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A fuzzy-logic based diagnosis and control of a reactor performing complete autotrophic nitrogen removal

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Abstract: This contribution explores the use of diagnosis and control modules based on fuzzy set theory and logic for bioreactor monitoring and control. With this aim, two independent modules were used jointly to carry out first the diagnosis of the state of the system and then use transfer this information to control the reactor. The separation in diagnosis and control allowed a more intuitive design of the membership functions and the production rules. Hence, the resulting diagnosis-control module is simple to tune, update and maintain while providing a good control performance. In particular the diagnosis-control system was designed for a complete autotrophic nitrogen removal process. The whole module is evaluated by dynamic simulation. Additionally, the diagnosis tool was demonstrated by analysis 100 days of experimental data.

Keywords: Fuzzy logic; control; diagnosis; biological wastewater treatment; nitrogen removal

1. INTRODUCTION

The automatic control of mixed-culture bioreactors is challenging given their highly nonlinear behaviour, interactive dynamics, model uncertainty and variations in the influent (flow rate, composition, temperature, etc…). Furthermore, only a few actuators are usually available to reject disturbances and maintain a stable operation complicated by competing microbial groups. In this context, gain-scheduling and model predictive control (MPC) schemes can be used to control a wide range of operation conditions of a reactor. However, the development of such advanced control strategies in bioreactors is usually hindered by the low accuracy of models describing the microbial metabolism, the long simulation times required to solve such models, and by the complexity of such controllers (Olsson 2011). In this respect, the simplicity of a controller is an important characteristic in a bioreactor since it is likely that frequent maintenance will be needed as a result of variations in the feedstock, seasonal conditions and even because of microbial evolution. Hence, a trade-off must be achieved between efficient control and monitoring tools on the one hand, and simplicity on the other hand in order to ensure the success of the control scheme.

Fuzzy decision methods have been used for diagnosis of performance since it is a means to formalise the knowledge accumulated by the process operators (Honda, Kobayashi 2000) and it is adapted to the use of expert knowledge and quantitative models. For instance, Comas *et al*. (2008) developed a fuzzy diagnosis method to establish the risk for occurrence of microbiology related settling problems in activated sludge systems. Likewise, fuzzy decision can also be used in control of bioprocesses, allowing synthesis of the available information from the process and applying it for the automatic control of the process (Ruano et al. 2010).

Complete autotrophic nitrogen removal (CANR) is a novel process that can increase the treatment capacity (volumetric removal rate) approximately 5 times compared to the traditional nitrification-denitrification treatment. This process achieves the complete stoichiometric conversion to nitrogen gas and a low quantity of nitrate by a combination of two processes, which are catalysed by aerobic ammonium oxidizers (AOB) and anaerobic ammonium oxidizers (AnAOB). The conversion performance can be compromised by competition by nitrite oxidizing bacteria (NOB) and heterotrophic bacteria (HB). Operating the system for selection of a desired microbial community composition and maintaining stable process performance can therefore be a difficult task. Actually, controllers depending on set point values for dissolved oxygen (DO), oxygen reduction potential (ORP), nitrogen species and pH alone may not be enough to deduce whether microbial community activities are balanced and performance is stable (Vangsgaard et al. 2012).

In the case of CANR, as in many other bioreactors, the coexistence of several kinds of microbial groups makes the design of a controller particularly challenging. For instance, an increase in aeration may be the convenient response to an increase in the ammonium load, but it can create problems if the NOB are not supressed. Hence, any control action must arise from a previous diagnosis of the state of the process and the microbial community. With this aim, fuzzy diagnosis and control have been previously combined in anaerobic digesters (Puñal et al. 2001, Puñal et al. 2003) and it is configured similarly to a state controller with a filter for state estimation.

The aim of this work is to design a fuzzy diagnosis and control tool for a single-stage autotrophic nitrogen removal process. The diagnosis of the process is based on stoichiometric ratios of formed or produced nitrogen species as previously used by (Pellicer-Nàcher et al. 2010, Mutlu et al. 2013). The controller acts subsequently given the diagnosis of the process and modifies the aeration and volume exchange ratio (ER). The performance of the fuzzy logic based diagnosis and control system is evaluated with a dynamic simulation.

