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Artificial neural network modelling of biogas yield from co-digestion of poultry droppings and cattle dung

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Abstract

Mechanistic modelling aimed at predicting biogas yield is marred with complex interactions and hence, a very tedious endeavour. Consequently, Artificial Neural Network (ANN) modelling approach was used to model the relationship among six physico-chemical properties of a mixture of poultry droppings and cattle dung to predict the volume of biogas produced i.e. pH, Total Dissolved Solids, temperature, mass of the slurry, Biochemical Oxygen Demand and Dissolved Oxygen. Three floating drum anaerobic digesters were loaded with 27 varying ratios of a mixture of poultry droppings and cattle dung using batch method, such that the three digester reactors ran nine different batches of mix ratio for a retention period of 27 days each. Slurry temperature, gas and slurry-gas interfaces were monitored using WZP pt100 and DHT 11 sensors installed on an Arduino microcontroller. The 3 -layer Feed-Forward model with Back-Propagation Multi-Layer Perception (MLP) architectures, 6-12-1 (6 nodes each in input layer, 12 nodes in hidden layer and single node in output layer) developed for biogas prediction yielded optimal results. The developed model used the default data separation of 60%, 20% and 20 % in Matlab R2015a software. Correlation Coefficient (R) of developed ANN model for biogas prediction were 0.9653, 0.9245 and 0.9842 for training, validation and test sets respectively. Statistical analysis showed that mass of slurry and TDS had best correlation with biogas volume (i.e.), while DO and BOD had the least correlation with biogas volume. The developed ANN modelled biogas production from the co-digestion of poultry droppings and cattle dung efficiently.

Keywords: Artificial Neural Network; Anaerobic digestion; Co-digestion; Supervised machine learning

1. Introduction

Biogas is a combustible mixture of gases produced from anaerobic digestion (AD) of organic materials. Biogas is about 20 percent lighter than air and has an ignition temperature in the range of 650 - 750 °C [1]. Biogas burns with a characteristic clear blue flame similar to that of Liquefied Petroleum Gas (LPG), making it a useful alternative to natural gas for cooking and other heating requirements. According to [2], the calorific value of biogas is around 20 MJ/m³ and it burns with 60 percent efficiency in a conventional biogas stove. Biogas is a suitable and a renewable substitute for natural gas in most energy applications and has been known and studied for centuries. However, due to the difficulties surrounding the determination of useful modelling parameters in the anaerobic digestion process, mechanistic modelling of this process for biogas production has been limited in terms of application. As a result, the anaerobic digestion process is often modelled as a Black Box empirical model [3]. Artificial Neural Network (ANN) as a black box modelling approach, is commonly used to overcome some of the complexities associated with the mechanistic modelling of the digestion process as reported by [4 – 6].

ANN is a computational structure, in which many simple computational elements called artificial neurons, perform a non-linear function among inputs [7]. Such computational units are massively interconnected and are able to model a system by means of a training algorithm. This algorithm attempts to minimize an error measure that is computed in different ways depending on the specific technique used to adjust the connections (i.e., the learning algorithm). At present, there exist two major approaches to training an artificial neural network (i.e. to adapt its parameters): Supervised and Unsupervised learning, as reported by [8]. ANNs have become the most popular soft computing methods for solving problems in engineering [9]. ANN has found applications in a number of engineering applications such as sensor data analysis, fault detection and process identification [10]. The aim of this study was to develop an ANN model to predict the volume of biogas produced from anaerobic co-digestion of cattle dung and poultry droppings using experimental data.

2. Materials and methods

Three floating drum anaerobic digesters were constructed made from a 2 mm thick steel plate each. Each digester had a volumetric capacity of 207 litres, with an internal diameter of 500 mm and a height of 900 mm and an active slurry volume of 180 litres. Each reactor consisted of two main sections: the main digester tank which has a diameter of 500 mm and a height of 900 mm, with a conical section of height 120 mm at the bottom to allow for easy dislodging; and the gas holder which has a diameter of 480 mm and a height of 900 mm. The top of the main digester tank is open while the bottom is closed with a conical section as described above; a 100 mm pipe is fitted to the base of the conical section to act as the digestate removal section. Also, a pipe of 60 mm diameter is fitted to the side of the main digester tank and welded to a position close to the bottom of the tank to act as the slurry inlet. The gas holder is inverted and placed on the digester tank with its open end floating while the other end is closed. Slurry temperature sensor (Wzp Pt100) was fitted to the bottom of the main digester tank by boring a 5 mm diameter hole and then sealing the hole after placing

