Optimization and Prediction of Daily Methane Production for Food Waste

By using

The Artificial Neural Network (ANN)

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Abstract

This study aimed to know how a neural network model can be used to predict the behaviour of particular methane production using a three-layer (3:12:1) feed forward back-propagation algorithm and the logsig-purelin transfer function to maximize maximum methane prediction. The artificial neural network performs admirably compared to the daily methane generation of (vegetable waste 5%, lipids 12.5%, meat residues 12.5%, cow dung 10% and water 60%) at various temperatures (19–30 °C) for 64 days. Among the three input variables (feedstock, temperature, and time), feedstock has the strongest correlation with the particular methane production value. Thus, the research validates the ANN model's ability to anticipate the biogas production curve's behaviour and forecast the optimal substrate temperature for maximum biogas production. The regression value(R) for the digester was 0.95769. The capability of ANN modelling acts as a preliminary draft and significantly lowers the time required for methane generation in-line control. The daily methane production was predicted at three temperatures (20, 25, and 30 ^{o}C) for 75 days, and it found out the best temperature reaction was 30 ^{o}C.

Keywords: **Biogas, Artificial neural network (ANN), Methane, Co-digestion, digester.**

1. Introduction

The ANN approach and framework can be used to explore and predict the AD viewed as simply of the anaerobic process or system's kinetic characteristics [1]. Due to the necessity of controlling and optimizing biogas production, mathematical models have been developed that can be utilized to promote a more effective system [2]. Several studies utilizing neural networks have been conducted in an attempt to forecast biogas yield based on the characteristics and composition of the substrates. Mathematical modelling can be utilized to improve the AD's process efficiency. the creation of an Artificial Neural Network (ANN) and an "*Adaptive Neuro Fuzzy Inference System*" (ANFIS) for the purpose of predicting the amount of biogas [3]. By co-digesting plantain peels with animal wastes and utilizing the best bio-digesters, the biogas generation process was modeled and optimized [4]. Predict the anaerobic digester's power production by considering a variety of factors and feed stocks, with a particular emphasis on the effect of primary factors such as temperature, pH, and nitrogen concentration on power production. A neural network tool was developed with the assistance of MATLAB programming to predict the anaerobic digester's power production [5]. A prediction model was developed to forecast biogas production during the anaerobic digestion of food waste. Biogas production neural network based on the Levenberg–Marquardt algorithm is investigated in order to develop a model for predicting biogas output [6]. The biogas generation process was modelled using artificial neural networks in order to represent it in a neural network model. However, the development of artificial neural network modelling was restricted to resolving its problem and implementing some of the necessary components. The results indicate that when compared to mathematical modelling, artificial neural network modelling gave superior outcomes with higher accuracy and reduced error [7]. The artificial neural network (ANN) was used to estimate the production of biogas from laboratory-scale up-flow anaerobic sludge blanket reactors treating cattle dung with co-digestion of various organic wastes. It can be estimated based on the number of working days, the chemical oxygen demand of the influent, the influent pH, the influent alkalinity, the influent ammonia, the total influent phosphorus, the hydraulic retention time, the waste adding ratio, the pretreatment and additive waste kinds [8]. Consideration is given to the effect of anaerobic digestion characteristics such as composition, temperature, and time. 