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Parametric Analysis and ANN Prediction of Biogas Yield from Anaerobic Biochemical Reactions of Non-Uniform Organic Substrates under Mesophilic Regime

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ABSTRACT

In an attempt to acquire affordable energy alternatives, without deviating from sustainable waste management goals, researchers in recent times have explored a number of options to expand the frontiers of research on biogas recovery. Thus, this study explores the optimization of biogas production through mesophilic anaerobic digestion (AD) of heterogeneous, non-uniform substrates. By comparing mono-digestion with co-digestion techniques, a thorough parametric analysis experimentally assessed the effects of temperature, moisture content, and pH on biogas yield. Under these intricate and fluctuating substrate conditions, an ANN model was developed to predict the biogas-yielding output from the same experimental conditions. The results of the experiment revealed different ideal temperature ranges: co-digestion produced larger yields throughout a wider range of 28.2–30.6°C, whereas mono-digestion peaked between 26°C and 28°C. Mono-digestion produced a maximum of 0.22 g/day at 26.4–29.3°C at 15% moisture content, whereas co-digestion increased production to 0.26 g/day at 28.2–31.6°C. A maximum experimental output of 0.26 g/day for co-digestion was found by pH adjustment. The ANN results showed remarkable accuracy, nearly matching pH-driven co-digestion yields (prediction: 0.27 g/day vs. experimental: 0.26 g/day) and reproducing experimental moisture-driven yields (0.22 g/day for mono-digestion). This demonstrates how well the model captures the non-linear interactions present in the digestion of various feedstock. It was further observed that biogas yield and temperature increase in *pari passu*. Biogas yield was also observed to be significant at pH values within the neutral range, indicating rich substrate content and a favourable bio-digester environment for microbial activities. Comparatively, an increase in moisture content led to a more significant biogas yield than other experimental conditions. The study unequivocally demonstrates that co-digestion is one of the best methods for optimizing biogas production from irregular substrates when operating under mesophilic conditions. An important contribution to the sustainable management of various organic wastes was achieved by validating the experimental outputs with ANN predictions, which offers a trustworthy predictive tool for maximizing AD performance.

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1. Introduction

The increasing global demand for renewable energy sources has intensified research into biogas production from organic substrates. The recovery of biogas via anaerobic disintegration of organic feeds is a conventional technique that is necessary for migration towards a sustainable energy approach [1-3]. The sequence involves chemical and biological disintegration of decomposable feeds by microbes in an oxygen-free environment, generating biogas which mainly comprises CH_4, CO_2, and other trace gases. The efficiency of this process is strictly dependent on the nature of organic feeds, which are often available on a daily basis for either mono-digestion or co-digestion processing approaches [4, 5].

Mono-digestion in this context implies decomposition of a single organic feed, whereas co-digestion relates to the decomposition process of diverse organic feeds, which, via synergistic conditions, can boost the rate of biogas yield. On the other hand, biogas-yielding capacity from a typical feedstock is determined by quantifying the amount of biogas generated under specified conditions [6, 7]. Mono-digestion normally integrates single organic feeds such as agricultural residues, food waste, or manure, whereas co-digestion dwells on the combination of diverse organic inputs, such as food waste with agricultural by-products [8, 9].

A number of investigations have been carried out in recent times to examine the complex biological breakdown of organic matter by microorganisms and the chemical reactions at play during anaerobic digestion of organic feedstocks, during which biogas evolves. For example, an experimental approach in addition to Response Surface Methodology (RSM) was adopted by Osei-Owusu *et al.,* [10] to determine the interactions between human excreta (HE), food leftovers (FLO), and kitchen residue (KR) and the energy output in terms of biogas. Unlike the methane (CH_4) yield from co-digesting these substrates at different ratios, it was observed that the sample denoted R9, with over 78.8% HE, 11.8% FLO, and 9.4% KR, yielded the highest methane rate of 764.79 ml/gVS and a synergistic index of 3.26. The RSM plot indicated that CH_4 and biogas yield increased with increasing proportions of HE and KR but decreased as the proportion of FLO in the substrate mix decreased. Locally sourced biochar (LSB) was added to food waste (FW) and cattle rumen contents (CRC), which were anaerobically co-digested in a cylindrical container for 36 days, with biogas yield determined via water displacement in an inverted cylinder [11].

The co-digestion sequence was also integrated into the Cone model, First-order kinetic model, and modified Gompertz model to determine the best fit. The peak biogas yield occurred on day 16 with over 0.7244 ml/gVS as a result of adding 10 g of LSB to the substrate, which acted as a catalyst by degrading or adsorbing inhibitory substances for improved biogas yield. The modified Gompertz model emerged as the best fit, with the lowest variance ranging from 57.33% to 225.1% between the actual and predicted methane yields and R^2 values ranging from 0.913 to 0.976.

Ikpe *et al.,* [12] co-digested waterleaf with cow dung (WCD), waterleaf with food waste (WFW), food waste with cow dung (FWCD), as well as co-digestion of these three sets of feedstocks in a batch experiment that lasted for 50 days. From the experimental outcome, WCD yielded an average biogas of 31%, with pH of 7.2 and a Carbon-to-Nitrogen (C/N) ratio of 29; WFW yielded an average biogas of 25%, with pH of 7.2 and a C/N ratio of 28. However, FWCD yielded an average biogas rate of 34%, with pH of 7.1 and a C/N ratio of 30, while co-digestion of the entire feedstocks yielded 46%, with pH of 7 and a C/N ratio of 32. It was observed that the process temperature played a key role in the co-digestion process.

Non-uniform mixing ratios of rice straw, cow dung, and piggery dung were co-digested by Ona and Agogo [13], with initial total solids of 20% for biogas production. The result indicated 36 L/kg as the highest cumulative biogas produced in 40 days via co-digestion of rice straw with pig dung in a ratio of 1:1. Furthermore, cumulative biogas yields of 33, 32, and 29 L/kg were produced from co-digestion of rice straw with pig dung in the ratio of 1:2 and rice straw with cow dung in the ratios of 1:1 and 1:2. The findings revealed that the higher biogas yield from rice straw with pig dung co-digestion was due to a better C/N ratio. In addition, co-digestion was observed to yield higher biogas rates compared to mono-digestion.

Ofon *et al.,* [14] co-digested food waste with pig dung, poultry droppings, and goat dung in a fixed ratio of 1:1, under thermophilic temperature conditions of 35 °C in a batch process of 40 days. These feedstocks yielded cumulative biogas quantities of 418 mL/g VS, 408 mL/g VS, and 319 mL/g VS, which were much higher than biogas recovered from mono-digestion of the same quantity and ratio of feedstock. The rate of biogas yield was determined by Szaja *et al.,* [15] in a batch experimental process at a temperature of 37 °C, using samples S1, S2, S3, and S4, which represented substrates including mono-digestion of sewage sludge (SS), co-digestion of SS with 1.5 g of orange waste, co-digestion of SS with 1 g of ice cream waste (ICW), as well as co-digestion of SS with 1 g of ICW and 1 g of orange waste. From the experimental findings, samples S3 and S4 yielded 407.6 and 401.6 mL/g VS, which were the highest, compared to samples S1 and S2 which yielded 351.3 and 344.3 mL/g VS.

In an experimental study by Oladejo *et al.,* [16], corncob pre-heated with cattle rumen was ground and separated into samples A and B using mechanical sieves of 0.30 mm and 0.45 mm aperture, and each sample was co-digested with poultry droppings to determine biogas yield. Design of experiment was generated for the co-digested samples using Central Composite Design (CCD). Operating parameters of the process, which included hydraulic retention time (HRT), process temperature, pH, total solids (TS), and volatile solids (VS), were optimized using RSM. The experimental procedures for samples A and B were 1.368 L/kg VS and 1.221 L/kg VS, with CH_4 contents of 60.44% and 57.58%. The optimized parameters for samples A and B were HRT (30 and 30 days), process temperature (40 °C and 40 °C), pH (8.0 and 6.0), total solids (12 and 4 g/kg), and volatile solids (12 and 12 g/kg), with an R^2 value of 0.9267 for sample A, indicating the accuracy of the model.

