Neural-fuzzy control system application for monitoring process response and control of anaerobic hybrid reactor in wastewater treatment and biogas production

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Abstract

Based on the developed neural-fuzzy control system for anaerobic hybrid reactor (AHR) in wastewater treatment and biogas production, the neural network with backpropagation algorithm for prediction of the variables pH, alkalinity (Alk) and total volatile acids (TVA) at present day time t was used as input data for the fuzzy logic to calculate the influent feed flow rate that was applied to control and monitor the process response at different operations in the initial, overload influent feeding and the recovery phases. In all three phases, this neural-fuzzy control system showed great potential to control AHR in high stability and performance and quick response. Although in the overloading operation phase II with two fold calculating influent flow rate together with a two fold organic loading rate (OLR), this control system had rapid response and was sensitive to the intended overload. When the influent feeding rate was followed by the calculation of control system in the initial operation phase I and the recovery operation phase III, it was found that the neural-fuzzy control system application was capable of controlling the AHR in a good manner with the pH close to 7, TVA/Alk < 0.4 and COD removal > 80% with biogas and methane yields at 0.45 and 0.30 m^3/kg COD removed.

Key words: anaerobic hybrid reactor; influent feed flow rate; neural-fuzzy control system; process response

DOI: 10.1016/S1001-0742(09)60334-X

Introduction

Anaerobic digestion is the biological wastewater treatment by varieties of microorganisms to degrade the organic substances to methane and carbon dioxide without aeration (Cakmakci, 2007; Punal et al., 2001; Steyer et al., 1999). Anaerobic hybrid sludge bed-fixed film reactor, sludge bed combined with nylon fiber fitted inside the reactor, is one of the high rate anaerobic reactors and widely used in agro-industries (Chaiprasert et al., 2003). The anaerobic process is sensitive to the changing environmental conditions inside the reactor, hence the control in the stability of the system is an important factor for reactor performance. Influent organic loading rate (OLR) and hydraulic flow rate can be used to indicate the stress imposed in the microbial population. If there are improper OLR or feed composition into the reactor, it will affect the stability of the anaerobic digestion process by increasing volatile fatty acids (VFAs) accumulation leading to a pH drop and resulted in a decrease in performance of COD removal efficiency and methane production, which may easily make the process fail at the end (Aygun et al.,

2008; Sanchez et al., 2005; Ahring et al., 1995). It requires several weeks to several months to recover the system depended on how serious the problem is. To control this problem, various common variables of anaerobic process including pH, alkalinity (Alk), total volatile acids (TVA), COD removal efficiency and biogas production and its composition should be routinely analyzed and monitored to ensure the stability and performance of the system. It is therefore a great challenge to have an anaerobic control system to make this process more reliable and usable for wastewater treatment and biogas production.

The developments of the control system for the anaerobic digestion system are important to keep the process stabile and to maintain high reactor performance. Many control systems have been developed to control these variables in the anaerobic digestion system, but most of them are too complex and some are expensive. In recent years, the interest in neural networks or fuzzy logic controls has been developed to predict the process variables and control in various systems. Neural network and fuzzy logic control systems have found a wide range of the control application to provide a rapid response to avoid process deterioration and failure. Neural network

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is a useful tool for modeling the complicated nonlinear and multivariable processes such as chemical engineering process, bioprocess, aerobic wastewater treatment process (Koprinkova-Hristova and Patarinska, 2008; Hong et al., 2007; Zeng et al., 2007; Wiltowski et al., 2005; Hamed et al., 2004; Palau et al., 1996). Especially as there are several of application studies of the neural network in anaerobic digestion system (Bestamin et al., 2007; Rangasamy et al., 2007; Strik et al., 2005; Holubar et al., 2002; Horiuchi et al., 2001; Guwy et al., 1997; Wilcox et al., 1995). Theory of fuzzy logic was introduced in 1965 (Takeshi, 1992). The advantage of fuzzy logic is that it does not require complex mathematical equations. Fuzzy logic systems have been applied in many of bioprocess and chemical engineering process (Huang et al., 2009; Maidi et al., 2008; Karakuzu et al., 2006; Traore et al., 2005; Sousa and Almeida, 2001). Generally, it is a new method and has advanced the control of the anaerobic digestion system (Perendeci et al., 2008; Carlos et al., 2007; Punal et al., 2003; Polit et al., 2002; Estaben et al., 1997). Either several neural network models or fuzzy logic control systems are used as a complementary tool in the design and development of intelligent systems in various types of anaerobic suspended biomass reactors or anaerobic attached biofilm reactors except in anaerobic hybrid sludge bed-fixed film reactor (AHR).

