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Modelling of Biogas Yield from Anaerobic Co-digestion of Food Waste and Animal Manure using Artificial Neural Networks

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Abstract: The anaerobic digestion process is a technology that recovers energy in form of biogas and nutrients from biodegradable waste streams in useable forms in the absence of oxygen. It is sustainable, renewable and a zero-carbon form of energy supply. In this research work, modelling of biogas yield from co-digestion of food waste and animal manure using artificial neural networks was carried out. An experimental three stage continuous anaerobic digestion plant was used to co-digest food waste and animal manure. The composition of food waste and animal manure used include fufu, eba, starch, rice, beans, yam, fish, meat, moi moi, pig and cow dung. The feedstock was ground into fine particles to increase its surface area, and then mixed with water in a ratio of 1:2. The actual biogas yield was compared to the predicted biogas yield using artificial neural networks model. The performance of the developed artificial neural networks model was validated, and the results obtained from the research work revealed the effectiveness of the model to predict biogas yield with a mean squared error (MSE) of best validation performance of 5.1115×10^{-4}. Also, the coefficient of determination (R^2) values of the training set, the testing set, the validation set, and the all data set were found to be high and close to 1, the values being 0.97193, 0.96510, 0.98378 and 0.97229 respectively. The high values R^2 demonstrates the appropriateness of the artificial neural networks model for accurate estimation of anaerobic co-digestion of food waste and animal manure. Besides, there was a good correlation between the actual and the predicted values of biogas yields. Therefore, the artificial neural networks model learned the relation between the input to the anaerobic digestion plant and the output in the biogas stream very well, thus the correct prediction of biogas yield.

Keywords: Anaerobic co-digestion; Animal manure; Artificial neural networks model; Biogas yield; Food waste.

1. INTRODUCTION

A major need of the industrial, commercial, and domestic sectors of any country is the availability of cheap and sustainable energy. Energy consumption and supply are important factors used for evaluating social Human Development Index Ranking (HDIR) and standard of living of any country [1]. Considering unavailability and rapid increase in costs of conventional energy supply coupled with poor waste management and increasing public health concerns about eco-friendly environment, conversion of food waste and animal manure to energy is becoming an economically viable option [2-4]. Solid waste management (SWM) and energy crisis are two major problems facing Nigeria. Solid waste disposal has become a menace in Nigeria. Nigeria has poor waste management policy. Throughout the country, one can see a rotting heap of solid waste in open places such as markets, institutions, streets, drainage system, uncompleted buildings, etc. (Figure 1). The quantity of generated solid waste in Nigeria is increasing as a result of increase in her population that is estimated at 187,896,647 persons. Nigeria population is equivalent to 2.48% of the total world population and is estimated to double that figure by the year 2050. Instead of indiscriminate dumping of generated solid wastes from Nigeria homes, institutions, markets, etc. in open places, it can be digested or co-digested anaerobically with other feedstocks such as cow dung, pig dung and sewage sludge to produce green energy such as biogas suitable for heating and lighting.

The anaerobic digestion (AD) process which involves the digestion and co-digestion of biodegradable waste is a well-established bioprocessing technology that leads to production of highly energetic biogas, which comprises mainly of methane (CH_4), carbon (IV) oxide (CO_2), hydrogen sulphide (H_2S) and water vapour (H_2O) [5-7]. The AD process is of growing interest in many developed countries like Sweden, Germany, Switzerland, USA, Canada, China, Japan, and developing countries like Nepal, India, South Africa and Nigeria due to decline in forest reserves, fossil fuel resources and their resulting effect on the climate of the world [8-10]. Throughout the decomposition of biodegradable waste in AD plants, several beneficial microbial metabolic processes that depend on the process and operation parameters (i.e., temperature, pH, organic loading rate, volatile

Figure 1. Open Dumpsite, Lucky Way, Benin City, Nigeria

solid, total solid, etc.) take place. To achieve an optimum biogas production, the aforementioned process and operation parameters should be properly monitored and controlled [10-14]. Besides, for easy prediction of biogas yield, modelling of the AD process is required. However, modelling of the AD process is very difficult and tasking [15-17] and this is due to the rigorous processes that take place during the digestion [18-19]. Due to the intricacies involved, the AD process is modelled as a black-box [20] using the artificial neural networks (ANNs) method [21]. An ANN also called Parallel Distributed Processing (PDP), connectionism or neuro-computing is a computational method where several simple computational elements (artificial neurons), perform a nonlinear function of their inputs [22]. Such computational units are vastly unified and can model a system by means of a training algorithm [22]. This algorithm tries to reduce a measured error that is computed in different ways depending on the exact technique used to regulate the connections (learning algorithm).