In the experimental study by Ikpe *et al.,* [17], food waste was co-digested with pig slurry in different proportions at a fixed moisture content of 1 and different masses, having mix ratios of 0.5:1, 1:1, 2:1, 2.5:1, 3:1, and 3.5:1. A fuzzy logic algorithm (FLA) was afterwards employed to optimize the process parameters. Optimal substrate pH, bio-digester temperature, HRT, and mix ratio of 7.1, 38 °C, 11, and 2:1 were obtained from the experimental procedure with cumulative biogas yield of 247 g. However, optimal substrate pH, bio-digester temperature, HRT, and mix ratio of 7.1, 40 °C, 11, and 2:1 were obtained from the fuzzy modelling, with cumulative biogas yield of 248 g.

Substrate combinations in experimental co-digestion of sawdust, banana stem, cow dung, paper waste, and rice bran were carried out by Kana *et al.,* [18]. The experimental process was modelled via Artificial Neural Network (ANN). The maximum experimental biogas yield was 10.144 L, whereas 10.280 L was obtained as the optimal biogas yield using ANN simulation, recording an increase of 8.64%. Anaerobic digestion of cow dung was experimented by Tufaner *et al.,* [19] in an integrated microbial electrolysis cell and anaerobic digestion (MECAD) system. ANN and an adaptive neuro-fuzzy inference system (ANFIS) were employed to model and optimize the input parameters (TS, VS, pH, oxidation–reduction potential (ORP), HRT, and organic loading rates (OLR)). For the testing dataset and overall dataset, R^2 values of 0.9844 and 0.9760 with biogas yielding rates of 171 mL/day and 204 mL/day were obtained using the ANN model. However, R^2 values of 0.9811 (testing) and 0.9774 (overall), with biogas recovery of 188 mL/day and 198 mL/day, were obtained using the ANFIS model.

Similarly, Machineni and Anupoju [20] integrated an ANN model into a particle swarm optimization (PSO) algorithm to simulate the anaerobic digestion process to maximize biogas yield from sweet sorghum bagasse (SSB). An R^2 value of 0.995 was obtained from the ANN-PSO model. The integration of ANNs into this analysis allows for the modelling of complex relationships between substrate characteristics, operational parameters, and biogas yield, thereby facilitating more accurate predictions and optimization strategies [21, 22].

The theoretical framework for analyzing biogas yield using Artificial Neural Networks (ANNs) is grounded in machine learning principles. ANNs are computational models inspired by biological neural systems, capable of recognizing patterns and making accurate predictions from input data [23, 24]. In the context of biogas production, ANNs can be trained with historical mono-digestion and co-digestion data that incorporate key variables such as substrate composition, temperature, pH, moisture content, and hydraulic retention time.

The application of ANNs is particularly advantageous because they can capture the non-linear interactions and multi-variable relationships that characterize anaerobic digestion (AD) processes [25]. Traditional statistical methods often struggle to adequately represent the complex biochemical pathways involved in AD, especially when the system contains heterogeneous or dynamically interacting substrates [26, 27]. In contrast, ANNs can model these relationships without relying on overly restrictive assumptions, making them a powerful tool for predicting biogas production under varying operating conditions.

Given the biochemical complexity of AD, this study proposes ANN as an expert system capable of processing the variability and non-linearity of organic feedstocks during digestion. ANNs excel in this regard by providing a flexible modelling framework that can adapt to diverse datasets and enhance predictive accuracy. Several studies have demonstrated that ANN-based models can reliably predict biogas yields across different substrate combinations, loading conditions, and operational parameters [28, 29]. This capability is particularly relevant in co-digestion systems, where synergistic interactions among multiple substrates can be leveraged to optimize biogas production.

2. Methodology

Research Objectives: The primary objective is to evaluate the effects of various factors on biogas yield from mono-digestion and co-digestion processes. Specific objectives may include identifying optimal substrate combinations, determining the influence of operational parameters (e.g., temperature, pH, retention time), and assessing the interaction effects between these variables.

Selection of Organic Substrates: This involved selecting a diverse range of organic substrates for both mono-digestion and co-digestion experiments. Substrates for the mono-digestion included varieties of food wastes (beans, corn, wheat straw, yam, rice, garri, cocoyam, potatoes, plantain, semovita, fufu, amala, banana, etc.), whereas substrates for the co-digestion involved multiple food wastes and livestock manure (cow dung, pig slurry, goat manure, poultry droppings, etc.).

Anaerobic Digestion Set-up: The anaerobic digestion process was conducted in batch reactors of 70-litre capacity (see Figure 1), equipped with gas collection systems to measure biogas production, a digital pH meter, deflated bicycle tubes for biogas storage, a digital thermometer, digital pressure gauge, control valves, etc. Each reactor was inoculated with a suitable microbial consortium to facilitate the digestion process. The reactors were maintained under controlled conditions, with regular monitoring of temperature and pH to ensure optimal microbial activity. The anaerobic digestion process consisted of mono-digestion, co-digestion, mono-digestion with 15 kg water addition, and co-digestion with 15 kg water addition. During the digestion process, biogas production was monitored at regular intervals. The volume of biogas produced was recorded on a daily basis, along with other parameters such as pH, bio-digester temperature, and HRT. The biochemical reactions that occurred during the anaerobic digestion process in the bio-digester are classified as hydrolysis, acidogenesis, acetogenesis, and methanogenesis, which are as follows:

i. *Hydrolysis*: Equation 1 depicts the chemical reaction during hydrolysis, where insoluble complex organic polymers ae biochemically transformed by hydrolytic bacteria

$(Clostridium\ and\ Bacteroides)$ into soluble molecules such as long chain fatty acids, sugars, as well as amino acids:

$$\begin{gathered} Lipids \rightarrow Fatty\ acids \\ Polysaccharides \rightarrow Monosaccharides \\ Protein \rightarrow \text{Amino Acids} \\ Nucleic\ Acids\ \rightarrow Purines\ \&\ Pyrimidines \end{gathered} \tag{1}$$

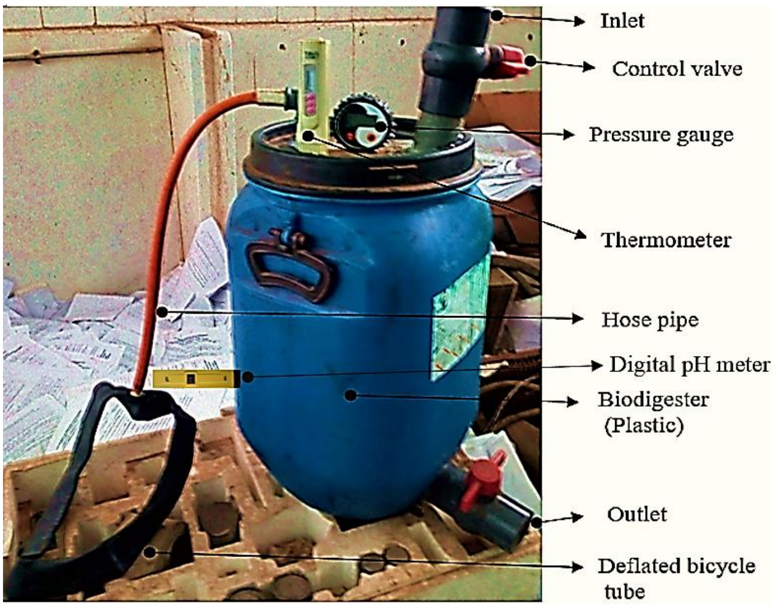


Fig. 1. Experimental set-up for anaerobic digestion

Equations (2)-(4) further elucidate the biochemical reactions that occur during hydrolysis phase, where carbohydrates, proteins and lipids transfigured to complex organic compounds.