In the present study, the integration of the neural network model and fuzzy logic control system, namely a neural-fuzzy control system for an anaerobic reactor is firstly developed. An adaptive intelligent system of a neural-fuzzy control system is established for the AHR. AHR used in this study was developed by the combination of suspended and attached growth biomass in the reactor (Chaiprasert et al., 2003). The neural network models were based on the backpropagation algorithm to predict important process stability variables such as pH, Alk and TVA. A neural network shows a valuable property in a trained neural network providing a correct matching in the form of output data for a set of previous unseen input data. Computing frameworks based on the fuzzy set theory and fuzzy if-then rules in the fuzzy logic system to control influent feed flow rate in the laboratory-scale AHR. This study is expected to obtain a neural-fuzzy control system as the prediction model and controlling system for the AHR to keep process stabile with high reactor performance in wastewater treatment and biogas production. The approach used in this study will make AHR more reliable, usable and give quicker process response.

1 Materials and methods

1.1 Anaerobic hybrid reactor

A 12.32-L laboratory-scale AHR in Fig. 1 was made of acrylic. The inner diameter and height of the reactor was 14 and 80 cm, respectively with a working volume of 10.78 L. The supporting media used in the packed zone of an AHR was nylon fiber with a density of 23.41 kg/m^3 and placed in the upper half of the reactor for microbial attachment. The bottom half of reactor contained suspended biomass called the sludge zone. The composition of synthetic wastewater was followed by Li and Noike (1992) using glucose as the representative of organic carbon source. The preparation of basal medium components including vitamin solution prepared in unit of mg/L and mineral solution was also explained by Romsaiyud et al. (2009).

1.2 Operating conditions of anaerobic hybrid reactor

During the operation of an AHR, the influent synthetic wastewater was continuously fed up flow into the AHR by a peristaltic pump with glucose concentrations in the range of 3–12 g/L. The reactor operated under the ambient temperature (30–35°C). The suitable daily influent feed flow rate for the experiments of the initial phase operation (Phase I) and the recovery phase operation (Phase III) was adjusted everyday following the value that was computed by the neural-fuzzy control system. In addition, phase II (overload operation) was carried out by two folds of the computed influent feed flow rate together with OLR. Experimental data was mainly collected effluent during the operating period for analysis of reactor stability and performance in wastewater treatment and biogas production.

1.3 Analytical procedure

To achieve process stability and performance, process variables such as pH, Alk, TVA, COD removal, biogas composition and biogas production rate were analyzed daily. TVA and Alk were determined by titration method of 2310 B and 2320 B-Standard methods (APHA, 1995), respectively. The COD concentration was analyzed according to a closed reflux by the colorimetric method of 5220 D-Standard methods (APHA, 1995). Biogas production was measured by a gas counter that uses the concept of water replacement. The composition of biogas was analyzed by gas chromatography equipped with thermal conductivity detector (GC-TCD, Shimadzu GC-9A, Japan) and Porapak-N 80/100 column.

