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Prediction of Methane Fraction in Biogas from Landfill Bioreactors by Neural Network Modeling

Allah Bakhsh Javid[1], Majid Arabameri[2], Ali Akbar Roudbari[3*]

[1] Dept. of Environmental Health Engineering, School of Public Health, Shahroud University of Medical Sciences, Shahroud, Iran.
[2] Vice-chancellery for Food and Drug, Shahroud University of Medical Sciences, Shahroud, Iran.
[3] Center for Health-Related Social and Behavioral Sciences Research, Shahroud University of Medical Sciences, Shahroud, Iran.

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Abstract

Background: *Predicting the methane percentage of biogas is necessary for selecting the optimized technologies of using landfill biogas for energy. The aim of this study was to predict of methane fraction in biogas from landfill bioreactors by Artificial Neural Network (ANN) modeling.*

Methods: *In this study, two different systems were applied to predict the methane fraction in landfill gas as a final product of anaerobic digestion, in system I (C1), the leachate generated from a fresh-waste reactor was drained to recirculation tank, and recycled. In System II (C2), the leachate generated from a fresh waste landfill reactor was fed through a well-decomposed refuse landfill reactor, and at the same time, the leachate generated from a well-decomposed refuse landfill reactor recycled to a fresh waste landfill reactor. We monitored the systems for 6 months, after which we modeled the methane fraction in landfill gas from the bioreactors using artificial neural networks. The leachate specifications were used as input parameters. Leachate samples were collected every 7 days from effluent port of each reactor. COD and NH4 were determined according to the standard methods (2005). The pH value was measured by a portable digital pH meter (Salemab, Iran).*

Results: *There is very good agreement in the trends between predicted and measured data. R values are 0.991 and 0.993, and the obtained mean square error values are 1.046 and 2.117 for training and test data, respectively.*

Conclusions: *ANN based approaches can be considered as a compromising approach in landfill gas prediction problem and can be used to optimize the dimensions of a plant using biogas for energy (i.e. heat and/or electricity) recovery and monitoring system.*

Keywords: Landfill gas, Prediction, ANN model.
[*]Corresponding to: AA Roudbari, **Email:** roodbari@shmu.ac.ir
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Introduction

Landfill gas (LFG) is generated during the natural process of bacterial decomposition of organic material contained in municipal solid waste (MSW) landfills.[1] By volume, LFG is about 50 percent methane and 50 percent carbon dioxide and water vapor.[2] It also contains small amounts of nitrogen, oxygen, hydrogen, less than 1 percent no methane organic compounds (NMOCs), and trace amounts of inorganic compounds.[3] LFG can be an asset when it is used as a source of energy to create electricity or heat.[4] It is classified as a medium-BTU gas with a heating value of 350 to 600 BTU per cubic foot, approximately half that of natural gas. LFG can often be used in place of conventional fossil fuels in certain applications.[5] It is a reliable source of energy because it is generated 24 hours a day, 7 days a week. By using LFG to produce energy, landfills can significantly reduce their emissions of methane and avoid the need to generate energy from fossil fuels, thus reducing emissions of carbon dioxide, sulfur dioxide, nitrogen oxides, and other pollutants from fossil fuel combustion.[6,7] A number of different technologies have recently been studied to determine the best use of biogas, however, to choose optimize technologies of using biogas for energy recovery it is necessary to monitor and predict the methane percentage of biogas.[2] Landfill methane models are tools used to predict methane generation over time from a mass of land filled waste. These models are used for sizing landfill gas (LFG) collection systems, evaluations and predictions of LFG energy uses, and regulatory purposes.[8,9] Compared to other alternatives (such as installation of a full-scale LFG recovery system or the use of test wells and the performance of a pump test program), models have advantages in terms of low cost and relatively rapid results.[10]