99.7% of the time, specific biogas production data can be estimated using an ANN model with such a accuracy of 10% deviation from the experimental values [9]. The energy performance of a 3.7 kW diesel engine was predicted using an artificial neural network (ANN). When 90% of data were in the training set, it was observed that ANN predicted technology has received were closer to empirically measured values [10]. The biological elimination of hydrogen sulphide from a biogas mimic (pH 7.0) was investigated for 189 days in an anoxic biological trickling filter and forecasted utilizing artificial neural networks (ANNs) [11]. Using an artificial neural network, study the production of biogas through anaerobic digestion of solid-phase kitchen food waste. The network was used to simulate and optimize biogas generation utilizing a mixture of food waste and cow manure as a substrate. The percentage of substrates used, the pH level of the plant, the digestion period, and the temperature of the digester were all used as input factors for the models, with biogas yield as the output [12]. The proposed ANN-PSO framework achieves mean square error (MSE) and correlation coefficient (R) values of 0.0143 and 0.9923 for biogas production from anaerobic co-digestion (ACoD) of palm oil mill effluent (POME) and cattle manure (CM), respectively [13]. To forecast the performance of the anaerobic bioreactor's biogas output, a three-layer artificial neural network (ANN) and nonlinear regression models were built. For ANNs and nonlinear regression models, the R2, IA, FA2, RMSE, and MB values were 0.9852 and 0.9878, 0.9956 and 0.9945, 0.9973 and 0.9254, 217.4 and 332, 36 and 222, respectively [14]. The Fuzzy Mamdani Model (FMM), Artificial Neural Network (ANN), and Response Surface Methodology (RSM) were used to model and optimize biogas production in a modular bioreactor system using varied substrates of poultry wastes (PW) and cattle dung. The FMM model's output seems to be somewhat better and superior in terms of predicting biogas and methane production rates with an acceptable conclusion [15]. Using artificial neural networks as a prediction model, it can estimate the amount of methane produced by different substrates in the form of silages. The methane production prediction model developed was a Radial Basis Function (RBF) with five inputs, two neurons in a hidden layer, and one output [16]. The purpose of this study was to optimize biogas production utilizing response surface technique and an artificial neural network (ANN). To construct the prediction models, the period of agitation, the substrate concentration, the temperature, and pH were all evaluated model parameters [17]. Under mesophilic and thermophilic circumstances, an artificial neural network was constructed to simulate and optimize the accumulated methane generation from agricultural solid wastes, cow dung, and their mixture [18]. The generation of biogas from food waste was investigated experimentally in triplicate in a batch reactor at 37 °C with an organic loading rate. Additionally, a database was created utilizing values from the literature in order to build a numerical model for food waste, fruit and vegetable waste, or mixes of both in co-digestion using artificial neural networks [19]. An anaerobic fermentation process for biogas generation was simulated using artificial neural networks in conjunction with wastewater purification in a contemporary wastewater treatment plant with a planned design power of 27,000 cubic meters per day. On the basis of large-scale industrial data, neural models were developed, validated, and tested [20]. Conduct a biennial study of methane production using the Intergovernmental Panel on Climate Change's and Backpropagation Neural Network technique throughout the whole state [21]. A new model based on blocks of spiking neural networks was developed to simulate the chemical reactions occurring in a reactor tank during the generation of useable biogas. The predictive architecture was implemented using the NeuCube computational framework [22].