1.4 Development of neural-fuzzy control system

The controlling of the AHR using the neural-fuzzy control system is presented in Fig. 2, which consisted of
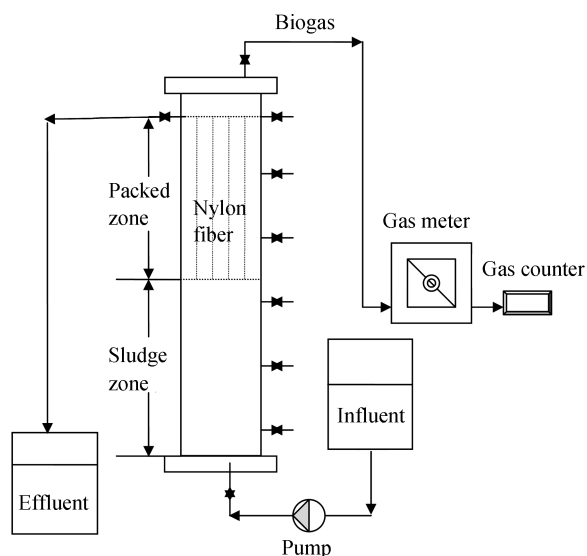

Fig. 1   Schematic layout of anaerobic hybrid reactor (AHR).

two parts, the neural network model (from appendix A) and the fuzzy logic control system (from appendix B). The neural network model was used to predict the pH, Alk and TVA at present day time t and then the fuzzy logic control system use this predicted value as input variables to calculate the daily influent feed flow rate of the AHR.

2 Results and discussion

The neural-fuzzy control system was developed by applying the neural network model design in type of a four-layer feedforward consisting of 1 input layer, 2 hidden layers and 1 output layer based on the backpropagation algorithm for predicting the variables pH, Alk and TVA at time t (present day) and fuzzy logic control system using these predicted variables for calculating the influent feed flow rate into the AHR. The daily computed influent flow rate from the control system was used to feed into laboratory scale of the AHR every day. To test the control system and its response for wastewater treatment and biogas production in the AHR, three phases of experiments were carried out. The patterns of influent feed flow rate corresponded to an OLR in phase I–III are shown in Fig. 3. The initial phase (Phase I) was the start-up period of the reactor with the influent flow rate fed in the range of 1.79–3.05 L/day by following the computation of the neural-fuzzy control system for 30-day operation. To check

the response of the control system, the second phase (Phase II) was done by overload feeding shock with two folds of the computing influent flow rate together with two folds OLR. The influent feeding flow rate and OLR were in the range of 2.23–6.75 L/day and 1.86–5.64 g/(L·day) for 10-day operation, respectively. The last phase (Phase III) was the recovery phase with the influent flow rate fed at the range of 2.08–3.22 L/day by following the computation of the control system for 26-day operation. The efficiency of the neural-fuzzy control system explained in terms of performance and stability during the experiment. The determination of the AHR performance and stability was evaluated by the change of pH, Alk, TVA, biogas production, biogas composition and COD removal in the reactor.

2.1 Process response and control of AHR in the initial phase I operation

In phase I in Fig. 3, the influent glucose concentrations of 3–7 g/L were fed at a flow rate of 1.79–3.05 L/day to the AHR. The initial OLR was 0.56 g/(L·day) and step increased to 1.98 g/(L·day) at 3.53–6.02 days of hydraulic retention time (HRT).

The typical factors should be monitored to evaluate the controlling and process response in terms of stability and performance. The pH, Alk and TVA were used for investigating the stability of the anaerobic system and these factors are related variables which were analyzed everyday during the experiment as input data set for controlling the AHR by neural-fuzzy control system. Removal of COD and biogas production during operation were determined to evaluate the reactor performance. The results shown in phase I in Fig. 4a, pH values were varied in range of 6.68–6.94 during the operation period of 30 days and system pH was suitable for methanogens to obtain maximal biogas yield in anaerobic digestion system. Liu et al. (2008) described the optimum pH to obtain the maximum biogas yield in the anaerobic digestion is in range of 6.50–7.50. The pH in the system was quite stable and could be maintained at 6.80 during the operation in phase I. It was related to Alk and TVA values in the reactor at the same
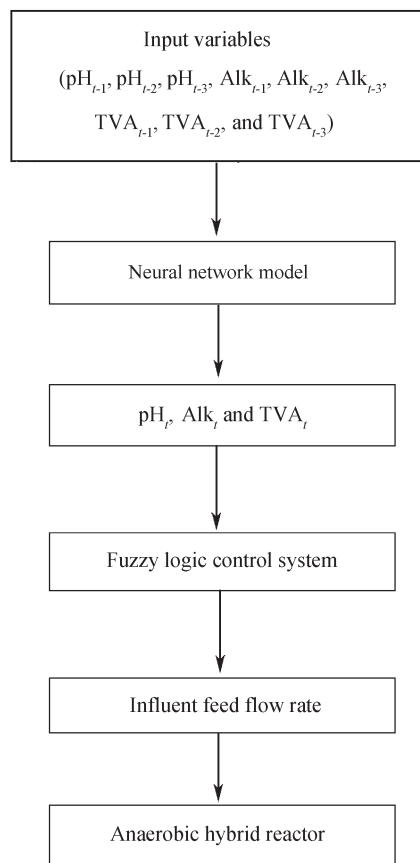