Significant development in the mechanistic modeling of anaerobic digestion process using mass balance principles and reaction kinetics has been observed.[11] The main advantages of these process models are that, they are based on the underlying physical process and the results obtained from these process models generally provide a good understanding and interpretation of the system.[11] The estimation of some parameters requires expertise and facilities, the absence of which hinders the preciseness of the model and limits its application and reliability.[12] On the contrary, black box models such as Artificial Neural Networks (ANNs) has shown to have distinctive advantage.[13] ANNs are now used in many areas of science and engineering and considered as promising tool because of their simplicity towards simulation, prediction and modeling.[14] The advantages of ANNs are that the mathematical description of the phenomena involved in the process is not required; less time is required for model development than the traditional mathematical models and prediction ability with limited numbers of experiments.[14] Application of ANNs to solve environmental engineering problems has been reported in many articles. ANNs were applied in biological wastewater treatment and physicochemical wastewater treatment.[15] An ANN–genetic algorithm-based approach was developed to predict NOx emission of a pulverized coal-fired boiler and combustion parameter optimization to reduce NOx emission in flue gas.[16] ANN-based vehicular exhaust emission models were

developed for predicting 8-h average CO concentrations, considering either meteorological and/or traffic characteristics as the input data.[17] In air pollution modeling, neural network-based (NN) models have been applied to predict various pollutant concentrations. Chelani et al constructed a tree layer NN model with a hidden recurrent layer to predict SO2 concentration at three sites at Delhi.[18] In their study, a multivariate regression model was also used for comparison with the results obtained by using NN model. Sahin et al applied multi layer Perceptron NN model to predict daily CO concentrations using meteorological variables as predictors for the European part of Istanbul, Turkey.[19] An ANN model was developed for predicting the methane fraction in landfill gas originating from field-scale landfill bioreactors operated with and without landfill leachate (LFL) recirculation.[20] The input parameters such as pH, alkalinity, chemical oxygen demand, sulfate, conductivity, chloride and waste temperature were used to predict the methane fraction in landfill gas. This paper proposes a multi layered ANN structure for future prediction of CH4 in Shahroud city landfill, Iran.

Materials and Methods

The landfill site is situated at the northeast of Shahrood city ,1 km west of the W43 road, which forms the eastern bypass to Shahrood airport, about 7 km east of the airport (Figure 1). The Shahrood city Landfill is a 20-hectare site that is owned by the Shahrood municipality and was operated from 1986-2008. This landfill has 18 trenches which range in design from an open dump without cover layer to a semi sanitary landfill with intermediate and final cover layer. Each trench is approximately 0.8 ha in area and 9 m high, with side slopes at a 4:1 grade.

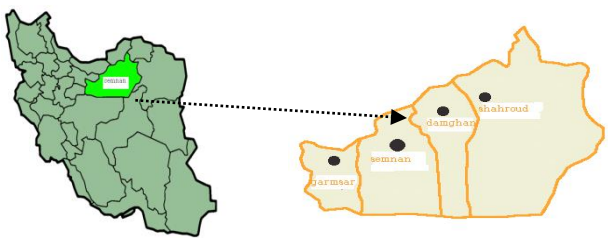

Figure 1. Schematic map of Iran and Shahroud city

The refuse in this study was collected from a trash in the Shahroud sanitary landfill site, Shahroud, Iran. Bulky wastes, Plastic bags and massive inorganic wastes were removed in the laboratory. All of the waste were then shredded and mixed to avoid leachate preferential flow in simulated landfill columns. The waste composition was as follows (by weight): Kitchen waste, 74.5±5.3%; paper, 10.3±2.4%; plastic, 9.3±0.6%; fabric, 3.2±0.2%; metal, 0.5±0.05%; and others, 2.2±0.5%. The well-decomposed refuse was excavated from an old bioreactor landfill cell with a more than 15 years landfill age in the Shahroud landfill site. Well-decomposed refuse was defined here as the refuse that had been taken through its various stages of anaerobic degradation and exhausted of its methane-producing potential. The content of organic matter and total nitrogen was respectively less than 5% and 0.3% for the well-decomposed refuse. The refuse was commingled and shredded into 2-5 cm pieces. Experiment data collected were thus used for predicting the methane percentage profile of the gas extraction well using the ANN. The input parameters to the model were leachate COD, pH, NH4-N and time, while the output parameter was the methane percentage of the LFG.

We used two types of reactors in this study; a simulated landfill reactor and an activated sludge reactor. The simulated landfill reactor made of Plexiglas has a diameter of 30 cm and height 110 cm (volume of 77.7 L). The reactor was wrapped with heat insulating materials to prevent temperature redistribution between the reactors and the surrounding environment. The aerobic-activated sludge reactor made of Plexiglas had a working volume of 8.65 L (diameter of 10 cm). The simulated reactors keep at 33±5 °C.

