Optimising biogas from food waste using a neural network model

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This study has been carried out to investigate the production of biogas by anaerobic digestion of solid-phase kitchen food waste using an artificial neural network. The network was used to model and optimise biogas production using mixed substrates of food waste with cow dung. The substrate mix percentage, plant pH level, digestion period and digester temperature were used as input parameters for the model, with biogas yield as the output. Food waste and cow dung were mixed at different compositions to a total mass of 2 kg and placed in 21 miniature digesters. The input and output parameters from the digesters were then considered in the model. The highest biogas performance level of 375 ml/g volatile solids on the 25th day of digestion was achieved by a substrate profile of 80% food waste and 20% cow dung at a temperature range of 30–40°C. On the basis of these results, kitchen food waste is shown to be highly biodegradable and an effective source of biogas.

1. Introduction

In India, ~25–35% of household food wastes constitute junk wastes. The most common methods of managing food waste are by land filling and it requires a huge area whereas firing the waste consumes more energy and it pollutes the environment. Another way of treating food waste is by recycling; this can possibly reduce the cost of waste treatments, odours, reduces landfills and air pollutants due to the burning/incineration process and so on. In recycling, the food wastes are converted into biomethane by way of anaerobic digestion and many studies have been carried out worldwide (Bajon Fernandez *et al.*, 2014; Curry and Pillay, 2012; Mezzullo *et al.*, 2013). The organic content is broken down at the basic level in the process of anaerobic digestion, thereby generating gas, which is known as biogas. Microorganisms assist the digestion process and the anaerobic fermentation produces carbon dioxide (CO₂), methane (CH₄), hydrogen (H₂) and traces of

other gases along with decomposed mass (Bajon Fernandez *et al.*, 2014; Middleton and Eccles, 2013).

The food waste and cow dung are the substrates that have been reported to increase the yield of biogas production by more than 44% (Avicenna *et al.*, 2015; Rongpin *et al.*, 2009). Biogas production by fermentation of bio-products is influenced by the genetic nature of organism, fermentation factors, physiological conditions, nature of the substrate material and also by the nature of the bioreactor that is used for production (Kumar *et al.*, 2009; Lai *et al.*, 2009). The resultant biogas production is controlled by the substrate sources and concentration, pH levels, architectural set-up of the reactor and fermentation temperature (Hanreich *et al.*, 2013; Labatut *et al.*, 2014; Sitorus *et al.*, 2013; Stantscheff *et al.*, 2014; Trisakti *et al.*, 2015). It has been well accepted that maintenance of an optimised fermentative environment is one of the most

Source	Characteristics			Country
	MC: %	VS/TS: %	C/N	
A dining hall	80	95	14.7	Korea
University's cafeteria	80	94	NA	Korea
A dining hall	93	94	18.3	Korea
A dining hall	84	96	NA	Korea
Mixed municipal sources	90	80	NA	Germany
Mixed municipal sources	74	90–97	NA	Australia
Emanating from fruit and vegetable markets, household and juice centres	85	89	36.4	India

NA, not available; MC, moisture content; TS, total solids

Table 1. Characteristics of food wastes reported in the literature

essential factors for improved biogas yield (Prakasham *et al.*, 2009; Wang and Wan, 2009). The carbon to nitrogen (*C/N*) ratio for optimal biogas production should be in the range of 25–30. The characteristics of food wastes are given in Table 1 as previously described (Zhang *et al.*, 2007). With the above reference, it is noted that in dining waste the *C/N* ratio is from 14.7 to 18.3 and the *C/N* ratio of vegetable and fruit waste is 36.4. Hence, the mixture of food waste, vegetable waste will have a *C/N* ratio of 25, which will be optimal for biodegradation of the raw resources since a high *C/N* ratio would have an effect on this process. Temperature also serves as a major factor in digesting food waste. The optimal temperature range of the mesophilic reaction is 30–38°C and that of the thermophilic reaction is 44–57°C (Tchobanoglous and Burton, 1991). Most of the digesters now operate at mesophilic temperatures (Hanreich *et al.*, 2013; Stantscheff *et al.*, 2014), with good stability and gas production. Therefore, mesophilic digestion was chosen for the study and it was carried out with ease which is the optimal temperature in India.

