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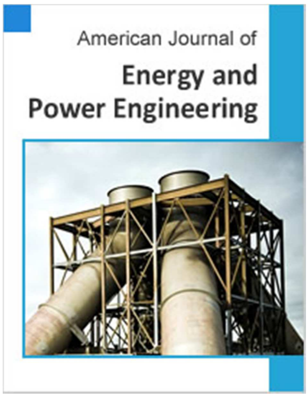

Development of a Predictive Model for Biogas Yield Using Artificial Neural Networks (ANNs) Approach

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Abstract

The modelling of anaerobic co-digestion of household food solid wastes and wastewater are complex and this is due to the rigorous processes that take place during the digestion process. The development of a predictive model that is capable of the simulation of anaerobic digester (AD) performances can go a long way in helping the operation of the AD processes and the optimization for biogas yield. The artificial neural networks (ANNs) approach is considered to be suitable and straightforward modelling method for AD process. In this research work, a multi-layer ANNs model with six input layer, ten hidden layers was trained using Lavenberg-Marquardt back propagation algorithm to simulate the digester operation and to predict the outcome of biogas yield. The performance of the developed ANNs models was validated and the results obtained from the research work reveal the effectiveness of the model to predict biogas yield with a mean squared error (MSE) of best validation performance of 5.1×10^{-4}. Moreover, the anticipated artificial neural networks model has a close correlation between the outputs and the targets. The outcome of the results showed that the R values of the training set, the testing set, the validation set and the all data set were found to be high, the values being 0.97193, 0.96510, 0.98378 and 0.97229 respectively.

1. Introduction

The anaerobic digestion (AD) process which involves the co-digestion of biodegradable organic waste is a well-established bioprocessing technology that lead 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) [1, 2, 3, 4]. The interest in converting biomass resources such as food waste to an alternative fuel source like biogas is receiving more attention in recent times [5, 6, 7]. The biogas yield obtained from AD process can be improved with better process and operation design through modelling, simulation and optimization as an integrated part of modern design practice [9, 10]. The mathematical modelling of AD process is very difficult and tasking. This is due to the rigorous processes that take place during the digestion process [11, 12]. Due to the intricacies involved, the AD process is often modelled as a black-box [13, 14]. Artificial neural networks (ANNs) models can be used to overcome some of the problems of comprehending the AD process [15, 16].

An artificial neural networks (ANNs) also called parallel distributed processing (PDP), connectionism or neuro-computing is a computational network where several simple computational elements (artificial neurons), perform a nonlinear function of their inputs [17]. Such computational units are vastly unified and are able to model a system by means of a training algorithm [18]. This algorithm tries to reduce measured errors that is computed in different ways depending on the exact technique used to regulate the connections (learning algorithm). In training artificial neural networks (ANNs), two major approach can be adopted; either to adapt to its parameters or to supervised and unsupervised learning [19]. In the supervised learning approach, precise examples of a target concept are given and the aim is to learn how to identify members of the class or to build a regression model using the description attributes [19]. In this circumstance, the synaptic weights among neurons are attuned in order to minimize the error between the known desired outputs and the actual output given by the neural network during the learning process [17]. However, in the unsupervised learning approach, the set of examples is provided without any preceding grouping and the aim is to ascertain core regularities and patterns, most often by recognizing groups of similar examples [20]. Training in this case involves on looking for a trampled representation of the collected original data and the error in this situation is the difference between this representation of the original data.

The desirability of ANNs comes from their outstanding information processing features applicable predominantly to nonlinearity, high parallelism, fault and noise tolerance, learning and generalization capabilities. In comparison to conventional data processing methods, ANNs provide a model-free, adaptive, parallel-processing and robust solution with fault and failure tolerance, learning, ability to handle ambiguous information. Subsequently training with known samples, artificial neural networks can be applied for predicting the outcome of a new set of independent input data as the networks have the capability to generalize [20, 21]. Nevertheless, artificial neural networks have certain limitations. There is always present of minor error related to all neural network outputs and this is due to the fact that the neural network is aimed at finding an approximation of a solution [22]. However, errors of neural networks usually vary depending on their architecture. Besides, the models need to be trained and validated with experimental data sets. ANNs models are valid only for the particular systems for which the models were developed [23, 24]. The artificial neural networks (ANNs) approach has been successfully applied for anaerobic digestion (AD) processes for many industrial cases [18]. Parthiban et al. [20] used the ANNs approach for the modelling of the sago wastewater treatment parameters using an anaerobic tapered fluidized bed reactor. In their research work, six experimental parameters in the treatment process were considered for the modelling. The input parameters used composed of influent flow rate, pH, COD, and hydraulic retention time, while the output parameters included effluent COD and methane (CH_4) gas yield. The ANNs simulations were carried out with MATLAB 7.1 using the back propagation training algorithm, which has proven to have great adaptability to various configurations and operation conditions [25]. The ANNs model was validated by replicative testing and their regression analysis fitting of all test data with the neural network model was 0.99924.