ANNs model has been used in AD plants to model the effect of trace gases, controlling the addition of sodium hydrogen trioxocarbonate (IV) ($NaHCO_3$) buffer, digester start up and recovery and advanced control [23]. Yeshona *et al.* [24] used ANNs as an efficient tool for the modelling and optimization of biofuel production. In their study, it was found that ANNs can be used for the modelling and optimization of biohydrogen, biogas, biodiesel, microbial fuel cell technology and bioethanol. Also, Nasr *et al.*, [25] investigated the effect of pH, alkalinity, chemical oxygen demand (COD), sulphate, conductivity, chloride, temperature and refuse age on the methane fraction (%) of total biogas yield. The ANNs model was developed to capture the effect of the inputs on methane fraction using field-scale bioreactors. The models proved to be resourceful and potentially suitable for large-scale methane production. In another study, a multilayer ANNs with two hidden layers and sigmoid function was trained to simulate the digestion process for optimum biogas production. The ANNs model successfully captured the core patterns in the training data-set with input parameters of temperature, total solids, total volatile solids and pH [25]. Mahanty *et al.* [26] modelled the co-digestion of industrial waste from different sources including paper, chemical, petrochemical, automobile and food using ANNs. From their findings, it was concluded that the model offered a better performance with regards to prediction ability and the significance analysis compared to the regression model. Thus, ANNs model is an efficient tool for control and simulation of AD process for optimum biogas yield. Therefore, in this research work, modelling of biogas yield from co-digestion of food waste and animal manure using ANNs were carried out. The quantity of biogas yield was predicted using ANNs and results obtained compared to actual biogas yield.

2. MATERIALS AND METHODS

2.1 Materials

Table 1 shows the list of materials used in this research work.

Table 1. List of Materials and their Usage

	List of Materials	Usage
1.	Electronic pH meter	The electronic pH meter was used to measure the pH readings.
2.	Anaerobic digestion plant	A three-stage anaerobic digestion plant was used for co-digestion of food waste and animal manure.
3.	Nose mask	It was used for protection against poisonous gases, contaminants from collected food waste and animal manure.
4.	Feedstock	It was used for production of biogas. The feedstock used in this research work include food waste such as fufu, eba, starch, rice, beans, yam, fish, meat and moi moi and animal manure such as pig and cow dung.
5.	Gesa thermometer	Connected to the three-stage continuous anaerobic digestion plant and it was used to monitor the mesophilic temperature reading of the slurry.
6.	Hand gloves	For protection
7.	Black polyethylene bag	For collection and sorting of food waste and animal manure.
8.	Wash bottles	Used for rinsing

9.	Gas cylinder	Used for biogas storage
10.	Manual compressor	For evacuation of biogas
11.	Laboratory oven	For determination of total solid
12.	Muffle furnace	For determination of volatile solid

2.2 Methods

2.2.1 Artificial Neural Networks Approach

ANNs is used to resolve complex problems that could not be addressed by conventional methods. In this research work, ANNs was utilized as a tool for modelling of biogas yield from a three-stage continuous AD plant. The ANNs model for anaerobic co-digestion of food waste was developed using ANN Toolbox of MATLAB 2014 software. The ANNs Toolbox is a built-in tool in MATLAB, and it provides functions and applications for modelling robust and complex nonlinear problems that cannot be easily modelled by conventional methods. Figure 2 shows the steps, stages, and approach of the ANNs modelling.

2.2.2 Preparation and Collection of Data

The input and target data were gotten from experimental results obtained from co-digestion of food waste and animal manure using a three-stage continuous AD plant (Figure 3) and then prepared in a Microsoft Excel Spreadsheet. The input sets used were total solid (TS), volatile solid (VS), temperature (T), organic loading rate (OLR), pH, hydraulic retention time, and feedstock (substrate).

