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# ADAPTIVE NEURO-FUZZY SYSTEM FOR BIOGAS PRODUCTION DETECTION AND CONTROLLING FROM CHEMICALLY PRESERVED AGRICULTURAL WASTES

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**Abstract –** The influence of co-digestion of agricultural solid wastes (ASWs), cattle (or) cow manure (CM), and co-digestion with chemical pre-treatment with NaHCO3 on the effectiveness of the anaerobic digestion (AD) system is investigated in this study. In mesophilic and thermophilic circumstances, an Adaptive Neuro-Fuzzy System (ANFS) approach was created to model and optimize Cumulative Methane Production (CMP) from ASWs, CM, and their mixture. Neuro-adaptive learning techniques endowed with algorithm methods for fuzzy modeling provide information on the data set. The learning process computes the function parameters which allow the associated fuzzy inference system to track the given input/output data. The task of the learning algorithm for this architecture is to modify parameters and formulate the ANFIS output to match the training data. In comparison to the unprocessed substrate, the chemical solvents with NaHCO3 improved the substrate's biodegradability and increased the CMP by at least 43%. With 99.9% of data falling within 10% of the median measured values, an ANFS model with five layers, 20 neutrons, and 50 epochs accurately predicts the CMP.

**Keywords –** Biogas Production Prediction, Chemically Treated Agricultural Waste, Adaptive Neuro-Fuzzy System, and Cumulative Methane Production

## 1. Introduction

The rising demand for fossil fuels has resulted in significant increases in global pollution and carbon emissions, highlighting the necessity of renewable energy supplies around the world [1]. Agricultural products also generate substantial amounts of agricultural solid wastes (ASWs), which must be managed and disposed of properly. Incineration is the most popular method for reducing the accumulation of ASWs. Burning ASWs, on the other hand, emit greenhouse gases (GHG) and fine particles into the atmosphere, contributing to global warming and air pollution [2]. A large proportion of manure produced by animal dairy and meat-producing facilities is also included in agricultural waste material. Anaerobic digestion (AD) is a very well-systemic implication and proven treatment technology that can be used to process ASWs and manure, reduce GHG emissions, and generate biofuel [3], [4]. Co-anaerobic digestion (Co-AD) of ASWs with animal waste is a potential monitoring system for the production of biofuel and fertilizers, with characteristics of ease of maintenance, sustainability, and highly energetic output. Various substrates were treated using the Mono-AD and Co-AD procedures. Co-AD overcomes technical challenges such as carbon-to-nitrogen ratio (C: N) constraints, substrate biodegradability (Biosub), pH, inhibition, and moisture content (percent MC), resulting in a faster reaction rate, higher biofuels generation, and performance improvement than mono-AD. To represent, influence, and identify the production of methane from AD processes fed with the chemically treated co-digested substrate under mesophilic and thermophilic circumstances [5], [6].

## 2. Aim and Scope

This article assesses the effect of co-digestion of ASWs and cow Manure (CM), and also the chemical pre-treatment of the substrate with NaHCO3, on the achievement of AD. With little experimental data, the created model can identify the optimal Top, chemical dose (D), COMPsub, and HRT for maximal biogas production and be utilized to optimize AD performance. The constructed ANFS model can also predict AD performance within untested situations, which preserves both time and resources.

## 3. Proposed Work

Adaptive Neural Fuzzy Inference System (ANFIS) is a commercial approach that is a combination of two techniques namely neural network and fuzzy logic to generate a complete shell. The system of ANFIS concerns the method of the artificial neural network learning rules to conclude and adjust the fuzzy inference systems parameters and structure. The major features of the ANFIS system support the system to achieve task intensity. These features are considered as fast and accurate learning, easy to implement, excellent explanation facilities, and strong generalization abilities, through fuzzy rules. This method is used as a teaching technique for the Sugeno-type fuzzy systems. When ANFIS is applied, the number and type of the fuzzy system are generally defined by the user part.

