A modular diagnosis system based on fuzzy logic for UASB reactors treating sewage
R. M. Borges, A. Mattedi, C. J. Munaro and R. Franci Gonçalves

ABSTRACT
A modular diagnosis system (MDS), based on the framework of fuzzy logic, is proposed for upflow anaerobic sludge blanket (UASB) reactors treating sewage. In module 1, turbidity and rainfall information are used to estimate the influent organic content. In module 2, a dynamic fuzzy model is used to estimate the current biogas production from on-line measured variables, such as daily average temperature and the previous biogas flow rate, as well as the organic load. Finally, in module 3, all the information above and the residual value between the measured and estimated biogas production are used to provide diagnostic information about the operation status of the plant. The MDS was validated through its application to two pilot UASB reactors and the results showed that the tool can provide useful diagnoses to avoid plant failures.

INTRODUCTION
Several positive characteristics of the upflow anaerobic sludge blanket (UASB) reactor, such as low cost effectiveness, operational simplicity, low energy demand and low sludge production, have contributed to spread its application for the wastewater treatment in the tropical regions of the world (Chong et al. 2012).

The association in series of UASB reactors with aerobic processes, such as submerged aerobic biofilter, activated sludge or moving bed biofilm reactor (MBBR) can achieve treatment efficiencies compatible with activated sludge processes, preserving the main advantages proportioned by the anaerobic digestion of organic matter (Khan et al. 2011). This is the main conclusion of a statistical study comparing the performance of 166 full-scale anaerobic and aerobic wastewater treatment plants in operation in Brazil (Oliveira & von Sperling 2011). Another important fact that has been increasing the interest on UASB reactors is the use of biogas as a renewable source of energy, which also contributes to the carbon emission reduction in the sanitation sector (Muhammad et al. 2012; Deng et al. 2014).

Despite the aforementioned advantages, the robustness of UASB reactors often leads plant operators to misconstrue the low demand for intervention and, consequently, to neglect the operation and maintenance routines. Wide fluctuations of hydraulic and organic loadings, as well as the intense variation in the height of the sludge bed within the process, are examples of disturbances that can lead to instability of performance (Leitão et al. 2006). In this context, a system capable of providing diagnoses of plant problems, giving support to efficient operation and for the human decision making, has been a key requirement for efficient wastewater treatment plants (Turkdogan-Aydinol & Yetilmezsoy 2010).

The fuzzy logic is known as an approach that can transfer expert knowledge into fuzzy models in the form of linguistic rules, also providing a convenient means of addressing uncertainties (Zadeh 1965). Since the measured values of the variables are translated into linguistic labels given by membership functions, a rule base can be used to model complex non-linear functions in the frame of fuzzy logic. For Carrasco et al. (2004), fuzzy logic presents advantages like flexibility and tolerance with imprecise data. It can be built on top of human experience, combining natural language in an easy-to-understand way and also being able...
to model complex non-linear functions, which makes fuzzy logic an appropriate tool to develop diagnosis systems. This means that relevant knowledge about the process should be incorporated into the model, even if this knowledge cannot be formulated by models based on a full mechanistic understanding of the process (Lübbert & Jørgensen 2001). The literature present a large number of methods to estimate parameters and process variables that cannot be measured directly, or when only ambiguous or imprecise information may be available (Komives & Parker 2003; Kanat & Saral 2009; Cecil & Kozlowska 2010; Balaman & Selim 2014; Mendes et al. 2015).

The gas-phase monitoring is a frequently applied technique for monitoring the efficiency and status of anaerobic digestion processes. Decreases in biogas production normally signal concomitant decreases in the treatment efficiency of continuous-flow systems. A fast predicting neural fuzzy model to predict the response of high-rate anaerobic systems to organic loading rate (OLR) and hydraulic loading rate (HLR) overload shocks was developed by Tay & Zhang (2000). The system response was given in terms of volumetric methane production rate, total organic carbon and volatile fatty acid. Polit et al. (2002) used fuzzy logic to estimate some parameters of a mass-balance model for anaerobic digestion processes with the aim of estimating biogas production. This model was developed with numerical values taken from the literature. Carrasco et al. (2002) developed an expert system (ES) based on fuzzy logic capable of diagnosing the state of a pilot-scale anaerobic digester, while Carrasco et al. (2004) applied the ES for the diagnosis of the acidification state in the plant. For that purpose, the biogas flow rate and the biogas composition were measured.

