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Prediction Modelling to Enhance Anaerobic Co-digestion Process of OFMSW and Bio-flocculated Sludge Using ANN

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ABSTRACT

Artificial neural networks (ANNs) simulate an anaerobic co-digestion process of Organic Fraction of Municipal Solid Waste (OFMSW) and bio-flocculated sludge for a mesophilic lab-scale semi-continuous feed reactor. The operational, substrate quality and process control parameters such as Organic Loading Rate, Hydraulic Retention Time, pH, VFA/Alkalinity ratio and Total Solids are input variables and methane yield and Volatile Solids removal are outputs for ANN modelling. The lab-scale experimental results are used to develop a prediction model using fitting application for ANN. The network architecture was optimized to achieve accurate predictions, resulting in a 5-19-2 architecture for methane yield and a 5-17-2 architecture for $\%VS_{removal}$. The training was performed using the Bayesian Regularization (trainbr) algorithm, leading to high coefficients of determination (R^2) of 0.953 and 0.978 for methane yield and $\%VS_{removal}$, respectively. The results demonstrate the effectiveness of neural network-based modelling in capturing complex relationships within the methane yield process, facilitating accurate prediction of crucial output parameters.

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INTRODUCTION

Large amounts of solid waste from the community are produced as a result of urbanization and population growth. 40–50% of the municipal garbage produced in urban areas is organic wet waste. Seasons, home size, economic level, and population all have an impact on the fluctuation in the composition of MSW waste streams (Intharathirat et al., 2015). Composting, vermicomposting, anaerobic digestion etc. are all methods of handling organic waste. The most common practice, landfilling, leads to greenhouse gas emissions from the landfill.

With an upward trend in population, sewage production will increase in the coming decades. As a by-product, Sludge is produced from the treatment of sewage to satisfy discharge norms (Abdel Daiem et al., 2021a). The recognized sewage treatment method is Up-flow Anaerobic Sludge Blanket (UASB) based because it has a low operating and maintenance cost. While UASB requires post-secondary treatment to meet sewage discharge norms before releasing the treated sewage into the environment. Sludge with very low porosity and a smaller quantity of solids to treat are produced during the secondary treatment process post-UASB.

The OFMSW and other forms of organic waste are treated using the historically popular,

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efficient, sustainable and affordable anaerobic digestion technique. This idea of producing waste-to-energy is very common. The path to optimum biogas yield in anaerobic digestion is determined by several complex processes with multiple phases including environmental (temperature, pH); process (volatile fatty acids and ammonia); physical and chemical characteristics of the substrate (volatile solids, COD); complex chemical structure and nutrient. For optimum biogas yield, several of these variables are required to be monitored and controlled. pH, Organic Loading Rate (OLR) and Hydraulic Retention Time (HRT) are variables that have a big impact on the anaerobic digestion process (Momčilović et al., 2018). Alternative anaerobic co-digestion of OFMSW with other organic waste is useful to get high amounts of biogas when the elemental composition of waste treated in anaerobic mono digestion is not conducive for producing sufficient to obtain the right quantity of biogas. The advantages of anaerobic co-digestion which is the concurrent digestion of two or more substrates depend on the synergy among the co-substrates because of their complementary properties (García-Gen et al., 2014). In several studies, a variety of co-substrates are used with OFMSW to maximise the generation of methane gas. Bio-flocculated sludge produced from a secondary settling tank (post-UASB) is the prominent co-substrate for the anaerobic digestion of OFMSW (Shroff & Shah, 2023).

Anaerobic digestion is a complex process and with the involvement of biomass kinetics, it is not possible to always define a mathematical equation driving a specific reaction (Yang et al., 2017). Artificial intelligence (AI) techniques such as Artificial Neural Networks (ANN) can be excellent alternatives to predict and optimize such complex processes like anaerobic digestion (Le et al., 2019). To estimate, predict and modelling between statistical data and analytical data, ANN is the most powerful modelling application that provides a quick and cost-effective replacement for traditional analytical methods (Nguyen et al., 2020, Betiku et al., 2015). Artificial Neural Network shows higher accuracy while the Response Surface method (RSM) predicted higher biogas yield (Dahunsi et al., 2016b).

Various studies have shown that ANN-based solutions are a reliable method for complex engineering problems. Based on earlier research, approaches and based on artificial intelligence are used to produce biogas from a mixture of municipal sewage sludge, OFMSW, and cow manure. The genetic algorithm (GA) optimization technique determined that the maximal methane output was 445.9 mL CH_4/gmVS (Saghouri et al., 2020). Chicken droppings anaerobically co-digested with pawpaw peels and optimize process parameters predicted biogas with ANN is 3875.10 (10^{-4} m^3/VS) with R^2 0.9828 which is high compared to RSM (R^2 0.9181) (Dahunsi et al., 2016a**.** When prediction of biogas from anaerobic digestion of agricultural waste (rice straw) with ANN Back Propagation model achieved R^2 0.998 which is higher compared to RSM (Sathish & Vivekanandan, 2016). The Radial Basis Function Neural Network (RBFNN) model of methane gas emission from an anaerobic pond (AP) of a palm oil mill has a 5-5-3 network architecture, the spread of 0.11, error-goals of 0.0005, R of 0.940652, and MSE of 0.003166 (Putro et al., 2020). When waste-activated sludge and wheat straw were digested together anaerobically, the MFFNN-MFO model produced extremely high correlation coefficients (0.9994) and RMSE (3.86) compared to the other models that were utilized (Abdel daiem et al., 2021b). The predicted model for traced biogas compounds H_2S and ammonia was developed using MATLAB toolbox with the determination of co-efficient (R^2) 0.91 and 0.83, respectively which helps to control, reduce and production of trace compounds in biogas (Strik et al., 2005). In bovine slurry fermentation, ANN with MLP with network 5-11-1 was the optimal choice for the estimation of methane emission (Dach et al., 2016).

