Expert system for the on-line diagnosis of anaerobic wastewater treatment plants

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Abstract A diagnosis system for anaerobic wastewater treatment processes is presented. The system is able to recognise the state and trend of the operation and suggest the appropriate control action. The on-line variables measured were gas flow rate and composition (methane and carbon monoxide), feed and recycling flow rates, temperature and pH, while the manipulable inputs are feed, recycling and buffer-addition flow rates. The diagnosis system comprises a structured rule base, incorporating expert knowledge using fuzzy logic features. The structure of the system is based on the classification of information related to the process in three categories: i) the state of the process, ii) its trend and iii) the recommended set-point values for the inputs manipulated: feeding, buffer and recycling pumps. The system was applied to diagnose the operation of a 1.1 m³ hybrid UASB-UAF treating wastewater from a fibreboard production factory under different conditions (overload and underload), corresponding to some of the typical causes of destabilisation in anaerobic wastewater treatment plants. These situations require control action in order to maintain the stability and the treatment capacity of the reactor. The application of the system developed for the purpose of managing the situation proved to be reliable for supplying the actual state and trend of the process, as well as the adequate set point values to recover stable operation and/or to avoid further destabilisation.

Keywords Anaerobic treatment; diagnosis; expert system; fuzzy logic; overload; underload

Introduction
Anaerobic wastewater treatment (AWT) is among the oldest biological wastewater treatment processes, having first been studied more than a century ago (McCarthy, 1981). It is a multi-step biological process in which organic matter is degraded into a gas mixture of methane and carbon dioxide. The biological scheme involves several multi-substrate multi-organism reactions that are performed both in series and in parallel (Henze and Harremoes, 1983).

The sensitivity to external perturbations is one of the major drawbacks of anaerobic wastewater treatment plants (AWTP). The risk of operation failure due to overload is a very typical problem associated with AWTP. As continuous control is required to ensure stable operation, several efforts have been made to find out more about process kinetics, mathematical modelling and to develop appropriate control strategies for anaerobic digestion. More specifically, artificial intelligence techniques such as artificial neural networks or fuzzy logic have been developed and applied in the last two years. The particular feature of these techniques is the interpretation of expertise in the control system, which constitutes an “expert system” when a rule base is implemented (Konstantinov et al., 1993). However, only few works on the advantages of artificial intelligence techniques can be found in the literature for AWT processes (Marsili-Libelli et al., 1996; Steyer et al., 1997; Giraldo-Gómez and Duque, 1998; Pullammanappallil et al., 1998; Genovesi et al., 1999, Steyer et al., 1999; Genovesi et al., 2000).

In this work an artificial intelligence approach, based on a rule base developed using fuzzy logic tools is considered. This approach aims to provide a reliable diagnosis of the present state and the future trends of AWTP on the basis of the available data acquired...
on-line. Besides, the system should provide the set-points of the final control elements (feeding, buffer and recycling pumps).

**Materials and methods**

Wastewater from a fibreboard factory has been anaerobically treated in a 1.1 m³ hybrid UASB-UAF reactor. It is important to note that most solids present in the wastewater are volatile suspended solids and colloids, making a step of pre-treatment necessary (Fernandez et al., 1995). By means of the addition of a flocculant solution an important fraction of the hardly biodegradable compounds (40% of the lignin and 80% of the phenols) is separated within the solids removed (70%), this also minimises the possible toxicity (Fernandez et al., 1995). The low content in nutrients and the low alkalinity of the wastewater make the addition of nitrogen and phosphorus salts and bicarbonate necessary, to maintain proper C/N/P ratio and buffer capacity, respectively, in the digester.

The on-line measured variables were feed flow rate (FF), recycling flow rate (RF) (both measured by using electromagnetic flow-meters 7Me2531 Siemens, Germany), biogas flow rate (GF) (mass flow-meters Brooks Models E5860i Rosemount, The Netherlands), percentage of methane in biogas (% CH₄) and carbon monoxide concentration (CO) in biogas (Ultramat22P Gas Analyser Siemens, Germany); temperature (two thermometers Pt-100) and pH (Siemens, Germany). The characteristics of the wastewater as well as of the AWT plant have been described in more detail elsewhere (Puñal et al., 1999).

Off-line measurements of alkalinity (total and partial), Volatile Fatty Acids (VFA) concentration and Chemical Oxygen Demand (COD) concentration were performed as well. Volatile Fatty Acids (VFA) were determined by Gas Chromatography using a Hewlett Packard 5840A equipped with a Flame Ionisation Detector (FID), following the methods described elsewhere (Fernández et al., 1995). Chemical Oxygen Demand (COD) was determined by a semi-micro method (Soto et al., 1989). A titration with sulphuric acid was used to determine alkalinity as CaCO₃. Total alkalinity can be considered, approximately, as the sum of bicarbonate alkalinity and VFA, expressed in terms of CaCO₃. Partial alkalinity, measured by titrating up to pH 5.75, roughly corresponds to bicarbonate alkalinity (Jenkins et al., 1983), while intermediate alkalinity (IA), which is the difference between total (at pH 4.30) and partial alkalinity is approximately the concentration of VFA (Ripley et al., 1986). As good operation of a digester depends on the adequate buffer capacity of bicarbonate and on non-excessive VFA concentrations, the IA/TA ratio can be used as a control parameter, recommended not to exceed a value of 0.3 (WPCF, 1967).