An ES for monitoring and diagnosis of an anaerobic treatment plant treating wastewater from a fibreboard factory was developed by Puñal et al. (2001). Genovesi et al. (1999) developed a fuzzy-logic-based diagnosis system and applied it as a fault detection and isolation procedure in an UASB reactor treating raw industrial wine distillery effluents. This system takes into account a first-order model of the biogas flow rate to provide the diagnosis. Türkdoğan-Aydinol & Yetilmazsoy (2010) developed a multiple inputs and multiple outputs fuzzy-logic-based model to predict the biogas and methane production rates in a pilot-scale 90 L mesophilic UASB reactor treating molasses wastewater. The authors considered five input variables, such as volumetric organic loading rate, volumetric total chemical oxygen demand, removal rate, influent alkalinity and pH, which were fuzzified and hence used in a system composed of 134 rules in the IF-THEN format. Further applications of fuzzy-logic-based models used to provide diagnosis of anaerobic digestion processes can be found in Scherer et al. (2009), Erdirencelibi & Yalpil (2011), Balaman & Selim (2014) and García-Gen et al. (2015).

The aim of the present work is to present the results of the development of a modular diagnosis system (MDS), based on fuzzy logic for UASB reactors treating sewage (Figure 1). The strategy aims to provide status diagnoses of UASB reactors from on-line measurements, such as feed flow (FF) rate, turbidity, temperature, rainfall and biogas flow rate. To provide diagnostic information about sludge washout, settleable solids measurements can further be included in the diagnostic system. The MDS is composed of three fuzzy modules and based on fuzzy models to estimate inlet chemical oxygen demand (COD) concentration and biogas production, which is different from previous works.

### MATERIAL AND METHODS

The proposed model was developed based on the concept of Fuzzy Inference System (FIS), which can be described as the process of formulating the mapping from a given input to an output using fuzzy logic. The FIS involves the development of membership functions, the definition of fuzzy logic operators and the formulation of IF-THEN rules. A basic structure of FIS is shown in Figure 2. The raw data collected to construct the FIS were first pretreated using the subtractive clustering method proposed by Chiu (1994). The purpose of clustering is to distil the natural grouping of the data from separate sets of inputs and outputs, thus generating a set of rules that produces a concise representation of a system’s behaviour. Before entering the process data into the clustering algorithm, each data set was normalized into the domain [0, 1] to avoid a negative influence on the clustering results from the variations in the numerical ranges of the different features.

![Figure 1 | Diagnostic strategy concept for UASB reactors.](image-url)
Pilot-scale experiment

The experiments were performed using three independent 5.0 m high UASB pilots, with a total volume of 47.6 L each, operated under similar conditions of FF rate, COD concentration and temperature. After inoculation, each reactor was fed with raw urban wastewater and the FF rate was initially maintained constant at 6.0 L h\(^{-1}\) through a remotely controlled peristaltic pump, with a hydraulic retention time of 8 hours. The operational conditions were characterized by the following parameters: organic loading rate of 1.48 kg COD m\(^{-3}\) d\(^{-1}\), volumetric hydraulic load of 3.0 m\(^{3}\) m\(^{-3}\) d\(^{-1}\) and an upflow velocity of 0.76 m h\(^{-1}\). The biogas flowrate (GF) of each reactor was measured using a volumetric flowmeter connected to a data acquisition system. The same device was used to acquire and store the liquid phase temperature during the treatment. Turbidity was measured using a portable turbidimeter (HACH Model 2100P) and the COD analysis were performed according to Standard Methods (APHA, AWWA & WEF 2012). The climatic data (rainfall precipitation and temperature) were obtained from a meteorological station located near the plant.

