Bioresource Technology 217 (2016) 90–99

Contents lists available at ScienceDirect

Bioresource Technology

journal homepage: www.elsevier.com/locate/biortech

Artificial neural network based modeling to evaluate methane yield from biogas in a laboratory-scale anaerobic bioreactor

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HIGHLIGHTS

- Comparative studies between OFMSW and VW in a laboratory-scale BLF.
- Evaluation of various parameter influencing CH_4 production in BLF.
- PCA of different environmental parameters represents a characteristic value.
- Evaluation of CH_4 yield from biogas in BLF through ANN based modeling.

ARTICLE INFO

Article history:
Received 30 December 2015
Received in revised form 6 March 2016
Accepted 8 March 2016
Available online 12 March 2016

Keywords:
Anaerobic bioreactor
Methane
Total volatile solid
Artificial neural network
Optimization

ABSTRACT

The performance of a laboratory-scale anaerobic bioreactor was investigated in the present study to determine methane (CH_4) content in biogas yield from digestion of organic fraction of municipal solid waste (OFMSW). OFMSW consists of food waste, vegetable waste and yard trimming. An organic loading between 40 and 120 kg VS/m^3 was applied in different runs of the bioreactor. The study was aimed to focus on the effects of various factors, such as pH, moisture content (MC), total volatile solids (TVS), volatile fatty acids (VFAs), and CH_4 fraction on biogas production. OFMSW witnessed high CH_4 yield as 346.65 L CH_4/kg VS added. A target of 60–70% of CH_4 fraction in biogas was set as an optimized condition. The experimental results were statistically optimized by application of ANN model using free forward back propagation in MATLAB environment.

1. Introduction

Landfill bioreactors (LFBRs) are termed as one of the novel technologies for simultaneous energy production and waste stabilization from biodegradable organic fraction of municipal solid waste (OFMSW) comprised of food waste (FW), vegetable waste (VW) and yard trimming. Recently, the potential of LFBRs was studied to produce more landfill gas (LFG) as compared to conventional dry tombs both in US and Abu Dhabi. The study proved an opportunity to successfully generate energy in an environment friendly manner that reduces the pollution potential and offsets the use of fossil fuels (Janajreh et al., 2013). Various techniques, such as reduction of particle size (Kim et al., 2008), moisture content (MC), mixing (Smith et al., 1996), leachate recirculation, temperature (Lee et al., 2008), pH (Selvam et al., 2010; Xu et al., 2011), addition of inoculum (Charles et al., 2009), and supply of additional nutrients were examined to enhance biodegradation of MSW. The anaerobic bioreactor could not reach a stable methane (CH_4) production phase during the study period due to a longer period of acid generation (Xu et al., 2014). Sil et al. (2014) observed that bio-methane potential assays with the mixed MSW (without segregation) derived a very low CH_4 potential as compared with other segregated wastes like FW and VW. Raga and Cossu (2013) observed inhibition of biodegradation processes at 45 °C in landfill for the experiment conducted between 35 and 45 °C.

In biological degradation process, the analytical parameters are non-linear in nature. Artificial neural network (ANN) has proved easier comparison to statistical methods for non-linear modeling (Desai et al., 2008). However, ANN being a black box learning

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http://dx.doi.org/10.1016/j.biortech.2016.03.046
0960-8524/

approach cannot interpret relationship between the system input and output parameters. ANN models have property called capacity, which roughly corresponds to their ability to model any given function. Information gained from modeling might direct the adjustment of process and reduces the number of characterizations required. Mathematical model-based simulations of bioreactors can suggest the tuning of process parameters, substrate and product concentrations, and nutrient additions with respect to time, pattern, concentration and composition to elicit the desired output. A black box model describes the functional relationship between system inputs and system outputs. The algorithm parameters involved do not necessarily have any physical meaning in terms of equivalence to actual process variables. However, they can model process trajectories. Neural networks are particularly suited to model complex non-linear processes.

ANNs had become a popular tool since the last decade for modeling environmental systems, such as air pollution (Abdul-Wahab and Al-Alawi, 2002; Nunnari et al., 2004; Karaca et al., 2005) and prediction of performance of wastewater treatment plant (Hamed et al., 2004). Nevertheless, literatures on the predictive capabilities of neural networks on biogas generation rate from MSW are also available. Ozkaya et al. (2007) showed relationship between the age of waste and CH_4 fraction that could be modeled by ANN considering the leachate components as input parameters and also presented neural network CH_4 modeling by choosing environmental factors, such as recirculation rate and temperature. Behera et al. (2015) applied ANN model to predict the performance parameter namely CH_4 percentage (%) with the input parameters of LFG extraction rate (m^3/h) and landfill leachate: food waste leachate ratio, respectively, which presented that back propagations were able to predict CH_4 percentage of the LFG in an acceptable range. Abu Qdais et al. (2010) employed ANN and genetic algorithm as tools to simulate and optimize biogas production from digesters under various operational conditions. The developed ANN model was used with genetic algorithm to optimize CH_4 (77%) in biogas.