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Figure 1: Experimental set-up of the digester.
A: Gas holder tank (evolution of gas shown as a function of rise in gas holder tank), B: Inlet pipe for feeding, C: Tripod stand, D: Outlet pipe for dislodging, E: temperature sensors, F: Personal Computer for temperature monitoring, display and database creation, G: Arduino microcontroller.

sensor with the use of sealant. While the gas and gas – slurry interface temperature sensors (DHT 11) were fitted to the floating drum and their wires passed through the top of the floating drum to the Arduino Uno microcontroller.

The feedstock i.e. poultry droppings and cow dung were collected from the University of Ilorin Teaching and Research Farm located within the University of Ilorin. About 50cl of each sample to be digested was taken to the Industrial Chemistry Laboratory to determine their properties before digestion. The mixing was carried out in ratios to obtain a valid means of imposing variability on the physical and chemical properties of the resulting slurry. The mass of cattle dung were varied over three ratios representing three different mass of the feedstock added in the mixture, which are M_{cd1} = 30kg, M_{cd2} = 45kg and M_{cd3} = 60kg. The mass of poultry droppings used in the experiment was varied over three ratios, represented by M_{pd1} = 30kg, M_{pd2} = 45kg and M_{pd3} = 60kg. The quantity of water added was also varied over three ratios to obtain several total solid concentrations and represented by M_{w1} = 30kg, M_{w2} = 45kg and M_{w3} = 60kg. The experimental setup was as shown in Fig. 1.

2.1. Choice of inputs to the neural network

Table 1 shows the descriptive statistics of parameters of the waste samples used in the ANN model development: Biochemical Oxygen demand (BOD), Dissolved Oxygen (DO), pH, mass of the slurry, Total Dissolved Solid (TDS) and average slurry temperature. BOD, pH and DO of the slurry mixture were determined according to the standard methods for determining these properties in wastewaters and this was done in the University of Ilorin, Industrial Chemistry Laboratory. The mass of slurry, total dissolved solid concentrations and temperature were determined with the use of weighing scale, handheld TDS measuring kit and temperature sensors respectively.

2.2. Network properties

MATLAB neural network tool was used to develop various artificial neural networks. This software allows the user to quantitatively and graphically monitor the network training and prediction processes. Model training was done using different combinations of parameters: inlet pH, inlet mass of slurry, average temperature of digesting slurry, inlet dissolved oxygen of slurry (DO), inlet biochemical oxygen demand of the slurry (BOD), inlet total dissolved solid (TDS) and volume of biogas production in order to achieve maximum determination coefficient (R^2) values and minimum root mean square (RMS) values. This was achieved by a rigorous trial and error method by keeping some training parameters constant and slowly moving the other parameters over a wide range of values. The neural network model was created in MATLAB 2015a. MATLAB Toolbox opens the Network/Data Manager window, which allows the user to import, create, use, and export neural networks and data [11].

The properties of the best performing network are as follows:

- Network inputs: pH, BOD, DO, TDS, Temperature and Mass of slurry
- Network outputs: Volume of Biogas
- Network type: Feed-Forward Back-Propagation.
- Training function: TRAINLM.
- Adaption learning function: LEARNGDM.
- Performance function: MSE.
- Number of hidden layers: 1
- Number of Neuron in Hidden layer: 12
- Hidden Layer Transfer function: tansig

Table 1: Range of Data Set and Statistics.

Inputs	N	Minimum	Maximum	Mean	Std. Deviation	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
BOD (mg/L)	27	7.8	100	24.251	4.9238	25.5842
DO (mg/L)	27	39.2	140	62.488	4.5473	23.6286
pH	27	6	7.9	6.422	0.1239	0.6441
Temperature (°C)	27	23.9	29	26.16	1.2369	0.238
TDS (mg/L)	27	1790	7860	6484.81	387.4676	2013.3408
Mass of Slurry (kg)	27	90	180	135	4.1602	21.617
Valid N (listwise)	27					