MDS development and testing

The MDS was developed within the frame of fuzzy logic using the inference system of the fuzzy logic toolbox in Matlab™ (The Mathworks 1998) and data acquired from reactor R1. Its structure is composed of three FIS modules, as shown in Figure 3.

**Module 1:** The first FIS module estimates the influent COD through turbidity and rainfall data and a Mandani fuzzy model (Mandani & Assilian 1975). For this, input and output variables were defined as Gaussian membership functions. The use of turbidity as an inferential parameter of total suspended solids (TSS) in various types of wastewater is quite often reported in the literature (Lacour et al. 311 R. M. Borges et al. | Modular diagnosis system based on fuzzy logic for UASB reactors Water Science & Technology | 74.2 | 2016 Downloaded from https://iwaponline.com/wst/article-pdf/74/2/309/460636/wst074020309.pdf by guest
on 30 October 2019 by guest

The rationale for this practice is based on the good linear correlation between turbidity and TSS in wastewater. Furthermore, the turbidity also shows good correlation with COD because TSS are the main source of organic matter (particulate and colloidal) in wastewater (Ashley et al. 2005). However, all the studies cited above show that rainfall significantly modifies the correlation between the values of turbidity, TSS and COD in wastewater. For this reason, to obtain the inference rules for FIS Module 1, the experimental data from reactor R1 were studied to assess the influence of rainfall on the influent. The rules obtained are shown in Table 1.

**Module 2**: The second FIS module estimates the current GF based on the previous OLR and GF, as well as the daily average temperature (T), which is collected from reactor R1. The OLR variation can be derived despite of any variation in the influent COD and FF or even from the variation on both at the same time. Its increase beyond the optimum level can severely disturb the process, increasing biomass washout and reducing COD removal and biogas production (Rincón et al. 2008). On the other hand, higher temperatures lead to higher microbial activity in the process. Thus, warm temperatures allow higher OLR without affecting the process efficiency (Poh & Chong 2009). A dynamic Takagi-Sugeno (TS) fuzzy model, obtained using the same procedure described by Takagi & Sugeno (1985) and through the subtractive clustering method proposed by Chiu (1994), was used to estimate the current biogas flow rate. For data set normalization into the domain [0, 1] we considered the lower and upper limits, respectively, for the temperature (15°C; 35°C), COD (100 mg L⁻¹; 1,000 mg L⁻¹) and biogas flowrate (0 L d⁻¹; 17.0 L d⁻¹). The sample time used to develop the model was 1 day. Table 2 presents the parameters of the TS fuzzy model acquired from the data, namely information about the centres of the Gaussian membership functions and the parameters of the linear sub-models.

**Module 3**: The third FIS module provides a diagnostic evaluation of the process based on the fuzzy logic approach. It uses all the responses given by modules 1 and 2, together with on-line data acquired from the process, as well as the residual value between the measured and the estimated biogas production, to provide diagnoses. The possible situations considered by this module are as follows: normal situation (N), organic load increase (OLI), hydraulic overload (HO), low methanogenic activity (LMA), organic underload (OU), hydraulic underload (HU), non-modelled perturbation (P), and sensor fault (SF). A rule base with an ‘IF conditions, THEN diagnosis’ structure, developed from the data set of reactor R1 together with human expert knowledge, is used to transform input values into a reliable diagnosis of the process status. Figure 4 illustrates the membership functions for FF, COD concentration, temperature and GF used as inputs for the diagnosis system. The residue can be obtained from the difference between the measured and the estimated biogas flow rate. The maximum acceptable residual value that can be considered ‘low’ is 4 L d⁻¹. The database of the process and human expert knowledge were used to formulate the inference rules. The output of the diagnosis system provides the status of the process, taken as fuzzy sets with their corresponding membership functions (singleton spikes). Table 3 shows the rule base used in the diagnosis system.