ANFIS is a data-driven procedure representing a neural network approach for the solution of function approximation problems. Data-driven procedures for the synthesis of ANFIS networks are typically based on clustering a training set of numerical samples of the unknown function to be approximated. ANFIS networks have been successfully applied to classification tasks, rule-based process control, pattern recognition, and similar problems. Here a fuzzy inference system comprises the fuzzy model proposed by Takagi, Sugeno, and Kang to formalize a systematic approach to generating fuzzy rules from an input-output dataset. ANFIS is a multilayer feed-forward network that contains five layers in its architecture. They are given by,

- Fuzzy layer.
- Product layer.
- Normalized layer.
- De-fuzzy layer.
- Total output layer.

In fig 1 fuzzy neural system is shown in which both fuzzy logic and neural network techniques are introduced to bring out solicitations such as control systems and pattern recognition. The main objective of the fuzzy neural system can be proficient by having each technique do its task by incorporating and approving one another. This kind of inclusion is application-oriented and appropriate for control and pattern recognition applications both. The fixed nodes are represented by a circle and the nodes represented by a square are the adapted nodes.

ANFIS gives the advantages of a mixture of neural networks and fuzzy logic. The aim of mixing fuzzy logic and neural networks is to design an architecture that uses fuzzy logic to show knowledge fantastically, while the learning nature of the neural network maximizes its parameters. The example of fuzzy neural systems are GARIC, ARIC, and ANFIS models

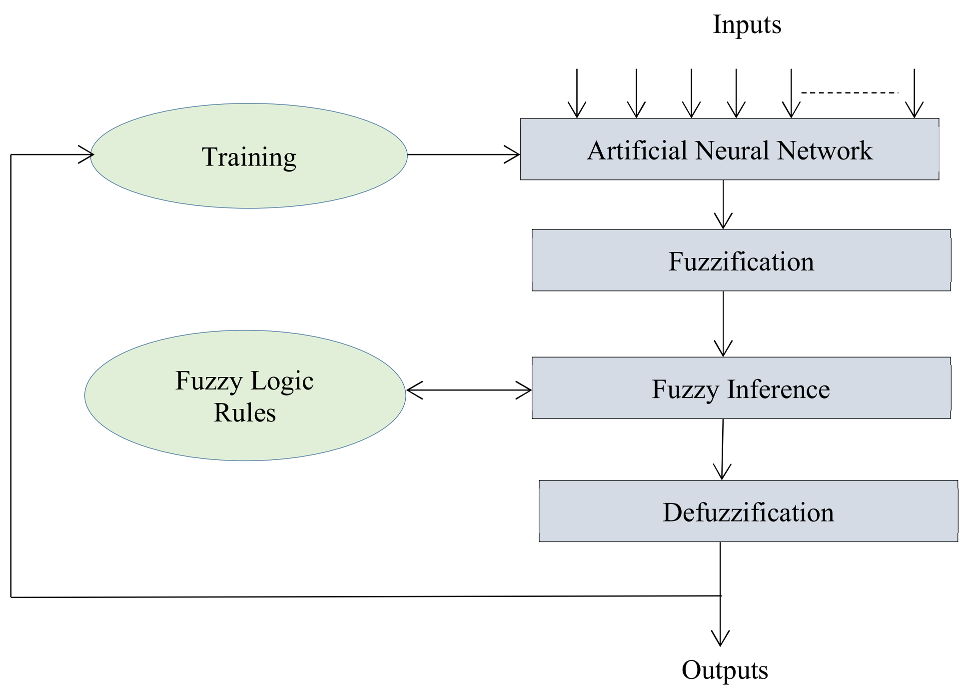


Fig.1. Fuzzy Neural Systems

The above diagram shows the fuzzy neural system in which training and fuzzy rules are applied in the artificial neural network. In this system neural network is used to regulate the functions and represent the fuzzy sets which are operated as fuzzy rules. These systems are used in the controller systems.

