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Hybrid neural network modeling and optimization of an anaerobic digestion of shrimp culture pond sediments in biogas production process

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Abstract

Hybrid neural network (HNN) has received great attention especially for modeling a nonlinear system. Hence, HNN for modeling and optimization for determining optimum temperature profiles with maximal biogas production was studied basing on mathematical models initially describing the anaerobic digestion in biogas production process. The experiment of a 30-day process was conducted using sediments from shrimp ponds to simulate the daily performance of the HNN consisting of two-hidden layers with 7 and 9 nodes and the optimization of ambient temperature with satisfactory results obtained: a significant higher yield at 3.30 times compared with conventional methods.

Keywords: Hybrid neural network, Optimization, Anaerobic digestion, Biogas production

1. Introduction

Manufacturing biogas from shrimp-farming sludge is complicating due to various factors directly impact on quantity of the produced biogas. There are several studies and analysis indicated that a hybrid-model is the most effective technique.

In this study, HNN constructed from neural network (NN) combined with the first principle models (FPM) was investigated. Kurt and Marcel [1] showed excellent performance of HNN in combination with a NN structure for modeling of the polymer chain length results in an optimum model. Hussain et al. [2] introduced the HNN with FPM for a fermentation process and for a temperature control of a chemical stirred tank reactor. Tsen et al. [3] developed HNN to improve the performance of a model predictive control scheme for a batch polymerization reactor. HNN controller for a batch reactor to produce methyl methacrylate, Kittisupakorn et al. [4] and a steel pickling process Daosud et al. [5] showed the best control results in all cases. Moreover, Kittisupakorn et al. [6] and Daosud et al. [7] indicated that HNN model predictive control provides much more satisfactory performance for a steel pickling process and a batch extractive distillation process respectively when compared to the conventional methods. Due to the predictive capability of HNN for complex systems, the aim of this work is to focus on establishing the HNN model of biogas production from anaerobic digestion of sediments from shrimp pond and designing the optimum temperature profile in order to maximize biogas production flow rate by using optimization technique.

2. Materials and methods

2.1 Anaerobic digestion process

Mathematical models and experimental data available in literatures [8] with a reference of fermented 80 liter of shrimp-culture-pond sediment by anaerobic digestion in a batch reactor were studied. During the experiment, the biochemical properties of sediments, the chemical compositions of biogas and the value of parameters were observed as shown in Table. 1, 2 and 3 respectively. The accumulative sum of biogas production in 30 days was 12.16 L or 0.40 L/day. The principle of mass balance equations were defined as the FPM which constructed as follow:

$$\frac{dX}{dt} = \mu X \tag{1}$$

$$\frac{dS}{dt} = -k_1 \mu X \tag{2}$$

$$Q_{est} = k_2 \mu X \tag{3}$$

Where X is concentration of biomass (g/l), S is the substrate concentration (g/l), μ is the specific growth rate of bacteria (day^{-1}), Q is biogas production flow rate (l/day) and k_1,k_2 are constants. Note that these equations are for an anaerobic digestion process in a batch reactor.

From the equations, μ is an important factor impacts on the growth of bacteria, substrate consumption and biogas production. μ depends on substrate concentration, pH,

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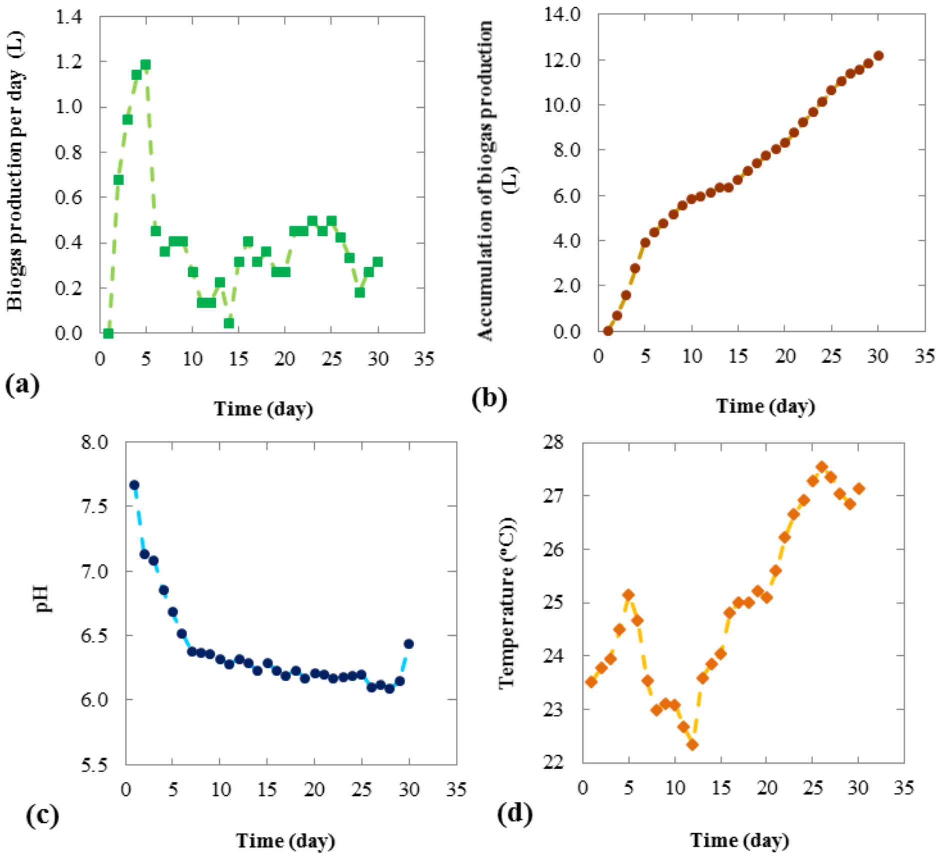

