Watermatex 2015
9th IWA Symposium on Systems Analysis and Integrated Assessment
14-17 June 2015, Gold Coast, Australia

Sensor fault detection methods applied on dissolved oxygen sensors at a full scale WWTP

Andersson, S.*, Hallgren, F.*
*IVL Swedish Environmental Research Institute, P.O. Box 210 60, 100 31 Stockholm, Sweden.
(Email: sofia.andersson@ivl.se, fredrik.hallgren@ivl.se)

Keywords: fault detection; sensor; wastewater

Summary of key findings

In this work, fault detection algorithms have been designed and validated in a full scale plant with promising results for both single and multiple sensors, measuring dissolved oxygen in a wastewater treatment plant. The single sensor method is based on monitoring the sensor's response to automatic cleaning. With this method clogging of the sensor, despite the automatic cleaning, was detected within a drift of less than 1 mgO_2/l compared to a reference sensor, with only one false alarm during 80 days of experiment. The multi-signal fault detection method is based on Principal Component Analysis (PCA), and is able to detect deviations due to sensor clogging. Both methods were considered possible to implement at a full scale plant to provide the operators with additional information of sensor performance in order to improve the operation of the plant. The simpler single sensor fault detection method was faster than the multi-signal method.

Background and relevance

In a wastewater treatment plant (WWTP) large amounts of data are generated from on-line sensors. With more and more stringent discharge limits together with demands on energy efficient operation, the reliability of sensors used in control activities are of great importance. Sensors in the activated sludge process of a WWTP are in a hostile and biologically active environment, making them susceptible to e.g. drifts and clogging. Especially, dissolved oxygen (DO) sensors are important since the concentration is greatly affecting both the treatment efficiency and controlling one of the most energy consuming posts of the plant: the blowers used for aeration of the basins. A faulty DO sensor can therefore cause both reduced treatment efficiency and excessive energy consumption.

Multivariate Statistical Process Control (MSPC) techniques such as Principal Component Analysis (PCA) has proven useful for both fault detection and isolation (Dunia & Qin, 1998; Baggiani & Marsili-Libelli (2009); Villez et al., 2009; Zhang et al., 2010) and can be considered an important tool to aid in the interpretation and decision making process of the plant engineer.

In this work, algorithms for detecting the drift of a clogged DO sensor has been developed and tested in a full scale WWTP. PCA has been used for multi-signal fault detection and were compared to a simpler single sensor fault detection method.

Method

The developed algorithms were tested on optical DO sensors placed in the aerated zones of one of the biological treatment lines at Bromma WWTP, Sweden. The sensors were all equipped with automatic cleaning with air. Despite the automatic cleaning, clogging of the sensors still occurs and manual cleaning is normally carried out about every other week.

The sensor used for the single sensor method was automatically cleaned with air every 100 minutes for 10 seconds. The cleaning results in a temporary increase in DO concentration, much like an impulse response. A change in the shape of the response was assumed as indication of clogging of the sensor. For each cleaning event the time constant (T) of the response, i.e. the time it takes to reach 63% of total amplitude, was calculated and compared to upper and lower threshold values obtained from a period when the sensor was measuring correctly. The criterion for fault was set to three consecutive values of T outside the established range.

The single sensor method was tested in two types of conditions: (1) the DO sensor used for controlling the aeration was kept clean in order to have a constant DO in the basin and (2) the DO sensor used for controlling the aeration was allowed to get clogged and thus controlling the aeration based on faulty measurements. Each test was initiated by manually cleaning the sensors, after that only automatic cleaning was used for the evaluated sensor.

For the PCA model, a training set consisting of four weekly datasets spread over the year was used in order to cover the different operational modes of the process during summer and winter. In the PCA model, the DO concentrations and corresponding air flow rates of the five aerated zones in the treatment line were used as variables.

