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Neural fuzzy modeling of anaerobic biological wastewater treatment systems

Joo-Hwa Tay & Xiyue Zhang
School of CSE, Nanyang Technological University, Nanyang Avenue, Singapore 639798
Email: cjhtay@ntu.edu.sg & P143089526@ntu.edu.sg

Abstract

Anaerobic biological wastewater treatment systems are widely used in strong organic wastewater treatment. However, modeling of these systems is rather difficult because the performance of anaerobic process is too complex and varies significantly with different reactor configurations, influent characteristics and operational conditions. A robust, adaptive model is necessary for the simulation and control of anaerobic systems.

As anaerobic systems are too complex to model using conventional kinetic methods, the advanced neural fuzzy technology is introduced and employed. A conceptual neural fuzzy model is developed with the integration of a fuzzy system and a neural network. The conceptual model inherits the robustness from the fuzzy system and the learning ability from the neural network, and has the potential adaptability for various applications. The conceptual model was applied for the simulation of two high-rate anaerobic wastewater treatment systems, i. e. UASB and AFBR. Satisfactory simulation results were obtained.

This paper presents the fundamental of neural fuzzy modeling and illustrates the development procedure of neural fuzzy models for anaerobic biological systems.

1 Introduction

Anaerobic biological processes, especially the modern high-rate anaerobic systems such as upflow anaerobic sludge blanket (UASB) reactor, anaerobic filter (AF), and anaerobic fluidized bed reactor

(AFBR), are becoming an increasingly attractive alternative for the treatment of industrial and domestic wastewater, because of their outperforming advantages over other processes. However, their startup and control are relatively complex, because of the low growth rate of the specific microorganisms and their high sensitivity to the variance of environmental conditions.

Mathematical models of biological wastewater treatment systems provide an useful tool for the simulation and control of system operation. However, it is a subtle problem to quantitatively describe the anaerobic processes, because of the biological nature of the degradation mechanisms involved. Physical and biochemical reactions in anaerobic process are so numerous and intimately interacting that the analytical description of the system behavior especially its kinetics are non-exhaustive.

The fuzzy modeling developed based on the pioneering idea of Zadeh[1] offers a powerful tool to describe a nonlinear complex system such as biological systems. Since 1980's, fuzzy theory has been successfully applied to the simulation and control of fermentation processes (Filev, et al.[2]), but only a few papers (Boscolo et al.[3]; Marsili-Libelli and Muller[4]) have appeared on the application of fuzzy theory to anaerobic digestion systems, and yet none of them referred to the modern high-rate anaerobic systems.

Another powerful tool for modeling nonlinear complex systems is the neural network technology which was developed from the investigation of properties of biological neurons in 1960's (Works[5]). The most important feature of neural networks is their ability to achieve accurate nonlinear mappings from input-output pairs of data without knowing their functional relationship (Emmanouilides and Petrou[6]). Though neural networks have been successfully applied to many areas, only a few papers appeared on the application of neural networks to anaerobic digestion (Emmanouilides and Petrou[6]; Guwy et al.[7]).

The integration of fuzzy logic and neural networks can combine their merits, and offer a more powerful tool for modeling. The fuzzy systems using neural networks as tools are termed *neural fuzzy systems*, they appear to achieve great progresses in the modeling and control of bioprocesses.

In this study, neural fuzzy modeling technology was employed in an attempt to build an adaptive and robust generic model for complex anaerobic wastewater treatment systems.

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2 Development of A Conceptual Neural Fuzzy Model for Anaerobic Wastewater Treatment Systems

Neural fuzzy modeling (or *neuro-fuzzy modeling*) is the application of various learning techniques developed in the neural network literature to fuzzy inference systems. Commercial computing software, i.e. MATLAB and fuzzyTECH which have been applied in various areas, are available for developing two kinds of neural fuzzy systems, i.e. *adaptive network-based fuzzy inference systems* (ANFIS) (Jang[8]) and *fuzzy associative memory* (FAM) systems (Kosko[9]).