Figure 1 Experimental data (a) daily biogas production (b) cumulative biogas volume (c) reaction pH (d) reaction temperature

Table 1 Biochemical properties of shrimp culture pond sediments

	Before	After		Before	After
pH	7.7	7.5	Total fixed solid (mg/l)	139,603	10,922
Total solid (mg/l)	139,859	15,978	Organic matter (g/l)	73.5	81.3
Total dissolved solid (mg/l)	24,500	9,700	Biological oxygen demand ,BOD (mg/l)	2,334	324
Total suspended solid (mg/l)	112,200	5,750	Chemical oxygen demand, COD (mg/l)	7,840	1,197

Table 2 Chemical compositions of biogas

Biogas compositions	CH_4	CO_2	N_2	H_2	H_2S
Analyzer (%)	44.34	4.91	17.23	Non detected	Non detected

Table 3 Value of parameters

k_1	2	k	-0.7974	k_q	12	a_3	-0.0444
k_2	5	a	-0.9949	k_3	19.434	E_1	16000
μ_{max}	0.9316	b	13.5861	a_1	1.68×10^{11}	E_2	34500
k_s	11.5905	c	45.6025	a_2	-5.10×10^{23}	R	1.987

temperature and biogas production flow rate which expressed as follow:

$$\mu(t) = \mu(s)\mu(pH)\mu(T)\mu(Q) \tag{4}$$

$$\mu(S) = \frac{\mu_{max}S}{k_s+S} + k \tag{5}$$

$$\mu(pH) = a(pH)^2 + b(pH) + c \tag{6}$$

$$\mu(T) = a_1 \exp\left(\frac{-E_1}{RT}\right) - a_2 \exp\left(\frac{-E_2}{RT}\right) - a_3 \tag{7}$$

$$\mu(Q) = \frac{k_q}{k_q+Q} + k_3 \tag{8}$$

Where μ_{max} is maximum specific growth rate of bacteria (day^{-1}), E_1,E_2 are gas energy (J/g.mole), R is the gas constant (J/g) and k_s,k,a,b,c,a_1,a_2,a_3,k_q,k_3 are constants.

The response of daily biogas flow rate, cumulative biogas volume, reaction pH and temperature are shown in Figure 1(a), (b), (c) and (d) respectively.

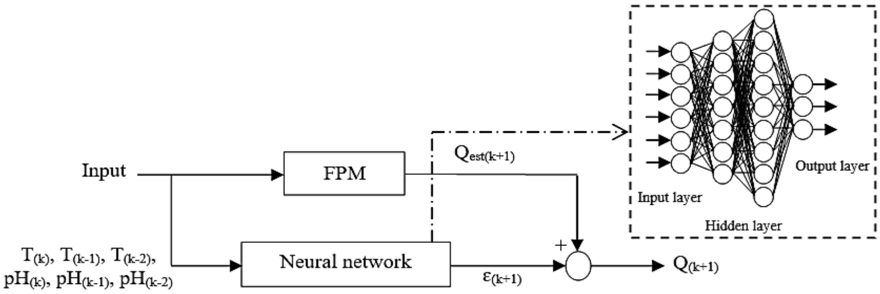

Figure 2 Approach of HNN

2.2 Hybrid neural network and optimization

HNN is an alternative approach to handle this task. The idea of HNN is to design NN that is able to predict the value of FPM error estimation. Figure 2 shows the output conjunction of NN and FPM with accurate biogas production flow rate.

Step of implementing NN in HNN: the input data consists of the reactor temperature and pH at time (k), (k-1) and (k-2) since they have direct effect on the predicted outputs. These data sets were further normalized for achieving a better performance of HNN model. To train the multilayer feed-forward NN, the Levenberg-Marquardt back-propagation algorithm was used. Mean square error (MSE) was used as a criterion for NN structure selection. After HNN model was achieved, compared the simulation results obtained from HNN, FPM, standard neural network and experimental data.

