Sensor validation and reconciliation for a partial nitrification process

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C.K. Yoo*,, K. Villez*, I.B. Lee**, S. Van Hulle* and P.A. Vanrolleghem***

*BIOMATH, Ghent University, Coupure Links 653, B-9000 Gent, Belgium

**School of Environmental Science and Engineering/Dept. Chem. Eng., POSTECH, San 31 Hyoja-Dong, Pohang, 790-784, Korea (E-mail: *ckyoo@postech.edu*)

Abstract Wastewater treatment plants (WWTP) are notorious for poor data quality and sensor reliability due to the hostile environment in which the measurement equipment has to function. In this paper, a structured residual approach with maximum sensitivity (SRAMS) based on the redundancy of the measurements is used to detect, identify and reconstruct single and multiple sensor faults in a single reactor for high activity ammonia removal over nitrite (SHARON) process. SRAMS is based on inferences, which are insensitive to the faults in the sensor of interest and sensitive to faults in the other sensors. It is used for four types of sensor failure detection: bias, drift, complete failure and precision degradation. The application of sensor validation shows that single and multiple sensor faults can be detected and that the fault magnitude and fault type can be estimated by the reconstruction scheme. This sensor validation method is not limited by the type or application of the considered sensors. The methodology can thus easily be applied for sensor surveillance of other continuously measuring sensors and analysers.

Keywords Data reconstruction; fault detection and identification; nitrogen removal; sensor validation and reconciliation; smart sensor

Introduction

Biological nitrogen removal from wastewater with high nitrogen loads can become a major cost, particularly when the wastewater contains only small amounts of biologically degradable carbon compounds (Abeling and Seyfried, 1992). The single reactor for high activity ammonia removal over nitrite (SHARON) process in combination with the anaerobic ammonium oxidation (Anammox) process has demonstrated its efficiency and flexibility in the treatment of sludge digestion wastewater, which is characterised by high concentrations of ammonia nitrogen. In comparison with conventional N-removal, the coupled SHARON and Anammox processes in theory result in a 60% reduction of the stoichiometrically required oxygen, while no carbon source needs to be added and sludge production is negligible (van Dongen *et al.*, 2001). The successful combination of the SHARON and Anammox processes is, however, highly dependent on the control of the nitrite/ammonia ratio in the effluent of the SHARON process (Volcke *et al.*, 2005). However, the SHARON process is highly nonlinear, time-varying, fast-responding and sensitive to disturbances such as hydraulic changes, influent composition changes and equipment failures (Van Hulle *et al.*, 2005). Although operators might be aware of poor performance, they are in general unable to find the causes or to predict the performance in time to correct the operation successfully due to the lack of any effective form of real-time monitoring. Moreover, WWTPs are notorious for poor data quality and sensor reliability due to the hostile environment in which the measurement equipment has to function (Rosén *et al.*, 2003). Regarding the aforementioned characteristics, the pursuit of suitable strategies for fault detection and sensor validation is a crucial step in the development of advanced process control systems for the SHARON process.

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To ensure correct operation of control systems, the measurement and control equipment in WWTPs must be mutually consistent. For monitoring quality standards, a high accuracy is needed, but only low demands are set on the time-scale. In control applications, on the other hand, a high measuring frequency and a short response time are essential (Rieger *et al.*, 2003). Process operators obtain information on the current process conditions from a range of sensor types. Hence, the accuracy of sensors is crucial to successful process control and monitoring, and the ability to detect sensor faults is very useful, especially in processes that are monitored and controlled based on process information from many sensors. Faulty sensors that are either completely or partially failing (hard fault or soft fault) provide incorrect information for monitoring and control. This can be detrimental to decision schemes that are based on, or supported by, on-line measurements. A complete sensor failure disables access to the relevant measurement. Monitoring or control based on the measurement is then infeasible. Bias, drift or precision degradation of a sensor signal, in fact partial failure of the sensor, causes the accuracy and reliability of the measurement to decrease, which may result in an erroneous control action and false perception of the performance of the monitored system or component. Therefore, prompt detection of the occurrence and correct identification of the location of sensor faults and reliable reconstruction (or recovery) of faulty sensors is of primary importance for efficient operation (Wang and Chen, 2004). In this paper, a sensor reconciliation method using maximum sensitivity based on the redundancy of the measurements is used to detect, identify and reconstruct faulty sensors in a biological process.

Methods

Numerous methods have been developed for fault detection and isolation (FDI). Generally, these methods fall into one of three broad categories: analytical redundancy, knowledge-based methods and measurement aberration detection (Kourti *et al.*, 1995; Dunia *et al.*, 1996; Qin and Li, 1999, 2001; Yoo *et al.*, 2003, 2004). Whereas FDI is relatively well established, sensor fault detection and validation is quite a new research area, which is required in hostile wastewater treatment but has few application results (Rieger *et al.*, 2004). In this paper, we used a structured residual approach with maximised sensitivity (SRAMS) for the detection and identification of faulty sensors using a normal, quasi-steady state process model suggested by Qin and Li (1999).