2. MODELLING AND METHODS

2.1 Reactor description and modelling.

The modelled system mimics a lab-scale reactor containing granular sludge performing CANR. The reactor has a cylindrical geometry and a volume of 4 L. The operating temperature was 30 °C and pH was approximately 7.5. The cycles comprised an anoxic feeding phase (10 min), a reaction phase with alternating oxic/anoxic periods, a settling phase (6 min), a decanting phase (10 min), and an anoxic idle phase (10 min). The reaction phase lasted 444 min and the total cycle time was 8 h. Air was supplied intermittently.

The model of the reactor is described in detail elsewhere (Vangsgaard et al. 2012) and just briefly mentioned here. It consists of two compartments: a one-dimensional multi-species biofilm model to describe the granules and a perfectly mixed domain to account for the bulk of the reactor. The model contains 13 state variables, in the form of 6 soluble compounds, 6 particulate compounds and the size of the granules. The transport of soluble species (S_i) is governed by diffusion and of particulate compounds (X_i) by advection within the granule (1-2). The individual mass balance in the bulk of the reactor (3) is an ODE which includes the in- and outflow, the reaction in the bulk and the transfer with the granules.

$$\frac{\partial S_i}{\partial t} = D_{i,bio}\frac{1}{r^2}\frac{\partial}{\partial r}\left(r^2\frac{\partial S_i}{\partial r}\right) + R_i \qquad (1)$$

$$\frac{\partial X_i}{\partial t} = -\frac{\partial (X_i u_F)}{\partial r} + R_i \qquad (2)$$

$$\frac{dC_i}{dt} = \frac{Q_{in}C_{i,in} - Q_{out}C_i - j_{i,bio}A_{bio}}{V} + R_i \qquad (3)$$

where R_i is the net reaction of each compound, r is the radial direction in spherical coordinates, Q is the flowrate in and out of the reactor, V is the volume of the reactor, $D_{i,bio}$ is the diffusivity inside the granules and u_F is the net advective velocity (4). The calculation of u_F at each space node *k* is done by integrating the growth of all the microbial groups in the volume comprised between 0 and *k* (5).

$$\frac{\partial L}{\partial t} = u_{F,D} - u_D \quad where\ u_D = u_{F,L}\left(\frac{L}{r_{max}}\right)^2 \qquad (4)$$

$$u_{F,k} = \frac{1}{A_k}\int_0^k A_k\left(\sum_{i=1}^{n}\frac{R_i}{\rho}\right)\Bigg|_k dr \qquad (5)$$

where L is the granule radius, r_{max} is the maximum granule radius, ρ is the molar density of the biofilm and u_D is the detachment velocity.

The system of thirteen partial differential equations (PDEs) has been solved by the method of lines, i.e. discretization of the space and numerical approximation of the space derivatives by finite differences, in order to obtain a system of ordinary differential equations (ODEs). Different numbers of discretization layers were tested and a number of 100 was found to be sufficient. The model was implemented and solved in MATLAB R2013a (The MathWorks, Natick, MA).

2.2 Decision tree for diagnosis.

In a previous study, appropriate metrics, related to ratios of consumption and production of several nitrogen species, have been formulated based on reaction stoichiometry and process knowledge (Mutlu et al. 2013). These are:

$$R_{AmmTot} = \left|\frac{\Delta NH_4^+ - N}{\Delta TN}\right|;$$

$$R_{NitAmm} = \frac{\Delta NO_2^- - N}{\left|\Delta NH_4^+ - N\right|};\quad R_{NatTot} = \left|\frac{\Delta NO_3^- - N}{\Delta TN}\right|;$$

$$R_{eff} = 1 - \frac{NH_{4,eff}^+}{NH_{4,in}^+};\quad R_{NitAmm,ef} = \frac{NO_2^- - N_{eff}}{NH_4^+ - N_{eff}}$$

(6-10)

Total nitrogen removal (ΔTN), is the difference between the sum of all nitrogen species at the end and at the beginning of each cycle, and similarly also defined for the individual N species. ΔTN is equivalent to the sum of N_2-N and biomass-N produced. ΔNO_2- is expected to be zero, unless there is a limitation somewhere in the overall process. In the decision tree, ΔTN=0 is the situation without AnAOB activity. In this case reactors should be reinoculated or bioaugmented.