2.2.3 Design of the Architecture of the Artificial Neural Networks (ANNs) Model

This stage involves the design of the ANNs architecture in terms of components of the neural network and its operations. The number of layers and the number of neurons in each layer were identified. The multilayered feed forward architecture was used for designing the ANNs model. It consists of three layers of nodes. Each node is a neuron that uses a nonlinear activation function except for the input node. The networks were designed to contain three layers (seven input layers, ten hidden layers and one output layer) (Figure 4). In trying to separate the data non-linearly, ten hidden layers prove to be the best decision boundary. The architecture of the ANNs model was decided by applying ten different numbers of hidden neurons in the hidden layer (from one to ten neurons) for three different trials of data separation (% of training set: % of validation set: % of testing set) including 60%:20%:20%.

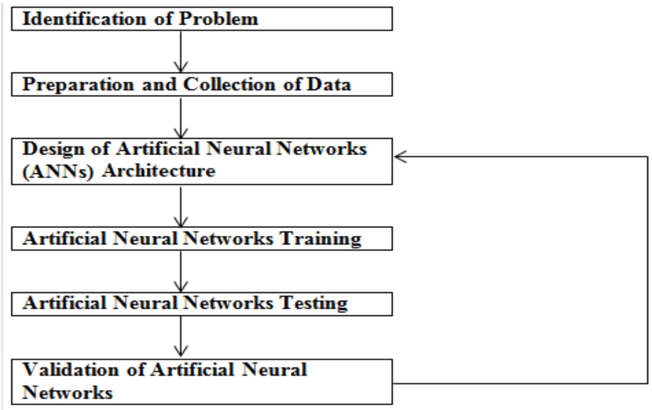

Figure 2. Artificial Neural Networks (ANNs) Approach

Figure 3. Three-stage continuous anaerobic digestion plant

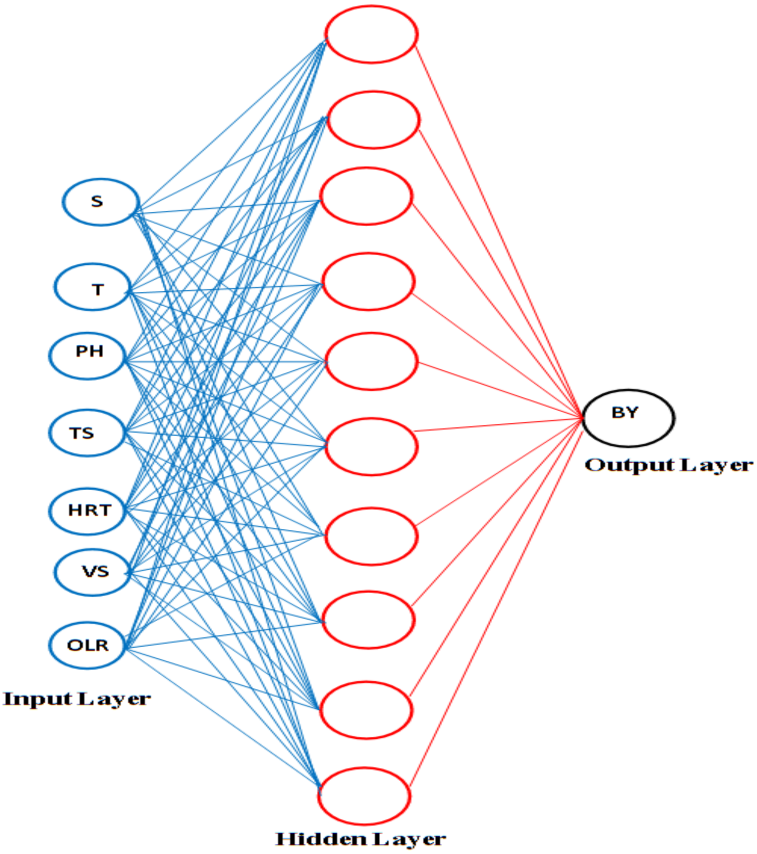

Figure 4. Artificial neural networks architecture

2.2.4 Artificial Neural Networks (ANNs) Training

This phase involves the regulation of data of the connection weights and biases to create the outputs (biogas yield) with the given inputs (S, T, VS, TS, OLR, pH, HRT). ANN training is very vital since it determines the generalization of the model. In this research work Levenberg-Marquardt back propagation training algorithm was used to train the artificial neural networks using MATLAB 2014 ANN Toolbox. The network calculated the errors on the training data set and the validation set. However, the training was stop when the validation error was minimum. The ANNs training diagram is shown in Figure 5.