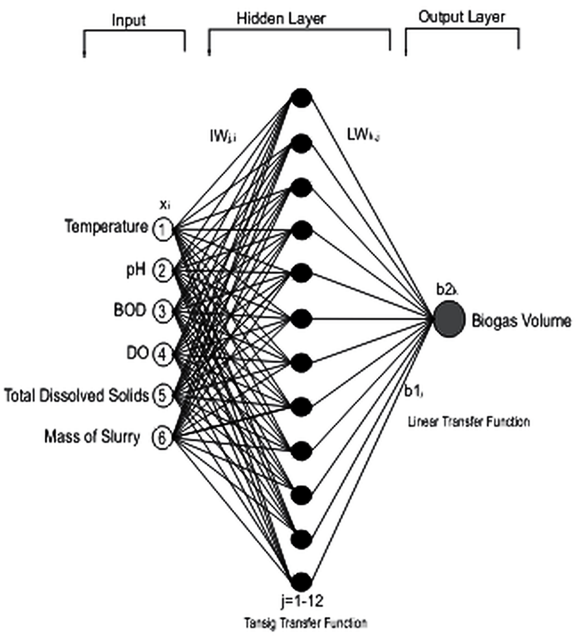

Figure 2: Optimal neural network architecture.

- Output Layer Transfer function: purelin

3. Results and discussion

3.1. Physico-chemical properties of slurry

Physico-chemical properties of cattle dung mixed with poultry droppings varied depending on the mix ratio as presented in Table 2. Also, pH values of slurry were close to the lower boundary of 6.0 suggested in literature to be optimum for gas production and volatile acid inhibition would have been expected due to the formation of organic acids but this was not the case and could be attributed to the concurrent formation of ammonia gas which helped to neutralize the toxic effect of volatile organic acids since poultry waste is known to be rich in Nitrogen. The temperatures of the digesting slurries for all the 27 batches were within the mesophilic range of 20 °C and 30 °C reported in [12 - 15] to be suitable for biogas production. The architecture of the ANN model which generated the best result is illustrated in Fig. 2.

From Fig. 2, twelve hidden neurons with data separation of 60%: 20%: 20% generated the smallest Mean Squared Error (MSE) for validation. It can be seen that each neuron in a layer is connected with all neurons in the following layer with weights and biases. The transfer functions applied for the neural network models were the hyperbolic tangent sigmoid function (tansig) and the linear transfer function (purelin). Tansig was used for the hidden layer while purelin was used for the output layer. The final form of the equation for the feed forward neural network model proposed was expressed by Equation 1. The computer - generated responses were in accordance with the feed forward backward propagation model equation presented by [3]. Table 3 showed R values and MSE values of the optimal artificial neural network model. Also, Fig. 3 showed the regression plots obtained from the study using the Matlab ANN module.

3.2. Volumetric analysis of biogas yield

Table 4 showed the values of experimentally - measured biogas yield and model - predicted biogas yield. The maximum volume of biogas obtained during the study was 18392 litres from sample 18 with a mix ratio of poultry droppings to cattle dung to water of 1 : 1 : 0.75; total mass 165kg; average temperature 26.6°C; TDS 7680 mg/l; DO 53.6 mg/l; BOD 13.2 mg/l; and input pH of 6.0. This result was in accordance with [16 - 17] Aduba *et al.* (2013) and Adeniran and Kareem (2014), that high amount of feedstock with about 7000 mg/l TDS gave optimal biogas production across all treatments. This may be due to unrestricted access of methanogenic bacteria to sufficient total dissolved solids. Also, sample 18 yielded the poorest prediction error of 6937 litres while sample 5 gave the least prediction error of 38.20 litres. Fig. 4 described error graph of the predicted biogas volume. Fig. 5 showed that measured values of biogas yield were significantly closer to predicted values of biogas yield with lesser absolute error.

The design of the neural network model and the data separation were clearly achieved by several training schemes. From the results of the different trials of the neural network models developed, the neural network with the smallest mean squared error (MSE) of 0.33 for validation was chosen. The MSE is an estimator of the average squared difference between the outputs and the targets. A lower value of MSE with a corresponding R-value close to 1 thus suggests a better result. The R value is an indication of the correlation between the outputs and the targets. Therefore, a higher value of R indicates a closer relationship and a zero R represents a random relationship. During the training stage, the connection weights of the neural networks were adjusted to minimize the MSE on the training set. Then, the neural networks were validated through the MSE of the validation set. As shown in the software's regression plot in Fig. 3, R values of close to 1 were observed for the training, validation test and all sets of data, which suggested that the prediction of the neural network model was linearly correlated with the experimental data. In addition, by considering Table 3, it is clear that there is a good agreement between the network - predicted biogas volumes and the measured biogas volumes. Therefore, it can be concluded that the proposed neural network model was capable of predicting the outcomes of biogas production from

Table 2: Effects of mix ratio of feedstock on TDS, DO, BOD and pH.

