Advanced monitoring and control of anaerobic wastewater treatment plants: diagnosis and supervision by a fuzzy-based expert system

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Abstract A fuzzy-based expert system (ES) for the diagnosis and supervision for anaerobic digesters is presented. The system was developed in a Microsoft Windows support using fuzzy logic inference together with a rule base for the implementation of expert knowledge. The ES runs on-line through three main modules, which determine the state and trend of the process, and the best set points for the actuation on the final control elements of the plant. Two further modules run in parallel, when they are required by the operator, using off-line and on-line information for the detection of inhibition due to toxic compounds in the process and for the validation of the on-line diagnosis.

The diagnosis and supervision ES was tuned up in order to adjust the membership functions describing the process, and lately tested, running on-line, to study the response of the rule base.

Keywords Anaerobic treatment; diagnosis; expert system; fuzzy logic and supervision

Introduction

Anaerobic digestion is a biological wastewater treatment process into which, for many years now, research has been carried out on process kinetics, mathematical modelling and on the development of appropriate control strategies. The incorporation of expertise in a control system may be done by means of a rule base (Konstantinov et al., 1993), which constitutes an “expert system”. The expert control concept offers new possibilities to develop high performance intelligent systems for the control of bioprocesses. This structure flexibly combines the advantages of the traditional approaches with those of expert system (ES) technology, and allows the enhancement of the control system because it is capable of intelligent decision-making based on informal interpretation of the complex behaviour of the process. If properly implemented, this structure is able to resolve various control problems, which usually remain outside the scope of conventional systems. In the literature, several approaches can be found where ES technology was applied for the anaerobic treatment of wastewaters (Ladiges and Kayser, 1993, 1994; Serra et al., 1993; Chynoweth et al., 1994; Moletta et al., 1994; Pullammanappallil et al., 1998).

Fuzzy logic was introduced by Zadeh (1965) as a theory which provides a convenient means to deal with uncertainties and to transfer expert knowledge to fuzzy models in the form of linguistic rules which may be processed by computers. No complex mathematical relationships are required in the construction of fuzzy logic applications. Besides, it is conceptually easy to understand, flexible and tolerant of imprecise data allowing the modelling of complex non-linear functions. Fuzzy logic may be built on top of the experience of experts and may also be mixed with conventional control techniques. The process of fuzzy inference involves membership functions, fuzzy logic operators and rules. The membership functions gives a degree of membership to a fuzzy set for a given input numerical value and set the output value. The rules represent the expert knowledge in a computable way; they have a left hand side and a right hand side. When the left hand side of a rule has more than one part, the fuzzy operator is applied to obtain a number representing the result of the
The operators used are and & or. The fuzzy set theory has been discussed in detail by Dubois and Prade (1980) and Zimmermann (1985) and applied to anaerobic processes by several authors (Bosclo et al., 1993; Marsili-Libelli and Müller, 1996; Müller et al., 1997; Giraldo-Gómez and Duque, 1998, Steyer et al., 1999).

In this work an ES able to provide a reliable diagnosis of anaerobic wastewater treatment (AWT) plants operation, based on the available data acquired on- and off-line, is developed. The ES gives information about the trend of the process in order to predict if it is getting better or worse. Besides, the operator is informed of the recommended set point values of the final control elements, in this case, feeding, nutrients and recycling pumps, to get a best operation in each moment. Two further modules were also developed: (i) a toxicity test, using off-line measurements; and (ii) a validation system, using off-line information to confirm process state.

Pilot plant
The low nutrients concentrations and the low alkalinity of the wastewater, which is produced at a fibreboard factory, makes the addition of bicarbonate and nitrogen necessary to maintain a proper C/N/P ratio in the digester. It is important to note that most of the suspended solids in the influent are volatile suspended solids and colloids, making the pre-removal of these solids necessary (Fernandez et al., 1995). Possibly recalcitrant compounds, especially phenols, are present as well. Wastewater from the factory is collected and homogenised in a 4.28 m³ feed tank, then pumped to a settler where solids are removed by addition of a flocculant. After this pre-treatment, an important fraction of the recalcitrant compounds (40% of the lignin and 80% of the phenols) is removed with the separated solids (70%). Therefore, the possible toxic effect on the biomass in the reactor is minimised.

On-line measurements of feed flow rate (FF), recycling flow rate (RF), biogas flow rate (GF), percentage of methane in the biogas (% CH₄), carbon monoxide concentration (CO) and hydrogen concentration (H₂) in the biogas and the pH were recorded every 15 minutes, which is considered an adequate sampling period given the response time of the system. This period represents between 0.21% and 1.04% of the hydraulic retention time (HRT). A PLC is responsible for data acquisition and regulation of the final control elements of the plant. Their set points were defined by the PC. Off-line measurements of alkalinity (total and partial), Volatile Fatty Acids (VFA) concentration and Chemical Oxygen Demand (COD) concentration were performed as well.