Leachate samples were collected every 7 days from effluent port of each reactor. COD and NH4 were determined according to the Standard Methods (2005). The pH value was measured by a portable digital pH meter (Salemab, Iran).

Artificial neural networks are known for their ability of learning, simulation and prediction of data. The inspiration of using neural network came from the biology of human brain.[14] Disadvantage of artificial neural network is its “black box” nature. The individual relations between the input variables and the output variables are not developed by engineering judgment so that the model tends to be a black box.[15] Further there is greater computational burden and proneness to over fitting and the sample size has to be large.[16] The network consists of numerous individual processing units called neurons and commonly interconnected in a variety of structures. The strength of these interconnections is determined by the weight associated with neurons.[16] The multilayer feed-forward net is a parallel interconnected structure consisting of input layer and includes independent variables, number of hidden layers and output layer. In this study, a three-layered back propagation neural network with tangent sigmoid transfer function (Tansig) at hidden layer and a linear transfer function (Purelin) at output layer was used. The back propagation algorithm was used for network training. Neural Network Toolbox V4.0 of MATLAB mathematical software was used for methane fraction prediction. Data sets were obtained from our study and were divided into input matrix [p] and target matrix [t].

The monitoring data (leachate COD, pH and NH4+-N and Time) was designed to meet the requirements of training and testing the ANN. To ensure that all variables in the input data are important, principal component analysis (PCA) was performed as an effective procedure for the determination of input parameters. It was observed that all input variables were important. The data sets (65) were divided into training (one half=33), validation (one fourth=16) and test (one fourth=16) subsets.

Results

To determine the best back propagation (BP) training algorithm, ten BP algorithms were studied. Tangent sigmoid transfer function (Tansig) at hidden layer and a linear transfer function (Purelin) at output layer were used. In addition, 5 neurons were used in the hidden layer as initial value for all BP algorithms. Table 1 shows a comparison of different BP training algorithms. The optimum number of neurons was

determined based on the minimum value of mean square error (MSE) of the training and prediction set.[16] The optimization was done by using Levenberg–Marquardt back propagation algorithm (LMA) as a training algorithm and varying neuron number in the range 1–15. Figure 2 shows the relationship between number of neurons and MSE. Figure 3 shows the optimized neural network structure. The data sets were used to feed the optimized network in order to test and validate the model. Figure 4 shows a comparison between experimental CH4 production values and predicted values using the neural network model. Table 2 shows the weights between the artificial neurons produced by the ANN model used in this work. Table 3 shows the relative importance of the input variables calculated by eq.[1] Table 4 shows the results of the sensitivity analysis for different combinations of variables.

Discussion

To determine the best BP training algorithm, ten BP algorithms were studied. Tangent sigmoid transfer function (Tansig) at hidden layer and a linear transfer function (Purelin) at output layer were used. In addition, 5 neurons were used in the hidden layer as initial value for all BP algorithms. Table 1 shows a comparison of different BP training algorithms. LMA was able to have smaller MSE compared to other BP algorithms. So, LMA was considered the training algorithm in the present study.

Table 1. Comparison of 10 back propagation algorithms with 5 neurons in the hidden layer

Backpropagation (BP) algorithm	Function	Mean square error (MSE)	Epoch	Correlation coefficient (R^2)	Best linear equation
Levenberg-Marquardt backpropagation	trainlm	0.00812355	29	0.983	y=0.931X + 0.107
Scaled conjugate gradient backpropagation	trainscg	0.01545691	92	0.974	y=0.974X + 0.324
BFGS quasi-Newton backpropagation	trainbfg	0.017437	64	0.976	y=0.942X + 0.911
One step secant back propagation	trainoss	0.0314241	28	0.972	y=0.932X + 0.89
Batch gradient descent	traingd	0.431132	102	0.686	y=0.343X+11
Variable learning rate back propagation	traingdx	0.424411	24	0.711	y=0.326X+14
Batch gradient descent with momentum	traingdm	0.520082	99	0.704	y=0.333X + 21.7
Fletcher–Reeves conjugate gradient back propagation	traincgf	0.0232129	23	0.926	y=1.48X−0.326
Polak–Ribi'ere conjugate gradient back propagation	traincgp	0.0143372	102	0.968	y=0.864X + 0.21
Powell–Beale conjugate gradient back propagation	traincgb	0.0532745	36	0.964	y=0.912X + 1.47

The optimum number of neurons was determined based on the minimum value of MSE of the training and prediction set.[16] The optimization was done by using LMA as a training algorithm and varying neuron number in the range 1-15. Figure 2 shows the relationship between number of neurons and MSE. MSE was 0.302148 when one neuron was used and decreased to 0.000331 when 6 neurons were used. Increasing of neurons more than 6 did not significantly decrease MSE. Hence, 6 neurons were selected as the best number of neurons. Figure 3 shows the optimized neural network structure. It has three-layer ANN, with tangent sigmoid transfer function (Tansig) at hidden layer with 6 neurons and linear transfer function (Purelin) at output layer.