2.1 Analysis of System Information Flow

To model a system, the information flow of the system should be well understood. Basic principles and mechanisms of anaerobic biological process can be found elsewhere in the literature (e.g. Malina and Pohland[10]; Speece[11]). The information flow of the system is too complex to map extensively. To simplify the complex overall anaerobic conversion process of substrate, the information flow is simply mapped as illustrated in Figure 1. With regard to the features of neural fuzzy systems, the anaerobic system is treated as a "grey box", the following development of the neural fuzzy model is based on this assumption.

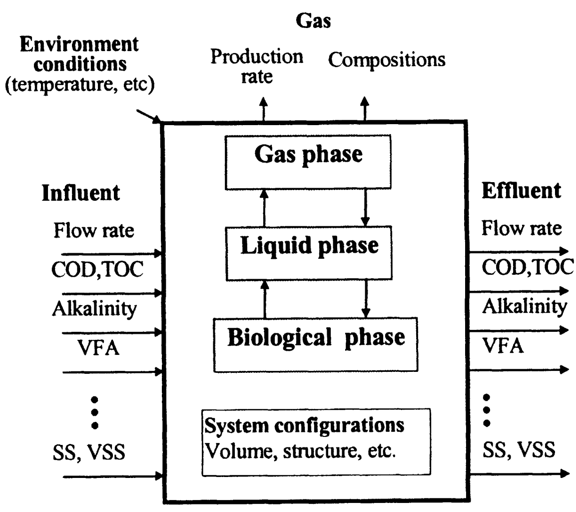


Figure 1 Information flow of anaerobic wastewater treatment system

2.2 Model Architecture

Based on the system information flowing pattern and the available techniques aforementioned, a conceptual neural fuzzy model is developed for anaerobic wastewater treatment systems. The architecture of the model is depicted in Figure 2.

The model is based on a fuzzy system, which is integrated with a multi-layer feed forward neural network with back-propagation algorithm. It is usually started with a pre-structured fuzzy system prototype. Some expertise of the system, such as membership quantification of the input and output variables and the inference rules, can be implemented in the initial fuzzy system, especially the explicit knowledge which the designer is quite sure of. Once a training data base is provided, the neural network automatically elicits the membership functions and maps the fuzzy sets to fuzzy rules, then helps to tune and optimize the model by learning from the training data.

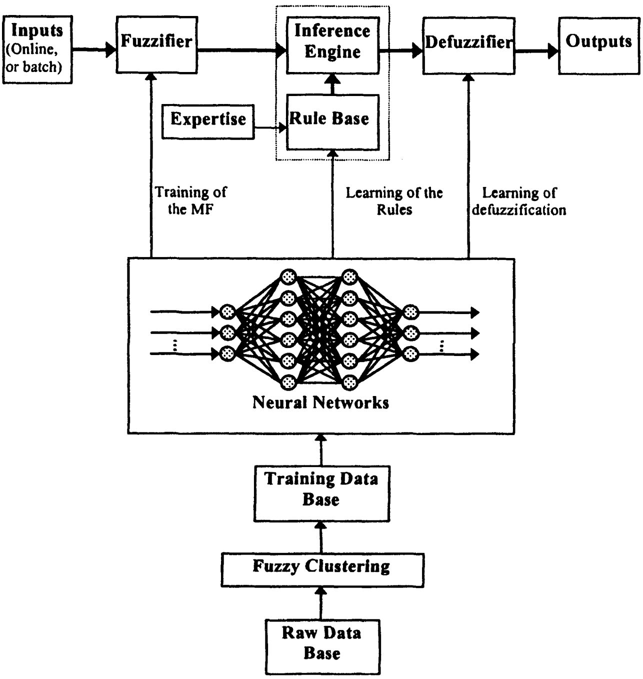


Figure 2 A conceptual neural fuzzy model for anaerobic wastewater treatment systems

The quality of the training data base is critical for the neural network to derive the correct information of the system. Thus it would be better for the raw training data base to be pretreated to remove the redundant data and resolve conflicts in the data. The pretreatment method used in this study is fuzzy clustering method which classifies patterns using fuzzy membership.