Fig. 2 Schematic of the controlling of anaerobic hybrid reactor using neural-fuzzy control system.
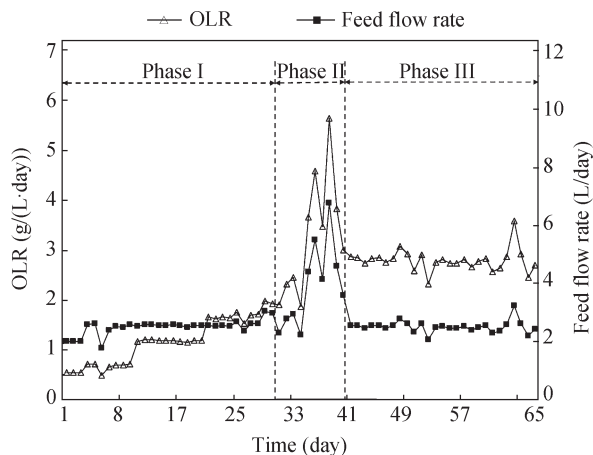

Fig. 3 Pattern of feed flow rate and organic loading rate (OLR) in phase I–III during the operation period.
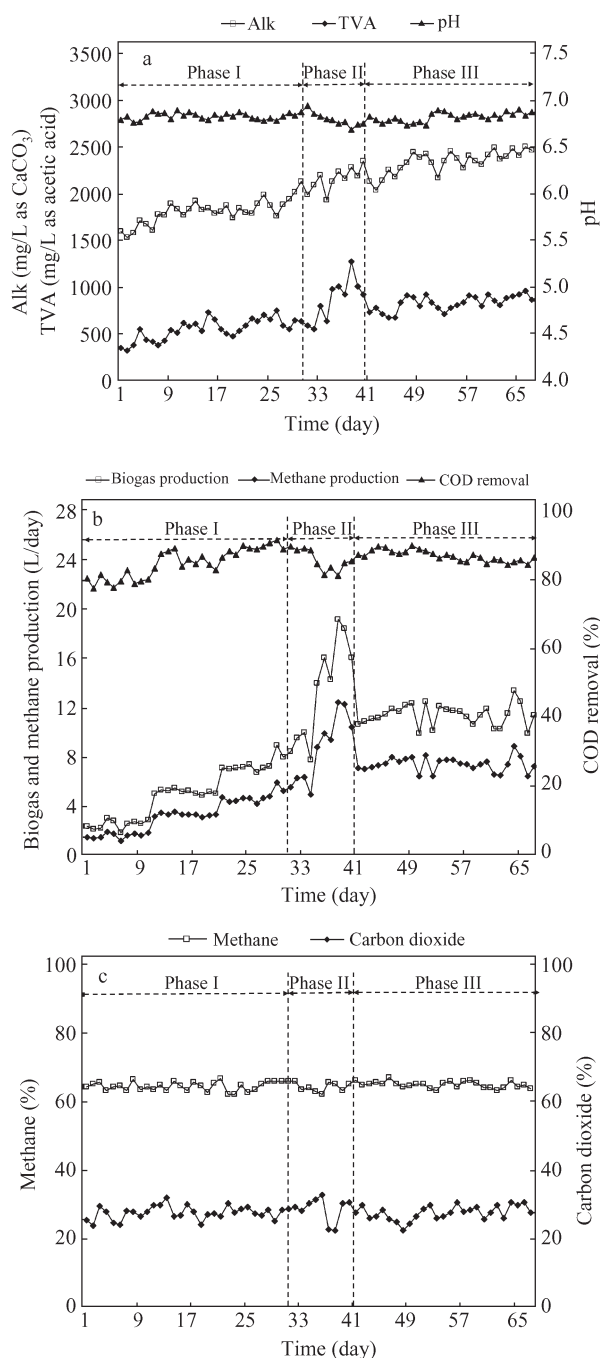
Fig. 4 Profile of pH, Alk and TVA in system (a), COD removal, biogas and methane production (b), and methane and carbon dioxide content in biogas (c) during operation period of phase I, II and III.