The present study involves the development of the ANN as a tool for modelling, monitoring and regulating the methane yield for anaerobic co-digestion of OFMSW and bio-flocculated sludge from the lab-scale study. ANN using fitting application (fitnet) is a promising tool for development of prediction model using process parameters for effective methane yield and $\%VS_{removal}$ efficiency.

MATERIAL AND METHODOLOGY

A batch experiment was conducted using different mixing ratios of OFMSW and bio-flocculated sludge from Secondary Settling Tank (50:50, 75:25, 90:10, 0:100, 100:0). The optimum co-digestion mixing ratio from a prior batch experimental investigation is determined to be a 75:25 mixture of OFMSW and bio-flocculated sludge from SST depending on the availability of substrate and the performance of biogas yield (Shroff & Shah, 2023). In the current study, a semi-continuous flow anaerobic digester is utilised to co-digest OFMSW and bio-flocculated sludge from SST (after UASB) with a mixing ratio of 75:25 for more than 200 days. From the study period, data from 102 days are utilised in the computing and modelling of the process. Depending on the field availability of the OFMSW, small variations are made in the composition of OFMSW.

Experimental Set Up

A semi-continuous anaerobic reactor with a 10L capacity is built with an acrylic sheet. Based on wet mass, the substrate is supplied. Initially, the reactor received 7 kg of substrates. The substrate is thoroughly mixed with a stainless-steel paddle mixer driven by a 12V DC motor at low speed (intermittent mixing only). A water jacketing system with heating rods is provided to maintain the temperature of the reactor (30-35°C). Biogas produced in the reactor is quantified using the water displacement method (**Figure 1**). The biogas is routed through a NaOH solution to absorb the CO_2 gas that was produced during the anaerobic co-digestion process.

ANN Architecture and Model:

The human brain is a complicated structure with a densely linked network of basic processing units or neurons. The simplified representation of the organic nervous system is called an artificial neural network or neural network. As a potent statistical modelling technique, artificial neural networks (ANNs) are drawing more attention in the ecological sciences. An artificial neural network (ANN) is a computer learning system that uses mathematical relationships between input-output variables to discover the link between a set of defined input data and output data with a wide range of operational conditions (Ramachandran et al., 2019). When a

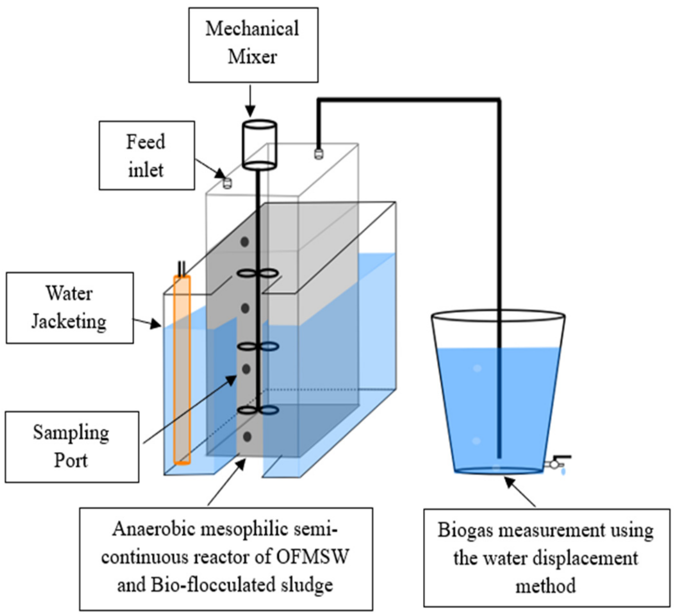


Fig. 1. Schematic diagram of the lab-scale anaerobic reactor model

group of nodes or neurons are connected by synaptic connections, a neural network is created. An input layer, a hidden layer and an output layer are there in ANN. Input variable (Total solids (%TS), Organic Loading Rate (OLR gmVS/L/d), pH, Hydraulic Retention Time (HRT), Volatile Fatty Acid to Alkalinity ratio (VFA/Alkalinity)) and output variable (Volatile Solids removal (%$VS_{removal}$ and Methane yield (L/kg$VS_{removed}$)) are included in the experimental data. ANN study was carried out with MATLAB to implement the feed forward training algorithm with the fitting application (fitnet). Compared to other algorithms such as GDX, CGP, BFG, OSS, RP, CGB, CGF, GD and GDm; Levenberg Marquardt (LM)and Bayesian Regularization (BR) have continuously scored higher in terms of providing the greatest performances ANN model (Chen et al., 2022). However, Levenberg-Marquardt, Bayesian Regulation and Scale Conjugated Gradient are the three training algorithms employed in this work.

