RESPIROMETRY ESTIMATIONS BASED MONITORING OF BIOLOGICAL WASTEWATER TREATMENT PROCESSES

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Abstract: A method is presented to monitor wastewater treatment processes by incorporating multivariable principal component analysis (PCA) with the knowledge of respirometry estimations. Respirometry is the measurement of an activated sludge respiration which reflects the oxygen rate consumed by biomass, and can be estimated from dissolved oxygen concentrations. Because dissolved oxygen concentrations which are available at most plants have the quick response time and easy maintenance, respirometry estimations based monitoring strategy has advantages for the fault detection. The improvement of some fault detection indexes are demonstrated through IWA's Benchmark simulations.

Keywords: Waste treatment, Monitoring, Estimation, Water pollution, Environment engineering.

1. INTRODUCTION

Process monitoring is implemented to ensure that process outputs comply with requirements on product quality, operation safety and efficient use of resources. With the enforcement of even stricter rules on discharges and applications of computer data-collection systems, it is interested in operation monitoring of wastewater treatment plants (WWTP) in recent years. Difficulties such as variably operating conditions, correlation, non-linearity, multi-time scale are often encountered when engineers deal with these data of wastewater treatment plants.

Process monitoring, that is fault detection, isolation and diagnosis, have gained successful applications in petrochemical industry (Kourti and MacGregor, 1996; Venkatasubramanian, 2001). Rosen (1998) and Rosen and Olsson (1998) summarized the data pretreatment methods, multivariable principal component analysis (PCA) and partial least squares (PLS) algorithm for monitoring of WWTP. Rosen and Lennox (2001) presented a methodology that is Bakshi's (1998) wavelet multi-scale analysis in combination with multivariable principal component analysis. Lennox and Rosen (2002) worked further, which an adaptive PCA method is adopted for the changing mean and deviation of process variables or disturbances. Teppola et al (1998) focused on monitoring of paper's wastewater treatment plants.

Analysis instruments are often installed at the entrance and the exit of wastewater because of restriction of investments and operation costs, and the assay time interval of other variables is about 1-2 hour(s). The insufficient of sampling data and the multi-scale sampling times is a challenge problem for WWTP monitoring. The practical usability of analysis instruments is not considered adequately (Lennox, 2002). So for on-line fault detection and diagnoses, more effective process monitoring methods are needed. On the other hand, it is noticed that dissolved oxygen sensors are used widely with sampling times in seconds. By measuring dissolved oxygen (DO) concentrations and further numerical computations, respirometry can be estimated. Respirometry can not only reflect the consumption rate of oxygen in activated sludge, but also is an indication of substrate degradation extent and the ability of microorganism metabolism. Because DO sensors have advantages in stability, quickness and low cost, hence on-line process monitoring based on respirometry (Spanjers, et al, 1998) or respirometric-titrimetric (Gernaey, et al, 2001) may be more practical.

In this work, respirometry measure principles are introduced. Then by making a general of mass balance and numerical differential, respirometry is estimated and combined with conventional data matrix of PCA to form one kind of hybrid PCA model. More mechanism information is added to PCA model and it is helpful to establish economical and quick on-line process monitoring strategies. Finally the approach to monitoring Benchmark of biological wastewater treatment processes is given and the improvement of some fault detection indexes is demonstrated.

2. RESPIROMETRY MEASUREMENT PRINCIPLES

Respirometry is the measurement of the respiration and interpretation of the biological oxygen consumption rate under well-defined experimental conditions. Although the principle of the respirometry measurement is simple, the restriction of some uncertain factors, such as the phase where oxygen concentration is measured and whether or not there is input and output of liquid and gas must be take into account carefully. The respiration rate is calculated by making a general mass balance for oxygen over the liquid phase as follows.

$$\frac{dS_o}{dt} = \frac{Q_{in}}{V}(S_{o,in} - S_o) + K_L a(S_o^0 - S_o) - r_o \quad (1)$$

Where S_0 is the dissolved oxygen concentration in liquid phase (mg/l), Q_{in} is flow rate of liquid entering the system (l/min), $S_{o,in}$ is dissolved oxygen concentration entered into the liquid phase, K_La is oxygen transfer coefficient (l/min), S_O^0 is saturated dissolved oxygen concentration, r_o is oxygen uptake rate (OUR) (mg/l·min), V is liquid volume of the respirometer. There are many kinds of methods to calculate respirometry in literatures.