Batch No	$M_{pd} : M_{cd} : M_w$ (kg : kg : kg)	TDS(mg/l)	DO (mg/l)	BOD (mg/l)	pH
1	30:30:30	4020	114	98	7.9
2	45:30:30	3450	140	100	7.9
3	60:30:30	4620	118	80	7.9
4	30:45:30	6030	62	40	7.3
5	45:45:30	2280	64	20	6.5
6	60:45:30	1790	58	20	6.6
7	30:60:30	2520	52	10	6.8
8	30:45:45	4460	62	26	6.0
9	60:60:30	7060	62	14	6.0
10	30:30:45	7160	61.6	9.2	6.0
11	45:30:45	7240	62	9.6	6.0
12	60:30:45	7660	61.8	7.8	6.1
13	45:60:30	7640	60	16	6.1
14	45:45:45	7630	59.6	14.4	6.1
15	60:45:45	7640	60.4	14.4	6.1
16	30:60:45	7650	60.4	15.4	6.1
17	45:60:45	7660	54	14	6.1
18	60:60:45	7680	53.6	13.2	6.0
19	30:30:60	7760	52	11.8	6.0
20	45:30:60	7740	53.8	13.8	6.2
21	60:30:60	7820	50	17.6	6.1
22	30:45:60	7830	49.2	17	6.0
23	45:45:60	7850	50.4	18.4	6.0
24	60:45:60	7840	48	15.4	6.0
25	30:60:60	7800	39.6	12.4	6.1
26	45:60:60	7860	39.2	12.8	6.1
27	60:60:60	7860	39.6	13.6	6.1

$M_{pd} : M_{cd} : M_w$ is mass of poultry droppings : mass of cow dung : mass of water

$$output_k = \sum_{j=1}^{j=12} \left[LW_{k,j} \left(\frac{2}{1 + \exp\left(-2.\left(\sum_{i=1}^{i=6} (IW_{j,i} \cdot X_i) + b1_j\right)\right)} - 1 \right) \right] - 0.23805 \tag{1}$$

where:

X_i is the input of the neuron;

IWj, i is the connection weight between an input neuron and a hidden neuron;

$LW_{k,\,j}$ is the connection weight between a hidden neuron and an output neuron;

$b1j$ is the bias value of a hidden neuron;

$b2_k$ is the bias value of an output neuron;

n is the total number of inputs; and

m is the total number of neuron in the hidden layer.

Table 3: R and MSE values of developed ANN Model.

	Training set	Validation set	Test Set	All
Number of rows	17	5	5	27
R value	0.8215	0.9981	0.9868	0.8388
% of Good forecast	82.2 %	99.8 %	98.7 %	
% of Bad forecast	17.8 %	0.2 %	1.3 %	