The characteristics of the wastewater as well as the AWT plant have been described in more detail elsewhere (Puñal et al., 1999).

Software and hardware
Fuzzy logic
The use of a rule base in the frame of fuzzy logic allows the translation of the values of the variables measured into linguistic labels given by membership functions. The knowledge of human experts was used to build up a diagnosis and supervision system based on fuzzy logic.

Mamdani’s fuzzy inference method (Mamdani and Assilian, 1975) is the most commonly applied fuzzy methodology. However, some parts of this system were implemented through the so-called Sugeno or Takagi-Sugeno-Kang method of fuzzy inference (Sugeno, 1985). In both methods, the first part of the fuzzy inference process (fuzzifying the inputs and applying the fuzzy operator) is the same. The output membership functions are only linear or constant in the last one, being the main difference between them. Output singleton spikes were used as membership functions. The use of this kind of fuzzy methodology in
some of the ES elements was decided since it is a more compact and efficient representation than a Mamdani system. Besides, the Sugeno inference method lends itself to the use of adaptive techniques for constructing fuzzy models (planned for future work). These adaptive techniques may be used to customise the membership functions, which enables the fuzzy system to obtain the best model from the given data.

The ES is structured in five different modules, three of them requiring only on-line data and the other two needing also off-line data. The first group is concerned with the evolution of the actual state of the process; the prediction of the future evolution of the system, if the actual operation is maintained; and the advice about the best set points to be selected for the feeding, recycling and nutrients pumps. The operation protocol of these modules is shown in Figure 1.

The other two modules correspond to the toxicity test and the off-line validation module. When new off-line measurements are available, the operator can detect toxicity and validate the on-line diagnosis results, running the off-line modules with the on-line basic ES structure at the same time.

(i) **Process state estimator**

In order to develop the diagnosis system, the Matlab Fuzzy Logic Toolbox was used. The module to determine the acidification state of the process uses the values of several variables measured together with the expert human knowledge incorporated in linguistic rules. The way in which membership functions are built in order for the diagnosis system to function properly. The variables selected were GF, CH\(_4\), CO, FF, RF and pH. The membership functions of GF and CH\(_4\) are shown in Figure 2, as examples of the fuzzyfication of the variables.

The output values or possible states of the process may be classified in seven possible categories, such as fuzzy sets with their corresponding membership functions. In this way,
each possible result corresponds to a numeric value: Organic Overload – High Acidification due to Organic Overload – (1); Medium (2) and Low (3) Acidification due to Organic Overload; Normal (4); Low (5) and Medium (6) Acidification due to Hydraulic Overload; and Hydraulic Overload - High Acidification due to Hydraulic Overload – (7).

Taking into account the inputs, a set of rules was written. Each rule is a linguistic expression of the human expert knowledge, establishes relationships between variables, which lead to a diagnosis output. A typical example of one of these rules is as follows:

**IF** GF is *low* and CH4 is *very low* and FF is *normal*, **THEN** the state is *organic overload*.

**(ii) Trend estimator**

As can be seen in Figure 1 the trend estimator uses the result obtained from the determination of the state of the process (normal state or overload) together with five on-line variables: biogas flow rate, percentage of methane in the biogas, carbon monoxide concentration in the biogas, feeding flow rate and pH.

The development of the fuzzy trend estimator follows the same steps as in the case of the determination of the state of the process, in which the description of the six required membership functions in order to obtain the output vector is necessary. Three possible trends were described as outputs for diagnosis of operation, using the Sugeno type fuzzy inference system: Getting Worse (1), No Change (2) and Getting Better (3). An example of trend rule is as follows:

**IF** current state is *normal*, CH4 is *low*, FF is *high* and CO is *high*, **THEN** the trend is *getting worse*.

In some cases, once the results from process state and trend are known, more information could occasionally be required. In those cases, off-line validation and toxicity modules can help to improve the supervision of the process.

**(iii) Pump commands**

This module determines the most appropriate steps to be taken for the system to return normal operation in the case of destabilisation. In this fuzzy system, only two inputs were used: the current state obtained from the process state estimator and the trend of the process.

The output of this module corresponds to the actions on three pumps controlled by the ES: feeding pump, recycling pump and nutrients and alkalinity dosage pump. Recycling flow rate depends of feeding flow rate, in order to maintain the upflow velocity constant, since this is an important parameter to the performance of the reactor, so the action on these two variables is linked. On the other hand, the action on nutrients and alkalinity flow rate is independent of the other two. This control action will be employed in the near future to implement close loop control strategies based in alkalinity concentration on-line measurements. The actions have been described through membership functions, using a Mamdani-type fuzzy inference system. The structure of the pump commands module, introducing only two input variables, makes possible to obtain a graphic representation of the control surface. In Figure 3 the surface obtained for the control of the feeding pump is shown.