The most important advantage of the model is its adaptability to the variation of system configurations, feed quality and operation conditions. The basic model frame can accommodate different variations by adapting its basic components such as training data base, input/output variables and their quantification of membership functions without changing the model structure and basic algorithms. Thus it can perform as a generic model frame for different kinds of anaerobic processes. The resulting fuzzy logic system can be easily integrated with control applications, and is faster and more compact on most target hardware platforms.

3 Application Examples

To validate the neural fuzzy model, two different kinds of complex high-rate anaerobic wastewater treatment systems, i. e. UASB and AFBR are employed to illustrate the application of the model.

3.1 Example I: UASB System

Original raw data are adapted from the work of Campos[12] in which three different size laboratory scale UASB reactors operated at mesophilic temperature were investigated over twenty months of startup and steady state operation. The operation data of two among the three reactors are employed, reactor I (volume at 7L) for building and training the model, and reactor III (volume at 13.6L) for verification.

A simple paradigm is chosen here with the emphasis on computing speed. The resulting model structure is depicted in Figure 3. Considering the structure of raw data base, the input parameters only include organic loading rate (OLR), hydraulic loading rate (HLR) and alkalinity loading rate (ALR). Outputs parameters include volumetric methane production (VMP) and organic outflow (OOR).

Figure 4 shows the simulated results for reactor I. The results shows that the model performs robustly in simulation of the reactor performance with respect to VMP and OOR.

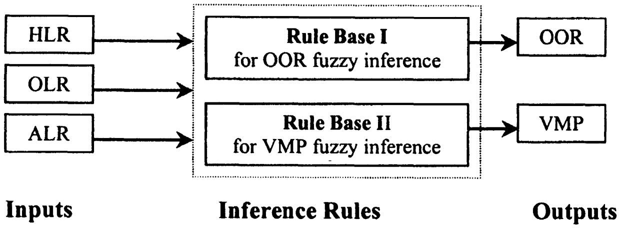
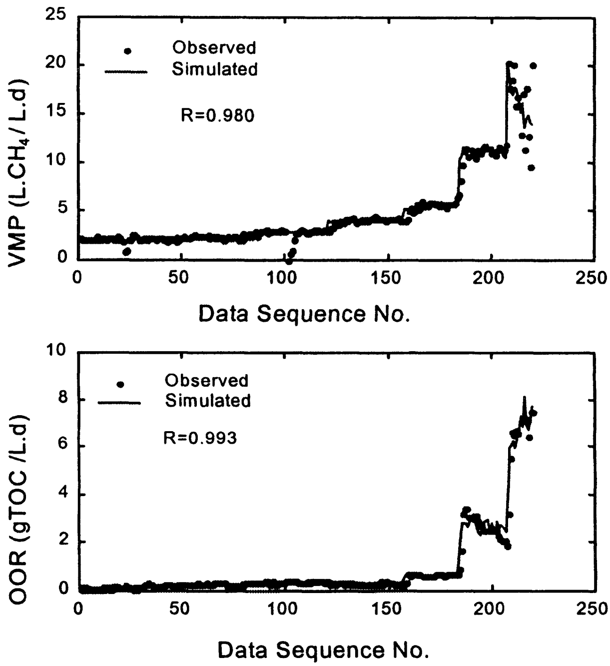


Figure 3 The resulting model structure of UASB



(R is the correlation coefficient of "observed" and "simulated")

Figure 4 Model simulation and observed results of Reactor I

Over 160 days operation data of reactor III are employed to test the applicability of the model to other reactors. A 10 day data set is provided for the model to adapt to the new reactor.