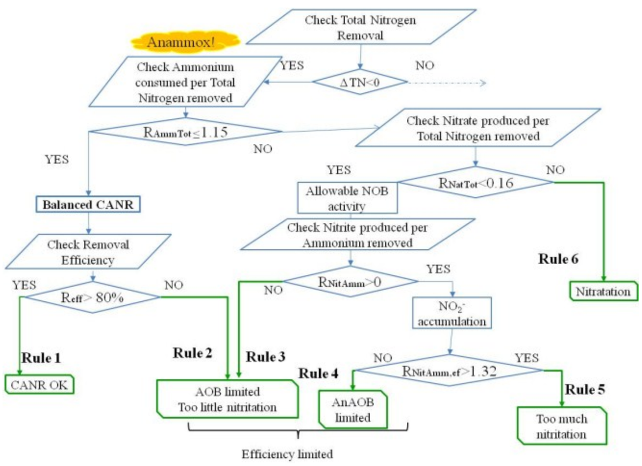

Fig. 1. Decision tree developed for diagnosis of SBRs performing single-stage CANR (from (Mutlu et al. 2013))

$R_{AmsmTot}$ is ammonium consumed per total nitrogen removed and forms a measure of the relative activity of microbial groups present in the system, i.e. the AnAOB versus AOB and NOB activity. R_{NitAmm} is nitrite produced over ammonium consumed. Unless zero, as in balanced cases, it measures prevalence of AOB activity over AnAOB and/or NOB. R_{NatTot} is the nitrate produced per total N removed and it is a measure of AnAOB versus NOB activity. Finally, a ratio of effluent nitrite over effluent ammonium concentration ($R_{NitAmm,ef}$) is introduced, which is a measure of the substrate composition at the end of an SBR cycle.

In the decision tree in Fig.1, the optimal performance is the case where balanced nitritation-anammox is inferred and more than 80% ammonium removal is observed (rule 1). If the removal efficiency is not sufficient, yet R_{AmmTot} is within the target range, the system is limited by nitrite production (rule 2). If the system moves away from balanced CANR, nitrite or nitrate accumulates. If these accumulations are still relatively small, within the allowable ranges, the AOB activity is still limiting (rule 3). If nitrate accumulates to more than the allowed levels, then nitratation is prevailing in the system (rule 6). When NOB activity is within allowable limits, the system is experiencing nitrite accumulation, which can be due to low AnAOB activity (rule 4) or to too high nitritation (rule 5).

2.3 Fuzzy diagnosis.

Given sensor readings from the current and the previous cycle, the goal of the fuzzy-logic diagnosis is to determine the state of the system with respect to the removal of nitrogen, the production of nitrate and the imbalances in the microbial community. The diagnosis developed in this work consists of the following steps:

Data collection and calculation of input values. Here, the raw data in the form of influent and effluent concentrations are collected and the above-mentioned ratios (6-10) are calculated.

Fuzzification. The trajectories of the input values are converted to linguistic variables/qualitative descriptors by means of membership functions (MFs). These MFs are created based on previous stoichiometric analysis (Mutlu et al. 2013), prior experience, and expert knowledge. The output variables are the following phenomena: i) Autotrophic Nitrogen Removal, (ANR) ii) Nitritation, iii) AnAOB Limitation and iv) Nitratation. All MFs for inputs and outputs are triangular or trapezoidal.

Scaling and centring of variables. In order to use comparable MFs the inputs were centred and scaled resulting in a universe of discourse equal to [-1,1] for R_{AmmTot}, R_{NitAmm}, $R_{NitAmmEff}$, R_{NatTot}. For R_{Eff} the universe of discourse was equal to [0,1] to keep the meaning of this input (efficiency in ammonium removal). The inputs were centred by subtraction of the cut-off value in the decision tree and scaled by the range of values encountered in an experimental campaign of three months or by the maximum theoretical span.

Fuzzy inference engine. The degree of certainty of the linguistic output variables is generated through a set of 30 IF-THEN rules (Table 2-5) constructed from the decision tree following the Mamdani fuzzy inference method (max aggregation/min implication). All the rules have the same weight.

It must be highlighted that the core of a fuzzy inference system is the production rules (Kovacic 2005). Therefore, although fine tuning of the controller response would be possible changing the MF boundaries, it is essential that the rules gather all the information available about the system and are self-consistent.