The diagnosis system incorporates knowledge of human experts in a rule base developed within the frame of fuzzy logic using the features of the fuzzy logic toolbox in Matlab. The use of a rule base in the frame of fuzzy logic allows translation of the values of the variables measured into linguistic labels given by membership functions (Zadeh, 1965). The knowledge of human experts was used to build up a diagnosis and supervision system based on fuzzy logic, using the Mamdani and Sugeno inference methods. The system supplies information, which can be classified in three categories: i) the state of the process, ii) its trend and iii) the recommended set-point values for the control elements: feeding, buffer and recycling pumps. Seven possible output values or possible states of the process (referred to the first category) may be distinguished. In this way, each possible result corresponds to one acronym: Organic Overload (OO); Medium (OMA) and Low (OLA) Acidification due to Organic Overload; Normal (N); Low (HLA) and Medium (HMA) Acidification due to Hydraulic Overload; and Hydraulic Overload (HO). Three possible trends (second category) were described as outputs for diagnosis of operation: Getting Worse (GW), No Change (NCh) and Getting Better (GB). Finally, the most appropriate steps to be taken for the system to return normal operation in the case of destabilisation...
are also given by the system (third category). This output corresponds to the actions on three pumps: feeding pump, recycling pump and buffer (and nutrients) addition pump. This system was described in more detail elsewhere (Puñal et al., 2001).

**Results and discussion**

In order to test the system, different experiments were carried out, considering the most frequent causes of destabilisation in real processes. The data shown in this paper illustrate the response of the system during a hydraulic overload and an organic underload.

**Hydraulic overload**

In Figure 1 the performance of the system during a hydraulic overload is shown. The system was initially treating 10 g COD/l wastewater at an OLR of 10 kg COD/m³·d with COD removal efficiency of about 80%. From day 3.5 to day 8 of operation, the influent organic loading rate (OLR) was increased by increasing the feeding flow rate from 20 to 40 l/h (Figure 1a). In Figure 1b, the subsequent increase in gas production from 120 to 170 l/h can be seen. The gradual decrease in the methane content of biogas from 52% to a minimum value of 40% can also be seen in Figure 1b, as well as the presence of CO from day 4 of operation.

The analysis of the operational parameters allowed the diagnosis system to detect the hydraulic overload. The diagnosed process state was first identified as HLA (Figure 2a), which as stated above, corresponds to low acidification caused by a hydraulic overload. The diagnosed trend indicates, as well, that the reactor performance is deteriorating (Figure 2a). However, the evolution of the process from day 5 to 6, led to further destabilisation, as the progressive decrease of methane content in biogas and the increase in CO composition indicate (Figure 1b). This behaviour appears diagnosed in Figure 2a as HMA, which corresponds to medium acidification caused by a hydraulic overload.

The system also calculates the adequate set-points for feed, recycling and buffer-addition pumps in order to recover stable operation. The estimated value is a percentage referred to the actual set-point of each pump. It can be seen (Figure 2b) how the recommended consign values would lead to a decrease in feeding flow rate during the overload. Furthermore, the diagnosis system recommends the increase in recycling and buffer-addition flow rates, in order to avoid the negative effects promoted by the overload, increasing mixing level and buffer capacity, respectively. Once the feed flow rate was decreased (Figure 1a) following the recommendations of the diagnosis system, the process recovered stability in terms of gas production and composition as can be seen in Figure 1b. Recovery of stable operation can also be seen in the diagnosis results provided by the expert system, shown in Figure 2 (a and b).

![Figure 1](https://iwaponline.com/wst/article-pdf/45/10/195/424796/195.pdf)

**Figure 1** Operational parameters during a hydraulic overload. a) Recycling flow rate (RF) and feed flow rate (FF). b) Gas flow rate (GF), methane (CH₄) and carbon monoxide (CO) content in biogas
Organic underload

The system was also tested performing an organic underload. This disturbance did not promote so severe a destabilisation in the reactor, although it should be avoided, as it leads to operation below the optimal capacity of the plant. In this case, the influent OLR was decreased on day 10 from 3 to 1.5 kg COD/m$^3$·d by diluting the influent from 10 to 5 g COD/l, while influent flow rate remained constant (Figure 3a). The response of the system can be seen in Figure 3b. The effect was especially noticeable in gas flow rate (GF), which decreased accordingly. An increase of the methane percentage in biogas can also be seen in Figure 3b, which may be due to the equilibrium displacement for CO$_2$ between gas and liquid phases.

Analysis of these results led the diagnosis system to detect a performance corresponding to normal operation in terms of process state and trend (Figure 4a), as no destabilisation took place. However, the system recommended changing the set points of control elements (shown in Figure 4b) increasing feed flow rate, in order to make the difference between the operational values smaller and the present capacity of the reactor, as well as the increase of buffer addition to maintain the buffer capacity within the reactor, when the feeding flow rate is increased.

Conclusions

This work presents a diagnosis system developed as a rule base using fuzzy logic features for anaerobic wastewater treatment (AWT) plants. The system was applied to a 1.1 m$^3$ hybrid UASB-UAF reactor, under different operational conditions, which represent some

![Diagram](https://iwaponline.com/wst/article-pdf/45/10/195/424796/195.pdf)
of the typical failures associated to AWT plants, such as overload and underload. The system uses the on-line data acquired to identify the state of the process, using the process state, together with the on-line data to obtain the trend of the process. The results provided by the diagnosis system comprise, as well, the recommended changes to be made to the final control elements (feeding, recycling and buffer + nutrient-addition pumps).

The system gave reliable information about the state and actual trend of the process as well as the adequate set-points for the manipulable inputs in order to lead the process to stable operation. The results presented in this paper show the capacity of the system to distinguish between disturbances, which may destabilise the system, such as an overload, and those, which do not represent major drawbacks for the proper operation of the process, (e.g. an underload) but should, however, be avoided in order to take advantage of the actual capacity of the plant.

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References