time. Less accumulation of volatile fatty acids (< 600 mg/L as acetic acid) and high Alk (> 1500 mg/L as CaCO$_3$) were found in the system. The alkalinity or buffer capacity level from 1000–5000 mg/L as CaCO$_3$ will be able to maintain a stable pH in the anaerobic digester (Wilcox et al., 1995; Graef and Andrews, 1974). For the stable process (reactor stability), Switzenbaum et al. (1990) reported that the ratio of TVA (as acetic acid) to Alk (as calcium carbonate) should have the ratio in the range of 0.1–0.35. The control feeding flow rate by neural-fuzzy system, the TVA to Alk ratio inside the reactor could be maintained at a value of

less than 0.4, indicating the reactor having a high buffer capacity reflected to high process stability. In this phase for OLR 0.5–2.0 g/(L·day) and 5.5–6.0 days HRT, it was sufficient food and contact time for methanogenesis within the suitable environmental condition at pH 6.7–6.9, TVA of 320–650 mg/L as acetic acid, Alk of 1530–1990 mg/L as CaCO$_3$ and TVA/Alk of 0.21–0.33.

COD removal and biogas production are the important parameters in the anaerobic system that can indicate the performance of the system. The results of biogas and methane production, COD removal and biogas composition during the 30 days control operation of the AHR by neural-fuzzy control system are presented in phase I in Fig. 4b and Fig. 4c, respectively. The result of the COD removal was high in the range of 82%–91% and resulted in biogas production and its composition. High methane content in biogas was found at 62%–67%. The biogas production increased following the increasing OLR from 0.5 to 1.98 g/(L·day). The biogas and methane production values were increased from 1.84 to 8.92 L/day and 1.19 to 5.88 L/day, respectively. Biogas and methane yields were high at 0.43–0.49 and 0.27–0.32 m^3/kg COD removed, respectively.

The neural-fuzzy control system application in the initial phase I was able to control an AHR in high stability and performance in wastewater treatment and biogas production with pH close to 7, TVA/Alk < 0.4, COD removal > 80%, biogas yield 0.45 m^3/kg COD removed and methane yield 0.30 m^3/kg COD removed.

2.2 Overload shock and process response in phase II operation

In phase II in Fig. 3, during day 31–40, overload shock was carried out by setting the experiment using the double influent feed flow rate from the computational control system at 4.15–6.75 L/day with 9 g/L of glucose concentration corresponded to double OLR at 3.46–5.64 g/(L·day) and HRT at 1.60–2.60 days. This incident occurred in short time. During five days of continuous shock loading, the control system responded to the decreasing influent feed flow rate down to optimize process into good stability and performance every time of the intended shock loading. The process response after shock loading is shown in phase II in Fig. 4a and phase II in Fig. 4b.

The AHR response for pH, TVA and Alk during shock loading in a short time for 5 days is shown in phase II in Fig. 4a. TVA after shock loading was increased from 550 to 1300 mg/L as acetic acid, whereas Alk was not shift much (2000–2200 mg/L as CaCO$_3$) leading to system pH was slightly dropped from 6.94 to 6.68. The ratio of TVA to Alk was increased from 0.26 to 0.56. This ratio of TVA/Alk was slightly more than 0.4, it represented that the AHR initiated to process upset.