2. Methods

2.1. The experimental design

Digester has been designed and executed to produce biogas. As shown in figure, it comprises of two 25-liter plastic anaerobic digester (1). Each digester is equipped with three terminals (supply feedstock, outlet biogas, and outlet sludge), each of which is controlled manually through a ball valve of variable size, as well as a floating piston-cylinder storage tank for biogas. Additionally, this digester include several sensors for monitoring and acquiring critical data collected by an Arduino microcontroller, such as (Hydrogen, Methane, Carbon dioxide, pH, & Ammonia). These sensors are controlled in accordance with the manufacturer's most recent standard documentation.

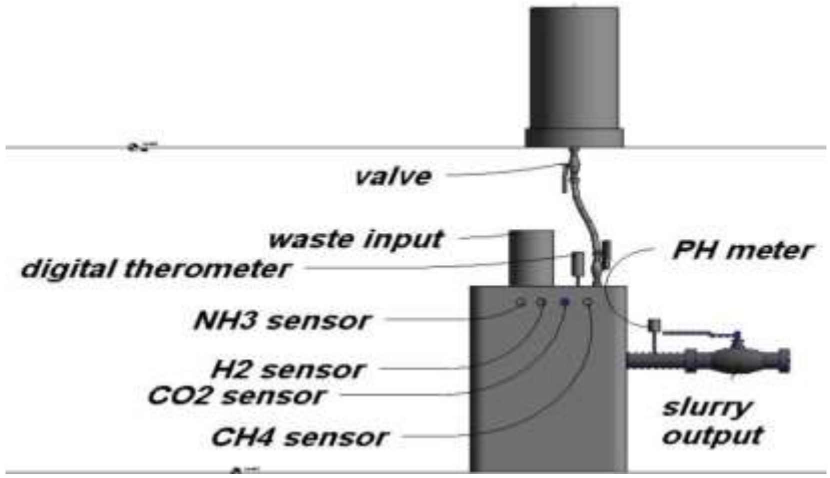

Figure 1. The digester system and floating storage tank

2.2 Substrate

The digester mixture consists of fats waste, meat residues, and vegetable wastes obtained from kitchen trash and cow dung in a proportional ratio to produce a microbial culture inside the digester, as illustrated in the table (1). Meat scraps and vegetable waste are minced to a thickness of approximately 1 to 2 cm. The inclusion of meat scraps, vegetable wastes, and cow dung enhances mixing efficiency and expands the surface area accessible for cell proteins to degrade biomass, resulting in a faster breakdown and a shorter anaerobic phase. The blender (automated mixers) is used to combine substrates and water until a homogenous mixture is produced. This mixture is then put in the digester, which has a functional capacity of 20 L. After feeding the mixture to the digester, the air is extracted using a suction that complies with the manufacturer's specifications (litres per minute). This process is performed for a minimum of six minutes to ensure that the reactor does not contain any oxygen or is oxygen-reducing. The process lasted 64 days in temperatures ranging from 19 to 30 degrees Celsius. Readings for CH_4, CO_2, H_2, NH_3, pH, daily biogas production, and total biogas production per tank have been obtained during this time period.

Table 1. The concentrations of substrates are used in the digestion process.

Digester	VW %	MR %	Lipid %	Ratio	CD %	Water %	Total Vol. (L)
1	5	12.5	12.5	20:40:40	10	60	20

3. Optimization using Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are complex theoretical structures focused on the human brain's hierarchical structure. The appeal of ANNs derives from their excellent information processing skills, which include nonlinearity, high parallelism, fault and noise resistance, as well as learning and generalization skills [23]. An *"input layer",* one or two *"hidden layers"*, and an *"output layer"* make up an ANN. The hidden layer's neurons help the network create the dynamic relationships that occur between the input and output parameters. An artificial neuron is defined by each circular node, and an arrow represents a relation from one neuron's output to another's input, as shown schematically in figure (2) [24].

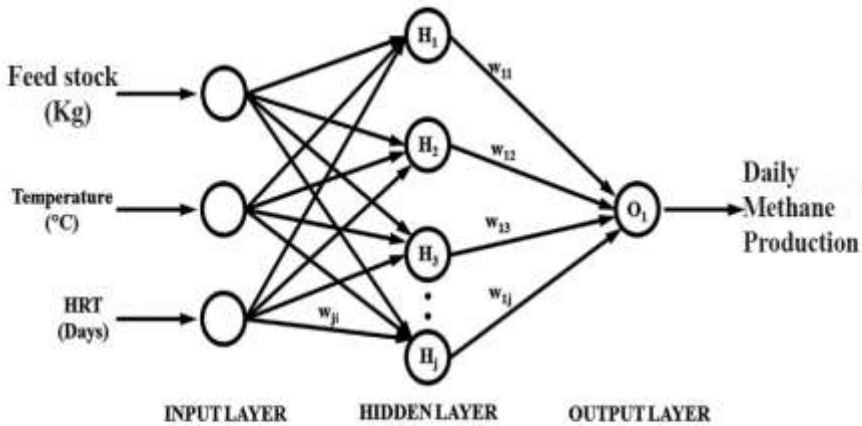

Figure 2. A schematic diagram of an ANN

A neural network model in MATLAB (R2019a) software application version was used for this purpose. The input variables are substrates of feedstock (kg), temperature (T) and (HRT) in days. The target was the daily production of methane and pH value obtained from this reactor of this experiment.