Furthermore, Behera, et al. [26] used ANNs modelling to predict the methane percentage in biogas recovered from landfill. The networks they used consist of 2 input nodes, 15 hidden nodes and one output node. In their research work, they obtained best mean absolute percentage of 2.1075 with correlation coefficient R value of 0.8795. The study of modelling on large anaerobic digester producing biogas from cattle waste using ANNs by Dhussa, et al. [27] was modelled using networks consist of 6 input neuron, 10 neurons each on 2 hidden layers and one output node. The networks were train using a number of training algorithms available in MATLAB and they achieved a very low mean square errors (MSE) values and high correlation coefficient R values between 0.82 and 0.93. Also, Yetilmezsoy, et al. [28] used ANNs to model biogas production in anaerobic treatment of molasses wastewater. They applied several training algorithms available in MATLAB to train the ANNs. Two networks architecture were produced to model the biogas and methane production. From their findings, an accuracy was measured using MSE around 6×10^{-5} correlation coefficient R at 0.87. This work was therefore originated to develop a predictive model using ANNs approach to model the co-digestion of biodegradable organic waste and wastewater from ice fish cold room and abattoir. The model prediction outcome will be based on the level and degree of accuracy of the mean squared error (MSE) performance and the correlation coefficient value of R.

2. Biogas Production from Anaerobic Co-digestion

The experiment data sets were obtained from anaerobic co-digestion of biodegradable organic waste, waste water from ice fish cold room and abattoir. The biodegradable organic waste comprises of food wastes collected from household in Benin City, Nigeria. The collected household food solid wastes were co-digested with waste water from cold room and abattoir. Cow dung was used as seeding agent to enhance hydraulic retention time. The experiment was done with three stage continuous AD plants with a total volume of 200 litres. Hydraulic retention time of 120 days were used. Biogas yield from the AD plant was collected and used as the output value.

3. Artificial Neural Networks (ANNs) Approach

The artificial neural networks (ANNs) model for anaerobic co-digestion of household food solid wastes, waste water from ice fish cold room and abattoir were developed using ANNs Toolbox of MATLAB 2014 software. The ANNs Toolbox is an inbuilt tool in MATLAB, 2014 and it provides functions and applications for modelling robust and complex nonlinear problems that cannot be easily modelled. The steps, stages and approach of the ANNs modelling is shown in Figure 1.

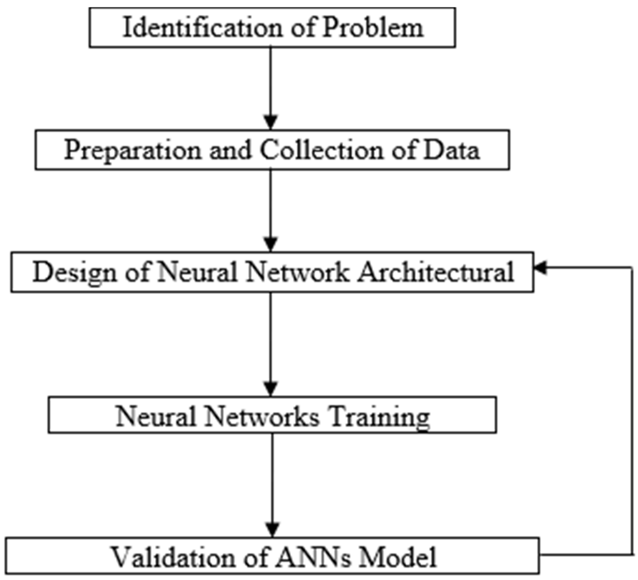

Figure 1. *Artificial Neural Networks Approach.*

4. Preparation and Collection of Data

The input and target data were obtained from experimental results and then prepared in a Microsoft Excel Spreadsheet. The input sets are total solid (TS), volatile solid (VS), temperature (T), organic loading rate (OLR), pH and feedstock (FS). The data set of 120 samples were separated into three subsets by random selection, as the training set, the testing set and the validation set. The data required for the ANNs models include input data and output data.