*Membership Function in ANFIS*

A membership function (MF) is a curve that explains how every point in the input space is mapped to a membership degree between 0 and 1. Here, four types of membership functions will be used to identify the fuzzy inference system (FIS) parameters, i.e. triangular MF (*trimf*), trapezoidal MF (*trapmf*), Generalized Bell MF (*gbellmf*), and Gaussian MF (*gaussmf*). The formula of each membership function is given in Table 1 below.

Table.1. Formula of fuzzy membership function

| **Membership Functions** | **Formula** |
|---|---|
| Triangular MF(*trimf*) | *trimf* (x: a, b, c)= max(min $\left(\frac{x-1}{b-a}, \frac{c-x}{c-b}\right)$, 0 |
| Trapezoidal MF(*trapmf*) | *trapmf* (x: a, b, c,d)= max(min $\left(\frac{x-1}{b-a}, 1, \frac{d-x}{d-c}\right)$, 0 |
| Generalized Bell MF (*gbellmf*) | *gbellf* (x: a, b, c)= $\frac{1}{(1+(\frac{x-c}{a})^{2b})}$ |
| Gaussian MF (*gaussmf*) | *gaussmf* (x: c, $\sigma$)= exp $(-\frac{1}{2}(\frac{x-c}{\sigma})^2)$ |

*Learning Algorithm of ANFIS*

Neuro-adaptive learning techniques endow with a method for the fuzzy modeling procedure to learn information about a data set. It computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. The parameters associated with the membership functions change through the learning process. To more efficiently cope with real-world problems, the task of the learning algorithm for this architecture is to tune all the modifiable parameters, to formulate the ANFIS output to match the training data.

To improve the rate of convergence, the hybrid network can be trained by a hybrid learning algorithm combining the least square method and gradient descent method can be used. The least-squares method can be used to identify the optimal values of the consequent parameter on layer 4 with the premise parameter fixed. The gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters.

When the gradient vector is obtained, several optimization routines can be applied to adjust the parameters to reduce some error measures. When the premise parameters are not fixed, then the search space becomes larger and the convergence of the training becomes slower. The hybrid algorithm is composed of a forward pass (LSM) and a backward pass (GDM). Once the optimal consequent parameters are found, the backward pass starts. In the backward pass, errors are propagated backward and the premise parameters corresponding to the fuzzy sets in the input domain are updated by the gradient descent method [11]. ANFIS uses a combination of least squares estimation and back-propagation for membership function parameter estimation. Two passes in the hybrid learning algorithm for ANFIS are shown in table.2.

Table 2. Passes of Hybrid Learning Algorithm

| | **Forward Pass** | **Backward Pass** |
|---|---|---|
| Premise parameters | Fixed | Gradient descent |
| Consequent parameters | Least square | Fixed |
| Signals | Node output | Error signal |

The output error is used to adapt the premise parameters using a standard back-propagation algorithm to minimize the mean square error function defined by Eq. (1). It has been proven that this hybrid algorithm is highly efficient in training the ANFIS.

$$E(\boldsymbol{\theta})= \sum_{i=1}^{m}(\mathrm{zi} - \mathrm{aiT}\theta)2=\boldsymbol{e^T e}=\boldsymbol{mi}=\mathbf{1}(\boldsymbol{z}-\boldsymbol{A\theta})^{\boldsymbol{T}}\ (\boldsymbol{z}-\boldsymbol{A\theta}) \qquad (1)$$

Where e = $z-A\theta$ is the error vector produced by a specific choice of $\theta$. In Eq. (1) the squared error is minimized and is called the least squares estimator (LSE) [7]. Therefore, the hybrid learning algorithm can be applied directly. More specifically, the error signals proliferate backward and the premise parameters are updated by Gradient Descent (GD) and node outputs go forward until layer 3 and the consequent parameters are identified by the Least Squares (LS) method. This hybrid learning is structured by defining, linear and nonlinear parameters illustrious each iteration (epoch) of GD update the nonlinear parameters, LS follows to identify the linear parameters.

