2010 International Conference on Biology, Environment and Chemistry
IPCBEE vol.1 (2011) © (2011) IACSIT Press, Singapore

Modeling anaerobic process for wastewater treatment: new trends and methodologies

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Abstract— **Anaerobic digestion is a multistep process involving the action of multiple microbes. In order to be able to design and operate anaerobic digestion systems efficiently, appropriate models need to be developed. Several Mathematical models have been introduced which suffer from lack of knowledge on constants, complexity and weak generalization. Novel techniques to provide correlation between the affecting factors and production criteria of reactors have been reported to be robust, simple and fast enough for control applications and on-line industrial implementations. In this paper, artificial neural networks (ANN), genetic algorithms (GA) and Fuzzy systems are reviewed. ANN models have been extensively used and gained a considerable attention among the researchers. However, integration of GA and Fuzzy systems looks extremely promising for the industrial fields in future. In addition, the advantageous and practical applications of these models for wastewater treatment are also fully discussed.**

Keywords-Anaerobic digestion, wastewater treatment, artificial neural networks, genetic algorithms, fuzzy systems

I. INTRODUCTION

Anaerobic digestion is a process that converts organic matter into a gaseous mixture mainly composed of methane and carbon dioxide through the concerted action of a close-knit community of bacteria. It has been traditionally used for waste treatment but there is also considerable interest in plant-biomass-fed digesters, since the produced methane is a useful source of energy [5]. Wastewater treatment has been a major challenge within the recent years regarding environmental and economical considerations. Many companies have erected biogas plants worldwide and a lot of experience was gained, leading to a continuous process optimization of anaerobic fermentation and the development of new and more efficient applications. Abundant biomass from various industries could be a source for biomethane production where combination of waste treatment and energy production would be an advantage [30]. Growing amount of organic wastes and wastewaters emitted from plants and industries have resulted in designing and construction of several bioreactors and digesters to produce biogas. High rate and efficient designs are rapidly developing. These reactors offer some advantages over their suspended growth counterparts such as: they operate at high solids retention times and very low hydraulic retention times (hours, when CSTRs require days); their design is simple; they are characterized by efficient heat and mass transfer; they require small volumes; they are robust to disturbances; biogas generation secures good mixing characteristics [20]. However the most crucial aspect of the anaerobic treatment is known to be control and monitoring possibility. It is well known that the functional and operational state of a bioreactor is subject to wide fluctuations due to process disturbances such as loading rates and pH changes. This has gained considerable concerns to overcome the alterations and consequently guarantee the safe operation of anaerobic digesters. The attention toward such issues gets more crucial when high rate bioreactors are utilized. On the other hand, an exact picture of what happens in bioreactors has been so much sophisticated and as a result, massive simplifications have been assumed to predict the necessary outputs of the process [18]. Mathematical modeling of wastewater treatment processes plays an outstanding role as a tool capable of providing diagnostics that will give support to the plant operation and the decision-making process. It is well known that the functional and operational state of a bioreactor is subject to wide fluctuations due to process disturbances such as loading rates and pH changes. This has gained considerable concerns within the last years to overcome the alterations and consequently guarantee the safe operation of anaerobic digesters. The attention toward such issues gets more crucial when high rate bioreactors are utilized. On the other hand, an exact picture of what happens in bioreactors has been so much sophisticated and as a result, massive simplifications have been assumed to predict the necessary outputs of the process [18]. Although many analytical models, mostly kinetic models, have been developed to describe the anaerobic treatment in bioreactors, they are not routinely used for control and on-line applications. The reason lies in their complexity and insolvable parameters. Furthermore, the kinetic models are highly affected by the environmental conditions rendering them to be too generalized for other substrates or environments [31]. Many analytical models, mostly kinetic models, have been developed to describe the anaerobic treatment in bioreactors; however, they are not routinely used for control and on-line applications. The reason lies in their complexity and insolvable parameters. Furthermore, the kinetic models are highly affected by the environmental conditions rendering them to be too generalized for other substrates or environments [31]. The objective of this paper is to review novel methodologies for modeling anaerobic treatment of wastewater. Numerous practical examples which are already reported are also covered.

II. Artificial Neural networks

Artificial neural networks (ANN), as powerful modelling methods have found a great deal of interest among the researchers in the last two decades. They can solve a wide range of problems and differential equations, particularly when the conventional approaches fail. The ability of ANNs in the modelling is traced back to their training mechanism which is inspired by biological neurons [Fig 1 a]. Fig 1b presents a three-layer network. The data processing can extend over multiple layers and the final error criteria such as mean squared error (MSE) are calculated at the output layer which measures the accuracy of modelling [10].