$$\text{Carbohydrate: } Polysaccharide\ (Starch) \rightarrow Oligosaccharide \rightarrow Disaccharide \rightarrow Monosaccharide (Glucose: C_6H_{12}O_6) \tag{2}$$

$$\text{Proteins: } Proteins \rightarrow Peptone \rightarrow Polypeptide \rightarrow Oligopeptide \rightarrow Amino\ acids\ (aminoaceticacid: NH_2 - CH_2 - COOH) \tag{3}$$

$$\text{Lipids: } Tri\ palmiticacid\ glycerel\ ester \rightarrow Tri\ palmiticacid\ + Glycerol \tag{4}$$

ii. *Acidogenesis*: The biochemical reactions that occur under this phase is marked by anaerobic disintegration of hydrolysed molecules by acidogenic bacteria $(Chloroflexi, Firmicutes\ and\ Proteobacteria)$ into short chain fatty acids (alcohol, organic acids and volatile fatty acids- VFAs) as expressed in Equation 5. The reaction is noticed to also occur via biochemical disintegration of glucose by acidogenic bacteria into acetic acid in Equation 6 and propionate in Equation (7).

$$C_6H_{12}O_6 \rightarrow 2C_2H_5\,OH + 2CO_2 \tag{5}$$

$$C_6H_{12}O_6 \leftrightarrow 3CH_3\,COOH \tag{6}$$

$$C_6H_{12}O_6 + 2H_2 \leftrightarrow C_2H_5\,COOH\ OH + 2H_2O \tag{7}$$

iii. *Acetogenesis*: Equations (8) and (9) depicts the biochemical reactions for the degradation of VFAs and other organic acids by acetogenic bacteria ($Syntrophomonos\ wolfie$, $Syntrophobacter\ wolinii$, $Clostridium, spp.$, $Streptococcus\ anaerobes$ and $Lactobacillus$), yielding acetic acids, CO_2 and hydrogen gas:

Propionic Acid

$$CH_3CH_2COOH \rightarrow 2H_2O \rightarrow CH_3COOH + CO_2 + 3H_2 \tag{8}$$

Butyric Acid

$$CH_3(CH_2)_2COOH \rightarrow 2H_2O \rightarrow 2CH_3COOH + 2H_2 \tag{9}$$

The anaerobic biochemical reaction that involves degradation of propionate to acetate during the process of acetogenesis is given by Equation (10).

$$CH_3CH_2COO^- + 3H_2O \leftrightarrow CH_3COO^- + H^+ + HCO_3{}^- + 3H_2 \tag{10}$$

The various biochemical reactions resulting from acetogenic phase, and driven by acetate are glucose degradation, ethanol as well as bicarbonate which are stated in Equations (11)-(13).

$$C_6H_{12}O_6 + 2H_2O \leftrightarrow 2CH_3COOH + 2CO_2 + 4H_2 \tag{11}$$

$$CH_3CH_2OH + 2H_2O \leftrightarrow CH_3COO^- + 2H_2 + H^+ \tag{12}$$

$$2HCO_3{}^- + 4H_2 + H^+ \leftrightarrow CH_3COO^- + 4H_2O \tag{13}$$

iv. *Methanogenesis*: The biochemical reactions responsible for methanogenesis, a phase that biogas evolves is given by Equations 14-16, which includes the products, by products and intermediates. This phase is characterized by anaerobic degradation of products from previous stages by Methanogenic archaea ($Methanosarcina$, $Methanobacterium, Methanococcus\ and\ Methanobacillus$) into biogas:

$$\underset{(Acetic\ acid)}{CH_3COOH} \rightarrow \underset{(Methane)}{CH_4} + \underset{(Carbon\ dioxide)}{CO_2} \tag{14}$$

$$\underset{(Ethanol)}{2CH_3CH_2OH} + \underset{(Carbon\ dioxide)}{CO_2} \rightarrow \underset{(Methane)}{CH_4} + \underset{(Acetic\ acid)}{2CH_3COOH} \tag{15}$$

$$\underset{(Carbon\ dioxide)}{CO_2} + \underset{(Hydrogen)}{4H_2} \rightarrow \underset{(Methane)}{CH_4} + \underset{(Water)}{2H_2O} \tag{16}$$

Collection of Data and Pre-processing: Having obtained relevant data from the experimental sequence, computational interpolation of the data was formatted into a structured layout for the ANN modelling. The procedure commenced by normalizing the data obtained from the experimental tests to avert weight variations, while making sure that the input components were equalized, which is vital for the effective outcome of the ANN model. Misrepresented values were addressed through imputation techniques, while outliers were identified and managed to avoid skewing the results. A dataset of 120 samples was generated and split into three subsets by randomly selecting from the experimental data, therefore forming the training, testing, and validation sets.

ANN Model Development: The next step involved the development of the ANN model. A feedforward neural network architecture was adopted for developing the ANN model, consisting of three layers, including three input neurons, ten hidden neurons, and one output neuron (see Figure 2). The input layer included parameters such as pH, bio-digester temperature, and HRT, while the output layer represented the biogas yield. The ANN profile was modelled by splitting the input data into three distinct trials (training, validation, and testing sets) in the order of 60%, 25%, and 15%.

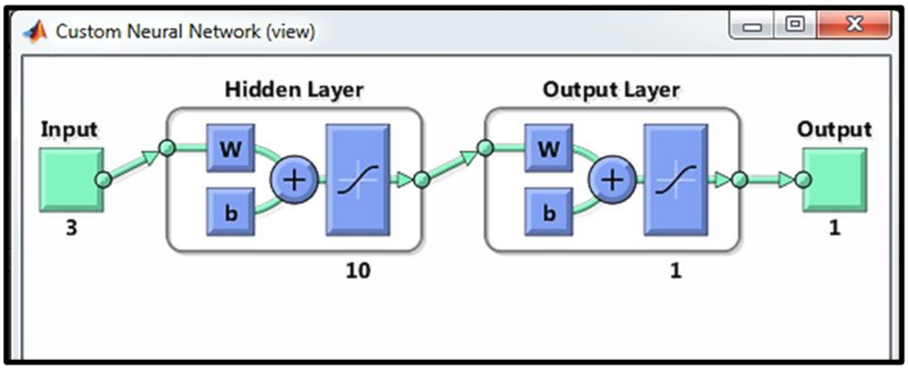


Fig. 2. ANN architecture for modelling biogas yield

Training and Validation: The ANN model was trained using a portion of the dataset, with the remaining data reserved for validation. The training process involved adjusting the weights of the network through backpropagation, minimizing the error between predicted and actual biogas yields. A neural network performance plot depicting the sequence of training, validation, and testing is shown in Figure 3, and no signs of overfitting were observed in the plot. A similar trajectory was also noted on the training, validation, and testing curves since the raw data were normalized prior to being employed in the analysis. Lower mean square error (MSE) is the primary criterion used to determine the accuracy of the trained network. Therefore, an error value of 4.7441e-05 at epoch 8 signifies a network capable of predicting biogas yield from mono-digestion, co-digestion, and other anaerobic conditions in the batch process. The training state, which clearly indicates the gradient function, training gain (Mu), as well as the validation check of the biogas yield, is shown in Figure 4.