*Proposed procedure of ANFIS Modeling*

There are three basic step blocks of ANFIS modeling, those are preprocessing of data, rule generation, and performance evaluation. These steps can be described completely by the following,

*Collecting the data*

At first, data are collected for the further process.

*Preprocessing original data*

The original data are preprocessed by using the ARIMA method. The ARIMA models are constructed based on significant lags of ACF and PACF. The best model is selected by minimizing the root mean square of error (RMSE), AIC, or SBC criterion.

*Non-linearity test*

Non-linearity test is needed to determine the nonlinearity properties of data.

*Determining the input variables*

The input variables of ANFIS can be selected based on significant lag periods of ARIMA or Subset ARIMA. All possible significant lags yielded from informal preprocessing are selected as input variables of ANFIS.

*Defining and partitioning the input variables*

The selected input variables are classified into some clusters using Fuzzy C-means (FCM).

*Setting the type of membership functions for input variables*

We can set a membership function which can be applied to input variables. In this study, we use four types of membership functions such as triangular function (*trimf*), trapezoidal function (*trapmf*), generalized bell function (*gbellmf*), and Gaussian function (*gaussmf*).

*Generating the fuzzy If-Then rules*

The output variables are associated with each input cluster based on the degree of possibility. The fuzzy i*f-then* rules are constructed using a linear Sugeno fuzzy model.

*Training the parameters of fuzzy inference system (FIS)*

FIS parameters are identified from training datasets. Fuzzy reasoning is used to infer new knowledge from the identified base. Consequent parameters are estimated using the recursive least square method and premise parameters are adapted using backpropagation gradient descent.

*Forecasting the training data and calculating the RMSE value*

After the significant models are constructed based on training data, we determine the predicted values and calculate the RMSE values. The best model is selected by minimizing RMSE.

*Forecasting the checking data and calculating RMSE value*

For assessment of ANFIS performance, the model result from previous steps is applied to forecast checking datasets and then calculate the RMSE values. The best model can be determined based on both RMSE values of training and checking data. For example, it is assumed that ANFIS has two inputs and one output. The rule base of the ANFIS contains if-then rules which are expressed below,

$$If\ x\ is\ A\ and\ y\ is\ B\ then\ z\ is\ equal\ to\ f(x,y) \qquad (2)$$

Where, A and B are fuzzy sets in the antecedents and z = f(x, y) is a crisp function in the consequent. Generally, f(x, y) is polynomial for the input variables x and y. When f(x, y) is a constant, then the zero-order Sugeno fuzzy model is formed where each rule consequent is specified by the fuzzy singleton. If f(x, y) is considered to be a first-order polynomial, then a first-order Sugeno fuzzy model is formed. For the first-order Sugeno fuzzy model, two rules may be stated which are described as follows,

- Rule 1: If x is A1 and y is B1 then f1 = p1x + q1y + r1
- Rule 2: If x is A2 and y is B2 then f2 = p2x + q2y + r2

Type 3 fuzzy inference system is proposed which is shown in Fig.2. Where the output of each rule is a linear combination of the input variables added by a constant term. The final output is the weighted average of each rule's output.