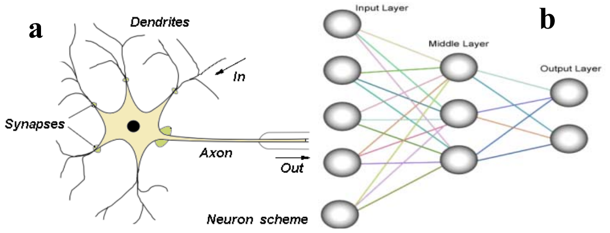

Fig 1: a) a schematic picture of biological neurons, b) representation of biological neurons as a feed-forward three-layer network

A well trained network learns from the pre-seen experimental dataset (training data) and generalizes this learning beyond to the unseen data which is called 'prediction' [9]. Furthermore, ANNs are able to model non-linear behaviours and complex processes. This is highly important in anaerobic treatment and bio-processes due to the special hydrodynamics and non-linear nature of the anaerobic digestion [11]. Based on the mechanism of human nervous systems, the ANN models can be classified into three major groups; 1) feed-forward network, 2) recurrent network and 3) unsupervised network (Fig 2). The most usual model is feed-forward network which has frequently been used in anaerobic treatment studies. Although, recurrent and unsupervised networks are powerful models developed to map the variables of anaerobic processes non-linearly, a few studies have applied them in on-line or control applications. This could be ascribed to the simplicity; accuracy and swiftness that feed-forward networks offer [14].

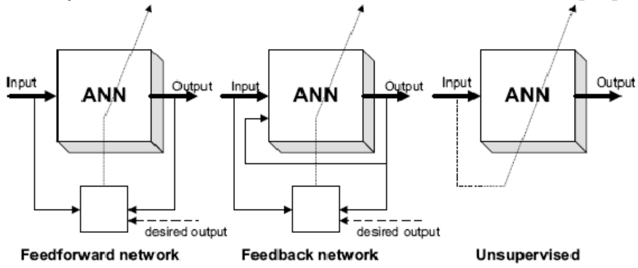

Fig 2: three general models of neural networks used in engineering analyses [32]

ANN together with other intelligent methodologies could be a promising alternative to the conventional techniques. Of the premier studies of this field, was the investigation carried out by Zhu et al., on modeling the wastewater process by time-delay neural networks in order to predict the quality attributes of the process [36]. A few years later, Gontarski et al. also proved the successful application of neural networks in the simulation of industrial anaerobic treatment plant in Brazil. They showed that the liquid flow rate and pH of the inlet stream were the major variables in controlling the plant and the neural network presented desirable results in minimizing the plant fluctuations [7]. In a different study, a hybrid technique providing principal component analysis (PCA) together with neural networks was used for optimal control of a wastewater treatment process [2]. The application of PCA in that case emerged as a novel idea at the time, since the input dataset could be reduced in order to solve the overfitting problem of the model. Zeng et al. (2003) employed back-propagation multilayer perceptrons (MLP) networks to model the nonlinear relationships between the removal rates of pollutants and the chemical dosages. Using this technique, the system could be adapted and operated in a variety of conditions showing a more flexible performance [35].

A few studies have reported the utilization of unsupervised learning algorithms. Hong et al. (2003) applied

Kohonen Self-Organizing Feature Maps (KSOFM) neural networks to analyze the process data obtained from a municipal wastewater treatment plant (WTP) [32]. KSOFM differ from feed-forward networks in a way that they provide a clustering methodology which leads to data reduction [17] and also project the data nonlinearity onto a lower-dimensional display. The latter creates an abstraction of various features of input signals in the absence of any supervisor signals [17]. As the authors reported, the KSOFM was computationally efficient, accurate, and reliable for the analysis of WTP and since the analysis and diagnosis of WTPs is a difficult task, the developed technique yields a great deal of significance [32]. There are also some other studies which have utilized unsupervised networks for modeling the wastewater treatment process [6, 12, 4].

Tay and Zhang developed a fast predicting neural fuzzy model to predict the response of high-rate anaerobic systems to different system disturbances 1 h in advance [31]. Three laboratory scale systems including an anaerobic fluidized bed reactor (AFBR), an anaerobic filter (AF), and an up-flow anaerobic sludge blanket (UASB) reactor were utilized. The reactors underwent two disturbing shocks, organic loading rate and hydraulic loading rate. The adaptive network based fuzzy system (ANFIS) used a database of system performance and implemented these data to predict the response of the anaerobic wastewater treatment system in the presence of OLR, HLR and alkalinity loading shocks. The adaptability of the neural fuzzy modeling used was proven to be acceptable in different operation conditions and therefore, it was suggested to be of high potential in real time control [31].