With these background information, an optimization study on CH_4 production from anaerobic bioreactor using OFMSW and VW as substrate was undertaken. In the present study, waste-to-energy aspects like anaerobic decomposition in Indian scenario were addressed to describe importance on the effects of various factors, such as pH, MC, total volatile solids (TVS), volatile fatty acid (VFAs), and biogas production rate. Also, CH_4 content in biogas by anaerobic digestion of OFMSW using anaerobic bioreactor was evaluated through ANN based modeling.

2. Methods

2.1. Preparation of feedstock

VW as well as OFMSW with MC in the range 40–60% was used in the study. The substrate to the bioreactor was VW and OFMSW collected from a typical residential colony of Nagpur, India. The composition of substrate was simulated based on the fraction of VW, FW and yard trimming collected from individual households from the colony. Cow dung and anaerobic sludge from a food industry with TS 7.28% and TVS 78% (dry weight basis) was used as inoculum during the start-up process of the bioreactor.

2.2. Experimental set-up

A single-phase laboratory-scale anaerobic bioreactor made of acrylic material with a working volume of 20 L equipped with 3 ports for biogas collection and leachate recirculation was fabricated. A shaft was used for mixing the waste during the study period. Mixing of the substrate for collection of sample was achieved by using stirrer. An acrylic perforated filter with 4 mm (0.004 m) holes was provided at the bottom of the reactor in order to prevent clogging in the leachate outlet tubes. Coarse gravel of 30–35 mm (0.003–0.0035 m) thick layer was provided for leachate drainage at the bottom of the bioreactor above this arrangement. A leachate outlet was also provided at the bottom providing a conical arrangement for easy filtering of leachate. Mesophilic condition of 32 ± 5 °C was maintained in the bioreactor. Hot water was circulated through silicone tubes around the walls of the reactor to maintain mesophilic temperature range during the study period. The whole reactor set-up was covered with dark-colored cloth material to prevent heat loss from the silicone tubes and to prevent any light source entering into the reactor. The required moisture level was maintained by pumping anaerobic sludge using a peristaltic pump through the feeding ports for subsequent studies on leachate recirculation.

Different sets of run were conducted in the laboratory-scale bioreactor. Anaerobic condition was achieved by operating the bioreactor with only 15 L of inoculum for the Run 1 (of 20 days) during the start-up period. In Run 2, 1.5 kg of VW was taken along with 15 L of inoculum and 3 L of water. Composition of Run 3 was 3 kg VW along with 15 L of inoculum and 3 L of water. In Run 4, 3 kg OFMSW consists of 2 kg of VW and 0.5 kg of FW and yard trimming each added with 15 L of inoculum and 3 L of water. Due to possibility of CO_2 absorption in water, simple water displacement technique was modified using brine solution (1 N NaCl) for biogas volume measurement.

2.3. Analytical methods

The characteristics of digestate within the bioreactor were analyzed to determine the organic removal efficiency. pH was determined using EUTECH cyber scan meter with a combination of glass electrode calibrated in buffers at 4, 7 and 9. TS and TVS were measured according to Standard Method 2540 G (APHA, 2005) through oven drying at 105 °C for 24 h and ignited at 550 °C for 16 h in a muffle furnace, respectively. VFAs were determined using titrimetric method (APHA, 2005). Biogas from different runs was measured using modified water displacement set-up and gas composition as CH_4 was analyzed using SHIMADZU Gas Chromatograph (GC 2010) equipped with Thermal Conductivity Detector (TCD) through PORO PACK Q column.

2.3.1. Optimization of analytical parameters and principal component analysis

A target for recovering 60–70% of CH_4 from biogas was set. The optimized conditions for attaining the analytical parameters corresponding to the target were determined using MINITAB® 15, statistical software. The foremost aim of data-exploration techniques was to synthesize and process the inter-relationship between observations in such a way to make the patterns clear to the researcher. Principal component analyses (PCA) are less concerned with *p*-values. PCA technique was used to gather various operation parameters, and correlate them to the bioreactor performance (Costa et al., 2009) to identify any patterns in the dataset and its optimization. The biplots axes in PCA are pair of principal components or dimensions. The points in the biplot represent daily observational data on the principal components, and the lines represent the parameters *viz.,* pH, MC, TVS, SCOD, TCOD, VFAs, biogas and CH_4 percentage in biogas. The lines approximated the variance of the parameters. The relative location of the scatterplot can be interpreted. Points that are close together correspond to observations that have similar scores on the components displayed in the plot. To the extent that these components fit the data well, the points also correspond to observations that have similar values