It was suggested by those research that during anaerobic digestion the biogas production is correlated to temperature [9-11] due to the effect of temperature on kinetic models [12-13]. An optimization based on HNN model was recommended to estimate an optimum temperature profile that maximizes a production flow rate. Thus, the optimum problem takes the form as:

$$\underset{T(t)}{\text{maximize}} \quad Q(t) \tag{9}$$

Subjected to HNN model, 22.10°C ≤ T(t) ≤ 27.85°C.

The sequential quadratic programming (SQP) algorithm, one of the most successful general methods for solving nonlinear constrained optimization problems [14] was obtained to treat this problem. The data flow diagram as shown in Figure 3.

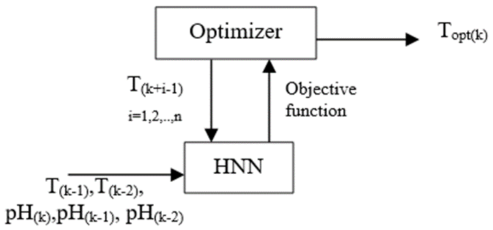

Figure 3 Optimization based on HNN model

3. Results and discussion

From simulation, the optimum structure of the NN in a HNN model consists of two-hidden layers with the sigmoid transfer function and one output layer with a linear transfer function. The numbers of nodes in the 1st and 2nd hidden layers are 7 and 9, respectively. The MSE value of this NN is 5.85×10^{-12}.

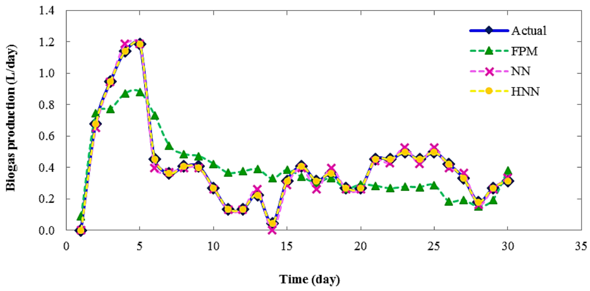

Figure 4 Comparison between FPM, NN and HNN for biogas production prediction

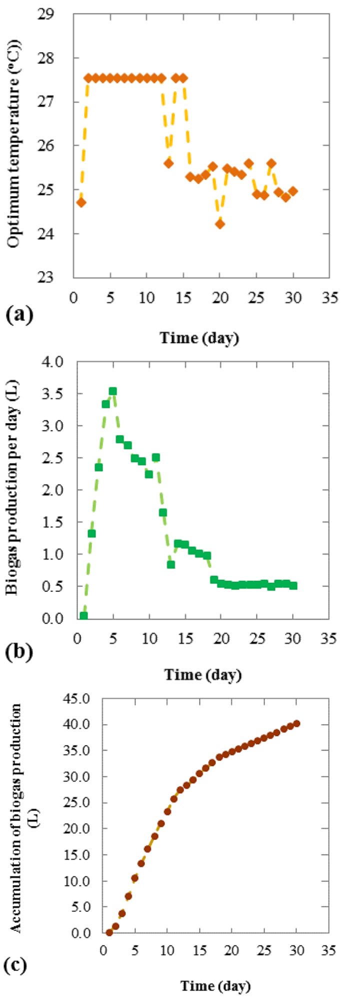

Figure 5 HNN based optimization result (a) optimum temperature profile (b) daily biogas production (under optimum temperature) (c) cumulative biogas volume

Figure 4 illustrates the simulation results that the HNN can predict value of biogas production flow rate more accurate than other conventional models. Nevertheless, the hybrid approach improved the performance of the model prediction [15]. Comparing the MSE value, it is clear that HNN shows the best performance due to the lowest MSE value of 1.11×10^{-27}. As seen in the results, the HNN is good and reliable alternative for the model of highly nonlinear systems such as this anaerobic digestion process.

Since HNN model gave an excellent prediction, this study at temperature between 22.10^{o}C to 27.85^{o}C the production flow rate was maximized by using optimization technique based on HNN. It was found that the proposed optimum operation as shown in Figure 5(a) provides a superior biogas production as shown in Figure 5(b). Figure 5(c) shows a cumulative volume of biogas was 40.11 L increased at 3.30 times compared to the conventional methods. The result indicated that the production was generally higher at the upper limit of temperature range. Thus, the optimum temperature profile from HNN optimization is capable to increase the biogas production flow rate.

4. Conclusions

The comparison of the simulations between the hybrid neural network, first principle model, standard neural network and experimental data were made: comprehensive evidence that the hybrid approach is a significant reliable alternative of nonlinear system. In addition, the satisfactory result was achieved when the hybrid modeling was incorporated with an optimization technique to establish an optimum operating temperature profile.

5. Acknowledgements

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