The data sets were used to feed the optimized network in order to test and validate the model. Figure 4 shows a comparison between experimental CH4 production values and predicted values using the neural network model. The figure contains two lines, one is the perfect fit y=X (predicted data=experimental data) and the other is the best fit indicated by a solid line with best liner equation y=(1.003) p+0.682, correlation coefficient (R2) 0.991 and MSE 0.000318. This agrees well with the correlation coefficient reported in the literature—a correlation coefficient of 0.992 for prediction of methane from a landfill,[21] 0.998 for prediction of organic acid from a landfill,[22] 0.961 for prediction of volatile fatty acid from fresh anaerobic digested wastes,[21] 0.991 for total gas production from old wastes landfill and 0.985 for biogas production from solid wastes landfill.[22]

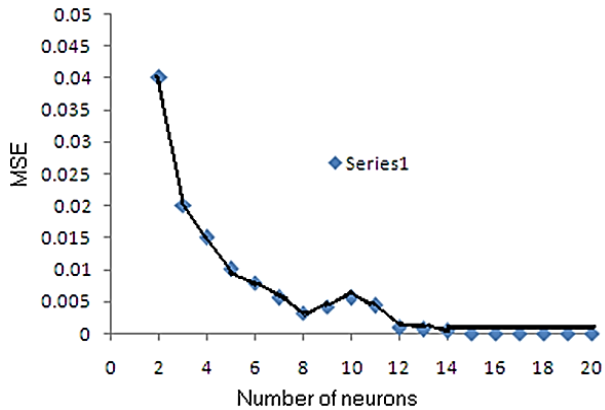

Figure 2. Relationship between number of neurons and MSE

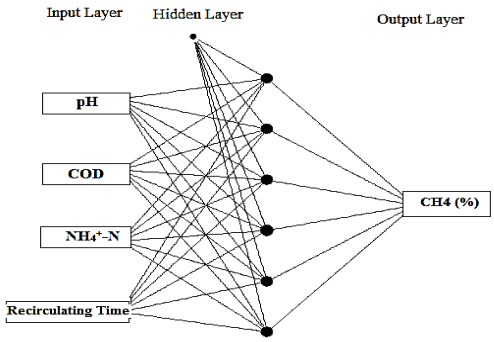

Figure 3. Optimized ANN structure

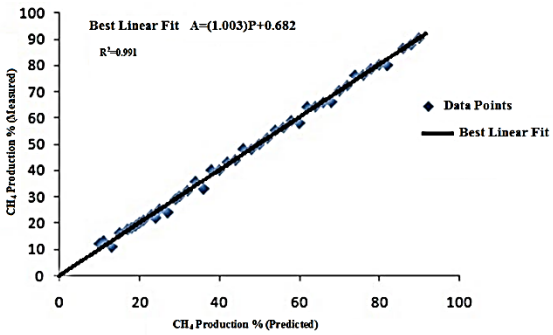

Figure 4. Comparison between predicted and experimental values of the output

In order to assess the relative importance of the input variables, two evaluation processes were used.[21] The first one was based on the neural net weight matrix and Garson equation.[21] He proposed an equation based on the partitioning of connection weights:

$$Ij = \frac{\sum_{m=1}^{m=Nh}\left(\left(\left|w_{jm}^{ij}\right|\right)/\sum_{k=1}^{Ni}\left|W_{km}^{ih}\right|\right)\times\left|W_{mn}^{ho}\right|)}{\sum_{k=1}^{k=Ni}\left\{\sum_{m=1}^{m=Nh}\left(\left|W_{km}^{ih}\right|/\sum_{k=1}^{Ni}\left|W_{km}^{ih}\right|\right)\times\left|W_{mn}^{ho}\right|\right.}$$

Table 2. Weight matrix, weights between input and hidden layers (W_1) and weights between hidden and output layers (W_2).