2.2.5 Black Propagation Network

The back-propagation network (BPN) was used in this research work because of its extensively training algorithm for a multilayer feed forward neural network. It comprises of an input layer with nodes representing input variables to the problem, an output layer with nodes indicating the dependent variables that is being modelled and hidden layers containing nodes to aid in capturing the nonlinearity in the data. In this research work, supervised learning was used. The networks can learn the mapping from one data space to another using example. By back propagation, it simply means the way the error computed at the output side is propagated backward from the output layer to the hidden layer, and finally to the input layer. In so doing, all links become unidirectional and there are no same layer neuron-to-neuron connections. Thus, the data is fed forward into the network without feedback.

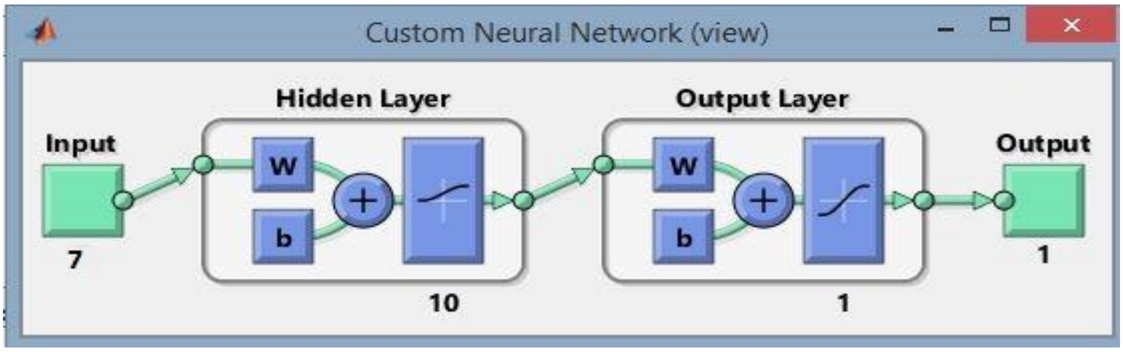

Figure 5. Artificial neural network training diagram

Figure 6. Mixture of food waste and animal manure

2.2.6 Validation of Artificial Neural Networks (ANNs) Model

The validation of ANNs model determines its ability to evaluate and solve the identified problems. In this research work, the experimental results obtained from co-digestion of food waste and animal manure was collected and uses to validate the developed artificial neural networks model.

2.3 Co-digestion of Food waste and Animal manure

The three-stage continuous anaerobic digestion plant was initially seeded with animal manure (mixture of cow dung and pig dung). Samples of collected feedstock (substrates) composition was ground into fine particles to increase its surface area, and then mixed with waste in a ratio of 1:2 as recommended by Ebunilo *et al*. [27]. Figure 6 shows mixture of properly mixed food, animal manure and water in ratio of 1:2.

3. RESULTS AND DISCUSSION

3.1 Results

The results of the best validation of the ANNs model training performance with ten numbers of hidden neurons and the data separation of 60%: 20%: 20% is summarized in Table 2.

Table 2. Results of artificial neural networks model

Sample Used	Percentage of Separation (%)	Number of Sample	R^2
Training	60	162	0.97193
Testing	20	54	0.96510
Validation	20	54	0.98378
All	100	270	0.97229

3.2 Discussion

The inputs to the ANN model were selected to be seven process and operational parameters, namely; temperature, percentage total solids, percentage volatile solid, organic loading rate, pH, hydraulic retention time, and substrate composition. The neural network with the smallest mean squared error (MSE) for validation was selected and this was based on the results of the different trials of the neural network model that was developed. The regression (R^2) value is the suggestion of the correlation between the outputs and the targets. The target is the desired output for the given input and the network was trained with a known input. Consequently, a bigger value of regression (R^2) closer to one (1) suggests a closer relationship and a zero R^2 represents a random relationship. The connection weights of the neural networks were attuned to minimize the MSE on the training set during the training phase. The best validation performance of selected ANNs that generate the least MSE value was 5.1115×10^{-4} (Figure 7), and this agree with the work of Behera *et al*. [28] and Yetilmezsoy *et al.* [29] that reported lower mean square error as a fundamental criterion used to determine the training accuracy of a network. The least value of MSE obtained for performance validation of the ANNs at 974 epochs is a confirmation of best results. Hence, the predicting ability of biogas yield by the ANNs model is effective.