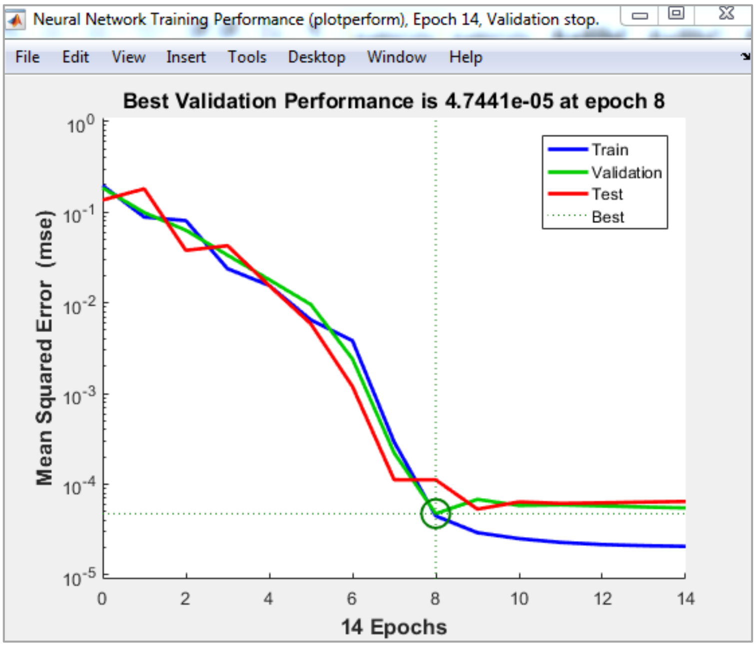


Fig. 3. ANN trained performance curve for Predicting biogas yield

After being trained on a dataset, the ANN determines the relative contributions of individual neurons to the error by means of backpropagation. Each selected neuron's relative contribution to the error is demonstrated through the neural network's learning of the loss function's gradient. Figure 4 displays the estimated gradient value of 0.0021254, indicating that the error contributions of each selected neuron are negligible. The algorithm that trains the neural network uses momentum gain (Mu) as its control parameter. The training gain must be less than one (1), while a Mu of 1.0e-14 (see Figure 4) indicates a network capable of predicting biogas yield with minimal errors.

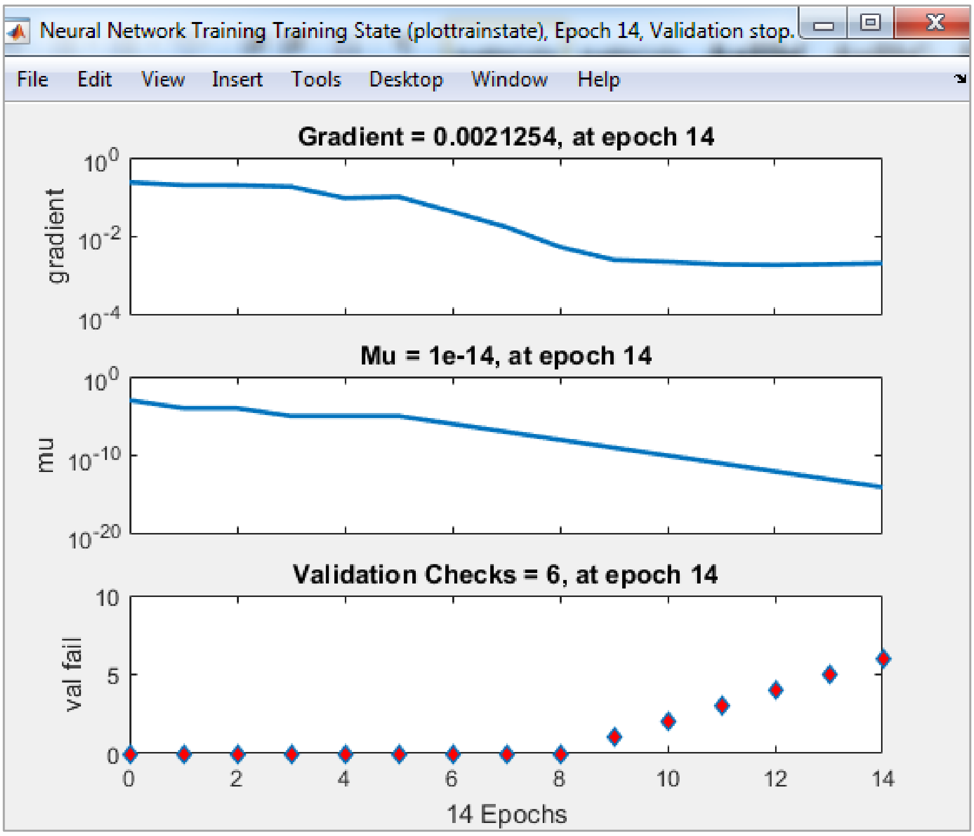


Fig. 4. ANN training state for predicting biogas yield

3. Results and discussion

The regression plot, which depicts the correlation between the input variables (pH, bio-digester temperature, and HRT) and the targeted output during training, validation, and testing of the ANN model developed for the mono-digestion process, is illustrated in Figure 5. The same procedure was carried out for co-digestion, mono-digestion with 15 kg water content, and co-digestion with 15 kg water content, as presented in Table 1. The results were also analyzed to reflect biogas yield from the experimental process for mono-digestion, co-digestion, mono-digestion with 15 kg water content, and co-digestion with 15 kg water content. Comparative analyses were conducted to assess the impact of substrate combinations on biogas production.

The training dataset is the subset of data used to train the model, allowing it to learn the underlying patterns and relationships inherent in the data. In a regression context, the training data consists of input-output pairs, where the model adjusts its weights and biases through optimization algorithms, typically gradient descent. The performance of the ANN model was evaluated from the training dataset using MSE. The validation dataset serves as an intermediary between the training and testing datasets. It was employed during the model development phase to fine-tune hyperparameters and make decisions regarding model architecture. On the other hand, the test dataset is the final evaluation set, used to assess the model's performance after training and validation are complete.

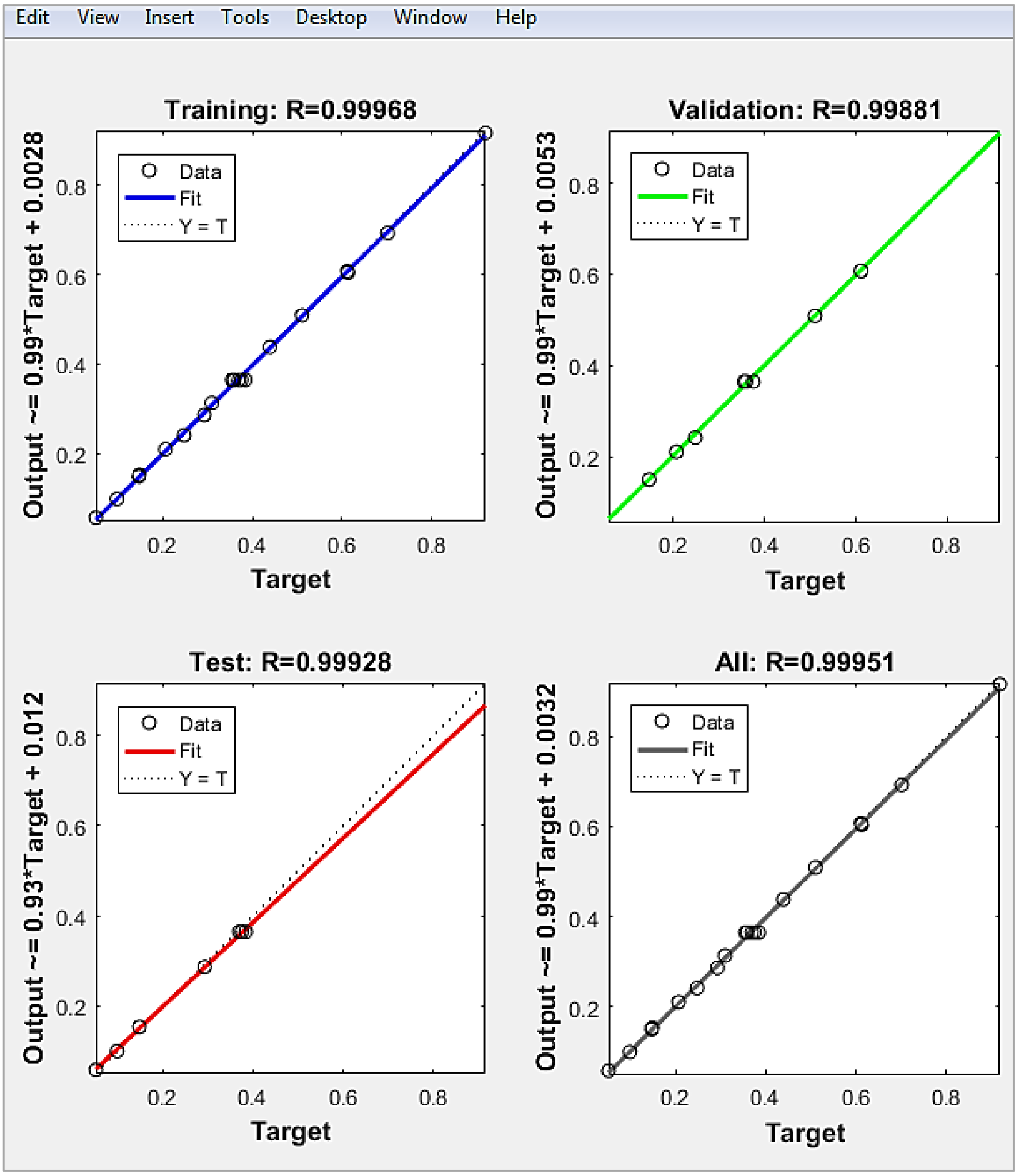


Fig. 5. Regression plot illustrating the training, validation and testing for mono-digestion