Mathematical models are more useful in providing information on the interactive behaviour of various factors in different types of fermentation (Martinez *et al.*, 2012; Wichern *et al.*, 2009). Compared with the conventional methods, optimisation by considering ‘one-factor-at-a-time’ is effective as it does not depict the combined effect of all the factors involved in particular complicated bioprocesses. In recent years, artificial neural network (ANN) has been successfully applied in multivariate non-linear bioprocesses as a useful tool to construct models and to predict outputs accurately for new input data sets (Haider *et al.*, 2008; Vijay and Rintu, 2010). ANN is an empirical model and a very powerful tool, which is symmetrical to the department of biological neural structures and effectively represents complex non-linear systems. It is also considered as a non-linear statistical identification technique

Figure 1. Configuration of multilayer neural network for predicting excessive biogas production

(Abu Qdais *et al.*, 2010; Gueguim Kana *et al.*, 2012; Prakasham *et al.*, 2011).

In this study, ANN has been used in obtaining the best optimised environment for the fermentation of food wastes and biogas production. In this model, four imperative input parameters were used for the composition of food waste and cow dung, plant pH level, age of the plant and temperature, while the output parameter is the biogas yield. The represented input and output collection of data are shown in Figure 1.

2. Materials and methods

2.1 Experimental procedure

The experimental study was carried out at Adithya Institute of Technology in Energy Engineering Laboratory. The food waste collected includes a mixture of boiled rice, wheat breads,

vegetable peelings and vegetable wastes. The cow dung was mixed with the food wastes to a total weight of 2 kg at various compositions in the 21 digesters each of 5 litre capacity. The mixed proportions of food waste and cow dung with different compositions in the 21 digesters are shown in Table 2. The pH value during the digestion period was measured using the pH tape. The readings were taken from the 15th day of digestion up to 45th day with the pH ranging from 6 to 8 noted. The pilot digester plant temperature was monitored at regular intervals and the temperature recorded. The quantity

of biogas produced was measured using the water displacement method.

The biogas sample was analysed periodically using the gas chromatograph (SHIMADZU – GC 2014) equipped with a thermal conductivity detector (TCD 2014) and flame photometric detector 2014 with quartz glass nozzle packed. These detectors were used for the analysis of organic sulfur compounds and the organic phosphorus compounds such as residual pesticides and malodorous components. The digesters with a composition of 0, 25, 50, 75 and 100% food waste were selected and the constituents are given in Table 3.

Sl. number	Pilot digester plant	Food waste		Cow dung	
		Weight: g	%	Weight: g	%
1	Digester 1	0	00	2000	100
2	Digester 2	100	05	1900	95
3	Digester 3	200	10	1800	90
4	Digester 4	300	15	1700	85
5	Digester 5	400	20	1600	80
6	Digester 6	500	25	1500	75
7	Digester 7	600	30	1400	70
8	Digester 8	700	35	1300	65
9	Digester 9	800	40	1200	60
10	Digester 10	900	45	1100	55
11	Digester 11	1000	50	1000	50
12	Digester 12	1100	55	900	45
13	Digester 13	1200	60	800	40
14	Digester 14	1300	65	700	35
15	Digester 15	1400	70	600	30
16	Digester 16	1500	75	500	25
17	Digester 17	1600	80	400	20
18	Digester 18	1700	85	300	15
19	Digester 19	1800	90	200	10
20	Digester 20	1900	95	100	05
21	Digester 21	2000	100	0	00

Table 2. Plant operating substrate profiles evaluated experimentally

2.2 ANN design and training

In this study, a total data set of 546 numbers of results among which a two-third data set of 364 numbers has been considered for training in ANN, and the remaining data set of 182 numbers for testing in ANN. The input/output data set was normalised within the range of ± 1 before training the network. The standard multilayer feed-forward and backward propagation hierarchical neural networks (BPNN) are designed in the 'MATLAB 2008a Neural Network Toolbox'. This network consists of three layers: an input layer, a hidden layer and an output layer as shown in Figure 1.

The number of iterations (epochs) to be executed is an important parameter in the case of BPNN training. Initially, there are four neurons in the input layer, three neurons in the hidden layer and one neuron in the output layer (4-3-1). This construction is taken for training and it is carried out with different numbers of epochs to find the best iterations. The mean square error (MSE) achieved from different iterations are shown in Figure 2. It is evident that the values of MSE regularly decrease during the progress of training. An inaccuracy of 0.00218 at 10 epochs, 0.00152 at 50 epochs is reduced to 0.0006136 after 100 iterations, and not much change has been found with further increase in the number of iterations. The output is qualified with different architecture by varying the number of neurons in the hidden layer(s).