Data normalisation

The first step in any data analysis is to do data normalisation. Data mining techniques particularly those used in classification and clustering, are crucial**.** The min-max approach is one of the several normalisation techniques employed in this study. To obtain reliable results, input and output variables must be properly normalised. To make the selected data acceptable for the activation function in the neural network, all of the data were scaled to the range [0-1] using the minimum and maximum values of each variable using Equation (1). The ANN model was created using the analytical parameters %TS, pH, OLR (gm VS/L/d), HRT, VFA/Alkalinity ratio, %$VS_{removal}$ and amount of methane generated.

$$Xn = \frac{X - \mathrm{Xmin}}{\mathrm{Xmax} - \mathrm{Xmin}} \tag{1}$$

X = experimental data
x_n = normalised value of the experimental data
x_{min} = minimum value of experimental data
x_{max} = maximum value of experimental data

Predicted output de-normalized using equation (2)

$$Xn*[(X_{max} - X_{min})] + X_{min} = X \tag{2}$$

RESULT AND DISCUSSION

Process and operational parameters of the present study

Input variables

Total solids concentration (%TS)

More acetic acid is produced in the reactor when the total solids (TS) concentration is high, which then starts the inhibitory actions. The TS content of the feed substrate changes from 12% to 32% in the current semi-continuous feed anaerobic co-digestion study. After feeding a high-solids substrate, an alkali addition was needed to stabilise the reactor since it was acidic.

Organic Loading Rate (OLR (gmVS/L/d)):

One of the most significant aspects of solid analysis is the measuring of the present organic matter. Volatile Solids make up 86% to 94% of total solids. The most crucial variable for an effective reactor operation is the organic loading rate. The OLR ranges in this research from 2 to 12 gmVS/L/d. The amount of organic material injected per unit volume of the anaerobic digestion each day is known as the organic loading rate. Volatile solids are a convenient way to represent the bulk of organic material. At higher concentrations, AD may be inhibited due to the build-up of volatile fatty acids that may result in a drop in the pH of the reactor.

pH

The phases of the anaerobic process are indicated by pH. A fast drop in pH is seen during fermentation when acidogenesis bacteria are active. The anaerobic process is activated and methane gas generation begins when the pH stabilises between 6.2 and 8.36.

Volatile Fatty Acid to Alkalinity ratio (VFA/Alkalinity)

Acidic and methanogenic populations in the reactor are less stable due to significant variations in the volatile fatty acid (VFA) content of anaerobic systems. VFA concentration in the reactor must be managed for optimal treatment efficiency and methane generation since an increase in VFA concentration in the system immediately affects chemical oxygen demand (COD) removal. The ability of the substrate to neutralise acids is known as its alkalinity in the digester. VFA/Alkalinity offers a CO_2 buffering capability for methane generation in addition to pH management. In this study, the VFA/Alkalinity ratio ranges from 0.1 to 0.54. A higher VFA/Alkalinity ratio indicates that the performance of the reactor is unstable.

Hydraulic Retention Time (HRT (days))

The amount of hydraulic retention time has a significant impact on upgrading or increasing biogas output. It displays the time frame during which production may begin to decrease while the organic substrate is still present in the anaerobic digester. HRTs ranged between 15 to 45 days (mean 34 days, maximum up to 74 days) in the overall study of more than 200 days.

Output variable

Methane yield (L/kgVS$_{removed}$)

The fermentation of certain OFMSW and other organic wastes (with a particular type of bacteria) yields methane. The process efficiency of any anaerobic system is typically measured by how much biogas or methane is produced. Maximising the gas yield rate as a result of the biodegradation of the organic part of the waste is the most crucial step to take into account while operating biogas reactors. This cannot be done without ongoing process monitoring and inspection. Reduced biogas and methane yield in anaerobic digestion systems may be an indication of unstable process conditions. The rigorous supervision of the biogas (both visual/on-site and computer-based) helps assure the stability of these vulnerable systems.

Volatile Solid removal (%VS$_{removal}$)

Before being disposed of in the environment, the anaerobic co-digestion process helps to lessen the pollutant load. 55.5% to 87 % of the Volatile Solids were reduced over the research period.

The summary statistics for the model variables are shown in **Table 1.** For all five variables—influent feed Organic Loading rate (gm VS/L/d), %TS, VFA/Alkalinity ratio, pH, HRT and outlet parameter methane yield (L/kg VS$_{removed}$),%VS$_r$—102 days complete data points are presented. The shown variations of the model components are taken into consideration in the current computational investigation.

Prediction model with ANN for anaerobic co-digestion

Many ANN models are constructed with various neurons and evaluated to find the optimum model that simulates reactor operations with the least amount of error (MSE). In the present study, artificial neural networks are used to model methane yield and %VS$_{removal}$. Input, hidden and output layers as well as a large number of neurons, make up the network's architecture

Table 1. Range of Statistical Values of Input and Output Variables

	Input Variables					Output Variable	
	%TS	OLR (gmVS/L/d)	pH	VFA/Alkalinity	HRT	$\%VS_{removal}$	Methane yield(L/kg $VS_{removed}$)
Max	32	12	8.36	0.54	45	87	258
Min	12	2	6.2	0.1	15	55.5	1
Mean	19	5.1	6.9	0.23	34	75	28