3. RESPIROMETRY ESTIMATIONS

Besides using a respirometer to measure respirometry, theoretically, in virtue of measuring dissolved oxygen concentrations in liquid, then Eq.1 based to calculate consuming rate of oxygen is an alternative approach. Here the differential estimation value of S_o needs to be constructed by the numerical differential based on the measured values of S_o. The simplest method is to calculate with backward differential. In this work, three point numerical differentiation formula is used to calculate the differential value of S_o

$$\begin{cases} \dfrac{dS_O(t-\Delta t)}{dt} = \dfrac{1}{2\Delta t}(-3S_O(t-\Delta t) + 4S_O(t) - S_O(t+\Delta t)) \\ \dfrac{dS_O(t)}{dt} = \dfrac{1}{2\Delta t}(-S_O(t-\Delta t) + S_O(t+\Delta t)) \\ \dfrac{dS_O(t+\Delta t)}{dt} = \dfrac{1}{2\Delta t}(S_O(t-\Delta t) - 4S_O(t) + 3S_O(t+\Delta t)) \end{cases} \quad (2)$$

Noticed this numerical differential needs to be dealt with for on-line monitoring strategies. When a new measured point is added, together with the former two measured values, three differential values can be obtained according to Eq.2. Since every measured value has been cited three times during recursive computations, there are three corresponded differential estimation values at every interval time. Theoretically, it is difficult to select one from three. Since this research aims at fault diagnosis, selecting the minimum at every point is as estimations of the numerical differential.

4. PCA INCORPORATING WITH EXTERNAL INFORMATION

There are three approaches to fault detection and isolation based on a first principle model, a data-driven empirical modeling and the knowledge inference. In the aspect of fault detection, the multivariable statistical analysis approach is proved very valid. For complicated processes, because of fault coupling and propagation, it is difficult to isolate the source of faults. Model based is the direct description of common-causal variations. When used in fault diagnosis, the main problem is that development of model, especially modeling the plant-wide needs large cost. Intuitively, combined partial relations such as mass balances and reaction dynamics with PCA model, though such knowledge may be not complete, it is possible to enhance some functions of FDI (Yoon and MacGregor, 2001).

Given the data matrix X (n×m), the data obtained from other equations can be appended to some rows or some columns of X.

$$X = GMH^T + BH^T + GC + E \quad (3)$$

Here, G(n×p) represents observed information matrix, augmented p columns in data matrix; H (m×q) represents variable information matrix, augmented q rows in data matrix; E is error matrix, coefficient matrix M, B, C have corresponding dimensionality, and need to be estimated, the detailed derivation can refer to Yoon and MacGregor (2001). In this paper, it is based on mass balance relationship to predication new estimated variables that is augmenting column in the data matrix. For example, at some observation time, the measured data matrix X_m(n>m) has been obtained, for the data matrix X_e (n×m_1, m_1<m) gained by mechanism relationship estimation, it can be constructed as follows:

$$X = [X_m \mid X_e] \quad (4)$$

For the augmented matrix X, various PCA modeling can be carried through. Also the output data matrix Y can be augmented in PLS.

$$Y = [Y_m \mid Y_e] \quad (5)$$

If it is PCA model originally, that is there is no output data matrix Y_m, when the output data matrix Y_e is augmented, PCA problem is converted into PLS. A key step is if such data matrix X_e or Y_e can be found to improve some specific index of PCA or PLS.

5. PCA MODEL OF BENCHMARK

The Benchmark WWTP (Alex, et al, 1999) designed by IWA and COST 624 has proven very useful for the evaluation of control strategies developed for N removal wastewater treatment plants. Biological reactor with a total volume of 5999 m^3 is subdivided into five well-mixed compartments in series with a 10-layer secondary settling tank which volume is 4000 m^3. Denitrification takes place in former two anoxic reactors, while later three aerated reactors serve for carbon removal and nitrification. Tuning airflow can control dissolved oxygen concentrations of aerated tanks. IWA's Activated Sludge Model No.1 (ASM1) (Henze, et al, 1987) and the double exponential setting velocity function (Takács, et al, 1991) are chosen as a representation of reactors and settling processes separately.