5. Design of Artificial Neural Networks Architectural

This phase involves the construction 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 artificial neural network models. The networks were designed to contain three layers, that is six input layer, ten hidden layer and one output layer. The architecture of the ANNs models 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 shows the ANNs architecture that generated the best results.

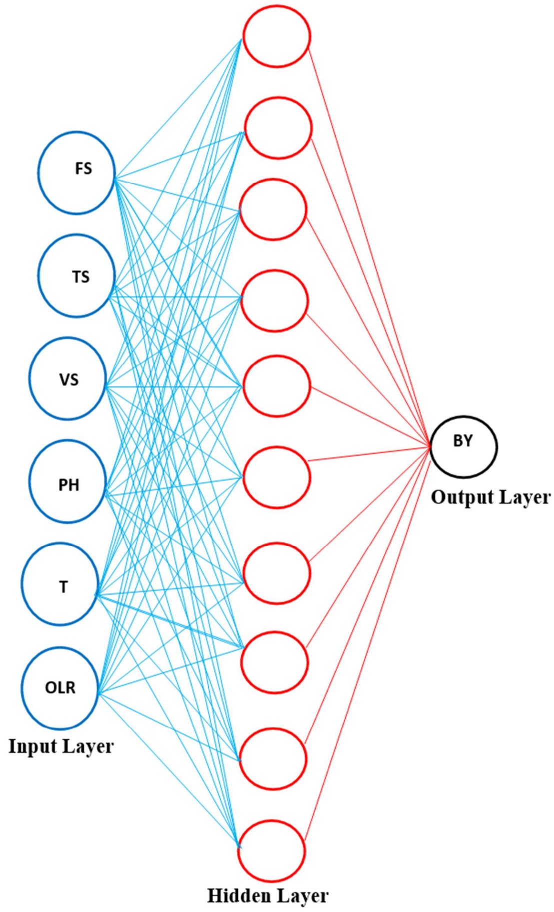

Figure 2. *Artificial Neural Networks (ANNs) Architecture.*

6. Artificial Neural Networks (ANNs) Training

This stage involves the regulation of data of the connection weights and biases in order to create the outputs (biogas yield) with the given inputs (FS, T, VS, TS, OLR, pH). Artificial Neural Networks training is a very vital phase since it determines the generalization of the models. In this research work Levenberg-Marquardt back propagation training algorithm (trainlm) was used to train the neural networks using MATLAB 2014 ANNs Toolbox.

7. Back Propagation (BP) Network

A back propagation (BP) network is a multilayer perceptron comprising of an input layer with nodes representing input variables to the problem, an output layer with nodes signifying 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 examples. 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 back propagation, all links are unidirectional and there are no same layer neuron-to-neuron connections, thus, the data are fed forward into the network without feedback. However, the neurons in back propagation ANNs can be fully or incompletely interconnected.

8. Validation of Artificial Neural Networks (ANNs) Model

The validation of the model determines its ability to evaluate and solve the identify problems required. In this research work, mean squared error (MSE) and correlation coefficient regression R values were calculated from experimental data and this was used to evaluate and validate performance of the ANNs models.

9. Results and Discussion

In this research work, the performance assessment of the predictive ability and validation of the developed ANNs models were evaluated by using mean squared errors (MSE) and regression R value. The designed ANNs and the data separation were clearly attained through the trial and error experimentation. The neural network with the smallest mean squared error (MSE) for validation was chosen and this was based on the results of the different trials of the neural network models developed. The mean squared error (MSE) is an estimator of the mean or average squared difference between the outputs and the targets (Equation 1). Thus, it is the sum of the variance and bias. A lower value of mean squared error (MSE) is an indication of a better result [26, 28].

$$\text{Error (e)} = \text{Target (T)} - \text{Output (Y)} \tag{1}$$

The regression (R) value is a suggestion of the correlation between the outputs and the targets. The target is the desired output for the given input and the network is trained with a known input. Consequently, a bigger value of regression (R) specifies a closer relationship and a zero R 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 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% are summarized in Table 1.