(**Figure 3**). The hidden layer neurons are connected to the input layer neurons via weights (W1...Wn) that specify the intensity of the input data connected to each node. These weights are then added with bias (b1 & b2) to regulate the magnitude of the input data**.** The ANN then goes through the testing procedure utilising a fresh set of data to confirm the predictive power of the artificial neural network. When the testing is successful, the architecture of ANN is fixed and may be used to determine process parameters with fresh input data. The suggested ANN model calculates methane yield (L/kg $VS_{removal}$) and (% $VS_{removal}$). Due to its excellent ability and robustness to tackle fitting difficulties, the Levenberg-Marquardt training method (trainlm), Bayesian Regularisation (trainbr) and Scale Conjugated Gradient (trainscg) are used in the training process (Mougari et al., 2021). The first set (70%) is used to train the model parameters (weights and biases) from a total set of 102 input data that were normalised and randomly divided into three sets. The second (15%) testing data is separate from the training dataset, serving as the benchmark for judging the performance of the model. The model's hyper parameters are adjusted using the last set of validation data (15%). Controlling the random dataset distribution, the number of hidden layers, the number of neurons, and the activation function are all important considerations for choosing the best ANN design in terms of the accuracy and simplicity of the model. The capacity of a network to approximate increasingly complex functions is known to be associated with the number of hidden layers and neurons. Using the trial-and-error technique (**Figure 2**), the ideal configurations of one hidden layer and between 2 and 20 neurons have been provided. A training procedure is used to update the weights continuously at various epochs until there is little difference between the calculated and experimental values.

Performance evaluation of the ANN model

A fully connected feed-forward neural (fitnet) network is utilised for this investigation. The input layer has five input variables, one hidden layer has n hidden neurons and one output layer has two output variables. A bias neuron is also present in the input and hidden layers and it provides each neuron in those layers with constant activity. The ANN model utilised the sigmoidal activation function (Olden & Jackson, 2002). As per equations (3) and (6) The suggested ANN architecture has been assessed based on the Mean Squared Error (MSE) and correlation coefficient (R). Figure 4 shows a graphic representation of the neural network performance using a regression curve and the best validation performance curve for training function Bayesian Regularization. According to equations (4) and (5), the mean absolute error (MAE) and mean absolute percentage error (MAPE) are computed.

Mean Squared Error (MSE)$=\frac{1}{x}\sum_{i=1}^{x}(P_{\mathrm{i}} - E_{\mathrm{i}})$ (3)

Mean Absolute Error (MAE) $= \frac{1}{x}\sum_{i=1}^{x} \left|E_{\mathrm{i}} - P_{\mathrm{i}}\right|$ (4)

