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State estimation of wastewater treatment plants based on model approximation

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ABSTRACT

In this article, we consider state estimation of wastewater treatment plants based on model approximation. In particular, we consider a wastewater treatment plant described by the Benchmark Simulation Model No.1 which consists of a five-chamber reactor and a settler. We propose to use the proper orthogonal decomposition approach with re-identification of output equations to obtain a reduced-order model of the original system. Then, the reduced-order model is taken advantage of in state estimation. An approach on how to determine an appropriate minimum measurement set is also proposed based on degree of observability. A continuous-discrete extended Kalman filtering algorithm is used to design the estimator based on the reduced-order model. We show through extensive simulations under different weather conditions that the estimator based on the reduced-order model with re-identified output equations gives good state estimates of the actual process.

1. Introduction

Wastewater treatment plants (WWTPs) have been widely used to minimize the environmental impacts of wastewater and to recycle water (Han and Qiao, 2013; Qu et al., 2013). A WWTP is a nonlinear process with a few tightly coupled operating units and is subject to significant variations in inlet wastewater flow rate and composition, which pose great challenges to the development of control and monitoring schemes for WWTPs.

In the context of control, proportional-integral (PI) controllers were commonly used for WWTPs (de Araújo et al., 2011; Machado et al., 2009; Samuelsson et al., 2005). While PI control is easy to implement, it cannot handle constraints nor optimality considerations. To address these issues, various model predictive control (MPC) algorithms were used for WWTPs. Set-point tracking MPC was used to control the effluent quality considering constraints on actuators (Shen et al., 2008; 2009). MPC schemes were also used to control the dissolved oxygen concentration in WWTPs (Han et al., 2012; Holenda et al., 2008). In O'Brien et al. (2011), MPC was applied to a WWTP to reduce power usage and improve the plant efficiency. Simultaneous design and control approaches with application to wastewater treatment industrial plants were proposed based on MPC in Bahakim and Ricardez-Sandoval (2014), Gutierrez et al. (2014) and Rafiei-Shishavan et al. (2017). Applications of MPC to WWTPs were also reported in Brdys et al. (2008) and Ostace et al. (2011). In our previous work (Zeng and Liu, 2015), an economic MPC algorithm was proposed to improve the effluent quality while minimizing the operating cost. It was demonstrated in Zeng and Liu (2015) that economic MPC could improve the effluent quality and reduce the operating cost at the same time. While economic MPC is a promising control method for WWTP, there are some issues that have not been addressed including the very high computational complexity of EMPC and the associated state estimation of WWTP.

In literature, there are some results on state estimation of WWTP. In Kiss et al. (2011), a state estimation algorithm was proposed based on two-time-scale decomposition for a simplified WWTP. In Busch et al. (2013), extended Kalman filter (EKF) and moving horizon estimation (MHE) were developed for a WWTP in which a simplified settler model was used. A distributed EKF scheme comprising two local estimators was developed based on the same simplified model in Zeng et al. (2016). In Rutkowski and Brdys (2007), a hybrid parameter and state estimation algorithm was proposed for WWTPs based on a grey-box model with state-dependent parameters. However, due to the use of simplified models in the above results, some of the key performance indices used in economic MPC are not easy to calculate. In this work, we investigate state estimation of WWTPs described by the BSM1 model and propose a state estimation method based on model approximation. The proposed approach gives good state estimates and can be used in economic MPC. Also, the proposed approach has

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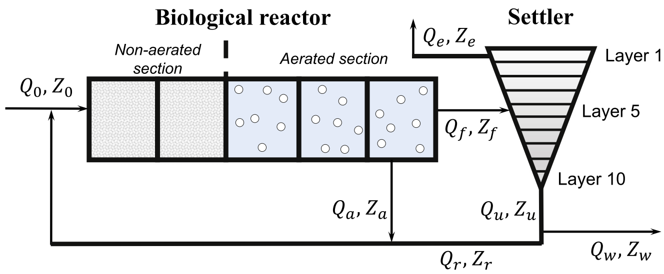

Fig. 1. A schematic of the wastewater treatment plant.

reduced computational complexity and the approach can be extended to the design of economic MPC to address the computational issue.

Specifically, the proper orthogonal decomposition (POD) approach is applied to obtain a reduced-order model that approximates the dynamics of the WWTP. Then, we use ordinary least squares to re-identify the output equations of the reduced-order model. The updated reduced-order model is then used in state estimation. An approach to determine a minimum set of measurements is also developed. Based on the obtained reduced-order model with selected measurements, we design a state estimation scheme using a continuous-discrete extended Kalman filtering algorithm. We carry out extensive simulations under different weather conditions. The results show that our proposed approach can provide good state estimates of the actual dynamics of the WWTP based on only three measurements. Moreover, the computational load of the proposed scheme is substantially reduced by comparing to the case where an EKF estimator is designed based on the full model.