Table 1
Summary of R-values from ANN regression models for anaerobic digestion process

Anaerobic Digestion Process	R-values from ANN Regression Models			
	Training	Validation	Test	All
Mono-digestion	0.99968	0.99881	0.99928	0.99951
Co-digestion	0.99972	0.99983	0.99924	0.99943
Mono-digestion (15kg water content)	0.99953	0.99752	0.99820	0.99842
Co-digestion (15kg water content)	0.99984	0.99973	0.99975	0.99974

The "All" dataset on the predicted ANN regression model, which is typically the aggregation of training, validation, and test datasets, has R-values of 0.99951, 0.99943, 0.99842, and 0.99974 for mono-digestion, co-digestion, mono-digestion with 15 kg water content, and co-digestion with 15 kg water content, respectively. The R-value serves as a reliable indicator of predictive accuracy, as it reflects the correlation between predicted and actual outcomes without being overly influenced by the model's complexity. In this case, the R-values obtained for the previously stated anaerobic digestion processes are considered "high" and very close to one (1), representing the consistency of the ANN model predictions across different subsets of data.

Therefore, a model that maintains a high R-value across validation sets is likely to be robust and reliable, as shown in Table 1. Figure 6, which utilized mono-digestion in the substrate mix, depicts the experimental and ANN-predicted biogas yield and bio-digester temperature from mono-digestion on a daily basis. From the plot, the curve for biogas yield maintains a significant correlation between actual (experimental) and predicted (ANN model) values, with minimum, maximum, and average values of 0.03, 0.22, and 0.1321 g, and 0.03, 0.22, and 0.1335 g, respectively. Although the bio-digester temperature curve does not exactly mirror the biogas yield curve due to differences in the dataset, it is observed that variations in bio-digester temperature, with minimum, maximum, and average values of 26, 28, and 27.5 °C, influence biogas yield. Therefore, bio-digester temperature and biogas yield generally increased and decreased in pari passu, which correlates with the findings of [30].

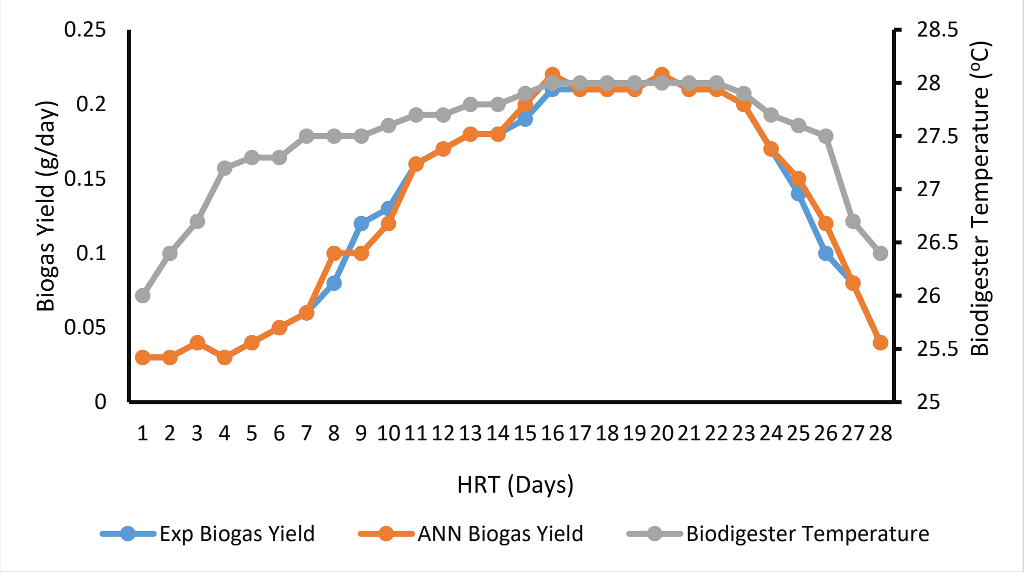


Fig. 6. Experimental and ANN predicted biogas yield and bio-digester temperature from mono-digestion per day

Compared to the results of mono-digestion in Figures 6 and 7, which utilized co-digestion in the substrate mix, illustrates an increase in the actual (experimental) and predicted (ANN model) biogas yield as well as bio-digester temperature. This included minimum, maximum, and average biogas yields of 0.03, 0.26, and 0.16 g/day, as well as 0.02, 0.27, and 0.17 g/day for the ANN predictions, with corresponding bio-digester temperatures of 28.2, 30.6, and 29.7 °C. Moreover, the plot maintained a high correlation between the actual (experimental) and predicted (ANN model) biogas yields, with bio-digester temperature increasing and decreasing in pari passu.

As illustrated in Figure 8, experimental and ANN-predicted biogas yields obtained from 15 kg water addition in the same mono-digested substrate mix included minimum, maximum, and average values of 0.04, 0.24, and 0.143 g/day, as well as 0.039, 0.24, and 0.142 g/day for the ANN predictions, with corresponding bio-digester temperatures of 26.4, 29.3, and 28.4 °C.

However, in Figure 9, experimental and ANN-predicted biogas yields obtained from 15 kg water addition in the same co-digested substrate mix included minimum, maximum, and average values of

0.03, 0.37, and 0.212 g/day, as well as 0.02, 0.37, and 0.214 g/day for the ANN predictions, with corresponding bio-digester temperatures of 28.2, 33.6, and 31.6 °C.

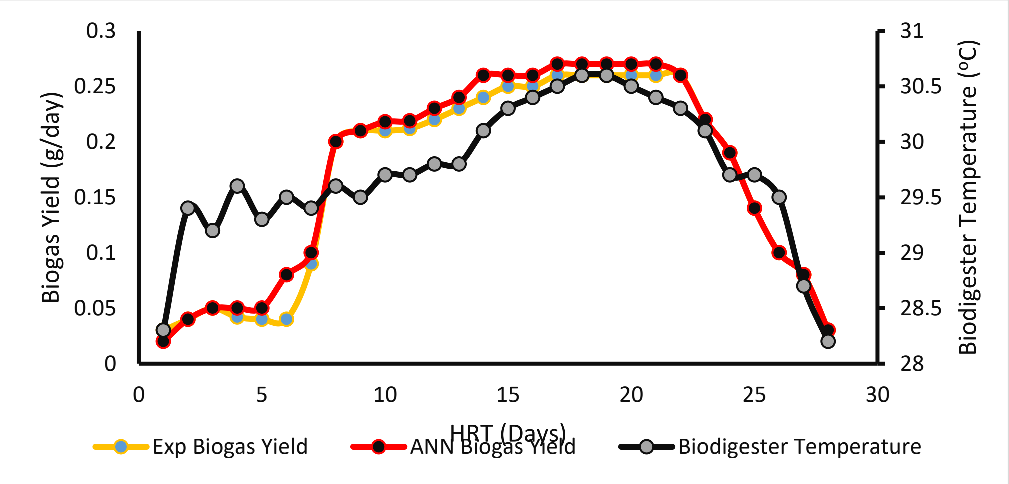


Fig. 7. Experimental and ANN predicted biogas yield and bio-digester temperature from co-digestion per day