Sl. number	Constituent	Digester 1	Digester 6	Digester 11	Digester 16	Digester 21
1	Methane: %	70	67	62	58	55
2	Carbon dioxide: %	25	28	33	36	38
3	Hydrogen sulfide: %	1.8	2	2.4	3.1	4
4	Nitrogen: %	1.01	0.99	0.98	0.94	0.84
5	Hydrogen: %	0.98	0.91	0.88	0.72	0.68
6	Carbon monoxide: %	0.18	0.24	0.39	0.61	0.74
7	Oxygen: %	0.08	0.08	0.07	0.08	0.06

Table 3. Partial sample constituent composition of biogas

Figure 2. Variation of the MSE of the trained data as a function of epochs

To find out the optimal architecture, 30 different networks with different number of layers of neurons in the hidden layer were designed and tested. The BPNN architecture is a technique that can be efficiently used to predict the biogas yield from a mixture of food waste and cow dung; a different multilayer BPNN architecture was also trained and used. The BPNN with one unseen layer having 17 neurons, trained with Levenberg–Marquardt algorithm, was found to be the optimum network model for biogas yield (4-17-1).

3. Results and discussion

The foremost idea of the current work is to study, anticipate and analyse the biogas yield due to the effect of composition of food waste and cow dung using BPNN analysis. The biogas yield is evaluated by the plant pH level, age of the plant and temperature condition.

3.1 Testing and performance of the BPNN

The performance value of each network is examined based on the association of coefficient, error distribution and convergence of the entire data set within the specified error range which lies between the network prediction and the experimental values using the test and entire data set. To resolve the optimum arrangement of neural network, the rate of blunder junction is investigated by changing the number of secret neurons and the number of hidden layers. From Table 4, the hidden neurons are identified and the networks with a single hidden layer of 17 neurons have given a correlation coefficient of 0.9996 and mean error of 0.0036% which means that the error distribution is uniform. Further, it is observed that 98.97% of the entire data set is within $\pm 4\%$ error (Table 5). Moreover, the increase in the number of neurons in the single hidden layer (beyond 17) and the error allocation is not uniform (Table 4). Hence, it has been decided and concluded that the selection of optimum architecture depends on the mean error %, maximum error %, minimum error %, error distribution % (i.e. frequency of error, Tables 4 and 5), correlation

Network architecture	Data set	MSE	Biogas production correlation	Error: %
4-3-1	Test	0.023600	0.4327	−3.8386
	Entire		0.5385	0.7066
4-5-1	Test	0.007350	0.9100	−0.8828
	Entire		0.9256	−0.2330
4-7-1	Test	0.00156	0.9863	0.1312
	Entire		0.9922	0.3581
4-10-1	Test	5.76×10^{-4}	0.9849	0.2463
	Entire		0.9929	−0.0196
4-11-1	Test	1.42×10^{-4}	0.9976	0.2121
	Entire		0.9976	0.1605
4-12-1	Test	5.70×10^{-5}	0.9948	0.1963
	Entire		0.9977	0.1209
4-13-1	Test	4.80×10^{-5}	0.9969	0.0478
	Entire		0.9981	0.0362
4-15-1	Test	2.20×10^{-5}	0.9024	0.0147
	Entire		0.9520	0.0181
4-17-1	Test	6.00×10^{-6}	0.9996	0.0036
	Entire		0.9985	0.0049
4-19-1	Test	1.30×10^{-5}	0.9991	0.1844
	Entire		0.9979	0.1115
4-21-1	Test	7.40×10^{-5}	0.9756	0.5754
	Entire		0.9799	0.5002
4-23-1	Test	1.00×10^{-6}	0.9989	0.26500
	Entire		0.9992	0.3189
4-25-1	Test	1.00×10^{-6}	0.9956	0.1482
	Entire		0.9955	0.2901
4-27-1	Test	1.00×10^{-6}	0.9609	0.0453
	Entire		0.9663	0.0294
4-31-1	Test	2.10×10^{-5}	0.9987	−0.0369
	Entire		0.9994	−0.0405

Table 4. Correlation coefficient between network predictions and experimental values using the test and entire data set of different network architectures and trained output parameters of biogas production. Optimum values shown in bold

coefficient and on the convergence of the entire data set within the specified/expected/reasonable error range. Table 6 shows the partial sample of tested data, forecast data and possibilities of error in the predictions of the biogas yield of the optimum architecture model 4-17-1. Thus, networks having a single hidden layer of 17 neurons are trained with Levenberg–Marquardt algorithm which has been selected as the optimum network model. It is also observed that the increase in the number of neurons in the single hidden layers has important improvement on the performance of the networks and thereby the performance slowly degrades. The association between the predicted values of the optimum neural network model and