MSE Validation=0.033

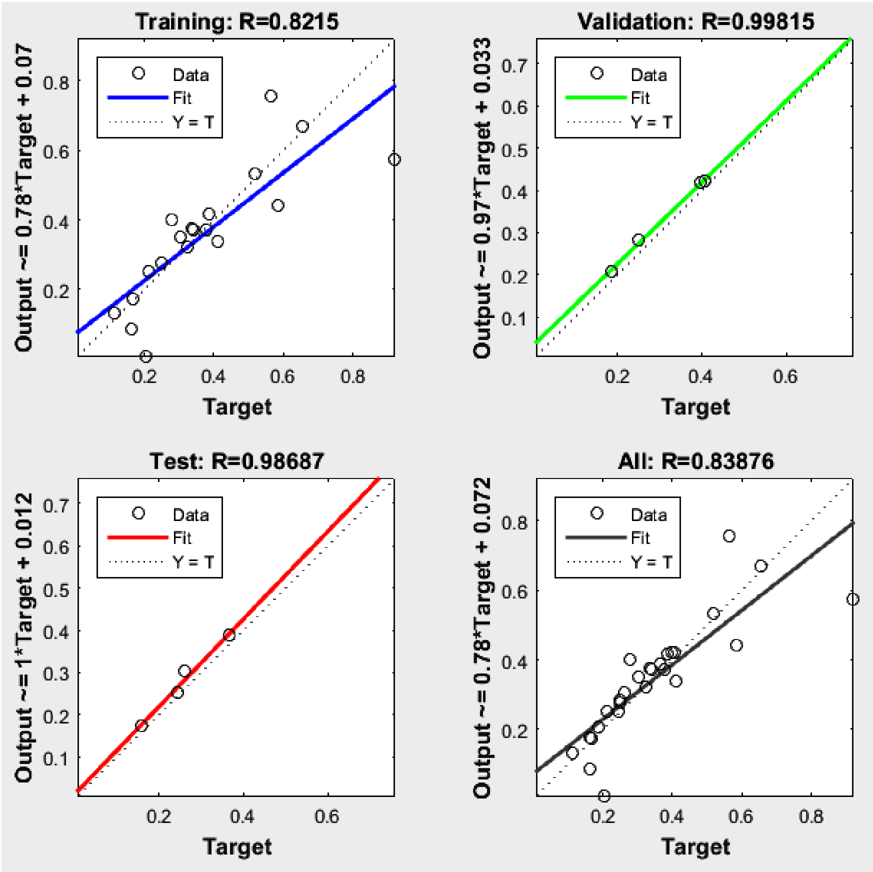

Figure 3: Regression plots of optimal neural network model.

Table 4: Measured and Predicted Biogas Volumes (litres).

Batch No	Measured Biogas (l)	Predicted Biogas(l)	Absolute Error(l)
1	2288	2638	350.00
2	3738	4153.4	415.38
3	4888	5058	170.06
4	3206	3497.2	291.14
5	6512	6473.8	38.20
6	3357	3473.8	116.79
7	3208	1728.7	1479.24
8	4104	184.7	3919.20
9	11280	15145.4	3865.40
10	6097	7040.4	943.34
11	5024	5650	625.96
12	4986	5491	505.04
13	13104	13360.8	256.80
14	4272.10	5027	754.94
15	6810	7438.6	628.68
16	7335	7742	406.98
17	11670	8855.2	2814.80
18	18392	11455	6937.00
19	7936	8383.6	447.66
20	8172	6727.6	1444.36
21	7680	8299.6	619.64
22	5229	6075.2	846.10
23	5580	7973	2393.00
24	10362	10657	295.04
25	6720	7545.4	825.46
26	8151	8416	265.06
27	7552	7450.8	101.24
Mean	6950.12	6886.71	1176.17

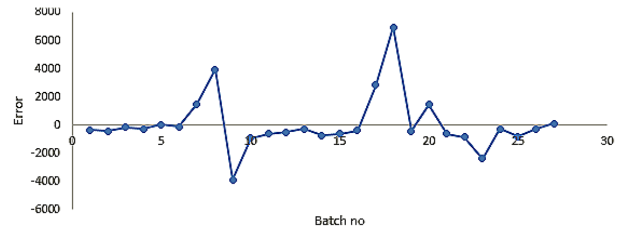

Figure 4: Error graph of the predicted biogas volume.

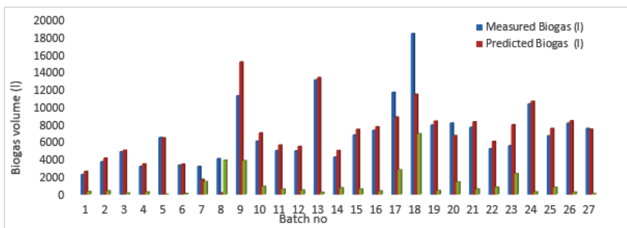

Figure 5: Bar chart of absolute error (in green bars), measured and predicted biogas volumes of the training set.

the anaerobic co-digestion of poultry droppings and cattle dung using experimental data. However, this neural network model is only valid for the particular experimental conditions (constrained) in which the data set was trained.

Future scopes where artificial neural network modelling may find application include modelling of the removal efficacy of biofilters for the treatment of H_2S using Multi-Layer Perceptron; estimating or predicting C and N bioconversion paths in co-digestion of manure with lignocellulose biomass; biogas rate prognosis; combining ANN with Genetic Algorithm (GA) tools for the simulation and optimization of biogas production in a digester; applying ANN for predicting methane fraction in landfill gas obtained from in situ landfill bioreactors; applying ANN to real-scale industrial data obtained from anaerobic fermentation process in a wastewater treatment plant (WWTP); prediction of trace compound concentration in biogas; and many other sub-fields of wastewater management.

