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Fuzzy model-based predictive control of dissolved oxygen in activated sludge processes ☆

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ABSTRACT

The paper is concerned with the design of a fuzzy model-based predictive controller for activated sludge wastewater treatment processes. The control purpose is to maintain the dissolved oxygen concentration in an aerobic reactor of the wastewater treatment plant at the set-point. The fuzzy model of the activated sludge processes is derived based on the Activated Sludge Model No. 1 (ASM1), including the structure of the fuzzy rules. The required fuzzy space of input variables is partitioned by fuzzy c-means cluster algorithm and the consequent parameters are identified using the method of least squares. Compared with both traditional PID control and dynamic matrix control schemes, the proposed fuzzy model-based predictive control paradigm achieves satisfactory benefits in terms of both transient and steady performances.

1. Introduction

The activated sludge treatment approach, which uses the bacteria and other microorganisms to remove contaminants by assimilating them, has been widely adopted in most wastewater treatment plants (WWTPs). Modeling and control of the activate sludge processes (ASPs) play an important role for improving the effectiveness of this approach. So far, some models have been proposed, such as Activated Sludge Models (ASMs) of International Water Association (IWA) including ASM1, ASM2, ASM2d and ASM3. It has been well recognized in the area that the ASM1 is the most successful one used to represent the processes dynamics [11,12,14,15]. However, due to the complexity of the model, e.g., high-dimensional with many nonlinear terms and parameters that are hard to identify, it is quite limited to apply ASM1 directly for controller design of WWTPs. To overcome this difficulty, big efforts have been made towards proposing more efficient models such as the modified ASM models, the intelligent models and hybrid models (see [2,5–7]). Fuzzy modeling approach [17,26,33,34], which is commonly adopted in approximating a broad class of nonlinear systems, becomes more and more popular to be used in modeling ASP. A large number of results have been available in the literature demonstrating that fuzzy models can adequately reflect the dynamics of the ASPs [9,10,18,20,31]. An efficient method of identifying the structure of fuzzy model is proposed in [37] and this modeling approach has been successfully applied to predict chemical oxygen demand of the ASPs.

In general, the complexity in controlling wastewater treatment processes are mainly caused by seriously high nonlinearity and various uncertainties due to, for instance, the time-varying influent parameters, the intricacy of structure and the huge number of coefficients of the model. Model predictive control, capable of dealing with multi-variable systems and constraints, has been extensively applied to ASPs (see [23,24,29,30], for example). In the existing results, there are many manipulated variables which are frequently employed, such as dissolved oxygen concentration [3,13,16,28], ammonia concentration [32], residual substrate [22], internal recycle flow rate and external carbon dosing rate. Effective control of dissolved oxygen can not only guarantee the common behavior and activity of the microorganisms living in the activated

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Nomenclature

S_I	soluble inert organic matter
X_I	particulate inert organic matter
X_{BH}	active heterotrophic biomass
S_{NH}	ammonium and ammonia nitrogen
X_P	particulate products arising from biomass decay
S_O	dissolved oxygen
S_{ND}	soluble biodegradable organic nitrogen
Y_H	heterotrophic yield
η_g	correction factor for anoxic growth of heterotrophs
b_H	decay rate for heterotrophs
μ_H	maximum heterotrophic specific growth rate
K_S	half-saturation coefficient for heterotrophs
K_{OA}	oxygen half-saturation coefficient for autotrophs
K_{NH}	ammonium half-saturation coefficient for autotrophs
S_S	readily biodegradable substrate
X_S	slowly biodegradable substrate
X_{BA}	active autotrophic biomass
S_{NO}	nitrate and nitrite nitrogen
f_p	fraction of biomass yielding decay products
S_{ALK}	alkalinity
X_{ND}	particulate biodegradable organic nitrogen
Y_A	autotrophic yield
η_h	correction factor for anoxic hydrolysis
b_A	decay rate for autotrophs
μ_A	maximum autotrophic specific growth rate
K_{OH}	oxygen half-saturation coefficient for heterotrophs
K_{NO}	nitrate half-saturation coefficient for heterotrophs

sludge, but also significantly reduce the operational costs of the wastewater treatment. It is worth mentioning that most of the research results of model predictive control are focused on neural network model [3,13], linear state-space model [16], bilinear model [8] and reduced ASM1 [32], the fuzzy model-based predictive control of ASPs has not been sufficiently investigated. In [19], the hierarchical fuzzy predictive control for nitrogen removal in biological wastewater treatment processes has been investigated. However, the parameters of the obtained fuzzy model lack definite physical meaning.