Table 1. *Results of Artificial Neural Networks Model.*

Separation (%)	Number of Samples	Sample Type	MSE	R
60	72	Training	4.5×10^{-3}	0.97193
20	24	Testing	2.0×10^{-3}	0.96510
20	24	Validation	5.1×10^{-4}	0.98378
100	120	All	-	0.97229

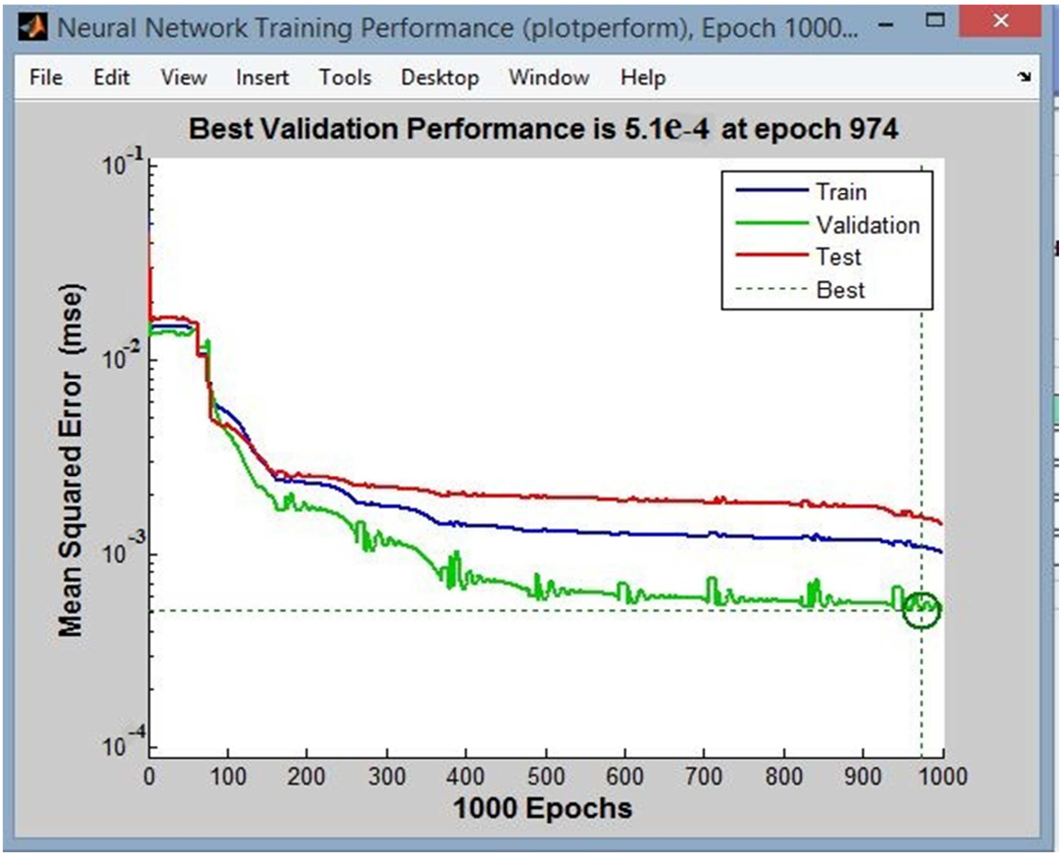

Figure 3. *Training of Artificial Neural Networks (ANNs) Model with 1000 Epochs.*

