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Fault detection of DO sensors subject to possible clogging

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Summary of key findings

This work deals with fault detection of DO sensors under possible clogging condition. The detection of the clogging condition is performed using two fault detection (FD) methods. Method 1 detects changes in the distance between signal spectra and method 2 detects changes in the signal standard deviation. Both FD algorithms are based on the likelihood ratio test implemented in a recursive decision rule. Real data from a dissolved oxygen (DO) sensor located in an aerated basin of an activated sludge process is used as case study. The sensor is used in a closed loop control. Results show that both methods give a quite similar detection results. Hence, in this case study, it seems sufficient to just monitor the standard deviation of the sensor signal. Before making any confirmative conclusions more experiments are, however, needed.

Background and relevance

In the last decades, the high complexity of industrial processes and the growing demand for safety and reliability has promoted an increase in the research activity concerning fault detection (FD) methods both for single and multiple sensor scenarios (see, for example, Zhang and Jiang, 2008). Wastewater treatment plants (WWTPs) are not an exception, the increasing stringent in the effluent standards and a more efficient operation of the plants make sensor FD an important aspect. In wastewater treatment applications, dissolved oxygen (DO) sensors are widely used both for monitoring and automatic control (e.g. feedback and feedforward control) of plant performance. It is recognized that the energy need for aeration could be decreased considerably by using DO control. Nowadays, DO control is standard in many WWTPs and DO sensors are used in almost 100% of the full scale plants. Therefore, fault detection of DO sensors is a crucial task in plant operation.

The development of a FD method is closely related to the behaviour of the fault to detect. In general, the fault behaviour belongs to one of the following types: bias, drift, outliers, change in noise level, permanent and missing value. Although clogging is a common situation in the operation of many sensors, this fault has not had enough attention in our opinion. Some observations have, however, been previously reported: Rosen and Olsson (1998) qualitatively described how the noise of the influent ammonia concentration sensor of a WWTP increases significantly, which might indicate poor sensor performance. They also suggested that the examination of the variance of the raw signal would not be enough, since there are variations in the signal apart from the noise that must be analysed. Schraa et al. (2006) reported that changes in the noise level of a sensor signal may indicate that the sensor is dirty, malfunctioning, or could be affected by a certain disturbance in the process. A different approach was given by Clarke and Fraher (1996), showing a model-based method to detect and correct faulty measurements in DO sensors subject to an induced fouling. Corominas et al. (2011) compared different univariate FD methods (e.g., Shewhart, Exponentially Weighted Moving Average (EWMA), residual EWMA) using the Benchmark Simulation Model No.1 long-term (BSM1_LT) in different scenarios. One scenario involved faults applied to a DO sensor under closed loop control of an aerated zone and monitoring the K_La (i.e., airflow). This problem poses special challenges, since if a sensor signal is used in a feedback control loop, a fault in the sensor may not be visible from the sensor signal itself because the controller strive to keep the (possible faulty) sensor signal equal to the set point.

Methods

Problem formulation Let y_k denotes a discrete-time random sequence obtained from sampling a sensor signal at the time instant $t = kT_s$, where $k = 1,2, \dots$, and T_s is the sampling time. It is assumed that y_k is Gaussian distributed with mean μ and standard deviation σ. Its probability density function is $p(y_k) = e^{-(y_k-\mu)^2/2\sigma^2}/\sigma\sqrt{2\pi}$, denoted by $\mathcal{N}(\mu, \sigma^2)$. The problem consists in the detection of any significant change in the dynamics of y_k when the sensor is subject to clogging situation. A parameter v related to the dynamics of y_k is assumed to belong to one out of two conditions:

$$\begin{array}{ll} H_0 : \mathrm{v} = \mathrm{v}_0 & \text{(Non-faulty condition)} \\ H_1 : \mathrm{v} = \mathrm{v}_1 & \text{(Faulty condition)} \end{array} \qquad (1)$$

To decide between H_0 and H_1 in (1), two FD methods based on a recursive decision rules (Basseville and Nikiforov, 1993) are outlined

$$\varepsilon_k = \begin{cases} \varepsilon_{k-1} + s_k & \text{if } \varepsilon_{k-1} + s_k > 0 \\ 0 & \text{if } \varepsilon_{k-1} + s_k \leq 0 \end{cases} \qquad (2)$$

where $\varepsilon_0 = 0$ is set as the initial value, and $s_k = \ln\left(p_{\mathrm{v}_1}(y_k)/p_{\mathrm{v}_0}(y_k)\right)$. An alarm time is obtained when $\varepsilon_k > h_{\max}$, where $h_{\max}$ is a predefined threshold.