The main contributions of this work include: (a) a detailed method for WWTP dynamic model reduction based on POD, (b) an output equation re-identification method that leads to reduced model-plant mismatch, and (c) an algorithm for selecting the minimum set of measurements for state estimation. Some preliminary results of this paper were reported in Yin and Liu (2018). Compared with Yin and Liu (2018), this work presents significantly extended explanations, a detailed state estimation algorithm based on a reduced-order model, results on reduced-order model validation, and significantly extended simulation results for different weather conditions.

2. Preliminaries

2.1. Notation

The operator D^{H} represents the conjugate transpose of a matrix D. D^{T} denotes the transpose of a matrix D. The operator $\Lambda(D)$ represents the set which contains all the eigenvalues of a matrix D. trace(D) returns the trace of a square matrix D. det(D) denotes the determinant of a square matrix D. $\lambda_i(D)$ indicates the ith eigenvalue of a matrix D. $\mathbb{K}_+$ represents a set that contains all non-negative integers. diag(v) is a diagonal matrix in which the elements of the vector v are on its main diagonal. For two matrices (or vectors) A and B of the same dimension, the operator $A \circ B$ denotes the Hadamard product that is calculated element by element as $(A \circ B)_{i,j} = A_{i,j} \times B_{i,j}$. When A and B are identical, the product $A \circ A$ is called the Hadamard power of A and is denoted by $A^{\circ 2}$.

2.2. Wastewater treatment process description

A schematic diagram of the WWTP based on BSM1 is presented in Fig. 1 (Alex et al., 2008). The process comprises a multi-chamber biological activated sludge reactor and a secondary settler. The biological reactor has two sections: the non-aerated section containing the first two anoxic chambers and the aerated section consisting of the remaining three chambers. More specifically, pre-denitrification reactions where nitrate is turned into nitrogen take place in the non-aerated section, while nitrification processes where ammonium is oxidized into nitrate occur in the aerated section.

Table 1
State variables of the biological reactor of the WWTP.

Definition	Notation	Unit
Inert soluble organic matter	S_I	g COD m^{-3}
Inert particulate organic matter	X_I	g COD m^{-3}
Readily biodegradable and soluble substrate	S_s	g COD m^{-3}
Slowly biodegradable and soluble substrate	X_s	g COD m^{-3}
Biomass of active autotrophs	X_{B_A}	g COD m^{-3}
Biomass of active heterotrophs	X_{B_H}	g COD m^{-3}
Particulate generated from decay of organisms	X_P	g COD m^{-3}
Particulate biodegradable organic nitrogen	X_{ND}	g N m^{-3}
Nitrite nitrogen and nitrate	S_{NO}	g N m^{-3}
Free and saline ammonia	S_{NH}	g N m^{-3}
Biodegradable and soluble organic nitrogen	S_{ND}	g N m^{-3}
Dissolved oxygen	S_O	g (-COD) m^{-3}
Alkalinity	S_{ALK}	mol m^{-3}
Total sludge concentration in settler	X	g COD m^{-3}

In this plant, wastewater with concentration Z_0 is fed into the first chamber of the biological reactor at flow rate Q_0. A portion of the effluent of the last aerobic chamber goes to the settler at flow rate Q_f and the rest is recycled back (inner recycle) to the first chamber at flow rate Q_a. The settler includes 10 nonreactive layers. The 5th layer is the feed layer. The outlets of the settler consist of three parts: (a) the overflow of the settler that contains purified water removed consecutively through the first layer at flow rate Q_e; (b) a portion of the underflow of the settler fed back into the first chamber at flow rate Q_r; (c) the other portion of the underflow removed from the settler at flow rate Q_w. In this model, eight basic biological reaction processes are considered, and 13 major compounds are taken into account in these reactions. The concentrations of the 13 compounds in the five chambers are the state variables of the model of the biological reactor. The 13 state variables for each chamber are shown in Table 1. The dynamics of the settler is modeled based on mass balances of the sludge considering solid flux due to gravity (Takács et al., 1991). Based on the BSM1 model, there are in total 145 states that capture the dynamics of the process. A detailed description of the WWTP model and the process parameters can be found in Alex et al. (2008).

The effluent quality (EQ) and the overall cost index (OCI) are two common criteria for assessing the performance of WWTPs. Detailed descriptions of EQ and OCI are given in Alex et al. (2008) and Zeng and Liu (2015). In practice, it may be challenging to calculate the values of the two indices directly due to the difficulty in measuring some of the states that explicitly affect the indices. From a state estimation perspective, EQ and OCI can be approximated by using the estimates of the process dynamics.

2.3. Available measurements for state estimation

For the WWTP, we consider that there are in total 49 measurements available for state estimation. In each chamber of the reactor, eight states/state-related variables are measurable (Alex et al., 2008; Busch et al., 2013), including the oxygen concentration, the concentration of free and saline ammonia (i.e., NH3 and $NH4^{+}$), nitrate and nitrate nitrogen concentration, alkalinity concentration, COD, filtered chemical oxygen demand (denoted as COD_f), BOD. In the secondary settler, the concentrations of oxygen, free and saline ammonia, nitrate and nitrate nitrogen, and alkalinity in the top and the bottom layers, as well as the filtered chemical oxygen demand