Motivated by the aforementioned observations, in this paper, the problem of fuzzy model-based predictive control of dissolved oxygen in ASPs is considered. The control goal is to maintain the concentration of dissolved oxygen in an aerobic reactor of the WWTP at the set-point. In the considered fuzzy modeling processes, the fuzzy space of required input variables is partitioned by the fuzzy c-means cluster algorithm and the consequent parameters of the fuzzy rules are identified using the method of least squares. Moreover, in contrast with recent studies on structure identification of the fuzzy rules, the premise variables and consequent structure in our approach can be obtained through ASM1 directly. By comparing performance with PID and dynamic matrix control (DMC) strategies, it can be seen that the fuzzy model-based predictive controller can efficiently control the dissolved oxygen with smaller overshoot and shorter settling time. The remainder of this paper is organized as follows. Section 2 briefly introduces ASM1 and the underlying WWTP. The actual modeling procedure and the model testification results are presented in Sections 3.1 and 3.2. Section 3.3 gives the controller design method and the related comparison results are given in Section 3.4. The last section of the paper presents some conclusions.

Notation: The notation used throughout the paper is fairly standard. The superscript “T” stands for matrix transposition; $\mathbb{R}^n$ denotes the n-dimensional Euclidean space; the notation $P>0$ (≥ 0) means that P is real symmetric and positive (semi-positive) definite and $A>B$ $(\geq B)$ means $A-B>0$ (≥ 0). I and 0 represent identity matrix and zero matrix, respectively. Matrices, if their dimensions are not explicitly stated, are assumed to be compatible for algebraic operations. The notation $\|\cdot\|_Q$ stands for the weighted norm, defined by $\|x\|_Q^2 = x^T Q x$ for all $x \in \mathbb{R}^n$, where Q is a positive-definite symmetric matrix.

2. Preliminaries

In order to make the results easier to understand, in this section, the relevant aspects of Activated Sludge Model No. 1 (ASM1) will be briefly introduced. Then, the underlying wastewater treatment plant (WWTP) which is designed based on the so-called Benchmark Simulation Model No. 1 (BSM1) is further given.

2.1. ASM1

As commonly considered, a well-known characteristic of ASM1 is that the matrix form is used to present the activated sludge processes (ASPs). The matrix is constructed with 13 components and these components are generally described by the following mass balance equation (see [14] for more details):

$$\frac{d\xi}{dt} = R(\xi) + \frac{Q}{V}(\xi_{in} - \xi) \tag{1}$$

where

$$\xi \triangleq [S_I \; S_S \; X_I \; X_S \; X_{BH} \; X_{BA} \; X_P \; S_O \; S_{NO} \; S_{NH} \; S_{ND} \; X_{ND} \; S_{ALK}]^T$$

is a vector gathering concentrations of the 13 components,

$$\xi_{in} \triangleq$$

$$[S_{I,in} \; S_{S,in} \; X_{I,in} \; X_{S,in} \; X_{BH,in} \; X_{BA,in} \; X_{P,in} \; S_{O,in} \; S_{NO,in} \; S_{NH,in} \; S_{ND,in} \; X_{ND,in} \; S_{ALK,in}]^T$$

stands for the concentrations of the process components in the influent water, Q is the influent flow rate, V is the reactor volume. $R(\xi)$ is the reaction rate modeled by the product of a reaction rate vector ρ and a stoichiometric matrix $\mathcal{S}$ where ρ and $\mathcal{S}$ are given in (2) and (3), respectively. For simplicity, in this paper, the notation with respect to time t or k will be dropped, e.g., ξ instead of $\xi(t)$ or $\xi(k)$ will be used, if it will not lead to ambiguity. Nevertheless, it should be kept in mind that the concentrations of the components are related to time:

$$\rho \triangleq \begin{bmatrix} \mu_H \frac{S_S}{K_S+S_S} \frac{S_O}{K_{OH}+S_O} X_{BH} \\ \mu_H \frac{S_S}{K_S+S_S} \frac{S_O}{K_{OH}+S_O} \frac{S_{NO}}{K_{NO}+S_{NO}} \eta_g X_{BH} \\ \mu_A \frac{S_{NH}}{K_{NH}+S_{NH}} \frac{S_O}{K_{OA}+S_O} X_{BA} \\ b_H X_{BH} \\ b_A X_{BA} \\ k_a S_{ND} X_{BH} \\ k_h \frac{X_S/X_{BH}}{K_X+X_S/X_{BH}} \left(\frac{S_O}{K_{OH}+S_O} + \eta_h \frac{K_{OH}}{K_{OH}+S_O} \frac{S_{NO}}{K_{NO}+S_{NO}} \right) X_{BH} \\ \rho_7 \left(\frac{X_{ND}}{X_S} \right) \end{bmatrix} \tag{2}$$