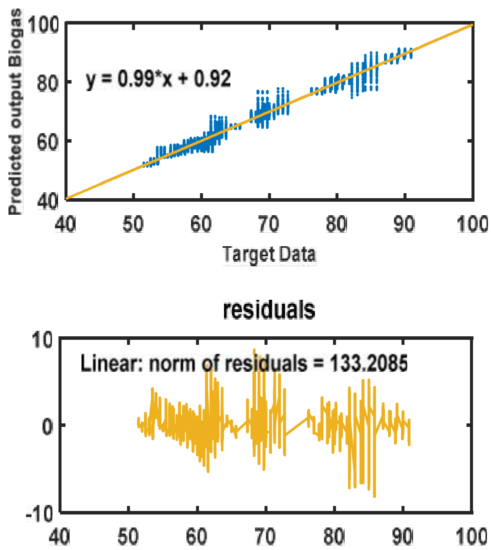

Fig 5a. ANFIS vs Experimental plot Linear regression model for Training data

Consequently, it can be concluded that the ANFIS model can be a good alternative to the conventional multiple regression-based method due to its ability to precisely discriminate the arbitrary non-linear functionalrelationships without requiring a mathematical model to define complex biochemical reactions between input and output data sets. This can be attributed to the advantage of artificial intelligence-basedmodels on complex interactions between multi-input and output-variables in a complex system, such as the anaerobic digestion process. The linear regression between the fuzzy-logic testing outputs and the corresponding targets indicated that the forecasted data clearly agreed with the experimental.

Volume 5- Issue 2, Paper 42 August 2022

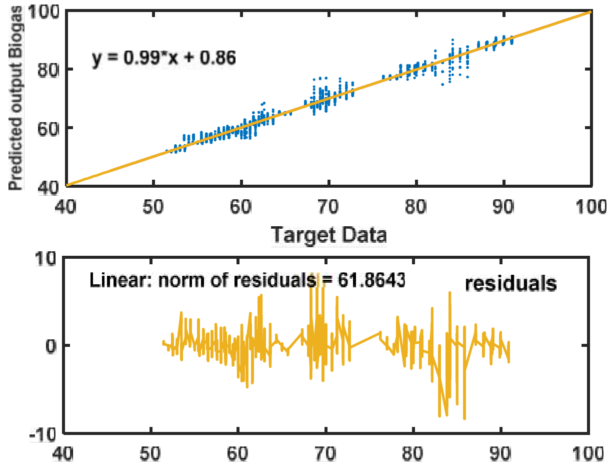

Fig 5b ANFIS vs Experimental plot Linear regression model for testing data

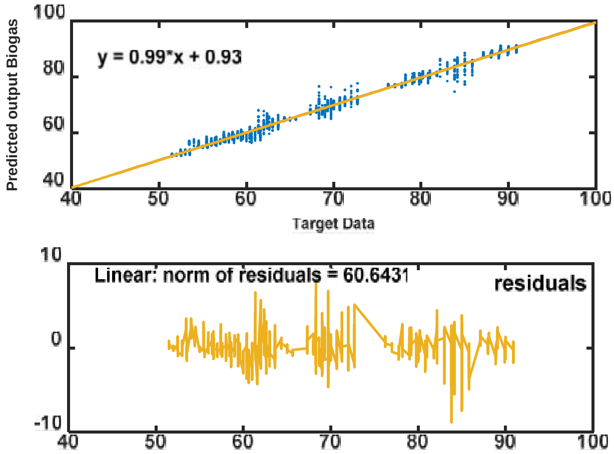

Fig 5c ANFIS vs Experimental plot Linear regression model for validation data

V. CONCLUSIONS

The present study was conducted to evaluate biogas production from anaerobic digestion as well as modelling of biogas production using ANFIS methods. Based on the experimental findings, a real-world modelling study was conducted as an important objective to develop an artificial intelligence-based model that could make a reliable prediction of biogas yield. The proposed ANFIS model produced precise and effective predictions with correlation coefficients greater than 0.98 for four different model components (pH, temperature, COD, and volatile fatty acid (VFA). The statistical indicator values returned for overall, training, and testing datasets indicated ANFIS models could reasonably simulate biogas production with high accuracy and low error. The applicability of the fuzzy-logic model is very simple, and there is no need to define the complex reactions and their mathematical or biochemical equations. Also, because the fuzzy-logic model is not very linear, it was shown that a complicated system like anaerobic digestion could be easily modeled.

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)
Volume 5- Issue 2, Paper 42 August 2022

References:

[1].Budiyono, W., Syaichurrozi, I., Sumardiono, S., 2014. Effect of total solid content to biogas production rate from Vinasse, International Journal of Engineering, Transactions B: Applications 27(2): 177-184

[2] Holubar, P., Zani, L., Hager, M., Fröschl, W., Radak, Z., Braun, R., 2002, Advanced controlling of anaerobic digestion by means of hierarchical neural networks. Water Research, 36(10), 2582-2588.

[3] Qdais, H. A., Hani, K.B., Shatnawi, N., 2010, Modeling and optimization of biogas production from a waste digester using artificial neural network and genetic algorithm. Resources, Conservation andRecycling, 54(6), 359-363.

[4] Guwy, A.J., Hawkes, F.R., Wilcox, S.J., Hawkes, D.L., 1997, Neural network and on-off control of bicarbonatealkalinity in a fluidised-bed anaerobic digester. Water Research, 31(8), 2019-2025.

[5] Yetilmezsoy, K., Turkdogan, F. I., Temizel, I., & Gunay, A., 2013, Development of ann-based models topredict biogas and methane productions in anaerobic treatment of molasses wastewater. Internationaljournal of green energy, 10(9), 885-907.

[6] Tay JH, Zhang X. ,1999, Neural fuzzy modeling of anaerobic biological wastewater treatment systems. J Environ Eng ;125(12):1149–59. https://doi.org/ 10.1061/(ASCE)0733-9372,125:12(1149).

[7] Salehi, K., Khazraee, S. M., Hoseini, F. S. and Mostafazadeh, F. K.,2014, Laboratory Biogas Production from Kitchen Wastes and Applying an Adaptive Neuro Fuzzy Inference System as a Prediction Model. International Journal of Environmental Science and Development; 5(3): 290-293.

[8] Addario, M. D. and Ruggeri, B. ,2018, Fuzzy approach to predict methane production in full-scale bioreactor landfills. Environmental Research and Technology 2018; 1(1): 4-13.

[9] Mousavi-Avval SH, Rafiee S, Sharifi M, Hosseinpour S, Shah A.,2017 Combined application of life cycle assessment and adaptive neuro-fuzzy inference System for modeling energy and environmental emissions of oilseed production. Renew Sust Energ Rev 2017;78:807–20.

[10] Khoshnevisan B, Rafiee S, Omid M, Mousazadeh H.,2014 Prediction of potato yield based on energy inputs using multi-layer adaptive neuro-fuzzy inference system. Measurement; 47:521–30.

[11] Nabavi-Pelesaraei A, Rafiee S, Mohtasebi SS, Hosseinzadeh-Bandbafha H, Chau KW, 2018Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production. Sci Total Environ ;631:1279–94.