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Fault detection of sensors in aeration control systems - the airflow ratio method --Manuscript Draft--

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Fault detection of sensors in aeration control systems – the airflow ratio method

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Abstract: In this paper, we consider the problem of detecting sensor faults in the aeration system of an activated sludge process. The purpose is to detect possible faults in dissolved oxygen and air flow sensors. The dissolved oxygen in each aerated zone is assumed to be controlled automatically. As the basis for a fault detection algorithm we propose to use the ratio of air flow rates into different zones. The method is evaluated by using the Benchmark Simulation Model no¹ (BSM1) by Monte Carlo simulations.

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INTRODUCTION

The problem of fault detection occurs when one wishes to determine, by processing available data, whether or not a system has been subjected to a change (fault). It is also often of interest to determine the most likely nature of a possible change. This is the diagnosis part.

Detection of sensor faults in wastewater treatment plants (WWTPs) is becoming important since the numbers of on-line sensors used in the plants are steadily increasing. The sensors are used for automatic control (eg. feedback and feedforward control) and monitoring of plant performance. A necessary condition for a control system to work efficiently is that the sensor used in a control law is reliable. If a sensor used in a feedback control strategy gives an incorrect value, too much resources (eg. energy for aeration) may be used or the treatment results may be poor (eg. high concentrations of ammonia in the effluent). The use of hardware redundancy, e.g. multiple sensors for the same variable, reduces the problem of a sensor fault, but a high hardware redundancy is expensive and introduces a higher complexity in the system. Instead of multiple sensors, analytical methods of detecting sensor faults can be used (Olsson and Newell, 1999).

As the variables in a WWTP are both cross-correlated and autocorrelated (Teppola, 1999) one should consider both these aspects when designing a sensor fault identification algorithm (Lee et al, 2006). Before the data analysis begins it is also important to perform data screening. If there are corrupted measurements such as outliers, missing values and noise, this should be dealt with (Rosen and Olsson, 1998). Many different approaches have been suggested for fault detection of biological processes. Yoo et al. (2002) propose a modified PCA considering the importance of each transformed variable and not only the relative magnitude of the variance change. Baggiani and Marsili-Libelli (2009) show that a dynamic PCA-based algorithm also can be used with success in order to detect sensor failures in WWTPs. Ciavatta et al. (2004) demonstrate that a Recursive Prediction Error (RPE) algorithm can be a powerful tool when assessing drift in an oxygen sensor. Fragkoulis et al. (2011) used a system model and a bank of adaptive observers to generate fault

sensitive residual. Corominas et al. (2010) present a comparison of different univariate fault detection methods (Shewhart, EWMA, and residuals EWMA) applied to the simulated results of the Benchmark Simulation Model No.1 long-term (BSM1_LT), where the sensor fault detection was studied in sensors under closed loop control. This problem poses special challenges, if a sensor signal is used in feedback control law, a fault in the sensor may not be visible from the sensor signal itself since the controller strive to keep the (possible faulty) sensor signal equal to the set point.

In this paper, the problem to detect sensor faults in the aeration system of an activated sludge process is considered. In particular, faulty dissolved oxygen (DO) sensors under closed loop control. As the basis for the fault detection algorithm we propose to use the ratio of air flow rates into different zones. The reason is that these ratios are less dependent on the influent load compared to using the individual air flow rates.

METHODS

The airflow method (AM)

One method to detect faulty DO sensors in several aerated basins is by monitoring the airflow rate in every basin. In this method, a sensor fault in basin i is decided if $\bar{q}_i(t) < a_i$ or $\bar{q}_i(t) > b_i$, where a_i and b_i are the minimum and maximum bounds respectively, defined as:

$$a_i = \alpha_{min} \cdot \min\{\bar{q}_i(t)|_{t \in A}\}; \quad b_i = \alpha_{max} \cdot \max\{\bar{q}_i(t)|_{t \in A}\}$$

where $\bar{q}_i(t)$ is a low-pass filtered value of the airflow rate into basin i , α_{min} and α_{max} are factors used to define the lower and upper thresholds, respectively. A is the set of data in non-faulty conditions.