Network architecture	Number of error frequency						
	4-10-1	4-13-1	4-15-1	4-17-1	4-19-1	4-22-1	4-25-1
Error frequency range							
< – 50	0.14	0.00	0.00	0.00	0.00	0.00	0.00
– 50 to – 45	0.07	0.00	0.00	0.00	0.00	0.00	0.00
– 45 to – 40	0.00	0.00	0.00	0.00	0.00	0.07	0.07
– 40 to – 35	0.00	0.00	0.00	0.00	0.00	0.00	0.00
– 35 to – 30	0.00	0.00	0.00	0.00	0.00	0.00	0.00
– 30 to – 25	0.14	0.00	0.00	0.00	0.00	0.14	0.00
– 25 to – 20	0.00	0.00	0.00	0.00	0.00	0.00	0.00
– 20 to – 16	0.00	0.60	0.00	0.00	0.00	0.00	0.00
– 16 to – 12	1.55	1.27	0.00	0.00	0.00	0.00	0.00
– 12 to – 8	2.06	1.41	0.60	0.07	0.00	0.27	0.27
– 8 to – 4	4.74	1.92	0.91	0.17	0.48	0.41	2.13
– 4 to 4 (percentage of data within this range)	82.27	89.54	95.12	98.97	98.28	98.08	86.88
4–8	5.15	2.88	2.06	0.45	0.27	0.41	6.66
8–12	4.53	1.37	0.87	0.34	0.14	0.27	6.32
12–16	1.27	0.91	0.44	0.00	0.00	0.00	0.69
16–20	0.27	0.50	0.00	0.00	0.00	0.00	0.41
20–25	0.14	0.40	0.00	0.00	0.00	0.00	0.55
25–30	0.00	0.00	0.00	0.00	0.00	0.00	0.27
30–35	0.00	0.00	0.00	0.00	0.00	0.00	0.00
35–40	0.14	0.00	0.00	0.00	0.14	0.00	0.14
40–45	0.00	0.00	0.00	0.00	0.00	0.00	0.00
45–50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
>50	0.00	0.00	0.00	0.00	0.27	0.00	0.00

Table 5. Comparison of error distribution in terms of error frequency of the entire data set for the selected network architecture of biogas yield from food waste and cow dung. Optimum values shown in bold

the experimental data for the calculation of biogas yield using the partial sample data sets is shown in Figure 3. This shows that the developed model has high accuracy for predicting the biogas yield of food waste and cow dung mixed digesters in terms of the plant pH level, age of the digester and plant temperature. The variation of the plant pH level, age of the digester and plant temperature against the percentage of food waste and cow dung digester is shown in Figures 4–6 predicted by the respective optimised ANN model. Further, Table 6 shows the results of the comparison between experimental and prediction from 4-17-1 architecture for food waste and cow dung digester. It was clearly observed from Figures 4–6 and Table 6 that the calculation of biogas yield was possible. It has been concluded that the ANN model could predict the biogas yield.

3.2 Quantitative analysis

From Figures 4–6 it is evident that all selected process parameters interact with each other and their interaction regulates

the overall biogas output values suggesting different concentrations of fermentation process parameters which are discussed as follows.

3.2.1 Influence of pH on the biogas yield

Figure 4 depicts the interactive influence of pH of the medium with food waste to cow dung ratio. It is clear from the fact that both the parameters are having different pressures on the metabolism of the microbial consortia used. The pH behaviour of the cultures shows a range of 6.0–8.0 during the highest point of biogas production. Sensitivity of methanogens to medium pH has been reported (Nagamani and Ramasamy, 1999) with a possibility of metabolic repression at an optimum biogas yield at pH between 6.7 and 7.1 and a satisfactory biogas production at pH between 6.6 and 7.6 has been reported (Nagamani and Ramasamy, 1999). In the end, the drift in pH in the digester is a function of the nature and concentration of the various co-substrates and the cell metabolic activities