Method 1 Let r_k^ϕ denotes a sequence computed by

$$r_k^\phi = \left\{\sum_\omega \left|\hat{\phi}_0(\omega) - \hat{\phi}_1(\omega)\right|\right\}\Big|_k \ , \ k = 1; 2; \dots \qquad (3)$$

where $r_k^\phi \geq 0$ is the distance between two spectra densities $\hat{\phi}_0$ and $\hat{\phi}_1$. Let assume that r_k^ϕ follows a Gaussian distribution $\mathcal{N}(m, \sigma_\phi^2)$, where m and σ_ϕ are the mean and standard deviation, respectively. If the spectra densities are equal (or very similar), r_k^ϕ will be equal (or close) to zero. Otherwise, $r_k^\phi > 0$. Since the aim is to detect a change in the distance between signal spectra, this can be done by detecting a change in the mean value of the sequence r_k^ϕ. The log-likelihood ratio test (see Nikiforov et al., 1993) assuming a change in the mean m of the distribution $\mathcal{N}(m, \sigma_\phi^2)$ gives

$$s_i = \frac{(m_1 - m_0)}{\sigma_\phi^2}\left[r_i^\phi - \frac{(m_0 + m_1)}{2}\right] \qquad (4)$$

where m_0 and m_1 are the mean value in non-faulty and possible faulty condition, respectively. Replacing (4) in (2), a recursive rule ε_k^ϕ is obtained. A sensor fault is decided if

$$\varepsilon_k^\phi > h_\phi \qquad (5)$$

where $h_\phi = \alpha_\phi \max\left(\varepsilon_k^\phi\right)\Big|_{1 \leq k \leq T_0}$ is a threshold value, α_ϕ is a threshold factor, $\max\left(\varepsilon_k^\phi\right)\Big|_{1 \leq k \leq T_0}$ is the maximum ε_k^ϕ obtained in non-faulty conditions, and T_0 is a predefined time to compute the threshold.

Method 2 In this method, the changing parameter is the standard deviation σ of the signal y_k (see problem formulation). Then, the log-likelihood ratio test gives

$$s_i = \ln\left(\frac{\sigma_0}{\sigma_1}\right) + \frac{(y_i)^2}{2}\left(\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}\right) \qquad (6)$$

where $\sigma_{(.)}$ is estimated from the data by first removing its mean value. Then, replacing (6) in (2), a recursive rule ε_k^σ is obtained. A sensor fault is decided if

$$\varepsilon_k^\sigma > h_\sigma \qquad (7)$$

where $h_\sigma = \alpha_\sigma \max(\varepsilon_k^\sigma)|_{1 \leq k \leq T_0}$ is a threshold value, α_σ is a threshold factor, and $\max(\varepsilon_k^\sigma)|_{1 \leq k \leq T_0}$ is the maximum ε_k^σ obtained in non-faulty conditions.

Results

A DO sensor installed in one of the aerated zones of a treatment line in a full-scale WWTP in Bromma, Sweden (see Figure 1.1a) is used as case study. The sensor is used to automatically control the DO concentration in the aerated zone by changing the valve position of the aeration system (see Figure 1.1b). The experiment consisted in stopping the periodical cleaning of the sensor (to promote clogging situations) so to evaluate the FD methods.

The sensor sampling time was $T_s = 6$ minutes. For Method 1, a parametric method assuming an autoregressive (AR) model with 4 parameters was implemented, where the AR-parameters were estimated using the Yule-Walker method (see details in Stoica and Moses, 2005).