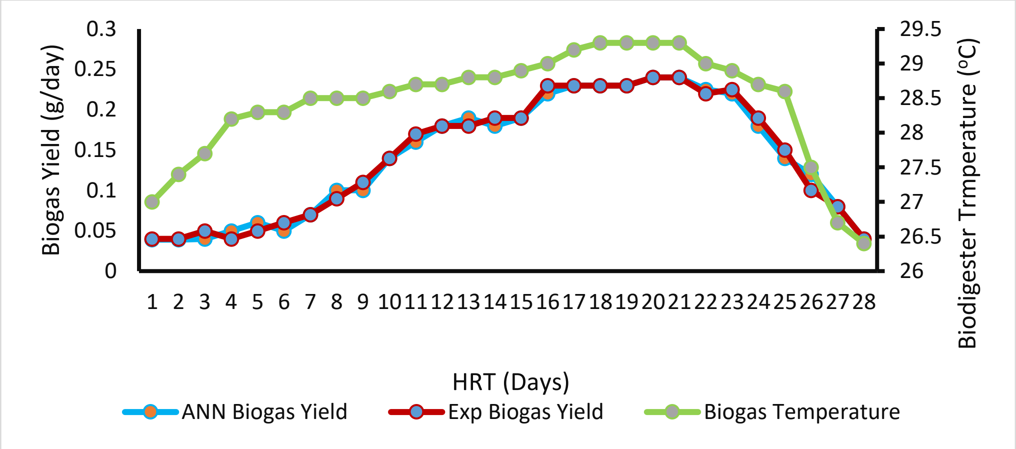


Fig. 8. Experimental and ANN predicted biogas yield and bio-digester temperature from mono-digestion (with 15 kg of water addition to substrate mix)

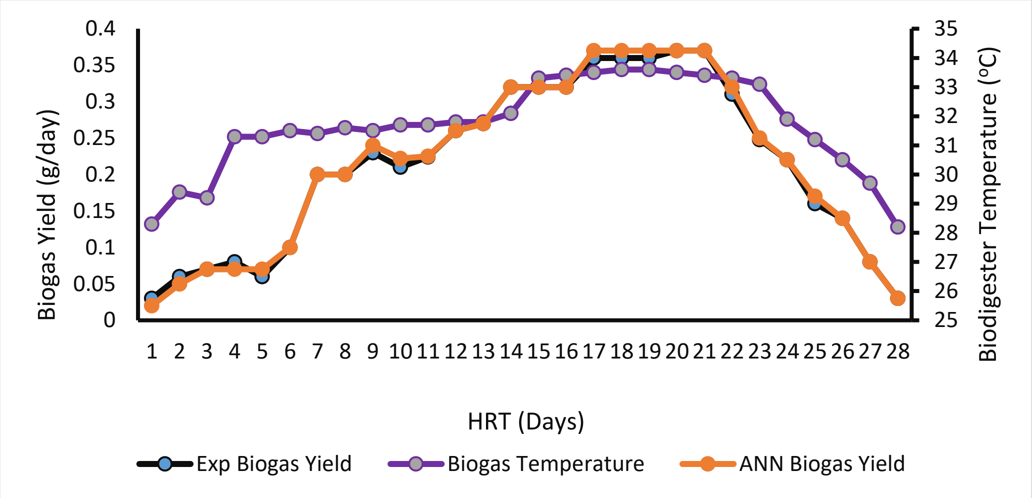


Fig. 9. Experimental and ANN predicted biogas yield and bio-digester temperature from co-digestion (with 15 kg of water addition to substrate mix)

Figure 10 represents the plot of experimental and ANN-predicted biogas yield and their corresponding pH and bio-digester temperature, obtained from mono-digestion of organic feedstocks highlighted in the methodology of this study. From the substrate mix, the maximum experimental and ANN-predicted biogas yield was 0.22 g/day, with corresponding pH and bio-digester temperature of 6.9 and 28 °C. For co-digestion, as represented in Figure 11, the maximum experimental and ANN-predicted biogas yield was 0.26 and 0.27 g/day, with corresponding pH and bio-digester temperature of 6.9 and 30 °C.

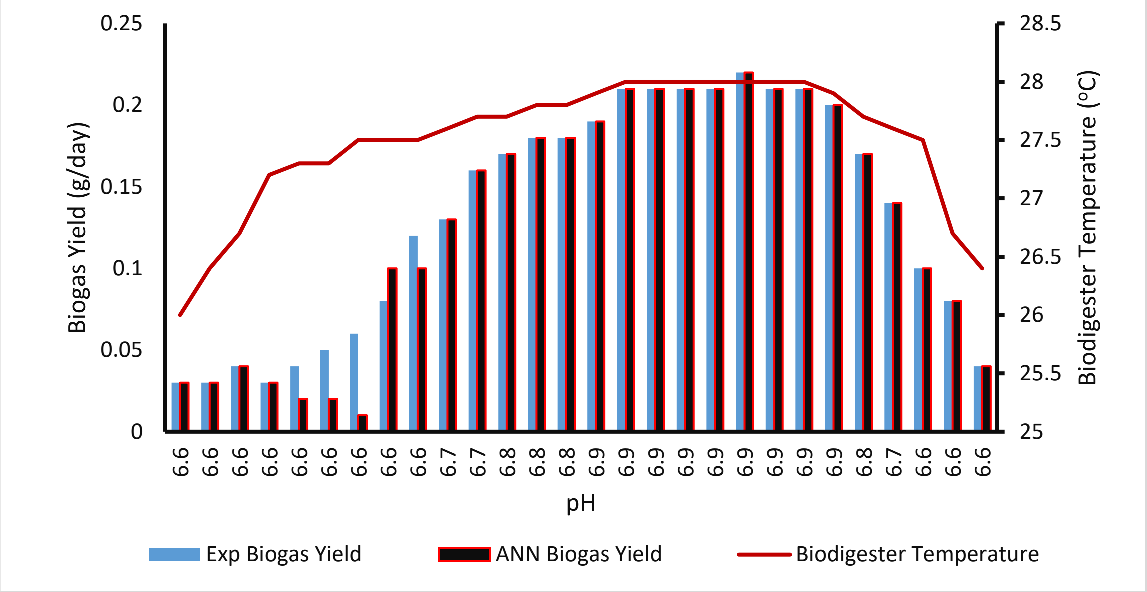


Fig. 10. Experimental and ANN predicted biogas yield and bio-digester temperature per substrate pH from mono-digestion

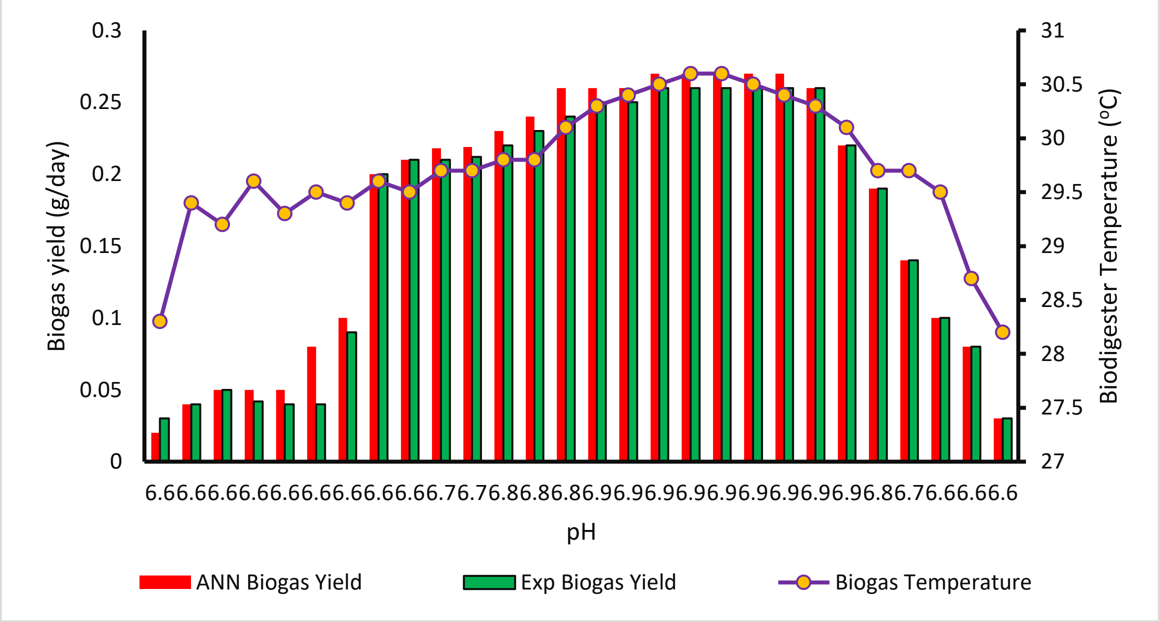


Fig. 11. Experimental and ANN predicted biogas yield and bio-digester temperature per substrate pH from