3.1 MATLAB Neural Network Toolbox

The neural network model was developed using the Neural Network Toolbox of MATLAB version R2019a. All data collected were not used from the models because a large number of variables could make the model vulnerable to minor changes or distortion in the data. Therefore, three (3) variables were uses as input are feedstock (kg), temperature (T) and (HRT) (days), while the target is the daily production of methane and pH values as showed in figure (3). In MATLAB, neural net toolbox, the 'inputs' constitutes a 3×64 matrix; the 'target' (the daily production of methane and pH values) is a 2×64 matrix. The input and target data were prepared in a Microsoft Excel Spreadsheet (EXCEL 2010) and then imported into MATLAB. The data set obtained by experimentation was separated into three subsets by random selection: the training set, the validation set, and the testing set. Both the input and the target data were imported into the MATLAB Neural Network Toolbox by sending information on the type of model to be processed by the neural network.

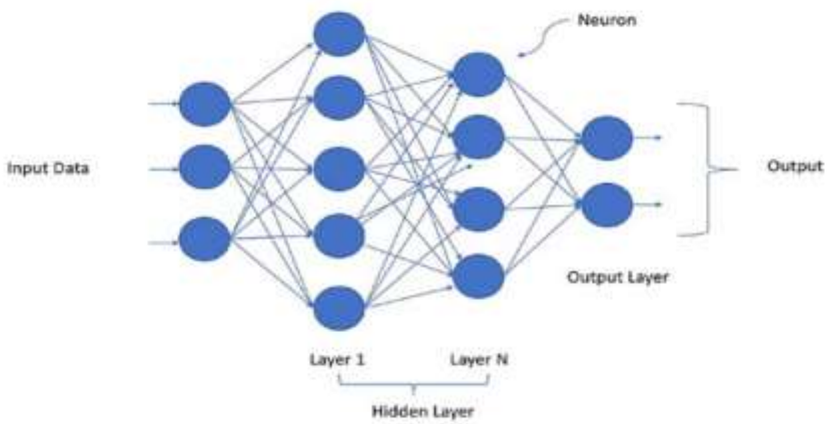

Figure 3. Architecture of the artificial neural network

3.2 Neural Network Fitting Tool Box

The various factors affecting the methane production, such as HRT (days), temperature (T), and substrate (kg), are imported into the MATLAB neural network toolbox in the matrix form of 3X64 matrix and target 2X64 matrix, which is then sent as information to the neural network for modelling and creating test code for methane production validation whereas 70 % of data took for training, 15 % of data for validating, and 15 % for testing. The neural network fitting tool (nftool) is depicted in Figure (4).

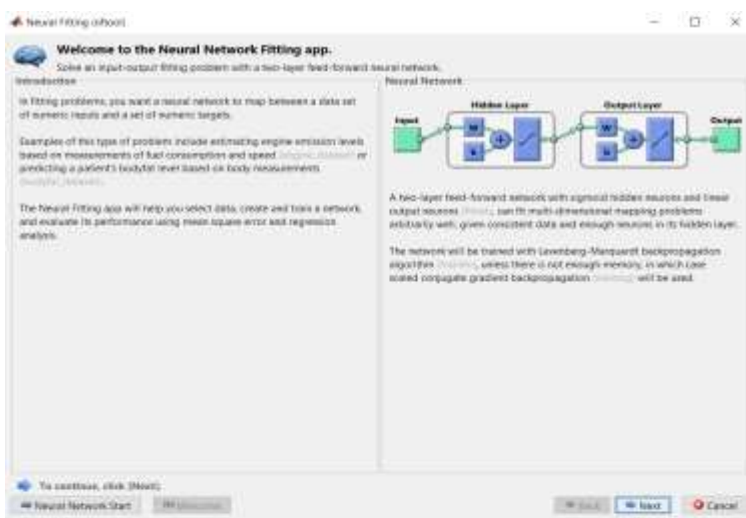

Figure 4. Neural Network Fitting Tool (nftool), A Two-Layer Feed-Forward Network with Levenberg-Marquardt Backpropagation Algorithm.

3.3 The ANN Training Results

The graphical representation of the ANN training results for this digester is shown in figure (5). Regression analysis was performed to investigate the correlation between the target and output based on the correlation coefficient value (R). The perfect fit between the training data and the produced results was indicated by the value of (R), equal to 1. Regression plot, the perfect fit which shows the perfect correlation between the output and target are indicated by the solid line. The dashed line indicates the best fit produced by the algorithm. This figure mentioned above observed that the output tracks the targets very well for training, validation, and testing; hence, the regression value for the digester was 0.95769.