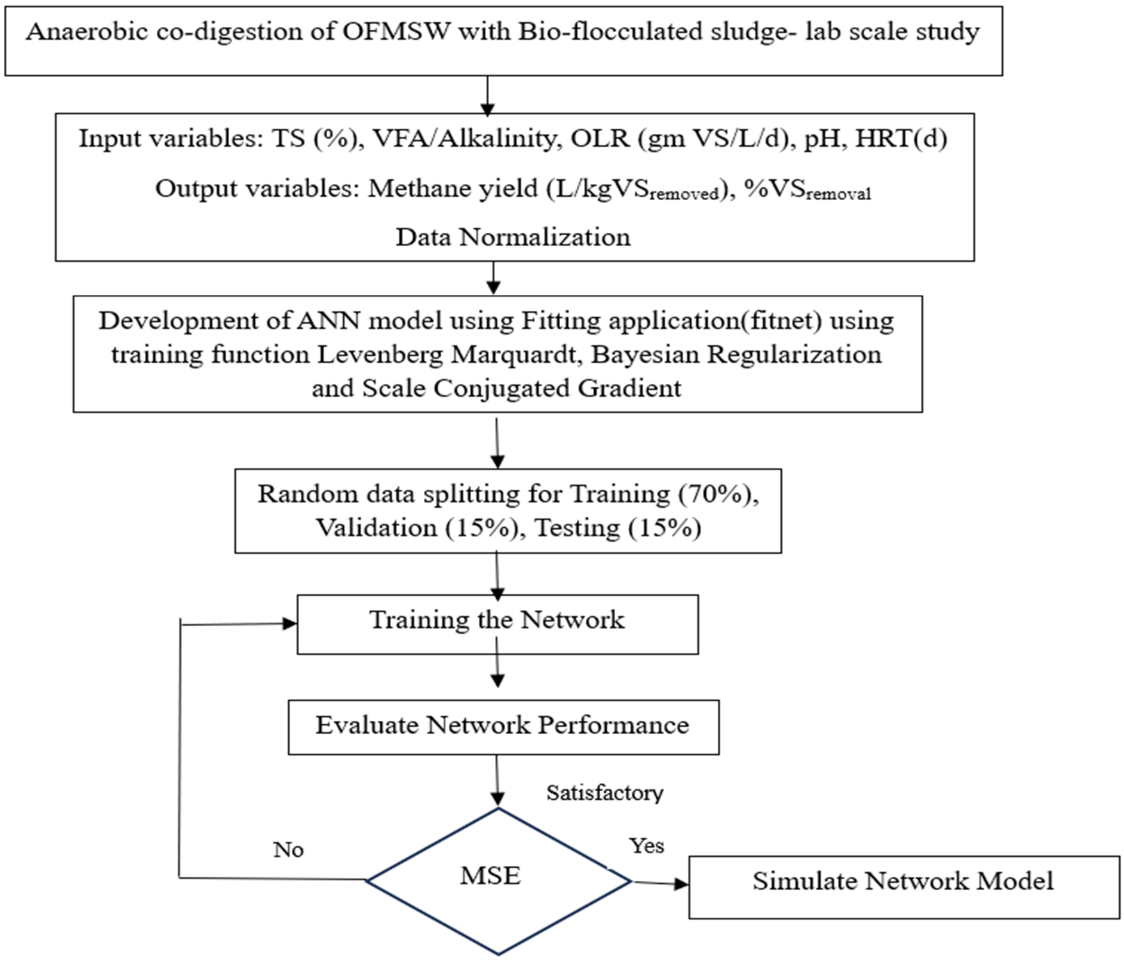


Fig. 2. Steps involved in the development of the prediction model using ANN

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{1}{x}\sum_{i=1}^{x}\left|\frac{E_i - P_i}{E_i}\right| X\ 100\% \tag{5}$$

$$R = \frac{\sum_{i=1}^{x}(P_i - \bar{P}i)(E_i - \bar{E}i)}{[\sqrt{\sum_{i=1}^{x}(E_i - \bar{E}_i)^2}][\sqrt{\sum_{i=1}^{x}(P_i - \bar{P}_i)^2}]} \tag{6}$$

Where,
x = number of datasets
E_i = experimental data
$\bar{E}_i$ = mean of experimental data
P_i= Predicted data output
$\bar{P}_i$= mean of predicted data output
R= coefficient of correlation

Bayesian Regularization

The lowest MAE, MAPE, and MSE values and R of several training techniques used at various numbers of hidden neurons are displayed in Table 2 & Table 3 for a trained ANN model for Methane yield(L/kgVS$_{removed}$) and %VS$_{removal}$ response. The feedforward Neural Network

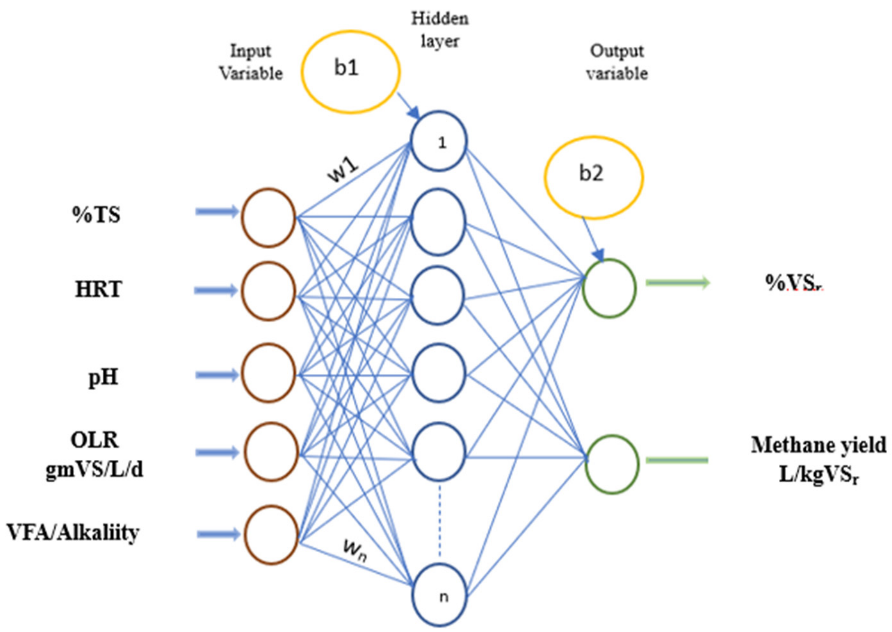


Fig. 3. Architecture of ANN

Table 2. R, MAE, MAPE, MSE value for Output Methane yield (L/kg $VS_{removed}$) at different training algorithms for different numbers of hidden neurons with the feedforward neural network using fitting application

Hidden Layer Neuron	LM				BR				SCG			
	MSE	MAE	MAPE	R	MSE	MAE	MAPE	R	MSE	MAE	MAPE	R
2	568.188	13.009	2.531	0.725	1027.096	15.261	2.248	0.384	1152.265	15.249	2.325	0.235
3	677.767	13.320	2.077	0.701	635.070	13.149	2.503	0.691	1107.895	16.177	2.826	0.280
4	461.516	11.303	1.710	0.784	448.313	10.900	1.326	0.792	1041.816	17.325	3.444	0.376
5	395.380	9.839	1.246	0.819	390.506	9.902	1.216	0.821	1029.209	14.404	2.215	0.376
6	429.094	9.946	1.167	0.802	350.341	9.155	1.172	0.841	773.812	13.806	2.375	0.612
7	344.614	9.298	1.381	0.846	269.346	8.614	1.284	0.881	734.673	13.370	1.693	0.634
8	300.628	8.093	1.225	0.869	223.961	7.857	1.251	0.902	701.532	12.455	1.651	0.647
9	294.632	9.680	1.636	0.871	194.512	7.221	1.197	0.916	616.299	13.102	2.387	0.715
10	**244.484**	**8.371**	**1.390**	**0.894**	198.977	6.715	1.271	0.915	582.927	12.867	2.133	0.718
11	373.662	7.562	1.241	0.838	126.602	5.299	1.013	0.946	722.063	12.990	1.987	0.632
12	330.975	7.890	1.164	0.851	63.896	3.866	0.664	0.973	687.430	13.547	1.714	0.660
13	363.801	8.498	0.969	0.837	101.487	4.651	0.658	0.957	905.477	13.650	1.938	0.500
14	256.022	6.244	0.790	0.887	152.058	4.740	0.522	0.936	620.549	12.364	2.377	0.699
15	300.583	8.759	1.439	0.870	140.407	4.493	0.582	0.941	529.669	11.976	1.779	0.748
16	391.676	9.634	1.389	0.827	99.133	4.418	0.675	0.958	699.647	12.877	2.063	0.645
17	327.440	10.125	1.897	0.854	77.599	3.524	0.486	0.968	**492.484**	**10.913**	**1.466**	**0.777**
18	348.508	8.101	1.460	0.862	74.568	3.432	0.535	0.969	530.072	10.345	1.315	0.757
19	389.716	8.749	1.196	0.841	**71.638**	**3.602**	**0.540**	**0.970**	664.208	12.493	1.848	0.672
20	290.542	8.918	1.737	0.871	76.677	2.966	0.392	0.968	526.769	11.534	1.782	0.750