The process responses of performance in terms of COD removal and biogas production are shown in phase II in Fig. 4b. The response of COD removal after shock loading decreased from 89% to 81% while the yields of biogas and methane were slightly decreased from 0.46 to 0.39 m^3/kg COD removed and 0.30 to 0.25 m^3/kg COD removed, respectively. It was affected by the short HRT (< 3 days),

which not enough contacting time for methanogens to convert acetic acid to methane (Chaiprasert et al., 2003). The methane content in biogas (phase II in Fig. 4c) was slightly decreased from 66% to 62%. When increasing OLR it was found that the biogas and methane production were increased from 7.76 to 19.11 L/day and from 4.98 to 12.44 L/day, respectively but yields of biogas and methane were tended to decrease. It was the warning sign that the system was initiated upset from the short shock loading.

In order to check the response of the neural-fuzzy control system, the system was disturbed by increasing the feed flow rate more than the normal feed flow rate. The process was responded by slight decreasing in pH, COD removal and biogas and methane yields. It was a sign to show that the process stability and performance will get upset and failure in the future if the system was longer overload operation. The developed neural-fuzzy control system had a rapid response and was sensitive to the intended overload. After shock loading the AHR in the short time, the obtained data set with affected to the process stability such as pH, TVA and Alk were input data to the control system. Then, the next day for the influent feeding according to the calculated feed flow rate by this control system was responded and controlled the system to feed influent in lower flow rate.

2.3 Control of AHR in the process recovery phase III operation

During day 41–67, in phase III in Fig. 3 was operated with the influent feed flow rate to the AHR followed by the computational value from the neural-fuzzy control system. This phase III was called the recovery phase and operated for 26 days to determine the process stability and performance. The calculated influent flow rate from the control system at the first day of phase III (day 41) was computed to reduce at 2.57 L/day from overload 6.75 L/day of phase II. The calculated influent feed flow rate in phase III for 26-day operation was in the range of 2.08–3.22 L/day. The concentration of feed glucose was 12 g/L. The reactor was operated at 2.32–3.58 g/(L·day) OLR and 3.35–5.18 days HRT. Process responses in term of stability and performance in wastewater treatment and biogas production are shown in phase III in Fig. 4a and phase III in Fig. 4b, respectively.

The result in process response of stability (phase III in Fig. 4a) showed TVA was decreased in the range of 650–950 mg/L as acetic acid compared to phase II while Alk was in the same latitude (2000–2500 mg/L as $CaCO_3$). The ratio of TVA/Alk was less than 0.4 (0.30–0.39) and pH was reflected to 6.73–6.90. The less TVA accumulation at high buffer capacity (Alk) and higher pH can maintain process stability was occurred after the AHR was followed by the control of the neural-fuzzy system.

Phase III in Fig. 4b describes the AHR performance in the COD removal, biogas and methane production and phase III in Fig. 4c shows the biogas composition during the control of the AHR by neural-fuzzy control system. The results indicate that the COD removal efficiency still exceeds more than 85% during the operating time. Biogas

and methane production were in range of 9.89–13.39 L/day and 6.43–8.86 L/day, respectively. Methane content in biogas was found in 63%–67%. The biogas and methane yields were in the range of 0.40–0.47 and 0.26–0.31 m^3/kg COD removed, respectively.

The high stability and performance of the AHR when controlled by the neural-fuzzy control system show similar results from the experimental study of Chaiprasert et al. (2003) using cassava starch wastewater. The neural-fuzzy control system application in the recovery phase III was able to control an AHR back to the high stability and performance in wastewater treatment and biogas production with pH close to 7, TVA/Alk < 0.4, COD removal > 85%, biogas yield 0.45 m^3/kg COD removed and methane yield 0.30 m^3/kg COD removed.