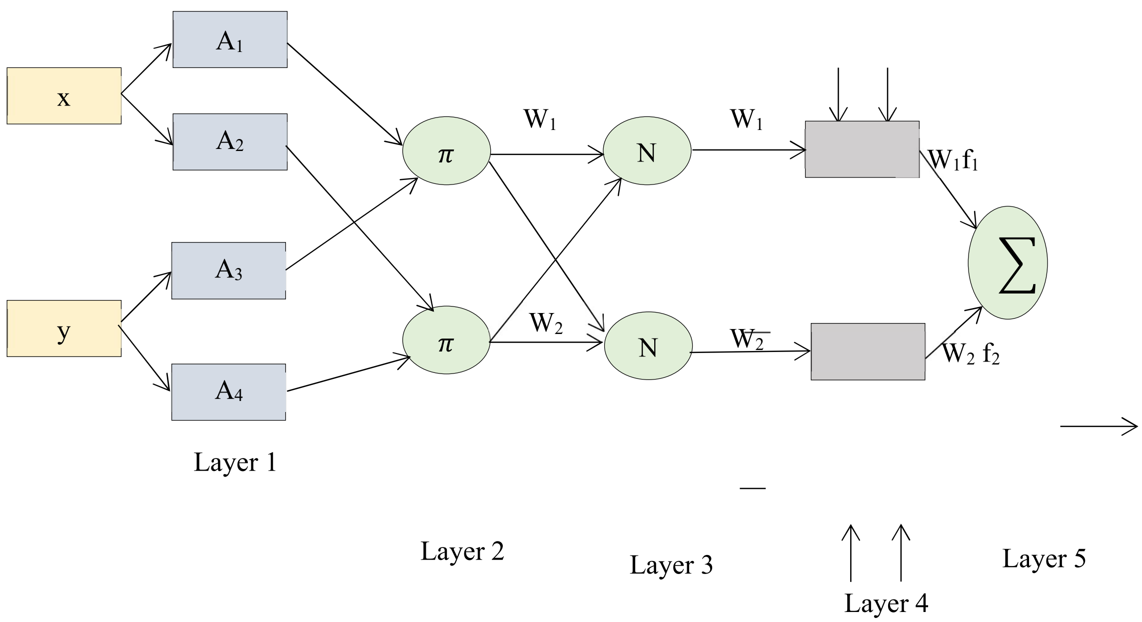


Fig.2. ANFIS structure

The output 'f' in figure 2 is written as,

$$f = \frac{w_1}{w_1+w_2} f_1 + \frac{w_1}{w_1+w_2} f_2 \ .$$

$$= w_1 f_1 + w_2 f_2$$

$$= (\overline{w_1}\ x)\ p_1 + (\overline{w_1}\ y)q_1 + (\overline{w_1})r_1 + (\overline{w_2}\ x)p_2 + (\overline{w_2}\ y)q_2 + (\overline{w_2})r2.$$

Where, f is linear in the consequent parameters ($p_1$, $q_1$, $r_1$, $p_2$, $q_2$, $r_2$). In the forward pass of the learning algorithm, the least squares estimate identifies the consequent parameters. In the backward pass, the derivative of the squared error for each node output propagates backward from the output layer to the input layer. In this backward pass, a gradient descent algorithm is used to update the premise parameters.

*Layers of ANFIS structure*

The individual layers in this system are described below,

*Layer 1:*

Each input node i in this layer is an adaptive node that produces a membership grade of the linguistic label. It is a fuzzy layer, in which v and d are the input of the system. O1, i is the output of the ith node of layer l. Each adaptive node is a square node with a square function represented using the below formula,

$$U_i^1 = \mu_{Ai(x)} \quad (3)$$

Where x is the input to node i, $A_i$ is the linguistic variable associated with this node function and $\mu_{Ai}$ is the membership function of $A_i$. Usually $\mu_{Ai(x)}$ is chosen as,

$$\mu_{Ai(x)} = \frac{1}{1+(\frac{x-c_i}{a_i})^{2b_i}} \quad (4)$$

Where $\{a_i, b_i, c_i\}$ is the parameter set that changes the shapes of the membership function accordingly. The value of ai and ci can be adjusted to vary the center and width of the membership function and then bi is used to control slopes at crossover points of the next membership function. Parameters in this layer are referred to as "premise parameters".

*Layer 2:*

This layer checks the weights of each membership function, it receives input values $v_i$ from the first layer and acts as a membership function to represent fuzzy sets of respective input variables. Every node in this layer is a fixed node labeled with M and output is calculated via the product of all incoming signals. The output in this layer can be represented using the below formula,

$$U_i^1 = w_i = \mu_{Ai(x)} \times \mu_{Bi(y)}, \; i=1,2 \quad (5)$$

Which are the firing strengths of the rules? In general, any T-norm operator that performs fuzzy AND can be used as a node function in this layer.