However, for mono-digestion of the same organic substrates with 15 kg water addition, as shown in Figure 12, the maximum experimental and ANN-predicted biogas yield was 0.24 g/day, with corresponding pH and bio-digester temperature of 6.9 and 29.3 °C. Furthermore, for co-digestion of the same organic substrates with 15 kg water addition, as shown in Figure 13, the maximum experimental and ANN-predicted biogas yield was 0.37 g/day, with corresponding pH and bio-digester temperature of 6.9 and 33.6 °C.

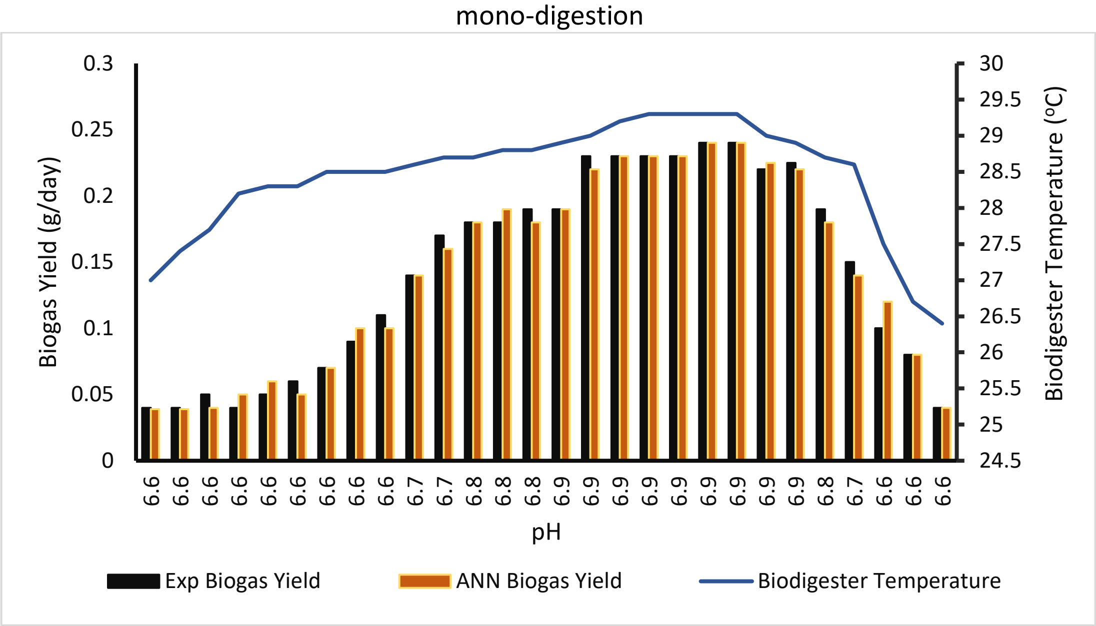


Fig. 12. Experimental and ANN predicted biogas yield and bio-digester temperature per substrate pH from mono-digestion (with 15 kg of water)

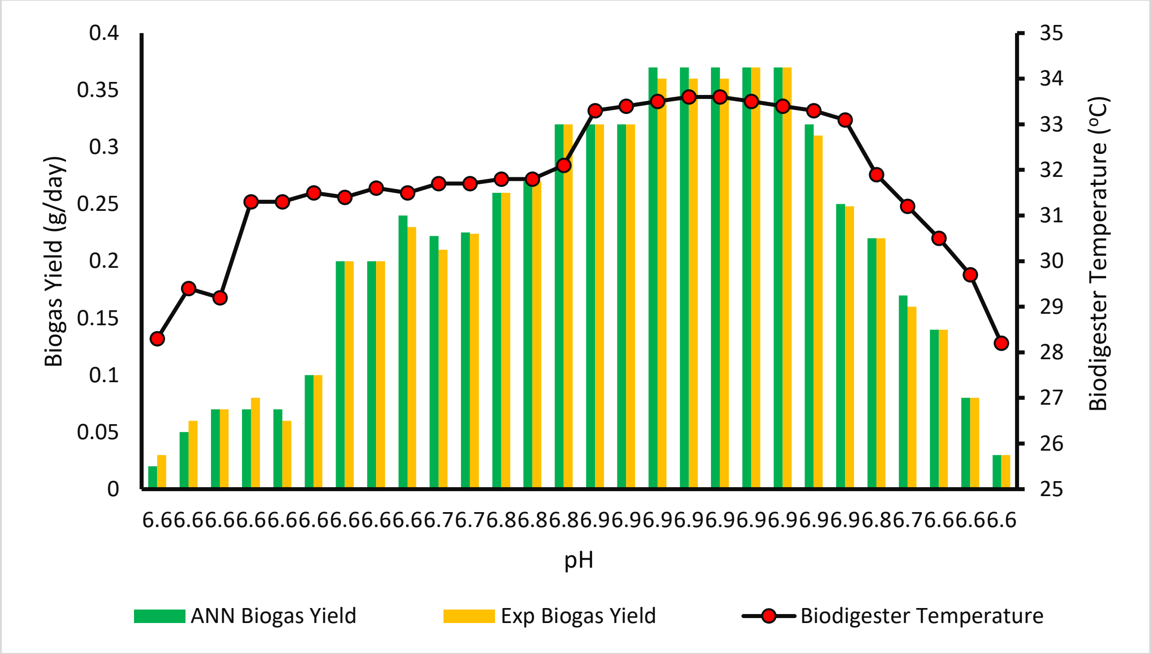


Fig. 13. Experimental and ANN predicted biogas yield and bio-digester temperature per substrate pH from co-digestion (with 15 kg of water)

The role of pH during the anaerobic digestion process is indispensable, owing to its influence on microbial activity and metabolic pathways. Therefore, the ideal pH for methanogenic bacteria to thrive in an anaerobic environment typically falls between 6.8 and 7.2, a stage at which organic feeds are transformed into biogas. The pH of 6.9 obtained from the batch experiments in this investigation falls within this range, as also reported by Ikpe *et al.,* [31]. Deviations from this range can hamper microbial activity and inhibit biogas yields. In this scenario, the addition of water to the organic mix may alter the pH level, thereby enhancing the overall digestion process. From the experimental procedure, mono-digestion, which involved a single type of substrate feed, presented minimal challenges in maintaining optimal pH.

However, for co-digestion, which involved the combination of multiple organic substrates, high variability was observed in the pH values, mainly due to the non-uniform characteristics of the feedstocks [32]. The adoption of ANN expert models for predicting the rate of biogas yield can be more complex as a result of this variability, since the training data must contain a wide range of pH levels to ensure accurate predictions.

