Fault detection and isolation of sensors in aeration control systems
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ABSTRACT

In this paper, we consider the problem of fault detection (FD) and isolation in the aeration system of an activated sludge process. For this study, the dissolved oxygen in each aerated zone is assumed to be controlled automatically. As the basis for an FD method we use the ratio of air flow rates into different zones. The method is evaluated in two scenarios: using the Benchmark Simulation Model no. 1 (BSM1) by Monte Carlo simulations and using data from a wastewater treatment plant. The FD method shows good results for a correct and early FD and isolation.

Key words | activated sludge, aeration control, fault detection, incidence matrix, monitoring

INTRODUCTION

Fault detection (FD) and isolation is an active area of research due to the increasing complexity of industrial processes and the growing demand for safety and reliability; the wastewater treatment plants (WWTPs) are not an exception. Besides the monitoring, the sensors are used for automatic control (e.g. feedback and feedforward control) 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 this sensor gives a wrong value, too much resources (e.g. energy for aeration) may be used or the treatment results may be poor (e.g. high concentrations of ammonia in the ef fluent). The use of hardware redundancy (e.g. multiple sensors for the same variable) reduces the problem of a sensor fault, but is expensive and introduces complexity to the system.

Many different approaches have been suggested for FD applied to single or multiple variables in biological processes. Yoo et al. (2002) propose a modified principal component analysis (PCA) considering the importance of each transformed variable and not only the relative magnitude of the variance change. Baggiani & Marsili-Libelli (2009) show a dynamic PCA-based algorithm that can detect sensor failures in WWTPs. Corominas et al. (2011) present a comparison of different univariate FD methods (Shewhart, EWMA, and residuals EWMA) applied to the long-term Benchmark Simulation Model no. 1 (BSM1_LT), where the sensor FD 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 strives to keep the (possibly faulty) sensor signal equal to the set point.

In this paper, the problem of detecting and isolating sensor faults in the aeration system of an activated sludge process (ASP) is considered and, in particular, faulty dissolved oxygen (DO) sensors under closed loop control. As the basis for the FD method, we use the ratio of airflow rates into different zones. The method is evaluated using two case studies: the Benchmark Simulation Model no. 1 (BSM1) by Monte Carlo simulations and a full-scale WWTP.

The paper is organized as follows. First, two methods for detecting faults in DO sensors are outlined. Next, two case studies are described and the results from the methods are shown. Finally, there is a discussion and conclusions are drawn.

MATERIAL AND METHODS

Consider an ASP with \( N \) aerated zones. The DO in each aerated zone is assumed to be controlled automatically. The airflow \( q_i(t) \) in every zone is known.

The airflow method

One method to detect faulty DO sensors in several aerated zones is by monitoring the airflow rate in every zone. For
airflow method (AM), a sensor fault in zone \( i \) is decided if:
\[
\bar{q}_i(t) < a_i \quad \text{or} \quad \bar{q}_i(t) > b_i; \quad \text{for} \quad i = 1, 2, \ldots, N
\]
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 zone \( i \). \( \alpha_{\min} \) and \( \alpha_{\max} \) are threshold factors used to define the lower and upper bounds, respectively. \( A \) is a set of data in non-faulty conditions.

**The airflow ratio method**

Airflow ratio method (ARM) calculates bounds on airflow ratios during non-faulty conditions and uses these bounds to detect sensor faults. For ARM, a fault is decided if:
\[
f_{ij}(t) = \frac{\bar{q}_i(t)}{\bar{q}_j(t)} > \gamma_{ij}; \quad \text{for} \quad i, j = 1, 2, \ldots, N; \quad i \neq j
\]
where \( \gamma_{ij} = q_{ij}^{\max} \) is a threshold calculated in non-faulty conditions. \( q_{ij}^{\max} \) is a threshold factor.

This structure gives a *fault signature*, i.e., given \( N \) zones in series, the response of the vector \( \phi = [\varphi_{1,1}; \cdots; \varphi_{ij}; \cdots; \varphi_{N,N-1}] \) is linked to the fault isolation in zone \( i \). Applications of the fault signature can be found in, for example, Fagarasan & Iliescu (2008), which is used as a tool for isolating the fault source.

The fault signature for every scenario can be ordered in an *incidence matrix*. Application of incidence matrix in biological processes has been used for isolation of multiple actuators and sensor faults in a wastewater treatment process (Fragkoulis et al. 2011). Table 1 shows the incidence matrix for the case of \( N = 3 \) zones in series. We use the notation \( DO_j \) for the DO sensor in zone \( j \).