The Airflow Ratio Method (ARM)

The ARM calculates bounds on airflow ratios during normal (non-faulty) conditions and uses these bounds to detect sensor faults. Consider a process with N aerated basins, a sensor fault is decided if:

$$f_{i,j}(t) > \gamma_{i,j}, \quad \text{for } i = 1, 2, \dots, N; \quad j = 1, 2, \dots, N \quad (i \neq j)$$

where $f_{i,j}(t) = \bar{q}_i(t)/\bar{q}_j(t)$, $\bar{q}_i(t)$ is a low-pass filtered value of the airflow rate into basin i . The threshold value is defined by $\gamma_{i,j} = \alpha_{i,j} \cdot f_{i,j}^{max}$, where $\alpha_{i,j}$ is the threshold factor. $f_{i,j}^{max} = \max\{\bar{q}_i(t)/\bar{q}_j(t)|_{t \in A}\}$ is the maximum airflow rate ratio in non-faulty conditions. In this study we use $\alpha_{i,j} = 1.05$.

Simulation model

Simulations are performed in BSM1 (Copp 2002), but with closed loop control of the DO sensors in basin 3 to 5. For simplicity, we use $K_L a$ as a measure of the air flow rate. The BSM1 is extended to include faults in the DO sensor (class A), following the fault modelling given by Corominas et al. (2010).

Simulated fault scenarios

The system is simulated for different DO sensor fault scenarios (positive and negative sensor bias and sensor drifts), faults location and weather influent files defined in

BSM1. For three aerated zones we will have six possible ratios ($f_{i,j}$). In order to estimate the detection delay and false alarms, Monte Carlo simulations varying the fault occurrence are made. In this abstract we only present results of one fault scenario, a positive bias of 0.5 mg O₂/l in the DO-sensor. Supplementary results can be found in Carlsson et al. (2013), where the effect of changes in the noise standard deviation and the influence of the threshold parameters have been studied.

RESULTS AND DISCUSSION

Figure 1 depicts in detail the ratio ($f_{4,5}$) for the case of a fault in basin 5. It can be seen that the variable ($f_{4,5}$) exceeds the threshold after the fault and a sensor fault is therefore decided. The time delay in the detection (t_{delay}) is indicated.

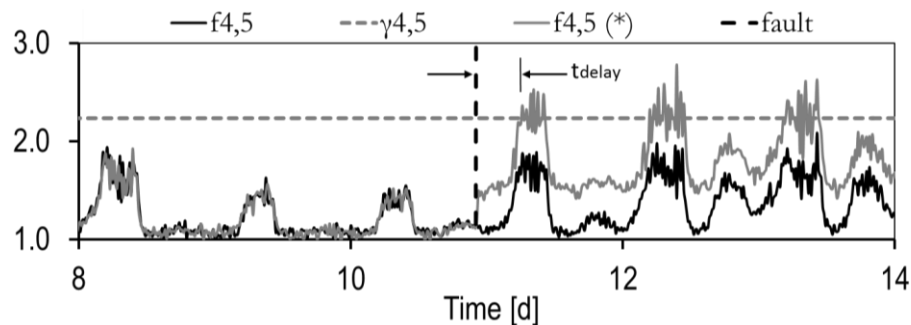


Figure 1. Ratio behavior. $f_{4,5}$ is the ratio in normal conditions (black), $f_{4,5}(*)$ is the ratio in faulty conditions (gray). Fault occurrence (dashed black), threshold $\gamma_{4,5}$ (dashed gray).

The effect of a bias fault in the DO sensor was studied considering different influent conditions (dry, rain and storm) and different location of the fault (basin 3, 4 and 5). A total of 20 simulations were done for every scenario. The results are shown in Table 1.

