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State detection of a wastewater treatment plant

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Abstract

This paper describes a simple rule-based approach for the state detection in a biological waste water treatment plant. The plant shows bi-stable behaviour that makes its control a challenging and difficult task. The good operating point is difficult to reach and easy to lose. The approach combines the mathematical model of the plant and the available measurement information. After the state detection, the control system uses the model developed for the operation point in question and calculates the outlet substrate concentration. The approach is tested by simulations with the Chemostat -model where the kinetics follows Haldane-kinetics.

Keywords: state detection, rule-based system, wastewater treatment

1. Introduction

Due to increasing environmental requirements and the importance of reliable wastewater treatment, efficient monitoring and control methods are becoming more and more important. An adequate model enhances the understanding of the biological processes and it can be a basis for better process design, control and operation [1]. The activated sludge process is the most generally applied biological wastewater treatment method [2]. In the activated sludge process, a bacterial biomass suspension (the activated sludge) is responsible for the removal of pollutants. Within the process, numerous biochemical reactions occur, most of them with highly nonlinear dynamics. An activated sludge plant for wastewater treatment is a complex system due to its nonlinear dynamics, large uncertainty in uncontrolled inputs, model parameters and structure, multiple time scale of the dynamics, and multi input-output structure [3].

Until recently, an intensive work on physical modelling of the wastewater plant was rather separated from using these models for controller design. Recent developments triggered out new research and applications in combining physical (white-box) models with intelligent methods [2,3]. The status of technology for chemical dosing control in water treatment processes is in a relatively low level. In general, methods of dosage control can be far from ideal, leading occasionally to inefficient plant operation, occurrence of unnecessary costs and in some cases decreasing water quality [4].

The state detection of wastewater plants is considered in [5]. The two-stage anaerobic wastewater pre-treatment is modelled and controlled. The biological state of the reactors is predicted using a fuzzy logic system and based upon this, proper control actions are taken automatically. The developed control system was successfully tested on a fully automated lab scale two-stage anaerobic digester. A new general approach to the global analysis of observability and detectability for nonlinear systems is proposed in [6]. Based on the definition of indistinguishability it is possible to derive the dynamics of the non-observable part of the system and thus to study its stability properties using methods of nonlinear systems theory.

This paper describes the biological wastewater purification as a Chemostat reactor model which is used in generating data for developing the state detection algorithm and evaluating the performance of the algorithm. The state detection is based on the reactor model and a simple rule-based system utilising the fact that the process is bi-stable, i.e. it has two separate operating points.

2. The modelling approach

Chemostat is a continuous biological reactor operating with the constant feed rate. It is potentially a multi-stable system, if the substrate at high concentrations is toxic for micro-organisms [7]. Then an increase of substrate flow turns a linear behaviour into a strongly nonlinear one. Chemostat -models give an insight to real-life bioprocess systems, in particular biological water treatment. This study is based on the original model of ideally stirred Chemostat [8] adopted by [7]. The aim is to demonstrate the possibilities of the modelling and state detection of this bi-stable system.

Bioreactor feed consists of substrate and biomass. High substrate concentrations inhibit the reaction and decrease the reaction rate constant, μ, according to Haldane kinetics. Following equations describe the system

$$
\begin{aligned}
\frac{dc_s}{dt} &= \frac{Q_{in}}{V}c_{s,in} - \frac{Q_{out}}{V}c_s - \mu(c_s)c_b \\
\frac{dc_b}{dt} &= \frac{Q_{in}}{V}c_{b,in} - \frac{Q_{out}}{V}c_b + \mu(c_s)c_b \\
\frac{dV}{dt} &= Q_{in} - Q_{out} \\
\mu(c_s) &= \frac{\mu_0 c_s}{\widetilde{K}^{-1}c_s^2 + c_s + K}
\end{aligned}
\qquad (1)
$$

In Eq. (1), c_s and c_b denote the concentrations of the substrate and the biomass, Q_{in} and Q_{out} the inflow and outflow, V is the volume of the reactor, μ reaction rate and μ_0 and K are constants. Simulations use the values given in [7].

3. Simulation results

The dynamic model of the process is done using Matlab® Simulink®. Simulink® model is used in generation of data for modelling and state detection purposes. Input concentration for the substrate varies between [35 90], and for the biomass between [5 20]. The reactor volume varies between [275 325]. The variables are taken from the uniform distribution at 30 minutes intervals. Fig. 1 shows the histograms of the simulated output variables. The histograms show two separate operation areas – one at low and another at high substrate levels. Correlation analysis was performed for the generated data. It showed that there is a strong correlation between the output variables measured at the same moment. The correlations between input and output variables were reasonable between two successive moments, but the correlations fade away when the time passes. This means that in time series models we need to consider only first order models.

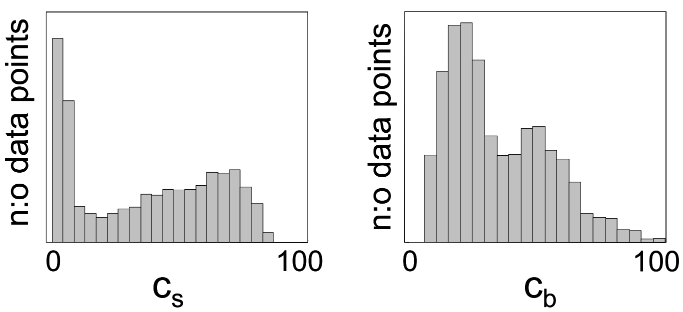

Figure 1. The histograms of the simulated output variables.