Tables 2-5. Production rules for diagnosis. The output variables are indicated in bold italic font. AZ=Approximately zero; F = Fair; H = High; L = Low; OK=Balanced; N=No; VH =Very high; VL= Very low; Y=Yes;

2.Output Autotrophic Nitrogen Removal (ANR)

$\downarrow R_{Eff}$ / $R_{AmmTot} \rightarrow$	L	H	VH
H	***VH***	***H***	***L***
F	***F***	***F***	***L***
L	***L***	***L***	***L***

3. Output Nitritation

IF [R_{AmmTot} not Low] AND [R_{NatTol} = Low] AND

$\downarrow R_{NitAmm,ef}$ / $R_{NitAmm} \rightarrow$	VL	L	H	VH
L	***VL***	***L***	***OK***	***OK***
H	***VL***	***L***	***H***	***VH***

IF [R_{AmmTot} =Low] AND

$\downarrow R_{AmmTot}$ / $R_{Eff} \rightarrow$	H	F	L
L	***OK***	***L***	***VL***

4. Output AnAOB Limitation

IF [R_{AmmTot} not Low] AND [R_{NatTol} = Low] AND

$\downarrow R_{NitAmm,ef}$ / $R_{NitAmm} \rightarrow$	VL	L	H	VH
L	***N***	***N***	***Y***	***Y***
H	***N***	***N***	***N***	***N***

IF [R_{AmmTot} is Low] OR [R_{NatTol} not Low], THEN [AnAOB Limitation = N]

5. Output Nitratation

$\downarrow R_{NatTot}$ / $R_{AmmTot} \rightarrow$	L	H	VH
L	***AZ***	***AZ***	***AZ***
H	***AZ***	***L***	***H***
VH	***AZ***	***H***	***VH***

Defuzzification. Here the output variables are translated into a numerical value by means of the output MFs and the centre of gravity method. The result is used for diagnosis for the operators of the process and as an input to the fuzzy controller.

2.4. *Fuzzy Controller*

The combination of the fuzzy diagnosis and control has been successfully reported for anaerobic digestion (Puñal et al. 2001, Garcia et al. 2007) and it is configured similarly to a state controller with a filter for state estimation.

Definition of controller objectives, degrees of freedom and controlled variables. The objective of the controller is to achieve high and stable complete autotrophic nitrogen removal. This objective can be split into two controlled variables: a high nitrogen removal and a balanced microbial community. Four potential degrees of freedom (manipulated variables - MVs) were identified in the system: mixer, heating jacket, air supply and exchange ratio (or equivalently the hydraulic retention time, given that the cycle time is constant). The heating jacket is assumed to perfectly control the temperature. Since the effect of mixing is not completely established, the mixer was not considered a suitable actuator. Therefore, the only available actuators for control are the exchange ratio (ER) and the air supply rate. For simplicity, the air supply was represented by the oxygen mass transfer coefficient, k_La, in the model.

The resulting diagnosis-control block results in a multivariable controller with two manipulated variables (MVs). The value of each of the MVs depend on three inputs from the diagnosis module (k_La does not depend on AnAOB limitation and ER does not depend on nitritation, tables 6-7). It can be inferred from the rules that the action on k_La is aimed at modifying the removal performance whereas the action on ER is aimed at modifying the microbial community composition.

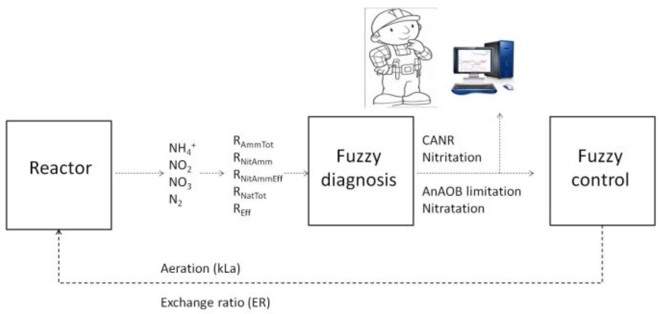

Fig. 2. Structure of the control and diagnosis fuzzy modules and information flow

Scaling and centring of variables. Since all the inputs are provided from the diagnosis module with universe of discourse [-1, 1] (Nitritation and AnAOB Limitation) or [0,1] (ANR and Nitratation), no centring or scaling is needed. The outputs from the fuzzy controller have a universe of discourse [-1,1] and are unscaled by multiplication with their corresponding nominal value, i.e. the design values of k_La and ER.