Sl. number	% food waste	Age: d	Temperature: °C	pH	Biogas production	
					Observed: mL/g VS	Predicted: mL/g VS
1	0	17	37	6.7	248.748	247.633
2	0	21	39	7.1	260.324	259.209
3	10	27	38	6.9	293.850	292.735
4	10	31	35	6.3	282.836	283.951
5	25	16	39	7.1	262.724	261.609
6	25	37	37	6.7	292.658	291.543
7	35	19	37	6.7	265.678	264.563
8	35	39	38	6.9	299.766	298.651
9	50	17	36	6.5	276.057	274.942
10	50	40	39	7.1	309.882	308.767
11	60	31	39	7.1	329.969	331.084
12	60	33	38	6.9	331.189	332.304
13	70	25	37	6.7	366.974	368.089
14	70	27	38	6.9	361.594	362.709
15	75	25	39	7.1	373.138	374.253
16	75	28	38	6.9	357.134	358.249
17	85	21	37	6.7	354.391	355.506
18	85	23	36	6.5	355.518	356.633
19	95	16	35	6.3	316.162	317.277
20	95	30	35	6.3	335.931	337.046
21	100	39	34	6.1	345.750	346.865
22	100	40	35	6.3	343.529	344.644

VS, volatile solids

Table 6. Partial sample predicted data

Figure 3. Correlation chart for experimental and ANN predicted biogas yield data

(Gueguim Kana *et al.*, 2012). Ideally, continuous monitoring of the pH level in anaerobic digestions should be adopted, as it generates more reliable process information. From Figure 4 it is clear that the satisfactory range of biogas production was achieved with the pH ranging from 6 to 8.

3.2.2 Influence of temperature on biogas yield

Temperature is an important factor that determines the rate of digestion. Most of the digesters operated in the mesophilic range (30–40°C), but it is also possible to operate the digesters in the thermophilic range (~55°C) but with higher working costs, lower process stability and with more structural requirements (Chen *et al.*, 2010; Kiely, 1998). From Figure 5, it is clear that the biogas yield has increased gradually with respect to temperature. For the temperature range at 30–45°C, the biogas yield is increased for the food waste and cow dung digester. It is clearly observed from Figure 5 in the mesophilic range that more biogas yield can be obtained. It is concluded that the mesophilic range could turn over more biogas yield without any additional sources.

3.2.3 Influence of the age of the plant on biogas yield

From all the range of studies of carbon sources, its influence is more effective as the food waste dominates in the fermentation media suggestive of the presence of food as a carbon source. It is clear from Figure 6 that biogas yield increases with increase

Figure 4. Variation in biogas production as a function of pH and food waste blend with cow dung trained and predicted by a neural network model

Figure 5. Variation in biogas production as a function of temperature and food waste blend with cow dung trained and predicted by a neural network model

Figure 6. Variation in biogas production as a function of plant age and food waste blend with cow dung trained and predicted by a neural network model

in age of the plant and maximum biogas efficiency (375 ml/g volatile solids (VS)) is observed with 20–35 d grown culture. From the earlier reports (Gueguim Kana *et al.*, 2012) it is observed that the biogas is effectively produced in the presence of carbon and nitrogen which is seen to be in the ratio 25–30:1. This regulates the metabolic processes of the microbial combination leading to biogas production. Nevertheless, when the mixture of this food waste has been utilised as a carbon source, the biogas production is observed with an increase in food waste absorption by up to 70–80% of the total carbon source.

Compared with any other bio stuff wastes and farm wastes, the food waste which is a composition of various kinds of wastes will yield 15% greater quantity of biogas. The dung is a waste from the animal after utilising maximum energy during digestion. So the biogas produced is less compared with food waste. In previously reported carbon source range (Curry and Pillay, 2012) its influence is more successful as the food waste concentration dominates the fermentation medium suggesting that the presence of food as a carbon source elevates the metabolic processes leading to biogas production.

4. Conclusion

This study shows that BPNN architecture is a technique that can be efficiently used to predict the biogas yield from food waste. Different types of multilayer BPNN architecture were trained and used and the BPNN with one unseen layer having 17 neurons, trained with Levenberg–Marquardt algorithm was found to be the optimum network model for biogas yield (4-17-1). It is believed that this approach can be used to forecast the biogas yield from food waste. In anaerobic digestion, the digester D17 had the highest biogas performance level of 375 ml/g VS in the 25th day of digestion, with the substrate profile of 80% food waste and 20% cow dung at a temperature range of 30–40°C. On the basis of the above results, it is concluded that biogas fabrication from dining waste and vegetable waste combination is highly attractive and can be used effectively at institutional level with the most favourable temperature range thereby reducing the use of fossil fuels.

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