**(iv) Toxicity test**

This module facilitates the detection of the presence of dangerous levels of toxic substances, and uses the information obtained from on-line measurements together with off-line data for this purpose. Three of the five inputs requested are on-line data: methane composition in biogas (CH4) and feeding and gas flow rates (FF and GF). The two further inputs correspond to off-line measurements: influent COD and phenol concentration, since this last parameter is a toxic substance present in the wastewater to be treated. However,
another one depending on the characteristics of the wastewater could easily substitute this parameter. The test is performed, when requested by the operator, using the last off-line data supplied to the PC, as well as the last on-line acquired data.

**(v) Off-line validation**

This module was implemented in order to validate the results obtained from the estimation of the process state. For this purpose, the last off-line data are required, when the operator requests the response of this module. The off-line validation system uses three inputs: the state of the process to be validated; and the off-line data, which corresponds to the influent COD and the total alkalinity concentration. In order to introduce the off-line variables corresponding to this module and to the previous one, the membership functions for influent COD, and effluent total alkalinity were defined (Figure 4), as well as for phenol concentration in the case of toxicity test.

**Results and discussion**

Tuning and testing of the expert system

In order to prove the reliability of the membership functions described, as well as the rule base of the ES, the developed fuzzy sets were tuned and tested by means of real experiments. These tasks were performed simultaneously with the development of the ES, this
permitting the consideration of suitable modifications until the final version was completed.

The tuning was done using actual data from different operational situations, representing organic shocks, hydraulic overloads, temperature failures, etc. Once the variables and their membership functions were tuned, the ES was tested running together with the process, allowing the analysis and improvement of the diagnosis and supervision outputs.

The data acquired for a specific period are presented in Figure 5. In this period the process suffered several disturbances, as can be seen in the evolution of the on-line data acquired. The plant was initially operated with 10 g COD/l concentrated wastewater at an OLR of 2 kg COD/m³ · d.

The results obtained from the process state estimator are shown in Figure 6. On day 60 the feeding flow rate was increased (Figure 5(a)), leading the ES to detect incipient low acidification due to hydraulic overload (Figure 6). The increase in feeding flow rate promoted the decrease of CO composition in biogas (Figure 5(b)), with no relevant effects on methane composition and biogas flow rate (Figure 5(a)). On day 71 low acidification caused by organic overload was diagnosed by the ES. Because of that the operator decreased the feeding flow rate from 20 to 10 l/h (Figure 5(a)). COD of the influent wastewater was determined, obtaining that it had increased from 10 to 20 g COD/l, this validating the good diagnosis of the ES. After two days of operation, the reactor recovered its normal performance. During the following 15 days the disturbances diagnosed by ES correspond to several faults on recycling pump (data not shown), promoted by the wash out of biomass.
and the consequent clogging problems due to the increase of influent COD concentration. On day 89 the operation was modified, feeding the reactor with concentrated wastewater (40 g COD/l). At this moment the ES detected the maximum levels of acidification (Figure 6), observing a slow adaptation due to the problems associated with the recycling flow rate.

Concerning the process trend (not shown here), the tendency of the reactor to improve the operation (Getting better) in most cases, as the plant returns to proper, or at least better operational performance after each disturbance.

Finally, the recommended values for pump commands are shown in Figure 7. It can be seen how a decrease in the feeding flow rate is recommended when the system gets worse due to acidification, especially when the system began to be operated with concentrated water, on day 89. In this case, the feeding pump was temporary stopped (Figure 7(a)) and the nutrients and alkalinity addition was kept at high values (Figure 7(b)) to avoid extreme acidification. The recycling pump regime was also modified (data not shown) to compensate for changes in the feeding pump in order to maintain the correct upflow velocity inside the digester.

Conclusions
This work presents the development of a fuzzy expert system (ES) to diagnose and supervise the operation of an anaerobic wastewater treatment plant. The system uses the on-line data acquired, as well as information from the off-line data, to achieveresults in different areas, relating to the state and trend of the process, the toxicity level, the changes to be made to the final control elements, and the validation and supervision of all information.

As a conclusion, it is reasonable to assert that the ES worked properly after its tuning and testing. ES is ready to supply good diagnostic data about the process state of the plant by means of the developed rule base introducing expert knowledge. ES can also predict the future trend in the system and estimate the best set points for the pumps, as final control elements of the operation, giving reliable information and good advices to the operator. Furthermore, and with the introduction of off-line variables, the ES has the capacity to validate the on-line results and to detect the presence of toxic compounds, which could destabilise the operation.

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References