with Bayesian Regularisation (BR) technique is the training strategy that provides the best R-value (0.986) for the $\%VS_{removal}$ processes at 17 hidden neurons, the lowest MAE value of 0.419 and the lowest MAPE value of 0.006 and lowest MSE value of 0.697. Furthermore, from two neurons to twenty neurons, the MAPE error has never surpassed 10% while employing the

Table 3. R, MAE, MAPE, MSE value for Output **%VS**$_{removal}$ at different training algorithms for different numbers of hidden neurons with the feedforward neural network using fitting application

Hidden Layer Neuron	LM				BR				SCG			
	MSE	**MAE**	**MAPE**	**R**	**MSE**	**MAE**	**MAPE**	**R**	**MSE**	**MAE**	**MAPE**	**R**
2	10.996	2.036	0.028	0.802	5.569	1.279	0.018	0.904	7.95	1.633	0.023	0.861
3	7.102	1.496	0.020	0.878	5.288	1.276	0.018	0.908	13.92	2.217	0.031	0.752
4	4.318	1.150	0.016	0.927	3.977	1.116	0.015	0.931	9.60	1.873	0.026	0.830
5	5.421	1.404	0.019	0.907	3.967	1.120	0.016	0.931	10.47	1.897	0.026	0.814
6	3.204	1.022	0.014	0.944	2.336	0.860	0.012	0.959	7.99	1.714	0.024	0.861
7	2.481	0.822	0.011	0.956	2.340	0.877	0.012	0.959	6.39	1.490	0.020	0.890
8	3.436	1.010	0.014	0.941	1.755	0.758	0.010	0.968	6.91	1.478	0.021	0.881
9	3.124	0.968	0.013	0.946	1.793	0.745	0.010	0.968	5.66	1.404	0.019	0.905
10	2.122	0.809	0.011	0.964	1.694	0.762	0.011	0.969	7.08	1.522	0.021	0.878
11	1.604	0.688	0.010	0.971	1.168	0.635	0.009	0.978	5.08	1.323	0.018	0.914
12	2.242	0.758	0.010	0.961	1.363	0.640	0.009	0.975	4.15	1.160	0.016	0.929
13	3.262	0.926	0.013	0.948	1.261	0.591	0.008	0.977	8.75	1.736	0.024	0.847
14	3.004	0.822	0.012	0.950	1.432	0.575	0.008	0.975	5.48	1.324	0.018	0.913
15	2.119	0.857	0.012	0.963	1.261	0.604	0.008	0.977	3.74	1.091	0.015	0.936
16	4.580	1.215	0.017	0.924	1.960	0.663	0.009	0.966	4.88	1.266	0.018	0.918
17	3.378	1.071	0.015	0.943	**0.697**	**0.419**	**0.006**	**0.986**	**3.84**	**1.107**	**0.015**	**0.936**
18	**1.947**	**0.747**	**0.010**	**0.968**	0.747	0.441	0.006	0.985	4.19	1.145	0.016	0.930
19	3.494	1.118	0.015	0.946	1.188	0.522	0.007	0.979	5.15	1.330	0.018	0.912
20	2.892	0.883	0.012	0.951	1.522	0.461	0.006	0.974	3.60	1.126	0.015	0.941