*Layer 3:*

Every node in this layer is fixed and marked with a circle labeled with N, indicating normalization to the firing strength from the previous layer. This layer performs pre-condition matching of fuzzy rules, i.e. they compute the activation level of each rule, the number of layers being equal to several fuzzy rules. The $i^{th}$ node in this layer calculates the ratio of the $i^{th}$ rule strength to the sum of all rules firing strength. The output of this layer can be expressed as $wi$ using

Below formula,

$$U_i^3 = \overline{w_i} = \frac{w_i}{w_1+w_2} \quad (6)$$

*Layer 4:*

This layer provides output values y, resulting from the inference of rules. The resultant output is simply a product of normalized firing rule strength and first-order polynomial. The weighted output of the rule represented by the node function as:

$$U_i^4 = \overline{w_i}\, f_i = \overline{w_i}(p_i x + q_i y + r_i) \qquad i=1,2 \qquad (7)$$

Where $w_i$ is the output of Layer 3 and $\{p_i, q_i, r_i\}$ is the liner parameter or consequent parameter set.

*Layer 5:*

This layer is called the output layer which sums up all the inputs coming from layer 4 and transforms fuzzy classification results into crisp values. This layer consists of a single fixed node labeled as „Σ". This node computes the summation of all incoming signals calculated using the below function,

$$U_i^5 = \text{overall output} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (8)$$

Thus, it is observed that when the values of the premise parameter are fixed, the overall output of the adaptive network can be expressed as a linear combination of a consequent parameter. The constructed network has the same function as a Sugeno fuzzy model. The overall output of a system (z) can be expressed as in Eq. 11. It can be observed that ANFIS architecture consists of two adaptive layers, namely the first layer and the fourth layer. The three modifiable parameters $\{a_i, b_i, c_i\}$ are the so-called premise parameter in the first layer, and in the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$ about the first order polynomial. These parameters are so-called consequent parameters.

## 4. Experimental Results & Discussion

Except otherwise stated, sample analysis followed the protocols indicated in Samples Was determined of Wastewaters. Test # 2450 was used to determine total solids (TS) and volatile solids (VS). Techniques # 4500D and # 5560 were used to estimate the ammonium (NH3) VFAs. The substrates were spun for 15 minutes at 5000 rpm in an Avanti JXN-30 Series centrifuge (life science, USA) during the ammonium experiment, and the obtained liquid was employed in the test. VFA tests were performed using a Hewlett Packard gas chromatography (GCFID) system (HP 68050 series, Hewlett Packard, USA). The biogas was gathered in 500 L plastic bags (Puxin, China), as well as the CMP was determined at 25°C using Almomani's water displacement methodology. In an Agilent GC-TCD (Agilent technology, Model number 7890A, USA) equipped with a 45–60 mesh matrices molecule sieve column, the composition of biogas was measured (Sigma-Aldrich, St. Louis, MO, USA). Protein and humic acid concentrations were calculated using the process outlined in prior research. The carbon, oxygen, hydrogen nitrogen, and sulfur concentrations of the substrate were measured using a Vario CHNS analyzer (Elementar Analysensysteme GmbH, Germany).

**Chemical Substrate Biodegradability**

The Anaerobic biodegradability (ABD) of the substrate is computed as follows,

$$\%AD_{\text{biodeg}} = \frac{SM}{TM} \tag{9}$$

where TM is the theoretical methane potential of the substrate is computed as follows,

$$TM = \frac{930xC+2790xH-350xO-600xN-175xS}{C+H+O+N+S} \tag{10}$$

where C, H, O, N, and S are the percentage of carbon, hydrogen, oxygen, nitrogen, and sulfur in the substrate on a dry basis, SM is the specific methane production, and is computed as follows,

$$SM = \frac{VM}{gVS} \tag{11}$$

Where VM is the total volume of methane produced from the substrate. In the following, the performance of the method for biogas production prediction is evaluated.

$$Ab_{RE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{CMP_{\text{exp}}-CMP_{\text{cal}}}{CMP_{\text{exp}}}\right| x100\% \tag{12}$$

Where $Ab_{RE}$ is the absolute error for the CMP expected and also the computed. Fig 3 shows the performance of the absolute error rate for different temperatures according to the number of days.