### Table 1 | Inference rules for COD estimation (mg L⁻¹)

<table>
<thead>
<tr>
<th>Rule</th>
<th>If</th>
<th>Then</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Weak Rainfall (mm³)</td>
<td>Low Turbidity (NTU)</td>
</tr>
<tr>
<td>2</td>
<td>Weak Rainfall (mm³)</td>
<td>Normal Turbidity (NTU)</td>
</tr>
<tr>
<td>3</td>
<td>Weak Rainfall (mm³)</td>
<td>High Turbidity (NTU)</td>
</tr>
<tr>
<td>4</td>
<td>Normal Rainfall (mm³)</td>
<td>Low Turbidity (NTU)</td>
</tr>
<tr>
<td>5</td>
<td>Normal Rainfall (mm³)</td>
<td>Normal Turbidity (NTU)</td>
</tr>
<tr>
<td>6</td>
<td>Normal Rainfall (mm³)</td>
<td>High Turbidity (NTU)</td>
</tr>
<tr>
<td>7</td>
<td>Strong Rainfall (mm³)</td>
<td>Low Turbidity (NTU)</td>
</tr>
<tr>
<td>8</td>
<td>Strong Rainfall (mm³)</td>
<td>Normal Turbidity (NTU)</td>
</tr>
<tr>
<td>9</td>
<td>Strong Rainfall (mm³)</td>
<td>High Turbidity (NTU)</td>
</tr>
</tbody>
</table>

Notes: Rain (mm³): weak (< 10 mm³); normal (10–25 mm³); strong (> 25 mm³). Turbidity (NTU): low (< 150 NTU); normal (150–280 NTU); high (> 280 NTU). COD (mg L⁻¹): low (< 200 mg L⁻¹); normal (200–700 mg L⁻¹); high ( > 700 mg L⁻¹).

### Table 2 | TS fuzzy models parameters for FIS module 2

<table>
<thead>
<tr>
<th>If</th>
<th>Then</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule</td>
<td>GF (k – 1)</td>
</tr>
<tr>
<td>1</td>
<td>0.37</td>
</tr>
<tr>
<td>2</td>
<td>0.65</td>
</tr>
<tr>
<td>3</td>
<td>0.29</td>
</tr>
<tr>
<td>4</td>
<td>0.58</td>
</tr>
</tbody>
</table>

Note: GF(k = – 1), T(k) and OLR(k – 1) values represent Gaussian centers of membership functions, with standard deviations of ± 0.12, 0.06 and 0.19, respectively; GF(k) are consequent functions of Takagi-Sugeno model.
RESULTS AND DISCUSSION

The results obtained from the sewage characterization showed expected values for all parameters, presenting a COD/biochemical oxygen demand (BOD) ratio of 2.22 (Table 4). UASB performance was relatively stable during the test periods, achieving a COD reduction of 74%, which is higher than the range of 55–70% usually reported in the literature (Oliveira & von Sperling 2014).

The results of BOD and TSS removal efficiency are also within the typical range of 65–80% reported for this type of process treating urban wastewaters (Khan et al. 2011).

Evaluation of modules 1 and 2

Figure 5 illustrates the efficiency of the Mandani fuzzy model from module 1 in estimating the COD based on the on-line turbidity measurement. The linear regression obtained from a data set of COD (y) and turbidity (x) in dry weather days resulted in the equation $y = 151 + 1.87x$, which presented a coefficient of determination, $R^2 = 0.83$. The maximum error found for the estimation of COD was 162 mg/L. Although the maximum error is not negligible, the average error of 30.9 mg·L$^{-1}$ can be considered low compared with the possible measurement errors of the variable. Thus, these results show that it is possible to relate
turbidity and COD using fuzzy logic when the effect of rainfall is considered. They are consistent with several studies on the subject, which showed that this relationship varies according to wet or dry weather conditions (Lacour et al. 2013; Hannouche et al. 2014).

The comparison between the measured and estimated GF by the Takagi-Sugeno fuzzy model is shown in Figure 6. Despite the great complexity of the anaerobic digestion, the results show a reasonable estimation of the process behaviour with a four rules fuzzy model. Although the error magnitude between the measured and the estimated biogas flow rate in normal conditions was not negligible, it allowed for MDS validation.