**Evaluation of the FD methods**

In order to evaluate the performance of the FD methods, the following indexes are used:
\[
FD = \left( \frac{1}{M} \sum_{k=1}^{M} n_{FD}^k \right) \cdot 100;
\]
where \( n_{FD}^k = \begin{cases} 1 & \text{if } t_{\text{fault}}^k < t_d < t_{\text{end}} \\ 0 & \text{otherwise} \end{cases} \) (4)
\[
FI = \left( \frac{1}{M} \sum_{k=1}^{M} n_{FI}^k \right) \cdot 100;
\]
where \( n_{FI}^k = \begin{cases} 1 & \text{if } t_d < t_i < t_{\text{end}} \\ 0 & \text{otherwise} \end{cases} \) (5)
\[
FA = \left( \frac{1}{M} \sum_{k=1}^{M} n_{FA}^k \right) \cdot 100;
\]
where \( n_{FA}^k = \begin{cases} 1 & \text{if } t_d < t_{\text{fault}}^k \\ 0 & \text{otherwise} \end{cases} \) (6)

where \( FD, FI \) and \( FA \) are the percentage of FDs, fault isolations and false alarms (FA), respectively. \( t_{\text{fault}}, t_d, t_i \), and

<table>
<thead>
<tr>
<th>Fault</th>
<th>( t_1 )</th>
<th>( t_2 )</th>
<th>( t_3 )</th>
<th>( t_4 )</th>
<th>( t_5 )</th>
<th>( t_6 )</th>
<th>( t_7 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative bias in DO1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Negative bias in DO2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Negative bias in DO3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Positive bias in DO1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Positive bias in DO2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>1</td>
<td>0</td>
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<tr>
<td>Positive bias in DO3</td>
<td>0</td>
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<td>0</td>
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<td>0</td>
<td>0</td>
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</tr>
</tbody>
</table>
The evaluation of this case study involved a random generation of the fault occurrence, which was evaluated via Monte Carlo simulations as described in the following steps.

Step 1: A set of dynamic simulations are executed for the three different influent events in non-faulty conditions. In this step, the threshold values (at and bi for AM, γij for ARM) are calculated.

Step 2: An influent event (dry, rain or storm) and a faulty DO sensor (3, 4 or 5) are selected. Set the simulation counter k = 1.

Step 3: BSM1 is simulated for 150 days in order to reach steady-state conditions.

Step 4: A dynamic simulation is performed during 21 days. During the simulation, it is defined that the time of the fault event may occur between day 7 and 14. The fault occurrence is generated randomly from a probability distribution over these days.

Step 5: If the kth run is lower than M (total of simulations), set k = k + 1 and go to Step 3. Otherwise, go to Step 2.

Case study 2: real data from a WWTP

The FD methods were tested in a full-scale WWTP located in Stockholm, Sweden. In this case, the setup consisted on three aerated zones of one treatment line. The DO in each aerated zone was automatically controlled. The valve position was used as the monitored variable for the FD methods. The data were collected using a sampling time of 6 minutes.

By default, the threshold values for AM (ai ; bi) and for ARM (γij) were calculated with α = 1.1 (10% over the maximum values given in non-faulty conditions). M = 20 total of simulation runs were executed for every influent event and faulty zone. Regarding the threshold factor α, the setting of this value assumes a uniform distribution of fij(t) in the interval [0 ; fij max].

RESULTS AND DISCUSSION

Case study 1: BSM1

As an example, a bias of +1 mgO2/l was applied to the DO sensor in zone 5 (DO5), which has the fault signature [φ3,4; φ3,5; φ4,5; φ5,3; φ5,4] = [0; 1; 0; 1; 0]. This means that only the ratios f3,5 and f4,5 are greater than their correspondent thresholds. Figure 1 shows the profile of these ratios in non-faulty and faulty conditions.

Case study 1: synthetic data from BSM1

The BSM1 (Copp 2002) was selected as the simulation platform. The BSM1 includes model, plant layout (five-compartment activated sludge reactor consisting of two anoxic tanks followed by three aerobic tanks), control systems and a benchmark procedure. The system was simulated using the MATLAB/Simulink® platform. Three different dynamic influents were considered: dry, rain and storm. The simulation time was extended from 14 to 21 days in order to have some more days for the FD evaluations. The DO feedback PI-control in zone 5 was also applied to zones 3 and 4. Every control loop has a set-point of 2 mgO2/l. The nitrate feedback PI-controller in the second anoxic compartment is kept as by default.

The implementation of the faults was assessed based on the approach developed by Corominas et al. (2011) and previous work from Rosen et al. (2008). The DO sensors belong to class A, with a response time of 1 minute, a measurement range of 0–10 mgO2/l and a noise standard deviation of 0.25 mgO2/l. Currently, no air flow model is defined in BSM1. For simplicity, K4,5 was selected as the monitored variable.

tend are the time of the true fault occurrence, the FD time, the fault isolation time, and the total evaluation time, respectively. M refers to the total number of simulation runs, k refers to the kth simulation.