3 Conclusions

The neural-fuzzy control system was designed under the concept of the combination of the neural network model and fuzzy logic control system. The developed neural-fuzzy control system was used with the available operational input variables (pH, TVA and Alk) for controlling the influent feed flow rate into the AHR under different system situations in three phases of the initial operational phase, overload influent feeding phase and the recovery operational phase. The process response and control of the AHR in wastewater treatment and biogas production under the controlling of feed flow rate by the neural-fuzzy control system, the experimental results showed the reactor succeeds in keeping the stability and high reactor performance. The controlling results by the neural-fuzzy control system during the operating AHR were evaluated by changing pH, Alk, TVA, biogas production, biogas composition and COD removal efficiency. COD removal efficiency can be achieved more than 80%, and high methane yield and good process stability were found during this experiment. The neural-fuzzy control system in this study is expected to have a great application for controlling these process variables of the AHR.

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Appendix

A. Neural network model design

This study was carried out to develop the neural network model to predict the variables pH, Alk and TVA at present day time t in the AHR. All of the neural network models in this study were developed by using Matlab program in MATLAB 6.1 (The Mathworks Inc., USA). These structures of neural network model for predicting pH, Alk and TVA at present day time t were designed in four-layer style feedforward neural network that consists of 1 input layer, 2 hidden layers, and 1 output layer. The input and output parameters of the neural network model were shown in Table A1.

Table A1 Input and output parameters of pH, Alk and TVA predicted model

pH predicted model		Alk and TVA predicted model	
Input[a]		Input[a]	
I_1	pH_{t-1}	I_{11}	pH_{t-1}
I_2	pH_{t-2}	I_{12}	pH_{t-2}
I_3	Alk_{t-1}	I_{13}	pH_{t-3}
I_4	Alk_{t-2}	I_{14}	Alk_{t-1}
I_5	TVA_{t-1}	I_{15}	Alk_{t-2}
I_6	TVA_{t-1}	I_{16}	Alk_{t-3}
		I_{17}	TVA_{t-1}
		I_{18}	TVA_{t-2}
		I_{19}	TVA_{t-3}
Output[b]		Output[b]	
O_1	pH_t	O_{11}	Alk_t, TVA_t

[a] t-3: value at last 3 days; t-2: value at last 2 days; t-1: value at last 1 day or yesterday; [b] t: value at present day.

The data were collected from the operational experiment of the lab-scale AHR treated synthetic wastewater. It was normalized between 0 and 1 before using to train and test (or validate) the neural network model. The data was normalized by Eq. (A1).

$$X_{norm} = \frac{X_n - X_{min}}{X_{max} - X_{min}} \tag{A1}$$

where, X_n is the value of original variable; X_{min} and X_{max} are the minimum and maximum values of the original variable, respectively; X_{norm} is the normalized variable. All of the neural network models in this study used the sigmoid function as a transfer function (f) in each neural network layers and the equation of the sigmoid function shown in the following Eq. (A2).

$$f(x) = \left(\frac{1}{1 + \exp(-x)} \right) \tag{A2}$$

The neural network models to predict pH, Alk and TVA at present day time t were trained by the backpropagation algorithm. By training the pH predicted model with six input nodes in the input layer as the historical information of pH_{t-1}, pH_{t-2}, Alk_{t-1}, Alk_{t-2}, TVA_{t-1} and TVA_{t-2}