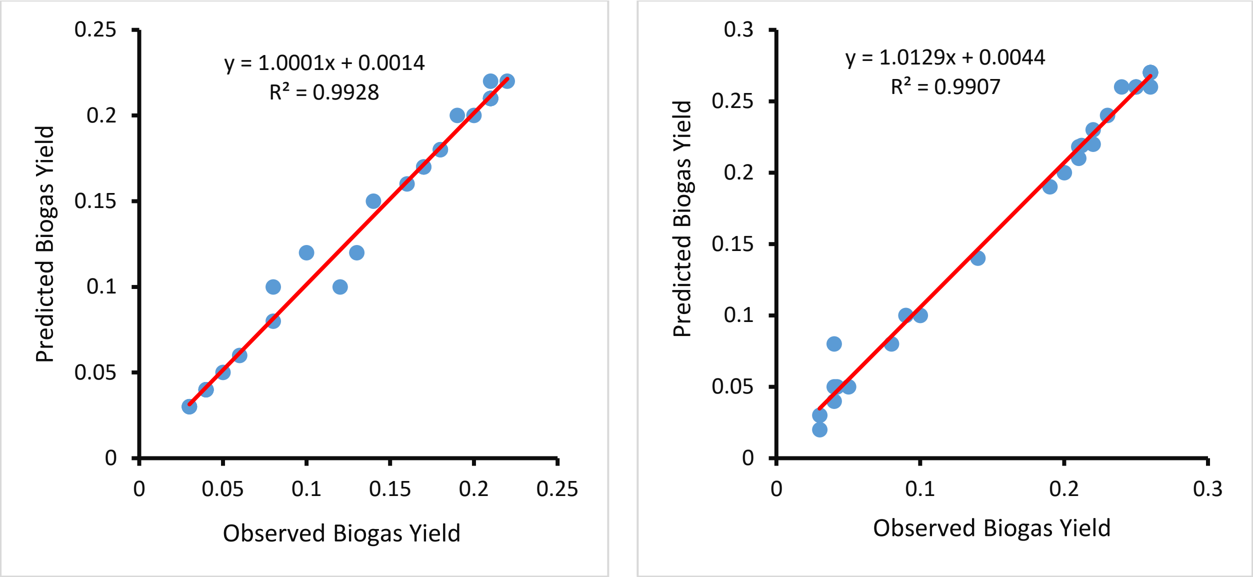
Temperature is another pivotal factor influencing the anaerobic digestion process. During anaerobic digestion of organic feeds for biogas production, the associated microbiome exhibits variable temperature optima, typically classified as the psychrophilic regime (below 20 °C) and mesophilic regime (26–40 °C), which supports stable microbial activity. On the other hand, the thermophilic regime (50–60 °C) enhances biodegradation of feed matter for improved biogas generation.

The bio-digester temperatures obtained from the batch experiments in this study are within the mesophilic regime, consistent with the findings of Eronmosele *et al.,* [33] and Ikpe *et al.,* [34]. The ANN models were adequately trained to simulate the bio-digester temperature and pH datasets, which impacted the rate of digestion and, consequently, the biogas yield across multiple digestion scenarios.

The adoption of ANN tools in predicting biogas production rates from anaerobic digestion of organic substrates has garnered immense attention in recent years. The R-squared (R^2) values derived from regression analyses in this study are vital indicators of the predictive accuracy of these models. R^2 is a statistical measure that represents the proportion of variance in a dependent variable that can be explained by an independent variable. Therefore, an R^2 value close to 1 signifies a high correlation between the predicted and observed values, suggesting that the model captures a large portion of the variability in the data.

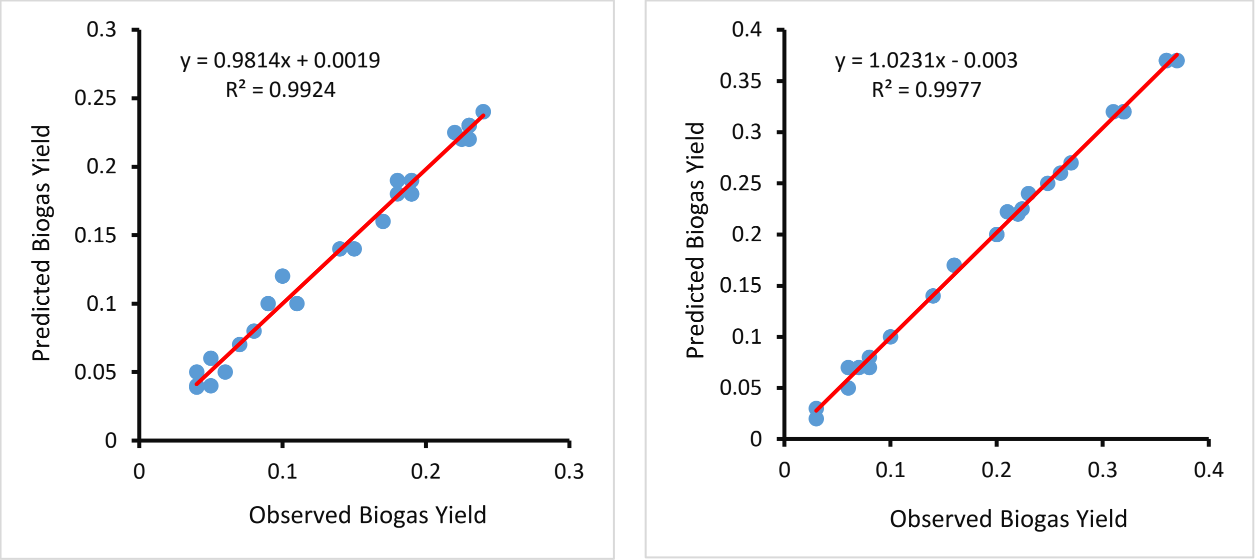
However, lower R^2 values signify a weaker relationship and suggest that the model may not effectively capture the intricacies of unknown data. In this study, R^2 values of 0.9928 and 0.9907, derived from mono-digestion and co-digestion (see Figure 14a and b), imply that the ANN models adequately predicted the complexities of biogas yield from single and mixed organic substrates. This is significant because co-digestion usually involves the combination of diverse feedstocks, which can complicate yield predictions. The high R^2 values indicate that the ANN models can demystify these combinations, generating resourceful data for maximizing biogas yields.

The R^2 values of 0.9924 and 0.9977 for mono-digestion and co-digestion with 15% water added to the substrate feeds (see Figure 14c and d) further highlight the models' predictive capacity. The addition of water can influence viscosity and microbial activity in the anaerobic bio-digester, potentially improving biogas yield. The high R^2 values in these scenarios indicate that the ANN models are adept at simulating the impact of water addition, thereby improving their usability in real-world scenarios. These R^2 values, which indicate a high level of predictive accuracy, signify approximately 99% accuracy in predicting biogas yield across diverse co-digestion scenarios. In other words, such high R^2 values are representative of robust models that can reliably predict biogas yield under varying conditions.



a) Regression plot for mono-digestion

b) Regression plot for co-digestion



c) Regression plot for mono-digestion (15 kg MC)

d) Regression plot for co-digestion (15 kg MC)

Fig. 14. Regression plots

4. Conclusion

The exceptionally high R^2 values of 0.9928, 0.9907, 0.9924, and 0.9977, all close to one (1), demonstrate that the ANN models achieved remarkable accuracy in predicting biogas yields across different digestion conditions. The strong correlation established between the predicted and observed data further accentuates the predictive capacity of the ANN expert models, indicating that the complex, nonlinear biochemical interactions between the organic feeds are adequately accounted for to improve biogas recovery.

These findings illustrate the adequacy of employing machine learning to train complex datasets and to simplify the ANN modeling sequence, which is capable of optimizing the complex biochemical disintegration within the organic feeds. Therefore, the accuracy of the ANN models developed through this sequence unravels the complex dynamics involved in biodegradable feeds, fine-tunes the interplay between operational parameters, boosts model efficiency, and supports data-driven decision-making in bio-digester design and performance.

Hence, the application of ANN as a smart modeling tool in biogas prediction represents a simplified route for achieving an efficient and sustainable bioenergy scheme, improving biogas recovery at both domestic and commercial scales, within local and global contexts.

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Conflicts of Interest

The authors declare no conflicts of interest.

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