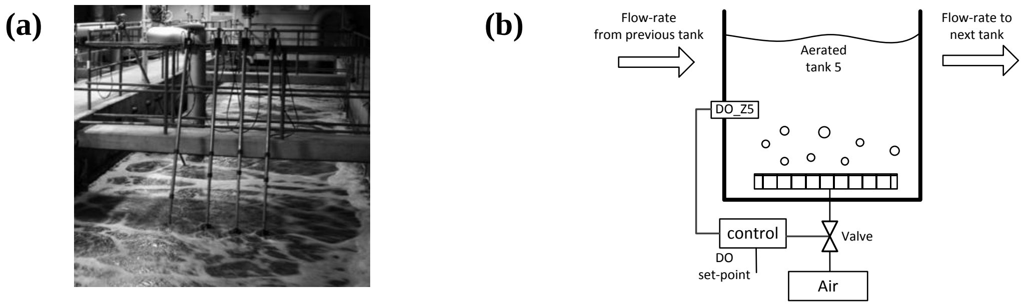

Figure 1.1. (a) Picture of sensors in an aerated tank of the WWTP; (b) DO control loop.

For detecting faults, a moving window of 6 hours ($N = 60$ samples) for collecting the sensor signal was used. $\alpha_{\phi} = \alpha_{\sigma} = 1.1$ (10% over the maximum value of $\varepsilon_k^{(\cdot)}$ given in non-faulty conditions) were set as threshold factors. $T_0 = 4$ days was used to compute the thresholds values h_{ϕ} and h_{σ}. The response at the end of the evaluation time (see Figure 1.2) suggests possible faulty situations. The gradual increase in the aeration and valve position toward maximum values around days 25th-27th is manifested by a clear increase in both ε^{ϕ} and ε^{σ}, which suggests the beginning of a faulty condition. Around days 28th-29th the DO sensor value starts to decrease, due to the feedback this gives an increase of the valve position and the aeration level, revealing a severe clogging situation in the sensor. This is also shown by an increase in both ε^{ϕ} and ε^{σ}.

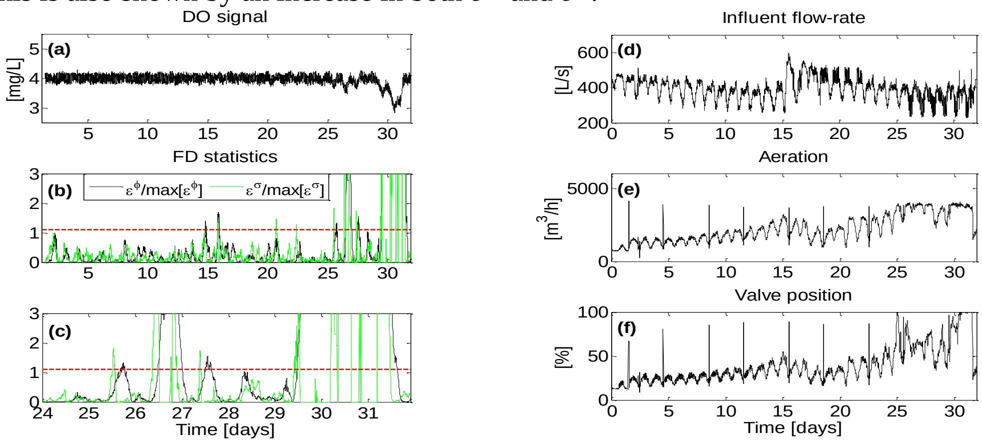

Figure 1.2. Response of the experiment: (a) DO signal; (b) FD statistics; (c) Zoom of last days in Figure (b); (d) Influent flow-rate to the basin; (e) Aeration in the tank; (f) Valve position of the aeration in the tank.

Discussion

In this trial, both methods show a quite similar behaviour (see Figures 1.2b and 1.2c). Therefore, it is in this example sufficient to use the classical method of monitoring the standard deviation of the sensor signal. Before making any confirmative conclusions, evaluations from more experiments are, however, needed. None of the proposed methods are by themselves able to distinguish between faults in the sensor, in the airflow/valve position or in the process. In order to get a more comprehensive diagnosis of the problem, additional information about the rest of the process is required.

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