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Systematic design of membership functions for fuzzy-logic control: A case study on one-stage partial nitritation/anammox treatment systems

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A B S T R A C T

A methodology is developed to systematically design the membership functions of fuzzy-logic controllers for multivariable systems. The methodology consists of a systematic derivation of the critical points of the membership functions as a function of predefined control objectives. Several constrained optimization problems corresponding to different qualitative operation states of the system are defined and solved to identify, in a consistent manner, the critical points of the membership functions for the input variables. The consistently identified critical points, together with the linguistic rules, determine the long term reachability of the control objectives by the fuzzy logic controller. The methodology is highlighted using a single-stage side-stream partial nitritation/Anammox reactor as a case study. As a result, a new fuzzy-logic controller for high and stable total nitrogen removal efficiency is designed. Rigorous simulations are carried out to evaluate and benchmark the performance of the controller. The results demonstrate that the novel control strategy is capable of rejecting the long-term influent disturbances, and can achieve a stable and high TN removal efficiency. Additionally, the controller was tested, and showed robustness, against measurement noise levels typical for wastewater sensors. A feedforward-feedback configuration using the present controller would give even better performance. In comparison, a previously developed fuzzy-logic controller using merely expert and intuitive knowledge performed worse. This proved the importance of using a systematic methodology for the derivation of the membership functions for multivariable systems. These results are promising for future applications of the controller in real full-scale plants. Furthermore, the methodology can be used as a tool to help systematically design fuzzy logic control applications for other biological processes.

1. Introduction

In biological wastewater treatment (WWT) the key to achieve high process performance is ensuring optimal environmental conditions, which allow the bacteria to work at the desired efficiency. These conditions can be accomplished by means of proper design of WWT systems. Nevertheless, since the influent to these systems – the main disturbance – is rather dynamic both in terms of flow rate and in terms of composition, the environmental conditions tend to move away from the optimal ones required by the microbial community. In order to cope with these fluctuations, on-line control strategies have to be implemented in the system. More specifically, Proportional Integrative Derivative (PID) control has been the type of controller commonly developed and tested for biological WWT systems (Lindberg and Carlsson, 1996; Serralta et al., 2002; Vangsgaard et al., 2014; Volcke et al., 2006; Wahab et al., 2009). However, as remarked by Aoi et al. (1992), given their non-linear behaviour, biological WWT systems may perform poorly when controlled by linear controllers such as PID. On the contrary, as fuzzy-logic controllers (FLCs) can incorporate the non-linear nature of such bioprocesses, they represent good candidates to overcome the challenges typically met with linear controllers. An additional advantage is that the design of FLCs does not require the availability of highly accurate models to describe the underlying biological processes. As a matter of fact, there are examples where modelling biological WWT processes becomes quite challenging

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List of abbreviations

AAE	Average Aeration energy
AOB	Ammonia-Oxidizing Bacteria
AnAOB	Anaerobic Ammonia-Oxidizing Bacteria
BSM2	Benchmark Simulation Model no 2
CP	Critical points
CS	Control Strategy
CV	Controlled Variable
FF	Feedforward
FIS	Fuzzy-logic Inference System
FLC	Fuzzy Logic Control
FS	Fuzzy Set
HB	Heterotrophic Bacteria
IAE	Integral Absolute Error
MF	Membership Function
MS	Microbiological Scenario
MV	Manipulated Variable
NOB	Nitrite-Oxidizing Bacteria
PN/A	Partial Nitritation/Anammox
RO	Volumetric oxygen-to-ammonium loading rate
SBR	Sequencing Batch Reactor
TN	Total Nitrogen
TV	Total Variation
WWT	Wastewater Treatment