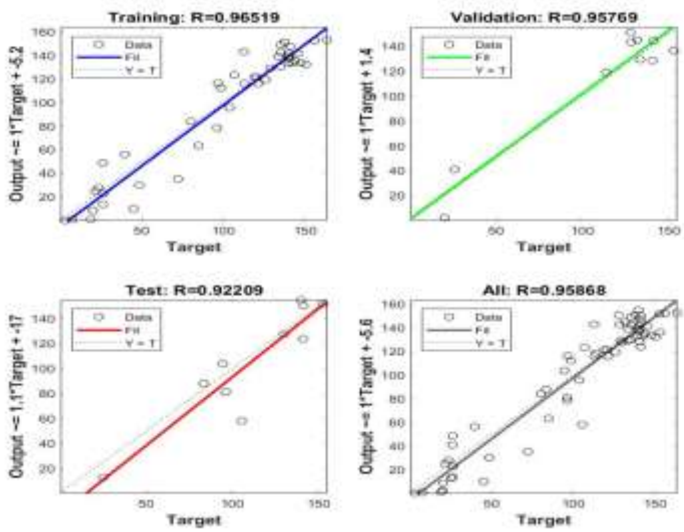

Figure 5. Linear Regression Graph Showing Correlations between Output and Target for Training, Validation, Test Sets and All for digester

3.4 The Validation (optimization) by using the Artificial Neural Networ

After getting outputs data using input and target data into Neural Network in MATLAB, it will get on a code that helps get validation when submitting input data to validate results. This procedure has been applied for this digester, as figure illustrated below. Bioreactor (digester) has a particular reaction style according to the nature of microbial culture and substrate. Figure (6) show the actual and validation of methane production for the digester.

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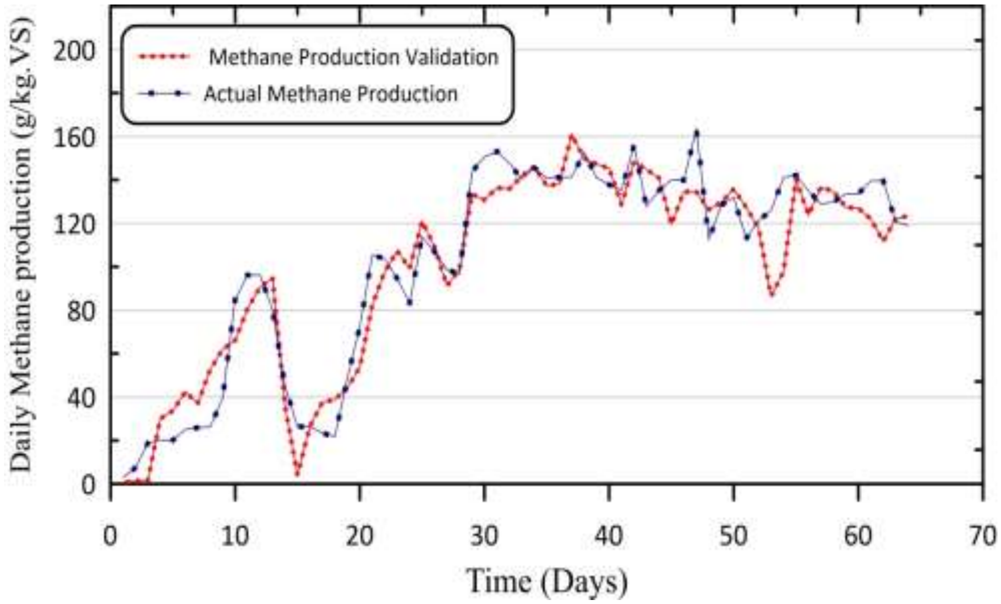