The relatively high coefficient of determination (R^2) value for validation of the selected ANNs was high and close to one (1), the value being 0.97193 and this was in line with the work of Ozkaya *et al.* [30]. The R^2 values obtained in this study which is close to 1 is a suggestion that the prediction of the ANN model was linearly correlated. The regression plots of the selected ANNs for training, testing, validation and all data set obtained from the ANNs Toolbox is shown in Figure 8. As presented in the regression plots, the anticipated neural network has a close correlation between the outputs and the targets. The outcome of the results confirmed that the R^2 values of the training set, the testing set, the validation set, and the all data set were found to be high and close to 1, the values being 0.97193, 0.96510, 0.98378 and 0.97229. The correlation between the data used in the validation process and the predicted values of biogas yields is shown in Figure 9. The ANNs model predicted biogas yield, which is an indication that the ANNs learned the relation between the input to the anaerobic digestion plant and the output in the biogas stream very well.

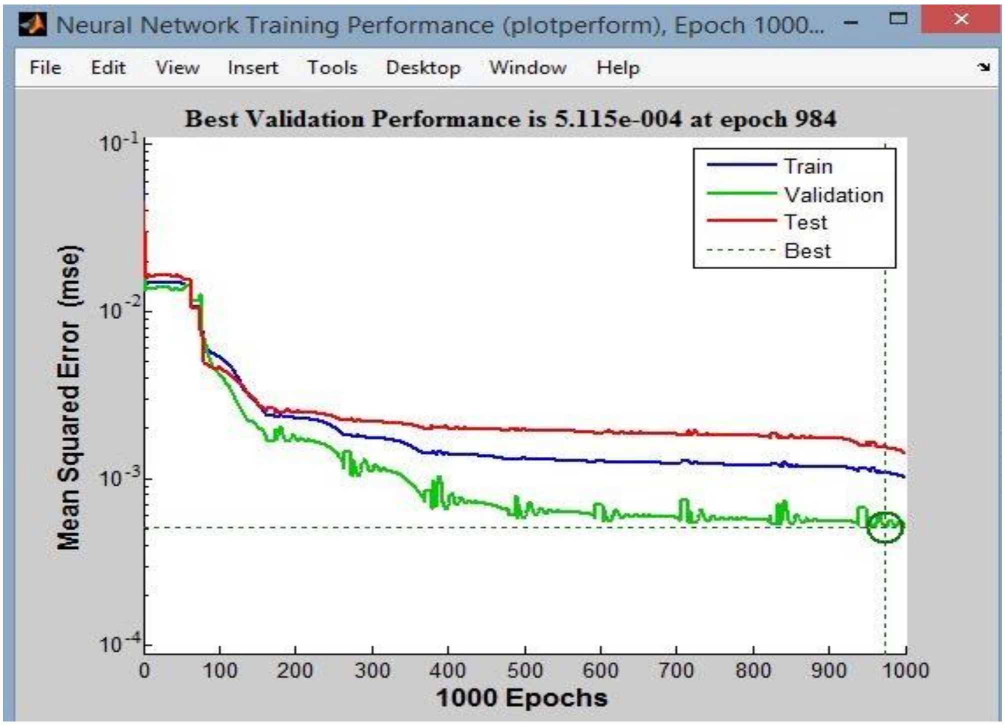

Figure 7. Training of artificial neural networks model with 1000 epochs and performance curve