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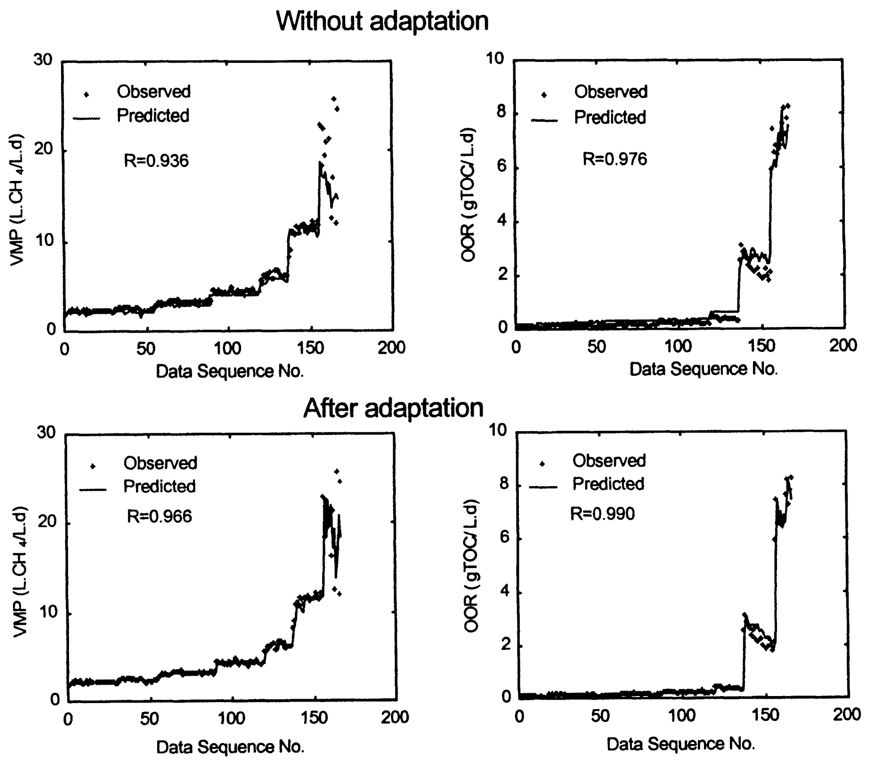
Figure 5 shows that the model performs satisfactorily even without adaptation, nevertheless, it is no doubt that the "in situ" training did improve the performance of the model considerably. As the figure depicted, the model became "closer" to the real system after adaptation.



(R is the correlation coefficient of "observed" and "simulated/predicted")

Figure 5 Model simulated and observed results of Reactor III

3.2 Example II: AFBR system

The data used are collected from 117 day performance test of a full-scale AFBR system (Lin[13]). The system has four reactors, each having a volume of 400 m^3. Data from Day 0 to Day 100 were used in the development of the model, the next 16 day data were employed to verify the model developed.

In attempt to simulate the process comprehensively, volatile fatty acid loading rate (VFALR) and the concentrations of its compositions acetic acid (AcA), propionic acid (PrA) and butyrate acid (BuA) are included in the inputs besides HLR and OLR. The structure of the resulting model is depicted in Figure 6.