Moreover, advanced controlling of anaerobic digestion has been also achieved using hierarchical neural networks [11]. Holubar et al. developed several configurations of feed-forward back-propagation neural networks to predict gas composition, methane production rate, volatile fatty acid concentration, pH, redox potential, volatile suspended solids and chemical oxygen demand of feed and effluent of a CSTR under pulse like disturbances of OLRs. The correlation coefficient between the measured data and calculated values were found to be bigger than 0.8 for all the predicted variables which was a promising result by which the controlling of CSTR could be accomplished.

On the other hand, hydrogen sulfide (H2S) and ammonia (NH3) as the main gaseous trace compounds in anaerobic digestion process were predicted in a CSTR digester by using ANN [29]. The obtained coefficients of determination (R2) were 0.91 and 0.83 for hydrogen sulfide and ammonia, respectively. A similar research was conducted on an AFB reactor for starch wastewater using MLP and the effects of OLR, HRT and efficiency of the reactor on its steady-state performance were modeled using ANN [26]. The mean square error (MSE) of the network performance was found the desirable value of only 0.0146. The findings of this research were of a great value since effluent COD and pH, alkalinity, VFA and biogas production were predicted by two input parameters: influent pH and OLR.

Neural networks have shown a more extensive application predicting methane fraction in biogas produced by field-scale land-fill bioreactors [23]. The methane production was modeled based on inputs such as pH, alkalinity, COD, sulfate, conductivity, chloride and substrate temperature. As a result, predicting hourly methane production, control achievement, optimization of energy conversion and construction time could be achieved. Pai et al. employed Grey Model ANN (GM-ANN) to predict suspended solids (SS) and COD of hospital wastewater treatment reactor effluents [24]. Results showed that GM-ANN could predict the hospital wastewater variations with the same accuracy as ANN did. Besides, while ANN needed a large quantity of data, GM_ANN could handle smaller quantities.

In another study, a real-time monitoring of wastewater treatment process was achieved with the aid of multivariate statistical methods and ANN [19]. In that study, Luccarini et al. installed some probes for the acquisition of signals such as pH, oxidation–reduction potential (ORP) and dissolved oxygen (DO) in a sequencing batch reactor (SBR) and manipulated these data in an ANN model. The research aimed to verify the treatment process based on the continuous signals obtained on-line from the reactor [19]. The signals from the plant were transmitted by telecommunication facilities and the data were reduced using PCA method and then analyzed. Therefore, by remote monitoring of a small-scale reactor ANN could approximate the performance criteria of the plant on-line. This novel work opened a new window for the remote controlling of reactors and benefiting ANN potentials to model such facilities.

III. GENETIC ALGORITHMS

Genetic algorithms (GAs) fall in a class of stochastic search strategies modeled after evolutionary mechanisms based upon evolutionary principles of natural selection, mutation, and survival of the fittest [28]. They have become a very popular strategy to optimize non-linear systems with a large number of variables. GAs are very different from most optimization methodologies comprising well-defined algorithms. The GA approach is to generate a large number of potential solutions and “evolve” a solution to the problem. One of the big keys to a successful genetic algorithm is in the development of a good “fitness function”. The fitness function is how each potential solution is evaluated by the algorithm, and is in essence, how the problem to be solved by the algorithm is defined [1035]. Optimization of wastewater treatment variables using GA models was reported by Cho et al., (2004). In their study, GA was integrated with a mathematical management model to reduce the treatment costs at a Korean plant and the application of GA was promising as concluded by the authors [1019].

There have been several hybrid systems developed that combined neural networks with GAs in various ways [8]. These generally fall into three categories: (1) using a GA to determine the structure of a neural network, (2) using a GA to calculate the weights of a neural network as depicted in Fig 3, and (3) using a GA to both determine the structure and the weights of a neural network.