4. State detection

Next, the steady-state model corresponding to Eq. (1) is used in describing the inherent mechanism making the control of the system difficult. In steady-state conditions, biomass concentration is solved from Eq. (1). The results of that are presented in Fig. 2a, which shows the biomass concentration as a function of the substrate concentration and the reactor volume. It is clear that the biomass concentration achieves its maximum value always with the same substrate concentration. This value can be calculated analytically to be

$$c_s\left(c_{b,max}\right)=\sqrt{K\widetilde{K}^{-1}} \tag{2}$$

Fig. 2b shows the biomass concentration as a function of the input concentration and the reactor volume. The figure shows two stable (and one unstable) operating points with the same input concentration of the substrate at high reactor volumes. When volume is small, there is only one stable operating point, but the conversion and the biomass concentration remain small. Thus it is desired to operate the reactor at higher reactor volumes. With the increasing volume the process becomes more sensitive for the volume changes. Thus the risk to end up at low conversion due to volume fluctuations increases. The input concentration of biomass has similar influence to the substrate concentration.

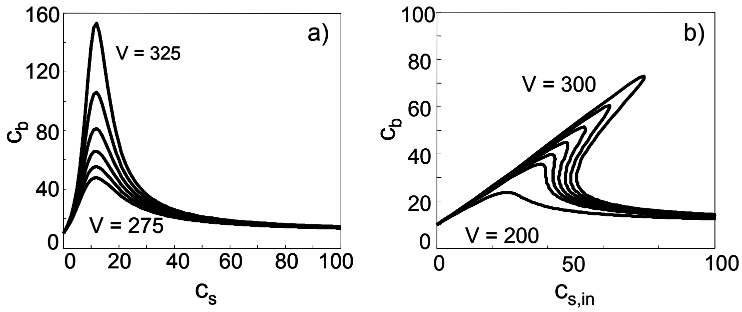

Figure 2. The biomass concentration as a function of the reactor volume and a) the substrate concentration, b) the input concentration of substrate.

The modelling is done separately for both operating points. Substrate concentration is the model output, because it is the most important variable from the monitoring and process control point of view in this case. The substrate concentration is modelled using only one previous measurement of substrate's input concentration. The first order models are accurate enough for both operating points. The sampling interval in both cases is 30 minutes. The linear regression models for the low and high conversion areas are

$$c_s(k) = 1{,}225 c_{s,in}(k-1) - 26{,}56 \tag{3}$$

$$c_s(k) = 0{,}052 c_{s,in}(k-1) + 3{,}636 \tag{4}$$

The model selection utilizes a simple rulebase derived from the generated data and knowledge obtained from the analytical model. Fig. 2b indicates that concerning the model selection three different conditions exist. The first occurs when the substrate feed is low leading to high conversion whatever the other variables are. Another occurs at high substrate feeds and leads inevitably to low conversion. In modelling, the area between these is problematic, because both operating points may be reached. Thus, two threshold values are identified from the data both being functions of the substrate and biomass input concentrations and the reactor volume. The threshold values are

$$f_1 = 0{,}6 c_{s,in} - c_{b,in} - 16 \tag{5}$$

$$f_2 = 5 c_{s,in} - 3{,}33 c_{b,in} - V + 11{,}67 \tag{6}$$

Negative values of Eq. (5) indicate that the process operates at high conversion and positive values of Eq. (6) that the process operates at low conversion. The problematic area is identified if Eq. (5) gives a positive value and Eq. (6) a negative value. Then the process operates at high conversion only if the substrate concentration in the reactor is below the value defined by Eq. (2). The corresponding rulebase is given in Table 1.

Table 1. The rulebase.

Rule	If	Then
1	$f_1 \le 0$	High conversion
2	$f_1 > 0$ AND $f_2 < 0$ AND $c_s \le$ Eq. (2)	High conversion
3	$f_1 > 0$ AND $f_2 < 0$ AND $c_s >$ Eq. (2)	Low conversion
4	$f_2 \ge 0$	Low conversion

5. Results

The performance of the model is tested with the dynamic simulator. No control is supposed and the reactor is simulated as an open loop. The testing included

500 state detections of which about 10 percent were erroneous. The correlation between modelled and actual outputs was 0.9.

The good results are inevitably due to the assumption that the model is perfect. In practise, the changes in model parameters will undoubtedly impair the performance and an updating scheme is a necessity. The biggest advantage of this approach is, however, in the simple solution and the modest requirements for the computing power. A disadvantage is that the model uses the measurement of the output concentration of substrate. In the most typical control case, this is not measured. In the future, the aim is to add a mass balance for oxygen and use that in modelling instead of the substrate concentration.

6. Conclusions

This paper describes a simple rule-based approach for the state detection in a biological waste water treatment plant. The plant shows a bi-stable behaviour that makes its control a challenging and difficult task. The good operating point is difficult to reach and easy to lose. The approach combines the mathematical model of the plant and the available measurement information of the input substrate concentration. After the state detection, the control system uses the model developed for the operation point in question and calculates the outlet substrate concentration.

The approach is tested by simulations with the Chemostat -model with no controls as an open-loop simulation. The model showed a conformity with the actual (simulated) process output, when the model is assumed perfect. In practise, model updating will be problematic when the process is changing with time, eg. when the quality of the incoming water changes.

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