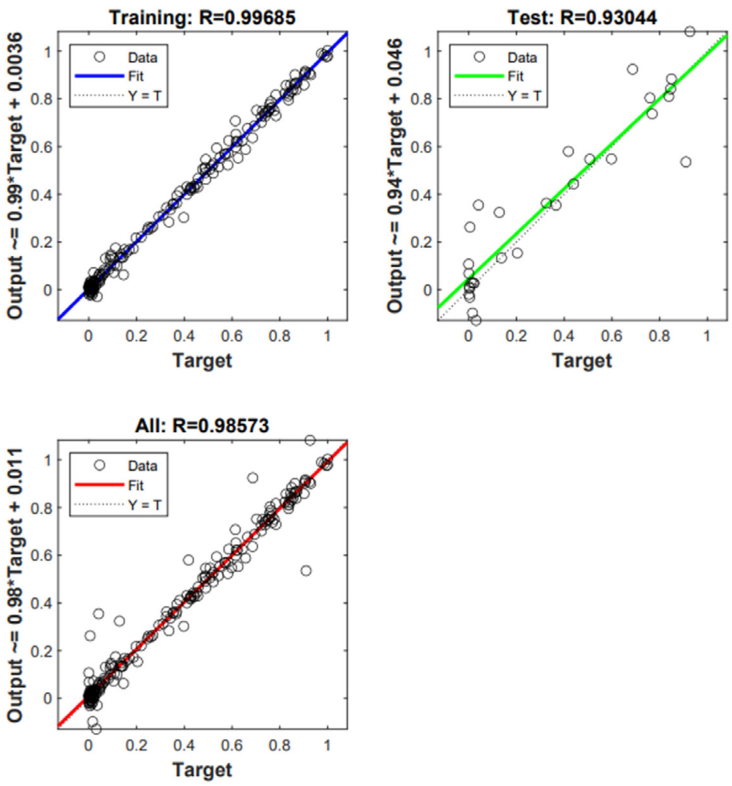


Fig. 4. Artificial Neural Network performance model with training function

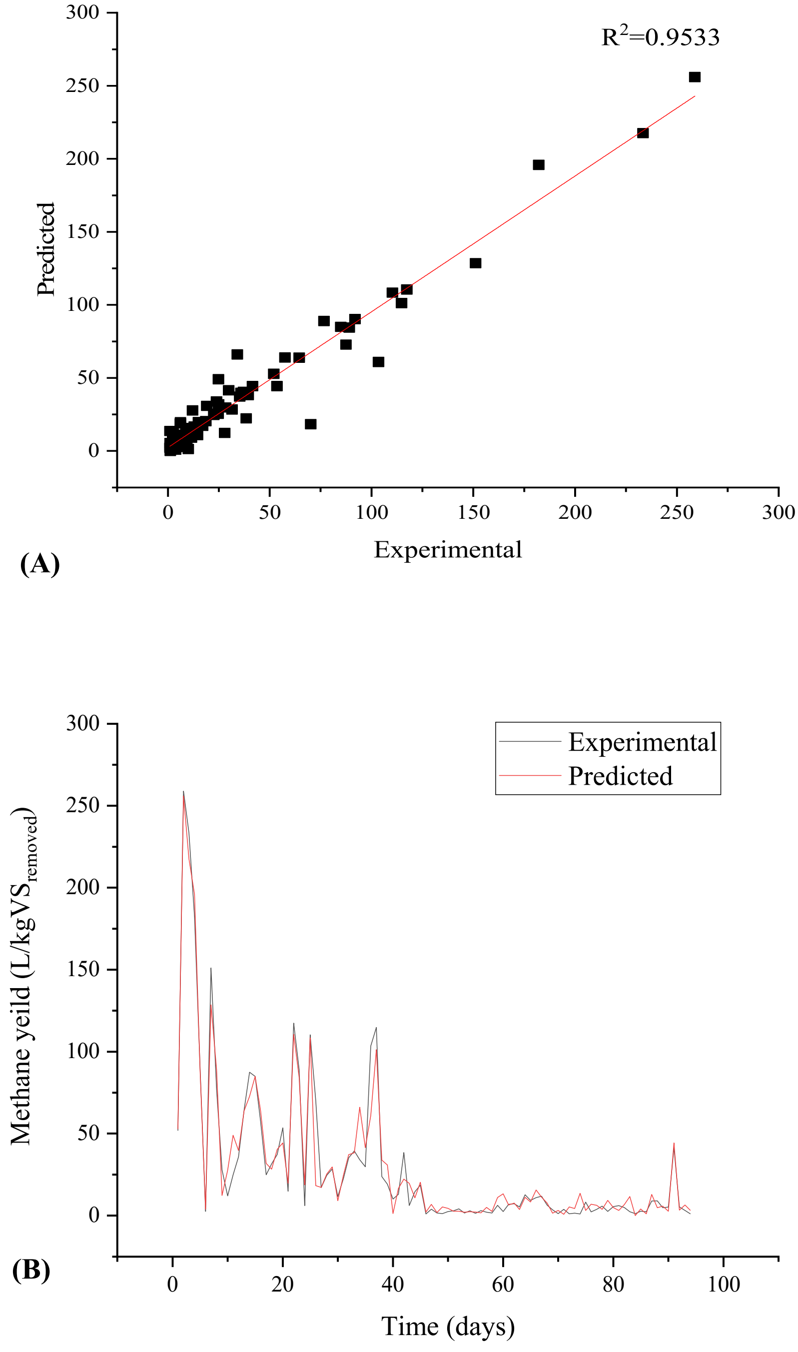
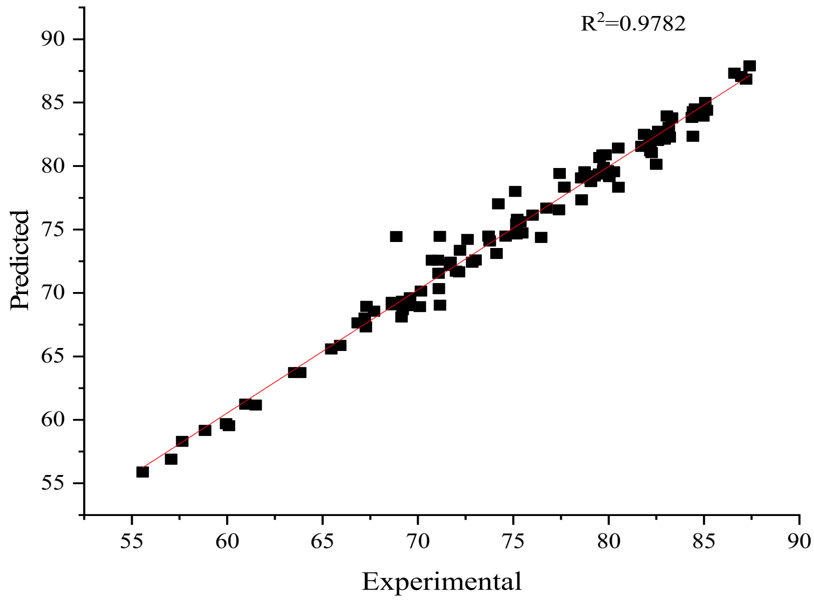
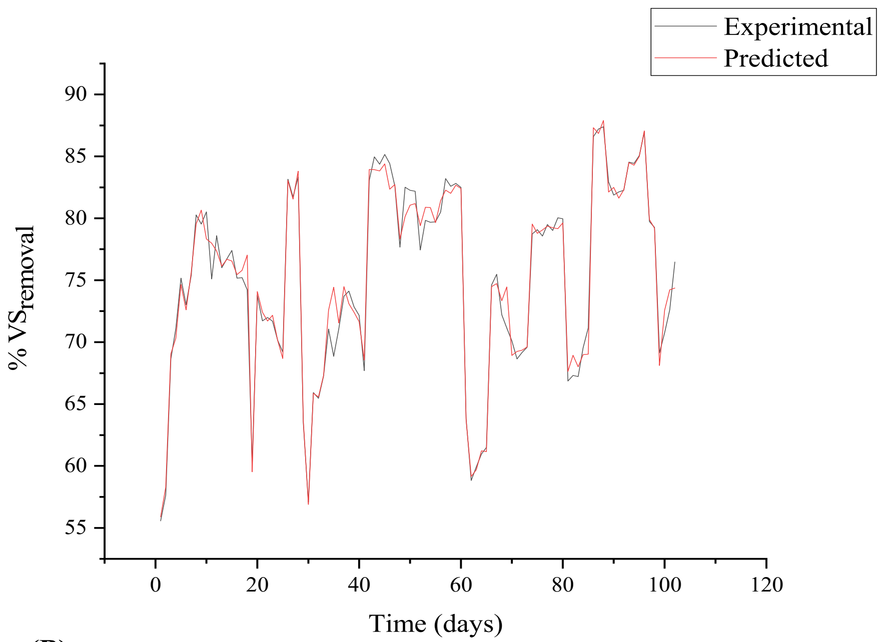