The Benchmark contains 145 state variables. There are 13 component variables which are (1) readily biodegradable soluble substrate S_S, (2) biodegradable particulate material X_S, (3) slowly biodegradable soluble material S_I, (4) slowly biodegradable particulate material X_p, (5) slowly biodegradable inert material X_I, (6) heterotrophic biomass X_{BH}, (7) autotrophic biomass X_{BA}, (8)oxygen S_o, (9) NH_4^++NH_3 nitrogen S_{NH}, (10) soluble biodegradable organic nitrogen S_{ND}, (11) particulate biodegradable organic nitrogen X_{ND}, (12) nitrate and nitrite nitrogen S_{NO}, and (13) Alkalinity S_{ALK}. In these components, S_{NH}, S_{NO}, S_o, and S_{ALK} are measurable known at present. Others can not be measured directly. Although there are so many variables, that used for monitoring are a few. In the secondary settler, what can be considered are only those state variables physically measurable and relating with effluent. In Lennox's (2002) study, the following variables were chosen to form PCA model: (1) NH_4^+ concentration of influent, NH_{4i}, (2) influent wastewater flow, Q_i, (3) total solid suspended matter in reactor 3, TSS_3, (4) effluent NH_4^+ concentration, NH_{4e}, (5) effluent nitrate concentration, NO_{3e}, (6) total suspended solids of effluent, TSS_e (7) Alkalinity in effluent, S_{ALKe}; (8) total suspended solids of return sludge, TSS_u (9-12) oxygen in reactors 1-4, $S_{o1\text{-}4}$. When TSS_3 and NO_{3e} cannot be measured online, it is needed to develop the new monitoring methodology.

As described in introduction, the consumption of oxygen is related to the degradation extent to the substrate. Using the oxygen concentration and respirometry estimation inside reactors as monitoring variables to form PCA model may have more advantages in quickness and applicability. Simulations given in next section verified such ideas. In this study, following practical measurable variables are chosen to form PCA model: (1-4) oxygen in reactors 1-4 $S_{o1\text{-}4}$, (5-8) respirometry estimations in reactors 1-4, $r_{o1\text{-}4}$, (9) influent flow, Q_i, (10) influent NH_4^+ concentration, NH_{4i}, (11) effluent NH_4^+ concentration, NH_{4e}. Three principal components are retained to represent about 90 percent data variances.

6. SIMULATIONS

Components of the influent are time-varied and various. It cost high to monitor by the online analysis and assay. After abnormal influent to the process, biological reacts are not only complicated in mechanism, but also the main biochemical index, such as biochemical oxygen demand (BOD), changed slowly. Once the living environment suitable for biomass is disturbed, the effluent quality will be affected in a long time. So, to monitor and discover various abnormalities come from inlet looks very important. Here two abnormal states are evaluated, that is: (1) the normal operation is impacted by violent variations in influent flow Q_0 caused by rain event; (2) Metabolism of autotrophic biomass in activated sludge reactors is impacted by the toxin pulse in influent. It can be described by amendment to μ_A in ASM1:

$$\mu_A' = \begin{cases} \mu_A & \text{other time} \\ 0.2\mu_A & 216.667 \le t < 216.667 + 6 \quad \text{hr} \end{cases} \tag{6}$$

(1) Monitoring the abnormal of influent flow Q_0.
Thought the storm event do not emerge constantly, great influences on WWTP operations are observed. Storm will directly force influent flow and components to vary drastically. Thought the control system can give corresponding action, or the operator can take some measures to keep away, however when attack is serious and the duration is long, it is needed to predict automatically as soon as possible, so as to maintain stationary operating. Results are shown in Fig.1. PI controller at reactor 5 controls DO concentration at the set-point, $S_{o,\,sp}$=2.0g/m^3.

(2) Monitoring toxin pulses of influent
Toxin pulse lasts 6 hours. The variation of μ_A would affect the activity of autotrophic biomass directly. Because of the control action and mass cycle, states variations observed practically were not so remarkable. From figures (Lennox, 2002), only S_{NO} varied evidently. So, when nitrate-measuring device is not installed in the outlet, it is not easy to diagnose the latent influence of toxin pulse using process monitoring strategies based on common PCA. It will be valid to combined PCA approach with other process knowledge. The results of diagnosing toxin

pulse emergence using the PCA model proposed in this paper are shown in Fig.2. 48 minutes after toxin pulse emerged, the predicted error square index SPE and *Hotelling* T^2 statistics performance were all exceed their confidence interval, bar chart showed the predicted errors of 11 variables in PCA model at this time. It not only need nitrate-measuring device by means of conventional approach, but the toxin pulse emergence can be diagnosed only after 4.5 hours.

7. CONCLUSION

On-line monitoring strategy incorporated respirometry estimation knowledge with multivariable principal component model is presented for WWTP. Respirometry estimations only need to measure dissolved oxygen concentrations inside activated sludge reactors and some related flow signals. Because DO consumption is related to the activity of biomass and the extent of substrate degradation, moreover it is universal to install dissolved oxygen concentration devices and flow meters which have quick response, stable operation, and easy maintenance at wastewater treatment plants, so it has advantages in the efficiency of fault detection and practicability to form the process monitoring strategy based on respirometry estimations. Using this new strategy for monitoring benchmark of IWA, some statistics index varied significantly and diagnosis could be given timely when two typical abnormal conditions on flow variation caused by rain event and toxin pulse of influent. It is the further work to estimate respirometry and oxygen transfer coefficients at the same time.