In order to test the PCA model, two experiments were carried out, each initiated by manually cleaning all sensors. Then the automatic and manual cleaning of one of the DO sensors in the basin was cancelled in order to allow the sensor to get clogged and thus controlling the aeration based on faulty measurements. For fault detection, the DModX (residual distance, root mean square) was used and a threshold value (Dcrit, critical distance) was used to define the maximum tolerable distance of DModX. Dcrit was chosen at 95% confidence interval in the evaluation and the threshold for fault detection was set to 1.5 times DCrit.

Results

Results from the single sensor fault detection during the two different conditions are presented in Figure 1.1.

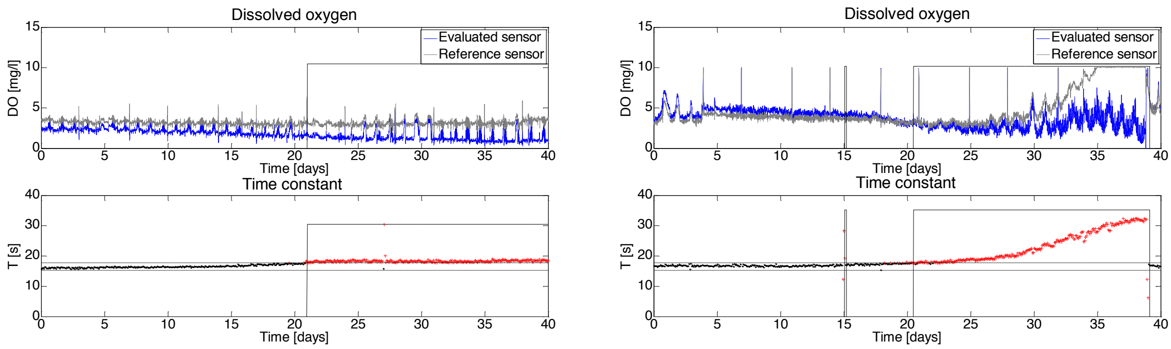

Figure 1.1 Dissolved oxygen (upper plots) and time constant (lower plots). Left: a clean sensor is controlling the aeration, keeping the DO concentration constant. Right: a clogged sensor controlling the aeration. The reference sensor was cleaned manually and automatically throughout the tests. The dashed lines in the lower plots mark the upper and lower threshold values for the time constant. Three consecutive values outside the normal range trigger a fault detection flag (black line). Fault is detected after about 21 days in both tests. One false alarm occurred at day 15 during the second test (right lower plot).

With a clean controlling sensor, a drift to lower concentrations can be noted for the evaluated sensor (upper left plot in Figure 1.1). When the controlling sensor was not cleaned and thus getting clogged with time, the drift in the DO measurements by the evaluated sensor is not as obvious due to compensation in aeration. However, a deviation compared to the reference is apparent towards the end of the period (upper right plot in Figure 1.1). In both tests, fault is detected after 21 days when the time constant (T) is above the upper threshold.

As there is a difference between the evaluated sensor and the reference measurements throughout the tests, the drift has been estimated by comparing the two measurements at the start of the trial and the difference at the time when fault is detected. The drift of the evaluated sensor compared to the reference was -0.62 mgO_2/l during the first test and -0.8 mgO_2/l during the second test. After manually cleaning of the sensor at day 39 during the second test, the method shows non-faulty values. The indication of fault at day 15 is considered a false alarm.

Regarding the multi-signal sensor fault detection method, the PCA model correctly detected the clogging during the validation period. The measured DO concentration was about 4-6 mgO_2/l lower than the reference at the time for fault detection. During the second period, the model gave out a few false alarms (Figure 1.2). During fault detection, the variable contributing the most to DModX, was the air flow rate in the experiment zone.