Neuron	W_1				W_2
	Input variables				
	Recirculation Time	pH	COD	NH_4^+-N	Output (CH_4 Production %)
1	0.4711	0.0911	-0.4512	0.4612	0.7479
2	0.0534	-0.1732	0.1011	0.4311	-1.5625
3	0.0651	0.0933	-0.0312	0.4712	0.979
4	0.1812	0.6566	0.2667	0.4147	-0.8978
5	0.7811	-0.9891	0.3212	0.6566	-0.8263
6	0.0365	0.8965	1.1123	1.9635	1.7465

where, Ij is the relative importance of the jth input variable on the output variable, Ni and Nh are the number of input and hidden neurons, respectively and Wis connection weight, the superscripts 'i', 'h' and 'o' refer to input, hidden and output layers, respectively and subscripts 'k', 'm' and 'n' refer to input, hidden and output neurons, respectively.

Table 2 shows the weights between the artificial neurons produced by the ANN model used in this work. Table 3 shows the relative importance of the input variables calculated by eq. [1] All variables have strong effect on CH4 production. The COD appears to be the most influential variable followed by recirculation time, pH and NH4+-N. The second evaluation process is based on the possible combination of variables.

Performances of the groups of one, two, three and four variables were examined by the optimal ANN structure using the LMA with 6 hidden neurons. The input variables were p1 (COD), p2 (recirculation time), p3 (pH) and p4 (NH4+-N).

Table 3. The relative importance of the input variables

Input variable	Importance %
COD	44.3
Recirculation Time	22.1
NH_4^+-N	14.4
pH	19.2

Table 4. Evaluation of possible combinations of input variables

Combination	Mean square error (MSE)	Epoch	Correlation coefficient (R^2)	Best linear equation
P1	0.5753	13	0.523	Y= 7.42X + 45
P2	263.65	10	0.346	Y= 5.32X + 528
P3	289.25	10	0.461	y=6.3X + 256
P4	352.41	9	0.532	y=5.12X + 425
P1 + P2	0.314256	13	0.423	y=2.39X+562
P1 + P3	0.536214	9	0.412	y=0.779X+15.2
P1 + P4	0.653625	9	0.416	y=0.678X + 11.5
P2 + P3	0.396525	10	0.537	y=0.543X−1.36
P2 + P4	0.465879	7	0.489	y=0.523X + 22.1
P3 + P4	0.489652	5	0.546	y=0.662X + 1.5
P1 + P2 + P3	0.115623	6	0.712	y=0.549X + 12.2
P1 + P2 + P4	0.124569	9	0.679	y=0.632X + 7.2
P2 + P3 + P4	0.146632	9	0.742	y=0.654X + 4.1
P1 + P2 + P3 +P4	0.132656	10	0.616	y=0.236X + 19.1

A three-layer back propagation neural network was optimized to predict the CH4 production from landfill site. The configuration of the back propagation neural network giving the smallest MSE was three-layer ANN with tangent sigmoid transfer function (Tansig) at hidden layer with 6 neurons, linear transfer function (Purelin) at output layer and Levenberg–Marquardt back propagation training algorithm (LMA). ANN predicted results are very close to the experimental results with correlation coefficient (R2) of 0.991 and MSE 0.000318. The sensitivity analysis showed that all studied variables have strong effect on CH4 production. In addition, COD is the most influential parameter with relative importance of 44.3 %. ANN results showed that neural network modeling could effectively predict the behavior of the process.

Table 4 shows the results of the sensitivity analysis for different combinations of variables. The sensitivity analysis showed that p1 (COD) was the most effective parameter among other variable in the group of one variable. The MSE (242.151) decreased up to 0.302536, which is the minimum value of the group of two variables when p1 (COD) was used in combination with p2 (recirculation time). The MSE (0.302536) decreased up to 0.112311, which is the minimum value of the group of three variables when p2 (recirculation time) was used in combination with p3 (pH) and p4 (NH4+-N). The best group performances according to number of parameters are highlighted in table 4. MSE values decreased as the number of variables in the group increased due to the contribution of all parameters (Table 4). It can be concluded that the COD is the most effective parameter. In addition, all variables have strong effect on CH4 production and it agrees well with the sensitivity analysis using Garson equation.

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Conflict of Interest

The authors declared that they have no conflict of interest.

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