The delay involved in the FD and fault isolation decision is taken into account. For AM, since the FD time is equal to the fault isolation decision time, both decisions have the same delay. This is not the case for ARM, since the FD and fault isolation decision are made separately. Therefore, FD index (IFD) and fault isolation index (IFI) are defined:

\[ I_{FD} = \left( 1 - \frac{1}{M_{\text{end}}} \sum_{k=1}^{M} \frac{t_{\text{FD}}^{(k)}}{t_{\text{end}}} \right) \cdot 100; \]

where \( t_{\text{FD}}^{(k)} = \begin{cases} \Delta d & \text{for correct FD} \\ t_{\text{end}} & \text{otherwise} \end{cases} \) \tag{7} \]

\[ I_{FI} = \left( 1 - \frac{1}{M_{\text{end}}} \sum_{k=1}^{M} \frac{t_{\text{FI}}^{(k)}}{t_{\text{end}}} \right) \cdot 100; \]

where \( t_{\text{FI}}^{(k)} = \begin{cases} \Delta l & \text{for correct FI} \\ t_{\text{end}} - t_{\text{fault}}^{(k)} & \text{otherwise} \end{cases} \) \tag{8} \]

where \( \Delta d = t_{\text{end}} - t_{\text{fault}}^{(k)} > 0 \) is the FD delay, and \( \Delta l = t_{l} - t_{\text{fault}}^{(k)} > 0 \) is the fault isolation delay.
Note in Figure 1 that $f_{4,5}$ is the first ratio above the threshold, thus a sensor fault is decided. The second ratio above the threshold is $f_{3,5}$, thus a fault in DO5 is decided. Note the delay in the FD ($\Delta t_d$) and fault isolation ($\Delta t_i$).

The same faulty condition was evaluated by Monte Carlo simulations. Results are shown in Table 2. Note that AM and ARM give similar results in terms of the amount of FD, isolations and FA. However, taking into account the time needed for isolation, the index $IFI$ shows better results for ARM. It follows that, in general, the time needed for fault isolation is lower for ARM than for AM.

The effect of different levels of bias was also studied, from $\pm 0.25$ to $\pm 1$ mgO$_2$/l, including the non-faulty condition (0 mgO$_2$/l). Figure 2 shows the percentage of FDs and FA for this evaluation.

The sensitivity analysis for the bias given in Figure 2 shows that ARM has a higher rate of FDs compared to AM. As expected, both methods give similar performance for high bias level ($\pm 1$ mgO$_2$/l). This performance decreases when the bias is $\pm 0.25$ mgO$_2$/l, which is the range of the noise standard deviation defined for the sensor modeling in non-faulty conditions.

**Case study 2: full-scale WWTP**

Figure 3 shows an example of the results obtained in the WWTP. In this case, a bias of $-0.5$ mgO$_2$/l was applied to the DO sensor in the second zone at $t_{\text{fault}} = 44.43d$; the valve position was monitored before and after the fault occurrence.

Observe that for AM, it is the valve position in the second aerated zone (V2) that crosses the threshold (giving $t_d = 44.94d$). For ARM, it is first the ratio V2/V1 (giving $t_d = 44.52d$) and then V2/V3 (giving $t_i = 44.56d$) that cross the thresholds. Hence, as indicated in Table 1, by using these two ratios, a fault in the second zone can be decided. Note that ARM gives fault isolation earlier than AM.

Since AM and ARM are FD methods based on monitoring the manipulated variables, this indirect way of monitoring makes the delay in the FD depend on the moment at which...
the fault occurs. For example, for ARM, if there is a fault in DO\textsubscript{i} sensor, the delay in the FD will be shorter/longer if the corresponding \( f_{i,j} \) ratio is close to its maximum/minimum value. The same analysis applies for AM.

Note that case study 1 used \( K_{La} \) as the monitored variable, whereas case study 2 used the valve positions. In practice, the difference in the performance of a given method using ratios calculated from the valve position or...
from the airflow will depend on the way these variables are related. If this relation is linear, then the results using the ratios of airflows or ratios of valve position will be similar.

Many of the current WWTP include individual monitoring of airflow and valve position in every aerobic zone. However, this is not always the case: some plants may only include measurement of the total airflow used in multiple zones and/or basic valves installed (which do not provide valve position measurement). Then, in order to implement AM and/or ARM, additional instrumentation in the individual zones would be required.

CONCLUSIONS

This study shows the performance of a simple FD method, ARM, developed in order to detect and isolate faults in DO sensors during closed loop control. The new approach is compared with AM, which monitors the aeration in every zone. Three aerated zones in a series are used as case studies, applying the method to the BSM1 and to a full-scale WWTP.

Both AM and ARM can be used for FD and isolation, although simulation and experiments showed that ARM gives better performance. In this respect, the definition of indexes for FD and isolation allowed quantifying and comparing the methods, taking into account not only the number of detections but also the time delay involved.

Although ARM was designed assuming that the flowrates change due to a fault in DO sensors, it is expected to get a fault indication if the process conditions change much from the condition the method is trained for. Nevertheless, any such alarm could be of valuable information to the operator, notifying that something is deviating and needs to be investigated.

The method can be extended in several ways, including the following.

- In many plants there are a number of parallel lines, each with a number of aerated zones. A natural extension of ARM is then to compute the ratios between zones in different lines.
- If there is a significant time delay in the air flows into different zones, this delay may be adjusted by calculating the ratio in Equation (3) as:

\[ \frac{\bar{q}_i(t)}{\bar{q}_j(t - \tau)} \]

where \( \tau \) is an estimate of the time delay between zone \( i \) and \( j \). This may improve the performance of the detection.

Note, however, that in order to calculate Equation (9) a time delay is unavoidable. An interesting topic for further research is to compare Equation (3) with (9) for systems with significant hydraulic delays.

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