4. Conclusion

The study shows that the developed artificial neural network model was able to predict volumetric biogas yield with R-value validation of 0.9981 from anaerobic co-digestion of poultry droppings and cattle dung under the particular experimental conditions. Simulation and validation results demonstrated that the developed artificial neural network model is effective and that artificial neural network-based modelling approach is a practical and consistent approach for predicting the complex relationships in anaerobic codigestion systems.

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References

[1] Extension, Biogas utilization and cleanup. Available online at: `http://articles.extension.org/pages/30312/biogas-utilization-and-cleanup`. 2015.

[2] Yu L, Wensel P C, Ma J & Chen S, Mathematical modeling in anaerobic digestion (AD), *J. Bioremed Biodeg S.* 4 (2013) 2.

[3] Souwalak J, Qiming J Y & James N, Development of artificial neural network models for biogas production from codigestion of leachate and pineapple peel, *The Global Environmental Engineers 1 (*2014) 42-47.

[4] Hanrahan G, Artificial neural networks in biological and environmental analysis: *CRC Press.* `http://dx.doi.org/10.1201/b10515`. (2011).

[5] Harmand J, Pons M & Dagot C, Available from: `http://apps.ensic.inpl-nancy.fr/COSTWWTP/Work_Group/Wg1/Magdeburg/Harma` nd_pres.pdf. (2012).

[6] Pons M N & Van Impe J, Computer applications in biotechnology 2004: Elsevier. Available online at: `http://dx.doi.org/10.1117/3.633187`. (2005).

[7] Adeniran K A, Adelodun B & Ogunshina M S, Artificial neural network modelling of biochemical oxygen demand and dissolved oxygen of Asa river water, *Environmental Research, Engineering and Management (EREM)*, 72, (2016) 3:59-73. `http://www.erem.ktu.lt/index.php/erem/article/view/16567`.

[8] Tomaž L & Miran L, The use of artificial neural networks for compounds prediction in biogas from anaerobic digestion – A review. *Agricultura* 7, (2010) 15-22.

[9] Basheer I A & Hajmeer M A, computational study on the performance of artificial neural networks under changing structural design and data distribution, *Eur. J. Oper. Res.* 138, (2002) 155-77.

[10] Hussain M A, Review of the applications of neural networks in chemical process control - simulation and online implementation, *Artif. Intell. Eng.* 13 (1999) 55-68.

[11] Nasr M S, Moustafa M A, Seif H A & El Kobrosy G, Application of artificial neural network (ANN) for the prediction of EL-AGAMY wastewater treatment plant performance- EGYPT, *Alexandria Engineering Journal*, 51, (2012), 1: 37-43.

[12] De la Rubia M A, Perez M, Romero L I & Sales D, Anaerobic mesophilic and thermophilic municipal sludge digestion, *Chem Biochem Eng*, 16, (2002) 119–124.

[13] Mednat M A & Usama F M, Anaerobic digestion for industrial wastewater treatment, in *Proceedings of 8th International Water Technology Conference, IWTC8, Alexandria, Egypt.* 2004.

[14] Uzodinma E O U, Ofoefule A U, Eze J I & Onwuka N D, Optimum mesophilic temperature of biogas production from blends of agro wastes, *International Journal of Biological Chemistry*. (2006). Available online at: `www.scialert.net`.

[15] Elsharnouby O, Hafez H, Nakhla G & Naggar M H E, A critical literature review on biohydrogen production by pure cultures, *Int. J. Hydrogen Energy,* 38, (2013) 4945-4966

[16] Aduba J J, Rohjy H A, Manta I H & Pamdaya Y, Development of anaerobic digester for the production of biogas using poultry and cattle dung: A case study of Federal University of Technology Minna cattle and poultry pen, *International Journal of Life Sciences, 2, (2013), 3: 139-149.*

[17] Adeniran K A & Kareem K Y, Effectiveness of using floating drum bio-digester to treat domestic sewage, *AFRREV STECH: An International Journal of Science and Technology*. 3. (2014), 34. Available on: 10.4314/stech.v3i3.4.