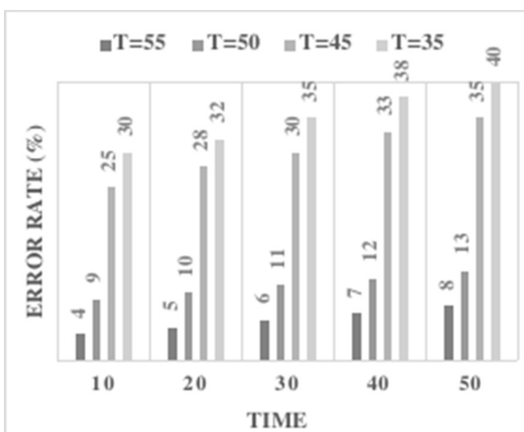


Fig.3. Error Rate Performance Analysis

The sensitivity (SEN) of each input variable in the ANFS is computed as follows,

$$SEN = \frac{\sum_{m=1}^{m=N_h}\left(\left(\left|w_{jm}^{ih}\right| \hat{A}\cdot\sum_{k=1}^{N_i}\left|w_{km}^{ih}\right|\right)^{x}\left|w_{mm}^{ho}\right|\right)}{\sum_{k=1}^{k=nI}\left\{\sum_{m=1}^{m=N_h}\left(\left(\left|w_{jm}^{ih}\right| \hat{A}\cdot\sum_{k=1}^{N_i}\left|w_{km}^{ih}\right|\right)^{x\left|w_{mm}^{ho}\right|}\right)\right\}} \tag{13}$$

where the effect of $j^{\text{th}}$ ID on the process outcome, $N_i$ is the number of input neurons, $N_h$ is the number of hidden neurons, and W is the connection weights. The letters 'i', ' $h$ ', and ' $o$ ' are corresponding to IL, HL, and OL, respectively. The counters ' $k$ ', ' $m$ ', and ' $n$ ' reflect the neurons in the IL, HL, and OL, respectively. Once the ANFS architecture was frozen, it was validated with 1116 ID new data set sets different from the training or testing data sets. The frozen ANFS is utilized after that to simulate and predict the CMP trends under unexamined circumstances.

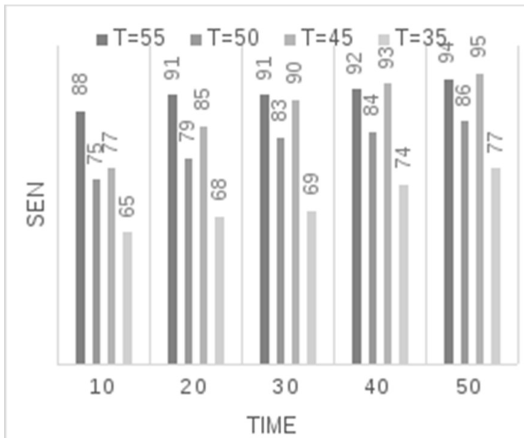


Fig.4. SEN Performance Analysis

## 5. Conclusion & Future Work

This study investigates the effects of co-digestion of agricultural solid wastes (ASWs), bovine (or) cow dung (CM), and co-digestion with chemical pre-treatment with NaHCO3 on the effectiveness of the anaerobic digestion (AD) system. An Adaptive Neuro-Fuzzy System (ANFS) technique was developed to estimate and optimize Cumulative Methane Production (CMP) from ASWs, CM, and their mixture in mesophilic and thermophilic conditions. Chemical solvents containing NaHCO3 improved the substrate's biodegradability and raised the CMP by at least 43% when compared to the untreated substrate. An ANFS model with five layers, 20 neutrons, and 50 epochs accurately predicts the CMP with 99.9% of data lying within 10% of the median measured values.

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