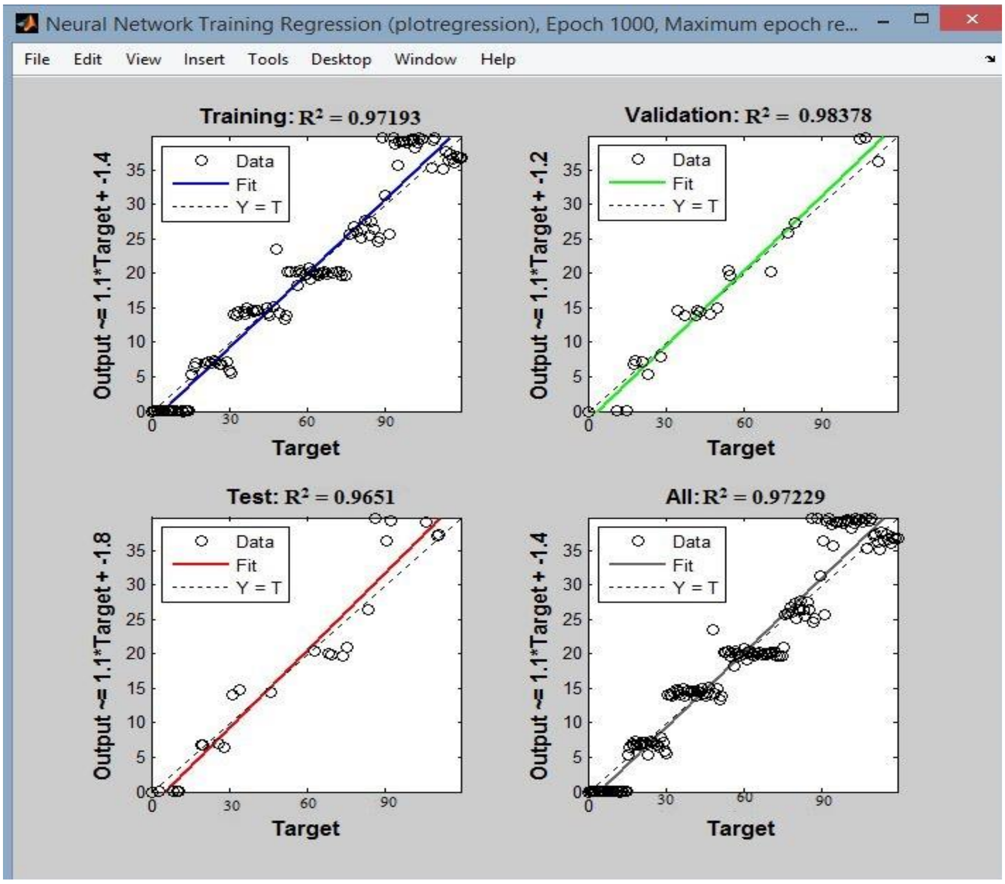

Figure 8. Regression plots of the artificial neural networks model

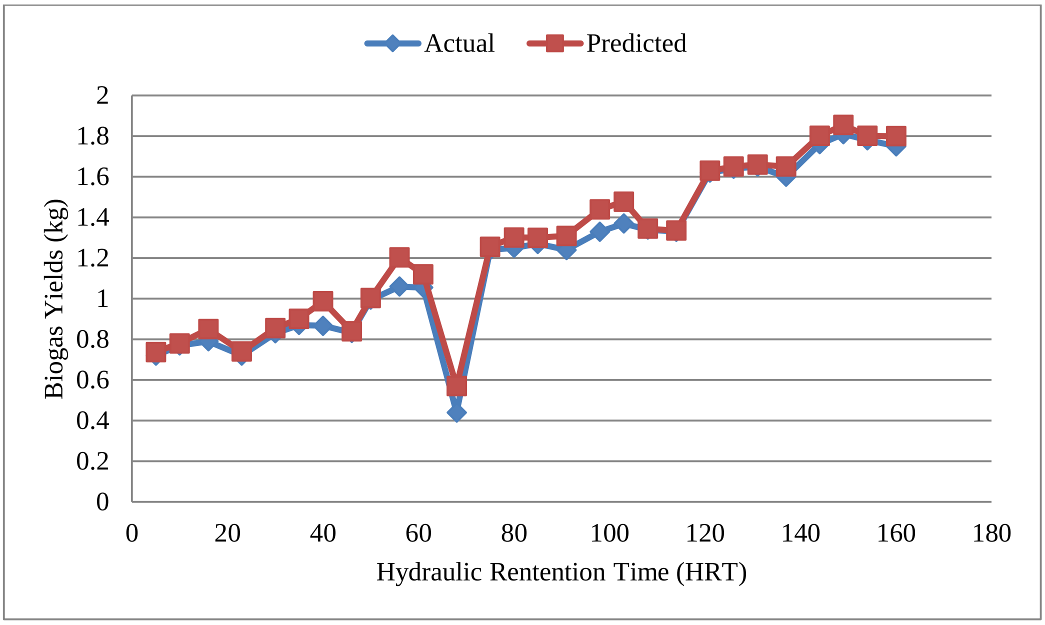

Figure 9. Actual biogas and predicted biogas yield by artificial neural networks model

4. CONCLUSION

In this research work, artificial neural networks model was used to model and predict biogas yield. The back-propagation artificial neural networks model with ten hidden layers was found to capture most of the important patterns in biogas yield from the anaerobic digestion plant as it fitted well with the measured biogas yield. The coefficient of determination (R^2) value for validation of the artificial neural networks model was found highly correlating to the actual biogas yield with R^2 of 0.9509, which suggests that the artificial neural networks is a useful tool in predicting biogas yield from the anaerobic digestion plant.

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