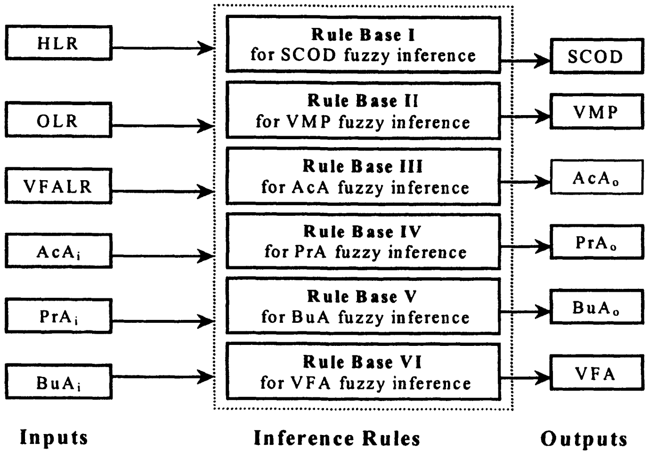


Figure 6 The resulting model structure of AFBR

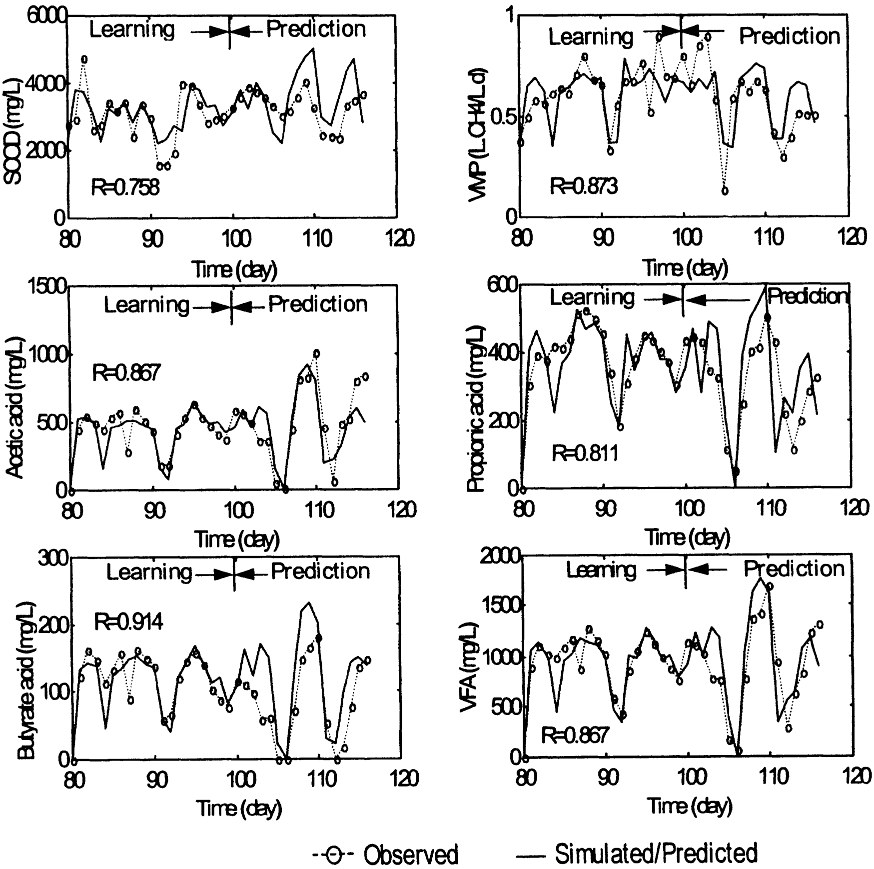
Figure 7 shows the model simulation and observed results from Day 80 to Day 116. It can be seen that the simulated results agree well with observed results. Based on the data observed before Day 100, the model predicted the next 16 day performance of the system at acceptable level.

4 Conclusions

Based on fuzzy systems integrated with neural networks, a conceptual neural fuzzy model for anaerobic wastewater treatment systems is developed in this study. The key advantage of the model is its adaptability to the variation of system configurations, influent quality and operation conditions.

Two application examples showed that the model was applicable to the modeling of anaerobic wastewater treatment systems. A neural fuzzy model developed based on a UASB system can be applied to another one with different size, and still work satisfactorily. In situ training can improve the performance of the model. The model developed for a full-scale AFBR can simulate the system performance well and give satisfactory forecasting based on the past observed information.

The model provides an alternative generic frame in the modeling of various anaerobic processes. Though a lot of questions remained to be solved, the model concept presented in this paper provides prospective industrial application potential for the simulation and control of complex anaerobic waste treatment systems.



(R is the correlation coefficient of "observed" and "simulated/predicted")

Figure 7 The model simulated and observed results of AFBR
(from Day 80 to Day 116)

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