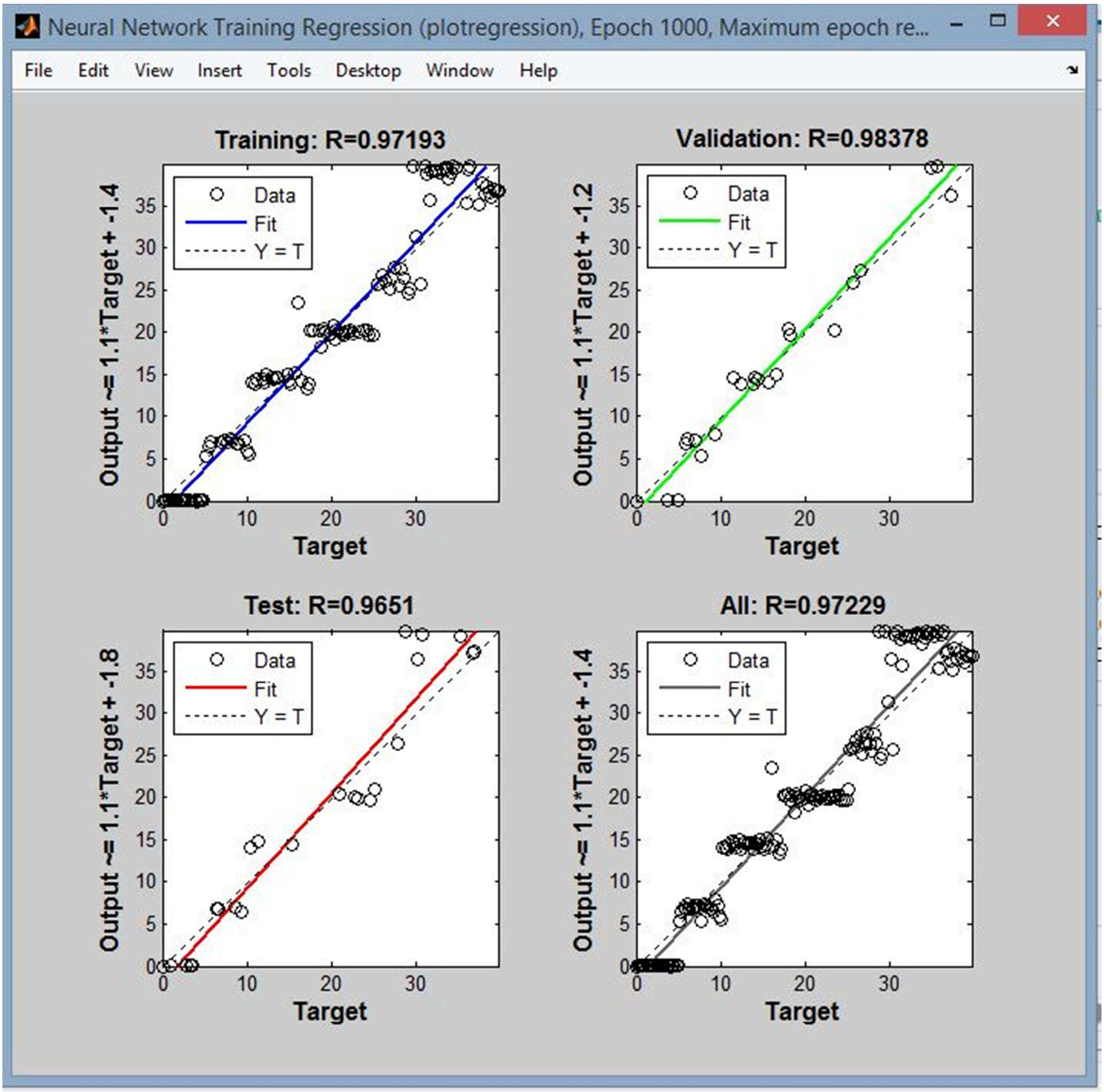

Figure 4. *Regression Plots of the Artificial Neural Networks (ANNs) Model.*

The best validation performance of selected ANNs generate the least MSE value of 5.1×10^{-4} and this agree with the work of Yetilmezsoy et al. [28]. Also, the MSE for the training set was found to be 4.5×10^{-3} while the MSE for the testing set was 2.0×10^{-3} (Figure 3). The least value of MSE obtained for performance validation of the ANNs at 974 epochs is a confirmation of best results. Thus, the predicting ability of biogas yield by the ANNs model is effective.

The R value for validation of the selected ANNs was high, the value being 0.98378, and this was in line with the work of Dhussa, et al. [27]. The regression plots of the chosen ANNs for training, testing, validation and all data set obtained from the ANNs Toolbox are shown in Figure 4. As presented in the regression plots (Figure 4), the anticipated neural network has a close correlation between the outputs and the targets. The outcome of the results confirmed that the R values of the training set, the testing set, the validation set and the all data set were found to be high, the values being 0.97193, 0.96510, 0.98378 and 0.97229 respectively.

10. Conclusion

This research work focused on artificial neural networks (ANNs) model approach for the computational predictions of biogas yield from co-digestion of household food solid wastes and waste water. The neural networks were validated using the MSE of the validation set. As shown in the regression plots, the R values obtained are close to 1 and this suggests that the prediction of the neural networks model was linearly correlated with the experimental data. Therefore, the artificial neural networks (ANNs) models developed could be used to predict the outcomes of biogas yield from the anaerobic co-digestion of household food solid wastes and waste water

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