and one output node in the output layer was pH_t. The number of data used to train the neural network model for each input nodes was 250 data. This model obtained the optimum numbers of hidden nodes in the first and second hidden layers were 25 and 20 nodes, respectively with high R^2 value from linear regression (0.9128). For the Alk predicted model, this model had nine input nodes in the input layer as pH_{t-1}, pH_{t-2}, pH_{t-3}, Alk_{t-1}, Alk_{t-2}, Alk_{t-3}, TVA_{t-1} and TVA_{t-2} and TVA_{t-3} and one output node in the output layer was Alk_t. The number of data used to train the neural network model for each input nodes was 250 data as the same of pH predicted neural network model. The optimum numbers of hidden nodes in the first and second hidden layers were 30 and 20 nodes, respectively. The training result of Alk model presented the R^2 value of 0.8193. The TVA predicted model, there were nine input nodes in the input layer as pH_{t-1}, pH_{t-2}, pH_{t-3}, Alk_{t-1}, Alk_{t-2}, Alk_{t-3}, TVA_{t-1} and TVA_{t-2} and TVA_{t-3} same as the Alk predicted model and one output node in the output layer was TVA_t. The number of data for each input nodes was 250 data likewise of pH and Alk
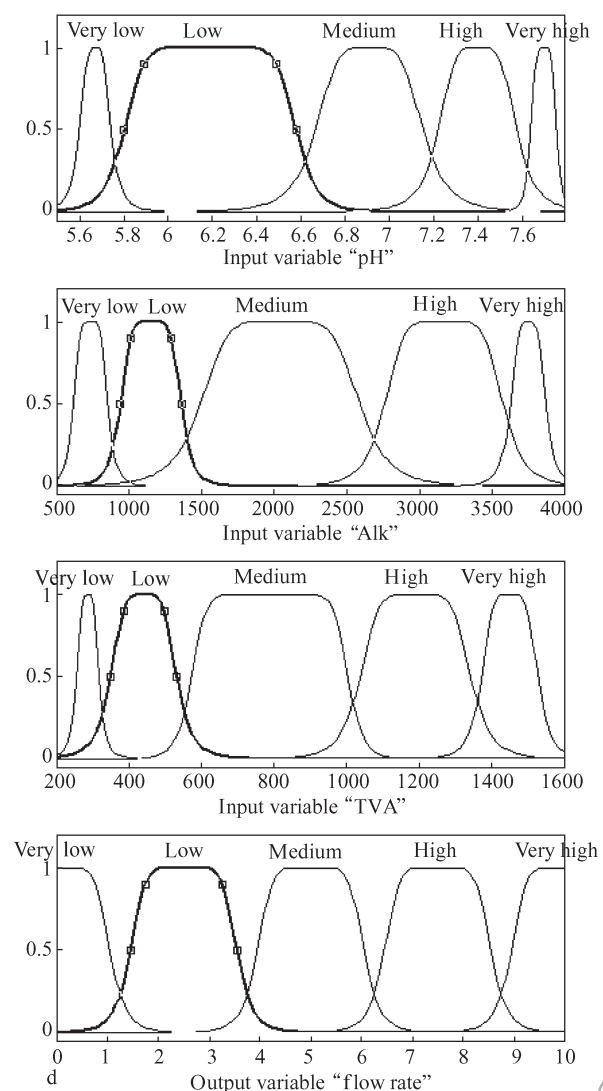

Fig. A1 Membership functions of pH, Alk, TVA and influent feed flow rate.

predicted neural network models. The optimum numbers of hidden nodes in the first and second hidden layers were 35 and 25 nodes, respectively. The highest R^2 value between the experimental and predicted results of TVA model was 0.9198. More generally, a higher value of R^2 ($R^2 > 0.8$) means that the model was satisfying and capability predicted (Holubar et al., 2002).

B. Fuzzy logic control system design

The developed fuzzy logic control system based on the theory of fuzzy logic for controlling the influent feed flow rate of the AHR. The controlled variables of pH, Alk and TVA were selected as the inputs and the influent feed flow rate was the output of the fuzzy control system, respectively. This study selected the type of membership function as generalized bell (gbellmf). Five terms of gbellmf membership function for the inputs and output namely very low, low, medium, high and very high were used. These gbellmf membership functions of pH, Alk,

TVA and influent feed flow rate are shown in Fig. A1, respectively.

According to the 4 variables as pH, Alk, TVA and influent feed flow rate associated with the 5 terms of gbellmf membership function as very low, low, medium, high and very high, the 625 rules of "if-then" rules were described and the 125 rules were chosen for this fuzzy controller, the 5 examples from 125 rules were represented as follows:

(1) If pH, Alk, and TVA are very low, then flow rate is very low;

(2) If pH, and Alk are low, and TVA is very low, then flow rate is very low;

(3) If pH, and Alk are medium, and TVA is very low, then flow rate is low;

(4) If pH is high, and Alk is low, and TVA is very low, then flow rate is low;

(5) If pH is very high, and Alk is medium, and TVA is very low, then flow rate is medium.