Figure 6. The Actual and Validation of Methane production

3.5 The Prediction of methane production by using Artificial Neural Network

The second benefit of the trained data is that methane production can be predicted at any temperature. In this experiment, three temperatures were taken (20, 25 and 30 ^{o}C) and for 75 days to determine which temperature is preferred for the bacterial reaction to take place and achieve the highest rate of production of methane for this digester which is contained from (cellulose 5%, lipids 12.5%, protein 12.5%, cow dung 10% and water 60%). Through Figure (7), as shown below, the temperatures chosen for the daily high production of methane for the three temperatures were observed, so at 20 ° C the highest methane production is 170 (g/kg.VS) on the 44th day, to gradually decrease and stabilize at less than 40 (g/kg.VS). As for at a temperature of 25 ° C, the highest methane production is at 150 (g/kg.VS) on day 36, then decreases and stabilizes at 119 (g/kg.VS). Finally, at a temperature of 30 ° C, the daily methane production rises to reach the highest peak of 182 (g/kg.VS). Then, it gradually decreases and stabilizes at 110 (g/kg.VS).

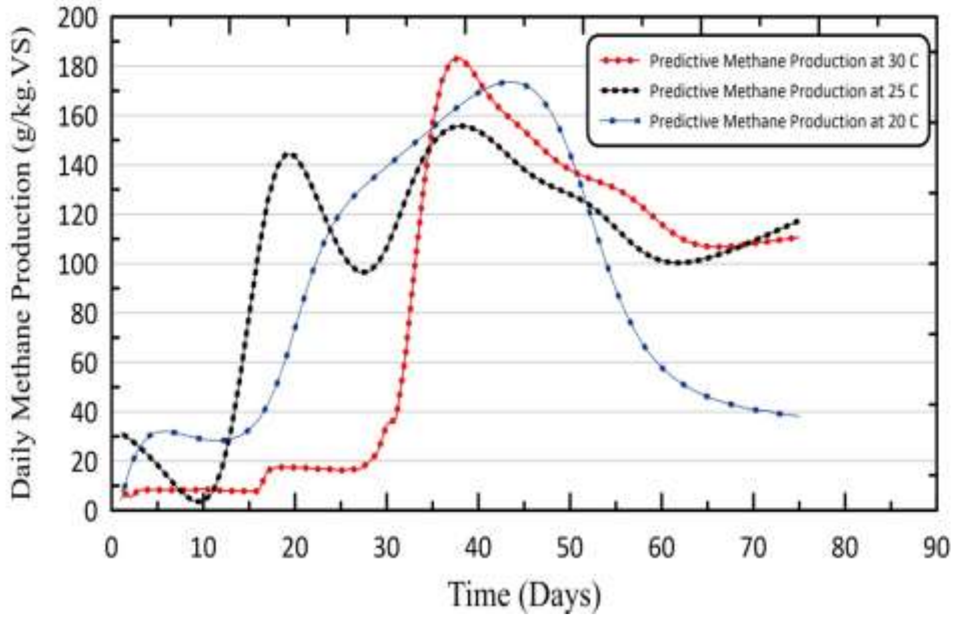

Figure 7. Prediction of methane production at different temperatures

4. Conclusion

The purpose of this study was to demonstrate how a neural network model can be used to forecast the behavior of particular methane production using a three-layer (3:12:1) feed forward back-propagation algorithm and the logsig-purelin transfer function to maximize maximum methane prediction. The artificial neural network performs admirably compared to the daily methane generation of cow manure combined with food waste at various temperatures (19–30 °C). Among the three input variables (feedstock, temperature, and time), feedstock has the strongest correlation with the particular methane production value. Thus, the research validates the ANN model's ability to anticipate the biogas production curve's behaviour and forecast the optimal substrate temperature for maximum biogas production. The capability of ANN modelling acts as a preliminary draft and significantly lowers the time required for methane generation in-line control.

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Nomenclature

AD	Anaerobic Digestion
FW	Food Wastes
ANN	Artificial Neural Network
VW	Vegetable Wastes
MR	Meat Residues
ANFIS	Adaptive Neuro-Fuzzy Inference System
MSE	Mean Squre Error
POME	Palm Oil Mill Effuent
R	Correlation Coefficient
Dig	Digester
HRT	Hydraulic Retention Time
TS	Total solid
CD	Cow Dung
CM	Cattle Manure
No.	Number

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