### Table 4 | Descriptive statistics of sewage characteristics

<table>
<thead>
<tr>
<th>Parameter</th>
<th>n</th>
<th>x</th>
<th>min</th>
<th>max</th>
<th>s</th>
<th>CV (%)</th>
<th>Efficiency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Influent total COD (mg·L⁻¹)</td>
<td>233</td>
<td>490</td>
<td>189</td>
<td>1,092</td>
<td>166</td>
<td>34</td>
<td></td>
</tr>
<tr>
<td>Effluent total COD (mg·L⁻¹)</td>
<td>125</td>
<td>127</td>
<td>45</td>
<td>379</td>
<td>59</td>
<td>46</td>
<td>74</td>
</tr>
<tr>
<td>Influent soluble COD (mg·L⁻¹)</td>
<td>106</td>
<td>224</td>
<td>120</td>
<td>403</td>
<td>45</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>Effluent soluble COD (mg·L⁻¹)</td>
<td>106</td>
<td>84</td>
<td>19</td>
<td>171</td>
<td>24</td>
<td>29</td>
<td>63</td>
</tr>
<tr>
<td>Influent TSS (mg·L⁻¹)</td>
<td>106</td>
<td>173</td>
<td>40</td>
<td>508</td>
<td>92</td>
<td>53</td>
<td></td>
</tr>
<tr>
<td>Effluent TSS (mg·L⁻¹)</td>
<td>106</td>
<td>43</td>
<td>4</td>
<td>120</td>
<td>24</td>
<td>56</td>
<td>75</td>
</tr>
<tr>
<td>Influent BOD₅ (mg·L⁻¹)</td>
<td>23</td>
<td>220</td>
<td>165</td>
<td>250</td>
<td>28</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>Effluent BOD₅ (mg·L⁻¹)</td>
<td>23</td>
<td>77</td>
<td>56</td>
<td>100</td>
<td>16</td>
<td>21</td>
<td>65</td>
</tr>
<tr>
<td>Influent turbidity (NTU)</td>
<td>108</td>
<td>177</td>
<td>47</td>
<td>365</td>
<td>70</td>
<td>39</td>
<td></td>
</tr>
<tr>
<td>Effluent turbidity (NTU)</td>
<td>108</td>
<td>47</td>
<td>9</td>
<td>150</td>
<td>23</td>
<td>49</td>
<td>73</td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>103</td>
<td>25.8</td>
<td>18.1</td>
<td>36.5</td>
<td>3.9</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Biogas flow rate (mL·h⁻¹)</td>
<td>145</td>
<td>10.8</td>
<td>0</td>
<td>16.4</td>
<td>6.1</td>
<td>56</td>
<td></td>
</tr>
</tbody>
</table>

n, sample size; x, sample mean; min, minimum value in the data set; max, maximum value in the data set; s, sample standard deviation; CV, coefficient of variation.

![Figure 5](image1.png) | Comparison between measured (○) and estimated (→) COD concentration by module 1.

![Figure 6](image2.png) | Comparison between measured (○) and estimated (→) biogas flow rate by module 2.
Diagnostic system validation

To evaluate the operational status of the plant, it is necessary to observe the membership of the diagnosis provided by the MDS. The higher the membership of the diagnosis, which can be assumed to have values from 0 to 1, the higher its candidacy to represent the actual operational state. Because more than one diagnosis applies in many situations, selecting only diagnoses with higher membership should be avoided for the proposed MDS. If the membership of normality is low, the state of the system can be characterized as organic or HO, organic or HU and LMA, depending on the membership value of each possible diagnosis. The non-modelled perturbation diagnosis is the candidate when its membership is high and the membership of the above mentioned diagnosis is low, meaning that an abnormal situation is taking place, but the models are not able to diagnose it. A SF diagnosis is given when a sensor failure happens, and it can occur independent of any disturbance in the process.

Diagnoses obtained by module 3 for reactors R2 and R3 are shown in Figure 7. Analysis of the inputs allowed the MDS to detect that both reactors were operating normally in the beginning. However, some typical disturbances associated with anaerobic digestion plants, as well as SFs, were detected by the MDS during the experiment. As fluctuations in the inputs were observed, diagnoses of abnormal states of the processes occurred, while the normal diagnostic membership decreased.