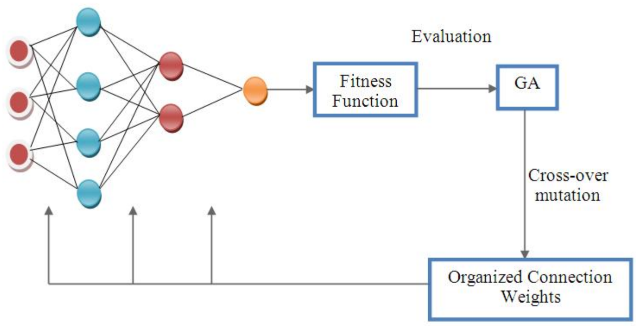

Figure 1. Fig. 3 Overview of the GA-ANN model

Yang Mu and Yu developed a hybrid model for simulation of biological hydrogen production in a UASB reactor was reported [34]. OLR, HRT, and influent bicarbonate alkalinity were fed to a model of ANN combined with a GA. H2 concentration, H2 production rate, H2 yield, effluent total organic carbon, and effluent aqueous products including acetate, propionate, butyrate, valerate, and caporate were determined as outputs of the model. Simulations showed that the model could describe the daily variations of the studies UASB reactor by predicting the steady-state performance of reactor regarding various HRTs and substrate concentrations. Hybrid models have also been studied on the biodegradation process of phenol in a fluidized bed reactor (FBR). The authors suggested that the feed-forward ANNs trained by a real-coded GA acted desirably for the simulation of biodegradation process in the FBR [33]. In a different study, Iqbal and Guira developed an optimization procedure for an activated sludge reactor. They built a multi-objective optimization (MOO) to take into consideration the maximized influent flow rate of wastewater and minimized exit effluent BOD [13]. The correct utilization of this method would be a necessity in the treatment process modeling and optimization as the non-linear and complex behavior dominating the bioreactor performance requires.

IV. FUZZY SYSTEMS

Fuzzy logic, a novel technique introduced in 1965 by Lotfi Zadeh, is a mathematical tool for dealing with uncertainty and relative importance of precision. It is a convenient way to map an input space to an appropriate output space [16]. The basis for fuzzy logic is similar to that for human communication or natural language. This statement underpins the whole concept of the technique. The theory of fuzzy logic is based upon the notion of relative graded membership and so are the functions of cognitive processes. The utility of fuzzy sets lies in their ability to model uncertain or ambiguous data so often encountered in real life, esp. biological issues [27]. At present, numerous applications of fuzzy logic in control and automation exist and many devices, plants and industrial facilities are instrumented with fuzzy control systems [15]. However, designing fuzzy logic controls would require a series of prerequisites, including the determination of the input and output variables, the parameters of membership functions, and the fuzzy control rules [1]. In spite of the extensive application in several areas of industry and research, fuzzy logic control has not been so popular in anaerobic digestion processes. Moreover, the need for a proper tool for screening out the essential control rules based on the experimental knowledge about the plant operation seems beyond the question. In order to overcome this challenge, Chen et al. conducted a three-stage study using fuzzy-neural hybrid controller for industrial wastewater treatment [1]. The first stage was identifying the state function of wastewater treatment system followed by searching for multi-objective control strategies, and finally, tuning fuzzy control rule base. The results of the simulations proved that the hybrid fuzzy control approach effectively achieved the required real-time control objectives and was shown as an efficient and cost-effective tool to deal with the unexpected uncertainties in the wastewater treatment process [1]. The authors also stated that their control architecture could be generalized to other physical, chemical and biological waste treatment systems.

In a different investigation, fuzzy-neural control system was utilized to real-time control and supervise the submerged biofilm wastewater treatment reactor [21]. The research aimed to maximize cost efficiency of the treatment operation and address the problem of controlling air flow rate. The results obtained indicated that using fuzzy logic combined with ANN models led to better outputs and less MSEs compared to pure ANN. As a general conclusion, the authors reported that the fuzzy-neural control system used performed desirably when dealing with unexpected uncertainties in the small-scale bioreactor [21].

Mingzhi et al. (2009) developed a fuzzy neural network to model the nonlinear relationships between the removal rate of pollutants and the chemical dosages in a paper mill wastewater treatment plant. The objective of their research was to adapt the system to a variety of operating conditions and also to achieve a more flexible performance. The developed model reached a reasonable prediction of the COD and BOD in a high efficient reactor [22]. A similar study was conducted by Pai et al. (2009) which employed fuzzy systems in combination with neural networks to predict SS and COD in the effluents of a hospital wastewater treatment. Regarding the maximum coefficient of correlation (R) and the minimum mean absolute percentage errors (MAPE) of the predictions, the developed model showed a satisfactory performance in comparison with the pure ANN models. Therefore, the model developed could be recommended in order to optimize design considerations of the treatment process [25].

V. CONCLUSION

An overview of the discussed models and methods reveal the significance of using them in several areas related to anaerobic treatment of wastewater. Prediction of effluent parameters, optimization of design factors and influent rates, modeling the process, controlling the performance of reactors are feasible applications proved by the reviewed literature. The major challenge in modeling wastewater treatment process may be the complex biological trend dominating the whole system. The conventional mathematical and kinetic models are not able to tackle with this complexity. The intelligent methods including ANN, GA and fuzzy offer considerable privileges over the common techniques. Although, the parameters of the novel methods should be carefully adjusted and fitted according to the problem conditions, but when well defined and trained, they could be able to present desirable responses and perform exact predictions.

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