Fig. 5. (A) Correlation between experimental data and predicted data of Methane yield (L/kgVS$_{removed}$) (B) Plot of Experimental and Predicted Methane yield (L/kgVS$_{removed}$) using ANN

BR training procedure. Using the BR training technique and 19 hidden neurons, the greatest R-value of the neural network after training is 0.97 for methane yield. It is interesting to note that the BR and SCG training algorithms produced the greatest and lowest MAE values at 19 hidden neurons and 2 hidden neurons. The BR training approach outperforms others in terms of MAPE performance criterion. Once more, BR and LM trained the most effective ANN model when compared to those who had the lowest MSE, MAPE and MAE values. The feedforward neural network (fitnet) is trained using the Bayesian regularisation (BR) approach. Neural Network architecture 5-19-2 shows the correlation between experimental and predicted data



(A)



(B)

Fig. 6. (A) Correlation between experimental data and predicted data of $\%VS_{removed}$ (B) Plot of Experimental and Predicted $\%VS_{removed}$ using ANN

for methane yield with R^2= 0.9533 in Figure 5 whereas $\%VS_{removal}$ with network architecture 5-17-2 shows R^2 = 0.9782 for the experimental and predicted data in Figure 6.

CONCLUSION

Anaerobic co-digestion of OFMSW with bio-flocculated sludge from SST (post-UASB) is the most prominent way to produce biogas generation. With different batch experiments optimum mixing ratio of 75:25(OFMSW: bio-flocculated Sludge from SST) is taken into consideration for the lab scale study of a mesophilic semi-continuous flow rector. The optimized network architectures, 5-19-2 for methane yield and 5-17-2 for $\%VS_{removal}$ indicate the importance of hidden layers in capturing non-linear relationships within the data. This research underscores the potential of neural network-based models as valuable tools for enhancing the efficiency and understanding of methane production processes. The accurate predictions achieved in this study contribute to the advancement of sustainable energy production from organic waste materials through improved process monitoring and optimization. Further parameters should be recorded from the experiment to analyse the performance of methane yield in depth. This achievement could significantly help in the effective anaerobic co-digestion process of OFMSW and bio-flocculated sludge from SST (post-UASB) for real application of treatment technology.

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CONFLICT OF INTEREST

The authors declare that there is not any conflict of interest regarding the publication of this manuscript.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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