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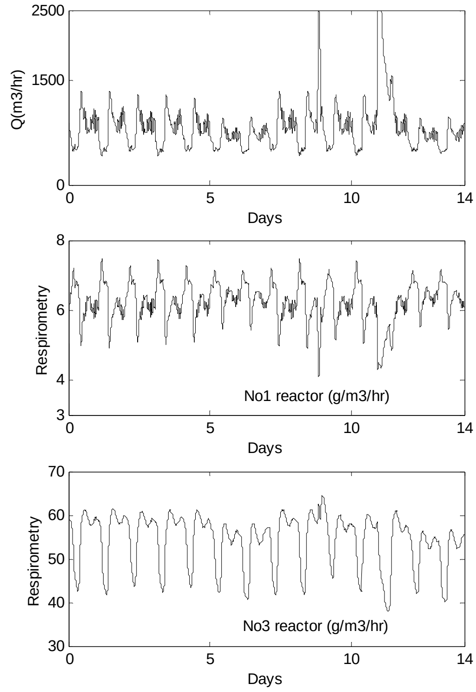

Fig. 1 monitoring storm events by PCA combined with respirometry estimations: variables

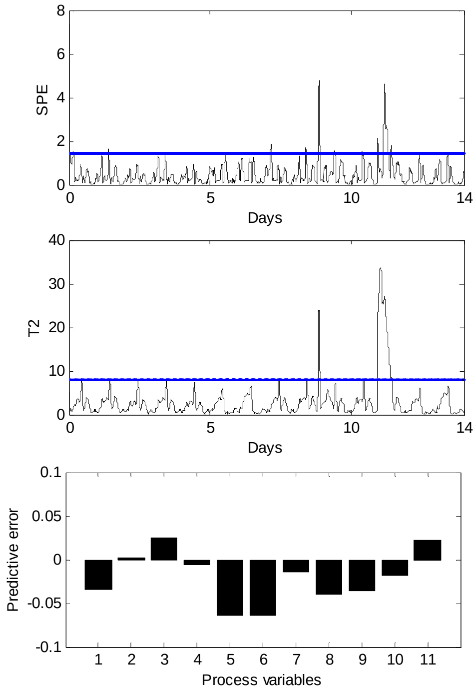

Fig. 1 monitoring storm events by PCA combined with respirometry estimations: indexes

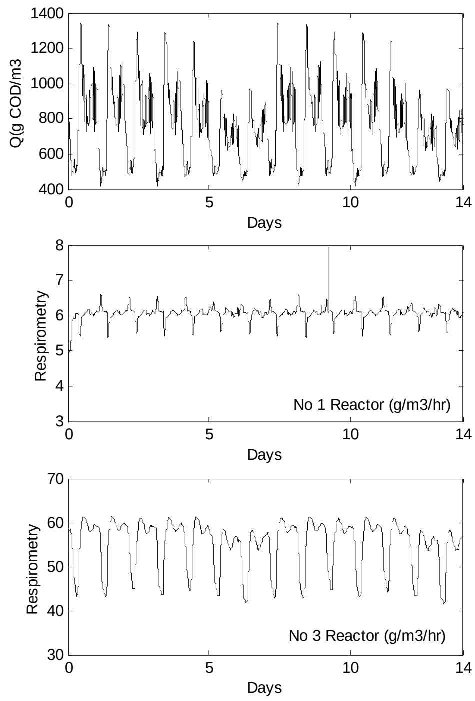

Fig. 2 monitoring toxin pulse by PCA combined with respirometry estimations: variables

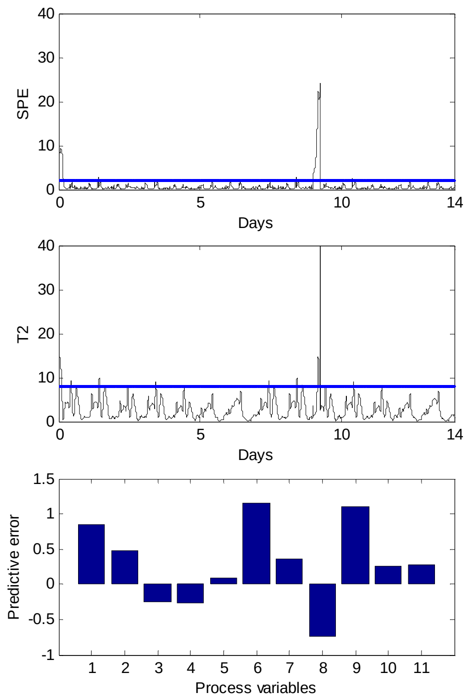

Fig. 2 monitoring toxin pulse by PCA combined with respirometry estimations: indexes