Fuzzification. The inputs to the controller are provided from the diagnosis block in fuzzified form. The outputs from the fuzzy controller, corresponding to the inputs to the reactor, are the variations to the nominal value of the manipulated variables.

Fuzzy inference engine. A set of 16 IF-THEN rules (tables 6-7), following the Mamdani fuzzy inference method (max aggregation/min implication), forms the inference engine. All the diagnosis inputs have an impact on the variation of k_La. As for ER, it can affect the washout of NOB when nitratation takes place. When the process is limited by AnAOB, ER increases the retention in order to ensure that the AnAOB are not washed out despite their low growth rate. All the rules have the same weight.

Tables 6-7. Production rules between the linguistic input and output variables for the control module. The output linguistic variables indicate the variation to the nominal value of the MV (in bold italic font). N = Negative, NL = Negative Large, P = Positive, PL = Positive Large, Z = Zero.

6. Output Variation of Aeration (k_La)

↓Nitritation/ANR →	VH	H	F	L
VL	***Z***	***Z***	***PL***	***PL***
L	***Z***	***Z***	***P***	***P***
M	***Z***	***Z***	***Z***	***Z***
H	***Z***	***Z***	***N***	***N***
VH	***Z***	***Z***	***NL***	***NL***

↓Nitratation/ANR →	VH	H	F	L
AZ	***Z***	***Z***	***Z***	***Z***
L	***N***	***N***	***N***	***N***
H	***N***	***NL***	***NL***	***NL***
VH	***NL***	***NL***	***NL***	***NL***

7. Output Variation of Exchange Ratio (ER)

↓Nitratation/ANR →	VH	H	F	L
AZ	***Z***	***Z***	***Z***	***Z***
L	***Z***	***Z***	***Z***	***Z***
H	***P***	***P***	***P***	***P***
VH	***P***	***P***	***P***	***P***

↓AnAOB Limitation/ANR →	VH	H	F	L
N	***Z***	***Z***	***Z***	***Z***
Y	***Z***	***Z***	***N***	***N***

Defuzzification. The crisp values of the controller outputs are obtained by the centre of gravity method. As their universe of discourse is [-1, 1], the crisp value is unscaled multiplying with the corresponding nominal values. Finally the result is added to the nominal value to obtain the current controller output, as described by (11-12)

$$\mathrm{kLa}(t) = \mathrm{kLa}_o + S_{\mathrm{kLa}}\, C_{\mathrm{kLa}} \qquad (11)$$

$$ER(t) = ER_o + S_{ER}\, C_{ER} \qquad (12)$$

where S_i is the scaling factor, C_i is the crisp value of the fuzzy output and subindex $_0$ denotes the nominal value.

3. EVALUATION OF DIAGNOSIS TOOL

The diagnosis tool was first tested assessing real data from the aforementioned lab-scale reactor during 100 days. This assessment was done a posteriori and did not influence the policy followed by the operator, hence open loop analysis.

The diagnosis results for the four outputs (Fig. 3) show the following evolution of the reactor: at the beginning the autotrophic nitrogen removal (ANR) is limited by the AnAOB metabolism and by too much nitratation. As nitritation becomes lower due to a decrease in the oxygen supply, the process is no longer limited by AnAOB and nitratation becomes less significant. However, since nitritation becomes then too low (after day 50), the ANR is still not satisfactory. As nitritation is recovered slowly, the ANR also increases but barely reaches the high level.

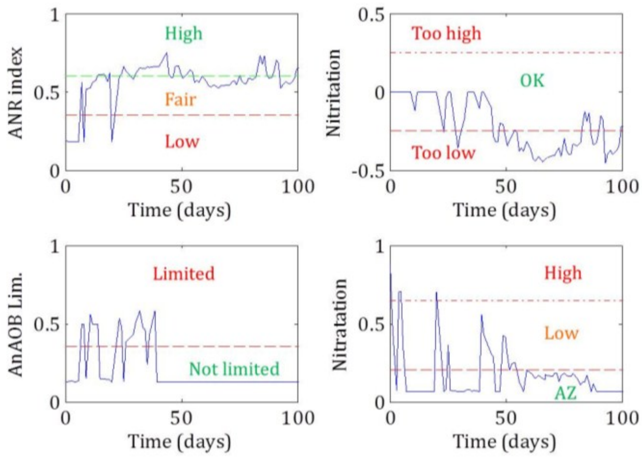

Fig. 3. Results of the diagnosis tool for 100 days of experimental operation data of the SBR as described in 2.1.