List of symbols

C	Concentration of generic compound
D	Diffusivity of soluble components
k_La	Oxygen mass transfer coefficient
d	Vector of system disturbances
$\Delta_U k_L a$	Unitary deviation of k_La
j	Flux in and out the granule
k_La_0	Nominal value for k_La
K_{SF}	Scaling factor
η_{TN}	Total nitrogen removal efficiency
LB	Lower boundary
LB_{OPT}	Lower boundary for optimal system operation
LB_{WORST}	Lower boundary for worst system operation
N_{biom}	Nitrogen stored into the biomass cells
Q	Flow rate
R_{AmmTot}	Ratio between NH_4^+ consumed and TN removed
R_{eff}	NH_4^+ removal efficiency
R_{NatTot}	Ratio between nitrate produced and TN removed
R_{NitAmm}	Ratio between NO_2^- produced and NH_4^+ consumed
$R_{NitAmm,Eff}$	Ratio between effluent NO_2^- and effluent NH_4^+
r	Reaction rate
r_{NOB}	Rate of NOB activity with respect to the rate of AOB activity
r_{AnOB}	Rate of AnAOB activity with respect to the rate of AOB activity
r_{HB}	Rate of HB activity with respect to the rate of AOB activity
S	Concentration of soluble components
S_S	Organic biodegradable matter
σ	Standard deviation
UB	Upper boundary
UB_{OPT}	Upper boundary for optimal system operation
UB_{WORST}	Upper boundary for worst system operation
u	Vector of system manipulated variables
u_F	Biofilm net velocity growth
VAR_{OPT}	Variable to be optimized by controller
X	Concentration of particulate components
X_I	Particulate inert matter
X_S	Particulate organic matter
x	Vector of system state variables
y	Vector of system controlled variables
z	Radial direction in spherical coordinates

given the interactive nature of the biological reactions and the intrinsic lag time in the response of some microorganisms to manipulation of operating conditions (Snip et al., 2014). In that case, the limitations of the dynamic model negatively affect the performance of a controller designed on the basis of it, and fine-tuning the controller may not be enough to obtain the optimal control performance (Mauricio-Iglesias et al., 2015). For these instances FLCs represent an effective alternative control technology since they can make use of process engineering knowledge gained from observations and experiences with operating biological systems which is otherwise hard to be described mechanistically. Thus mechanistic knowledge can be integrated with additional insights on the processes to control, allowing a better control performance. Furthermore, control objectives for biological applications are often affected by some degree of fuzziness where, for the same controlled variable, a range of set points rather than a single value can be identified as optimal (Tong et al., 1980). In such situations, FLCs offer the flexibility to include for the same variable a range of set points rather than a single value to be tracked.

With regards to the tuning of design parameters, FLCs typically require a large number of design decisions, which makes them very flexible in function of specific requirements on control response. However, this large number of degrees of freedom also comes with the challenge of making proper design choices in a systematic way. This in turn limits the application range of FLCs for complex systems such as WWT plants. As described in Lababidi and Baker (2006), the generic work of a fuzzy-logic inference system (FIS) consists of three main subsequent operations: “fuzzification”, “fuzzy inference” and “defuzzification”. More in detail, the fuzzification converts numerical (crisp) values of the input variables into fuzzy inputs, on the basis of which the fuzzy inference deduces the corresponding fuzzy outputs. The latter are then converted into crisp values through the defuzzification. While the “fuzzy inference” operation basically relies on linguistic rules, “fuzzification” and “defuzzification” are performed according to so-called membership functions (MFs). As stated by Seborg et al. (2004), the definition of the MFs plays a major role in determining the FLC performance. Nevertheless, a systematic procedure for it has not been established yet, which in turn can hinder the good performance of FLCs and lead to unexpected behaviours. For this reason, the present study will illustrate through a case study on a biological WWT system how the membership functions of feedback fuzzy-logic controllers applied to biological systems can be systematically defined. For the definition of the MFs, the control objectives are defined first. On the basis of the control objectives, cut-off values for the MFs are identified and MFs can thus be built up. The case study will be a single-stage side-stream partial nitritation/Anammox (PN/A) granular system.

Once implemented, the performance of the novel controller is evaluated on the basis of the results from simulations of the PN/A reactor model by Vangsgaard et al. (2012) with different types of disturbances. In particular, step increase and decrease in influent