On days 9 and 14, the influent COD values of 790 and 810 mg·L⁻¹, respectively, together with high values of biogas production, caused the diagnosis of OLI for both reactors with membership of 0.8 and 0.9, respectively. On days 19 and 21, COD was higher than 600 mg·L⁻¹, but lower biogas production, causing a low membership (0.2 and 0.3, respectively) of the OLI diagnosis for reactor R2. According to Leitão et al. (2006), the OLR increase has a complex effect on the performance of a UASB, which is mostly contradictory. The increase in the efficiency of high rate anaerobic reactors with increasing OLR is reported by several researchers (Kalyuzhnyi et al. 1997; Ruiz

![Figure 7](image-url)
et al. 1997). However, that increase reached a specific OLR, beyond which problems such as sludge bed flotation and excessive foaming in the gas-liquid-solids separator were verified. Higher OLR can favour the formation of biogas pockets in the sludge bed that ultimately cause sludge flotation. Furthermore, when the increase in OLR is due to an increase in the influent COD content, a decrease in SS removal efficiency may occur.

On days 18 and 22, the state of OU was diagnosed for R2 and R3 because the COD was below 400 mg·L⁻¹ on both days. Leitão et al. (2006) showed that a diluted sewage with less than 300 mg/L of COD can decrease the UASB efficiency. However, UASB reactors showed maximum COD removal efficiency of 60% when the COD concentration was higher than 300 mg·L⁻¹. According to Peláez (2007), longer shocks of higher inflow and dilution rate decrease the mean size and the settleability of the sludge granules, as well as the biomass methanogenic activity. This phenomenon is one of the major problems experienced by full-scale UASB reactors when exposed to low OLR associated with hydraulic shocks during periods of intense rainfall.

On days 28 and 29, a COD higher than 600 mg·L⁻¹, together with a temperature of approximately 24 °C and biogas production of approximately 16 L·d⁻¹, led the MDS to diagnose OLI for R2, although with low membership. On days 19, 21 and 26, the temperatures were approximately 23, 22 and 21 °C, respectively, and were followed by a decrease in biogas production, which led to a diagnosis of LMA. A diagnostic SF was identified at reactor R3 on day 29, which prevented the biogas production measurement. The reduction in operational temperature retards the hydrolysis step of the particulate organic matter, decreases the maximum growth rate and reduces substrate consumption rates (Lettinga et al. 2010). COD removals of 65% at 20 °C and 55–65% at 13–17 °C were consistently observed in different studies (Elmitwalli et al. 1999). A decrease in the effluent quality was also observed, together with a decline in the gas production rate.

The non-modelled perturbations diagnosed can be related to chloride toxicity or physico-chemical analysis error. During the 30 days of this experiment, hydraulic overloading and underloading were not observed, explaining the absence of diagnoses related to these perturbations.

Another major disruption in full-scale UASB is biomass washout in the anaerobic effluent (Leitão et al. 2006). This problem can be diagnosed by the system proposed here as a result of significant fluctuations in hydraulic and organic loading rates, as well as by unfavourable environmental conditions, such as low temperatures or toxicity. However, the incorrect control of the accumulated biomass inside the UASB results in excessive expansions of the sludge blanket even under normal operating and environmental conditions. In the next version of the diagnostic system presented here, an inference rule will be inserted to enable the problems related to a lack of control for accumulated biomass in the UASB.

**CONCLUSIONS**

Although UASB reactors are commonly considered an ‘easy to operate’ technology for sewage treatment, the development of ESs for diagnosis and operational control can significantly enhance the environmental services provided by them. In this work, a MDS based on fuzzy logic for UASB reactors treating domestic wastewater was developed, applied and validated. Fuzzy models obtained from experimental data were used to estimate COD removal and biogas production in the reactor. The results showed that MDS can contribute to providing useful diagnoses to avoid reactor destabilization or plant failures.

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