4. EVALUATION OF THE DIAGNOSIS-CONTROL MODULE

The diagnosis-control module was evaluated by dynamic simulation of 7 days operation with a step input disturbance (at t = 4 days the ammonium concentration of the influent was increased by 10%). The initial conditions were taken from a steady state solution of an equivalent continuous reactor.

The diagnosis results (Fig. 4) show that the system is stabilised in approx. 4 cycles, with a decrease in nitratation and an increase in nitritation. The increase in ammonium concentration in the influent at t = 4 days is not reflected in the diagnosis because the aeration is sufficient to cope with the increase in ammonium load.

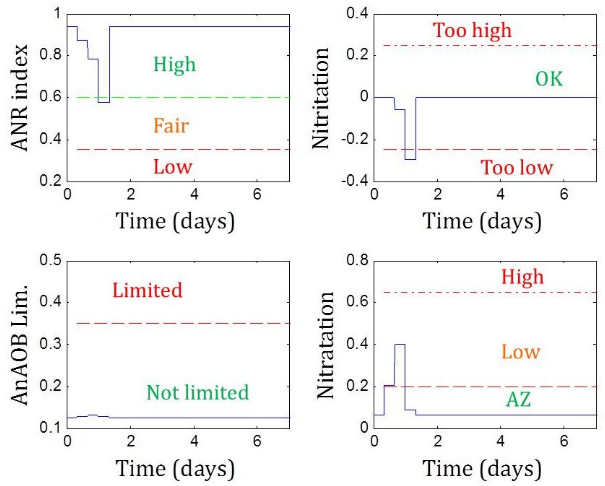

Fig. 4. Simulation test: Diagnosis of 7 days of dynamic operation under step disturbance in influent ammonium load.

Concerning the controller performance, Fig. 5 shows the nitrogen removal both in terms of N_2 produced and percentage of nitrogen removed, defined as the ratio between the N_2 produced and the nitrogen load in the influent (in this case in the form of ammonium). It can be seen that the controller is able first to stabilise the percentage of nitrogen removed increasing it from about 85 % to about 95% after two days. At t = 4 days the decrease in the percentage of nitrogen removed reflects the increase of the influent load but indeed not in the N_2 concentration. As it can be seen, the percentage of nitrogen removed is recovered in 1.5 days to reach again 95%

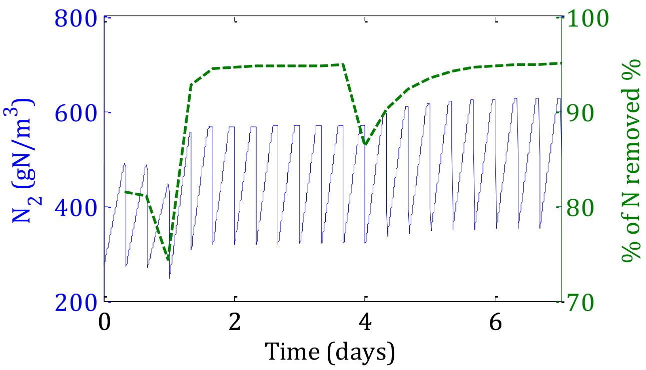

Fig. 5. Concentration of N_2 produced (left axis) and percentage of nitrogen removed (right axis) during 7 days of simulated dynamic operation. On day 4, a step disturbance in influent ammonium load is introduced (see text).

5. CONCLUSIONS AND PERSPECTIVES

It was demonstrated that diagnosis and control of a granular bioreactor can be suitably achieved by the fuzzy-logic method. The advantages are the simplicity of the control structure in comparison with the complexity of the microbial ecology of the reactor, and the possibility to bring together quantitative, qualitative and even expert knowledge. As aforementioned, it is essential that this information is properly represented in the production rules which represent the core of the fuzzy inference system.

Using online measurement of the nitrogen species in the reactor, the diagnosis of the system is carried out first and this information is passed on to the controller that decides on the appropriate action to be taken. The separation of diagnosis and control was an efficient way to implement the tool and followed the intuition of the operators of the reactor. As a future perspective, the diagnosis-control module is expected to be implemented in the lab-scale reactor in the near future.

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