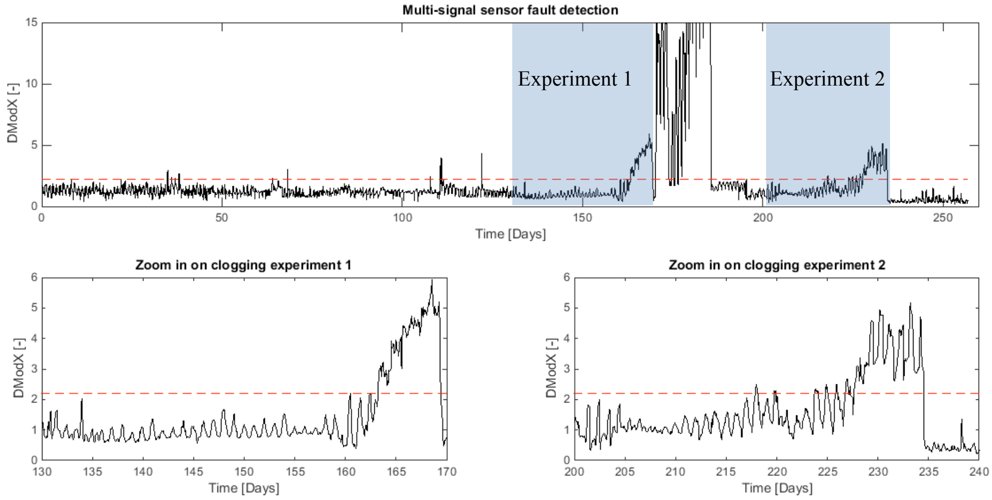

Figure 1.2 DModX for the PCA model. Manual cleaning of the experiment sensor was carried out on day 131 and day 169 of during experiment 1 and on day 201 and day 234 during experiment 2. The fluctuations in DModX are related to daily variations in influent load which is affecting the oxygen demand.

The performance of the DO sensor fault detection methods are summarized in Table 1.1.

Table 1.1 Summarized performance of the fault detection methods.

	Method			
	Single sensor fault detection		**Multi-signal sensor fault detection**	
Test scenario	Controlling sensor cleaned	Controlling sensor clogging	Controlling sensor clogging (experiment 1)	Controlling sensor clogging (experiment 2)
Time to fault detection[1]	21 days	21 days	33 days	28 days
Sensor drift[2] at fault detection	-0.8 mgO_2/l	-0.6 mgO_2/l	-4.7 mgO_2/l	n.a.
False alarms	0	1	0	2
Diagnostic interval	100 minutes		60 minutes	

1. From last manual cleaning. 2. Compared to reference sensor.

Discussion

The fault that has been studied in this work is clogging of a sensor, which normally is happening continuously and rather slowly. As a result of this, the selection of the threshold value becomes critical for how fast a fault is detected. For the multi-signal sensor fault detection in particular it is a compromise between how fast a fault can be detected and the risk for false alarms.

The advantage of the single sensor fault detection is mainly its simplicity and it could easily be implemented in the sensor. It has been shown to be far more robust to external process deviations, or abnormal situations compared to the multi-signal method. It has also shown no correlation between fault detection and specific DO concentration. This is important in order to be a useful complement to the WWTP’s monitoring and control system, which will send alarms on values above or below set limits of DO. The results from the multi-signal sensor fault detection was valid throughout the experiments, however, the process deviations were large at the time for fault detection. The PCA model detected the fault much later than the single sensor fault detection method.

Acknowledgements

The authors acknowledge funding support under the European Union's Seventh Framework Programme managed by the Research Executive Agency (REA) http://ec.europa.eu/research/rea (FP7/2007_2013), Grant Agreement N.315145 (Diamond).

References

Baggiani, F. & Marsili-Libelli, S. (2009). Real-time fault detection and isolation in biological wastewater treatment plants. Water Science & Technology, 60 (11), 2949-2961.

Dunia, R. & Qin, S.J. (1998). Joint diagnosis of process and sensor faults using principal component analysis. Control Engineering Practice, 6 (4) (), 457-469.

Villez, K., Steppe, K. & De Pauw, D.J. (2009). Use of Unfold PCA for on-line plant stress monitoring and sensor failure detection. Biosystems Engineering, 103 (1), 23-34.

Zhang, Y., Zhou, H. & Qin, S.J. (2010). Decentralized Fault Diagnosis of Large-scale Processes Using Multiblock Kernel Principal Component Analysis. Acta Automatica Sinica, 36 (4), 593-597.