Influent	Basin	Method	t_{delay} [d]	FD [%]	FA [%]
Dry	3	AM	-	0	0
		ARM	0.17 +/- 0.16	100	0
	4	AM	2.90 +/- 2.18	100	0
		ARM	0.38 +/- 0.30	95	5
	5	AM	3.28 +/- 2.72	50	10
		ARM	3.29 +/- 2.99	95	0
Rain	3	AM	0.78 +/- 0.71	50	0
		ARM	0.10 +/- 0.11	100	0
	4	AM	8.74 +/- 3.47	60	0
		ARM	0.28 +/- 0.29	95	5
	5	AM	5.27 +/- 4.61	50	0
		ARM	4.60 +/- 4.19	70	0
Storm	3	AM	2.12 +/- 1.27	60	0
		ARM	0.11 +/- 0.12	100	0
	4	AM	6.05 +/- 4.09	70	5
		ARM	0.26 +/- 0.24	95	5
	5	AM	4.09 +/- 2.30	40	0
		ARM	5.33 +/- 3.05	60	0

FD = percentage of successful fault detections; FA = false alarm frequency

It can be seen that, compared to AM, ARM gives better results in terms of time delay in the fault detection and also in the total amount of fault detections. The amount of false alarms in both methods was similar.

CONCLUSIONS

A fault detection method, ARM, has been proposed for detection of faults in DO sensors in a serie of aerated zones. The DO in each zone is assumed to be controlled. In a simulation study, ARM shows promising results for correct and early fault detection. Eventually, it will not be possible to distinguish between a fault in a DO sensor and in air flow rate sensor. In this study, we have, for simplicity, used K_{La} as a measure of the air flow rate. In practice an air flow rate sensor should be used. An interesting alternative is to use the air valve position instead of the airflow rate.

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REFERENCES

- Baggiani, F., and Marsili-Libelli, S. 2009 Real-time fault detection and isolation in biological wastewater treatment plants. *Water Science and Technology*, **60**(11), 2949–2961.
- Carlsson, B., Zambrano, J. 2013 Fault detection of sensors in aeration control systems – the airflow ratio method. Technical report available on www.it.uu.se/research/publications.
- Ciavatta, S., Pastres, R., Lin, Z., Beck, M.B., Badetti, C. and Ferrari, G. 2004 Fault detection in a real-time monitoring network for water quality in the lagoon of Venice (Italy). *Water Science and Technology*, **50**(11), 51–58.
- Corominas, L., Villez, K., Aguado, D., Rieger, L., Rosén, C. and Vanrolleghem, P. 2010 Performance evaluation of fault detection methods for wastewater treatment processes. *Biotechnology and Bioengineering* **108**(2), 333–344.
- Copp, J. B. (ed.) 2002 The COST Simulation Benchmark-Description and Simulator Manual. Office for Official Publications of the European Communities, Luxembourg.
- Fragkoulis, D., Roux, G., and Dahhou, B. 2011 Detection, isolation and identification of multiple actuator and sensor faults in nonlinear dynamic systems: Application to a waste water treatment process. *Applied Mathematical Modelling*, **35**, 522–543.
- Lee, C., Choi, S. W. and Lee, I. B. 2006 Sensor fault diagnosis in a wastewater treatment process. *Water Science and Technology*, **53**(1), 251–257.
- Olsson, G. and Newell, B. 1999 *Wastewater Treatment Systems – Modelling, Diagnosis, and Control*, IWA Publishing, London, UK.
- Rosen, C. and Olsson, G. 1999 Disturbance detection in wastewater treatment plants. *Water Science and Technology*, **37**(12), 197–205.
- Teppola, P. 1999 *Multivariate Process Monitoring of Sequential Process Data – A Chemometric Approach*. PhD thesis, Department of Chemical Technology, Lappeenranta University of Technology, Lappeenranta, Finland.
- Yoo, C.K., Choi, S.W. and Lee, I. 2009 Disturbance detection and isolation in the activated sludge process. *Water Science and Technology*, **45**(4–5), 217–226.