Principal component analysis (PCA)

Sensor validation based on statistical models relies on the use of normal process data to build process models (Qin and Li, 1999). Principal component analysis (PCA) models are predominantly used to extract variable correlation from data. PCA decomposes the data matrix ($\mathbf{X}$), which contains m sensors and N samples for each sensor into a score matrix $\mathbf{T}$ and a loading matrix $\mathbf{P}$ by singular value decomposition (SVD).

$$\mathbf{X} = \mathbf{T}\mathbf{P}^{\mathbf{T}} + \tilde{\mathbf{T}}\tilde{\mathbf{P}}^{\mathbf{T}} = \hat{\mathbf{X}} + \tilde{\mathbf{X}} = [\mathbf{T}\tilde{\mathbf{T}}][\mathbf{P}\tilde{\mathbf{P}}]^{\mathbf{T}} = \bar{\mathbf{T}}\bar{\mathbf{P}}^{\mathbf{T}} \quad (1)$$

where $\hat{\mathbf{X}} = \mathbf{T}\mathbf{P}^{\mathbf{T}}$ is the model matrix and $\tilde{\mathbf{X}} = \tilde{\mathbf{T}}\tilde{\mathbf{P}}^{\mathbf{T}}$ is the residual matrix. The principal component subspace (PCS) is $S_p = \mathrm{span}\{\mathbf{P}\}$and the residual subspace (RS) is $S_r = \mathrm{span}\{\tilde{\mathbf{P}}\}$. A sample vector $\mathbf{x}$ can be projected on the PCS and RS respectively:

$$\hat{\mathbf{x}} = \mathbf{P}\mathbf{P}^{\mathbf{T}}\mathbf{x} \equiv \mathbf{C}\mathbf{x} \in S_p \quad (2)$$

$$\tilde{\mathbf{x}} = \tilde{\mathbf{P}}\tilde{\mathbf{P}}^{\mathbf{T}}\mathbf{x} \equiv (\mathbf{I} - \mathbf{C})\mathbf{x} = \tilde{\mathbf{C}}\mathbf{x} \in S_r \quad (3)$$

$$\mathbf{x} = \hat{\mathbf{x}} + \tilde{\mathbf{x}} \quad (4)$$

PCA uses the squared prediction error (SPE) as a fault detection index

$$\mathrm{SPE} = \|\tilde{\mathbf{x}}\|^2 = \|\tilde{\mathbf{C}}\mathbf{x}\|^2 = \mathbf{x}^{\mathbf{T}}(\mathbf{I} - \mathbf{C})\mathbf{x} \leq \delta_\alpha \tag{5}$$

The detection limit for SPE can be determined with Q-statistics. If a sensor fails, which breaks the normal correlation, the residual will increase above the detection threshold (Qin and Li, 1999).

Sensor fault identification with SRAMS

If the normal process model is built as a PCA model, the model residuals are used to detect sensor faults. In the presence of a sensor fault, the sensor measurement ($\mathbf{x}$) will contain the normal values of the process variables and the fault, that is,

$$\mathbf{x} = \mathbf{x}^* + \Xi_i f_i(t) \tag{6}$$

where $\mathbf{x}^*$ is a vector of normal sensor values, $f_i(t) \in \mathscr{R}^{l_i}$ is a vector of the fault magnitude and $\Xi_i \in \mathscr{R}^{nxl_i}$ is a matrix of fault directions, l_i is the dimension of the fault. While $\Xi_i = [00\cdots1\cdots0]^T$ represents a single sensor fault in the ith sensor, Ξ_i contains the corresponding columns of the identity matrix to represent multiple sensor faults. Using Equation (6), the model residual, $\boldsymbol{e}(t)$, can be written as follows

$$\boldsymbol{e}(t) = \boldsymbol{Bx}(t) = \boldsymbol{Bx}^*(t) + B\Xi_i \boldsymbol{f}_i(t) = \boldsymbol{e}^*(t) + \boldsymbol{B}\Xi_i \boldsymbol{f}_i(t) \tag{7}$$

where $\boldsymbol{B}$ is the model matrix which is $\tilde{\mathbf{P}}^T$ in the PCA model and $\boldsymbol{e}^*(t)$ is the model residual which contains measurement noise. A fault will cause the residual $\boldsymbol{e}(t)$ to increase (Qin and Li, 1999).

When a sensor failure is detected, it is of primary importance to correctly identify the faulty sensor. In this paper, we applied the structured residual approach with maximized sensitivity (SRAMS) suggested by Qin and Li (1999). This generates a set of residuals where one residual is most sensitive to one specified subset of faults, but insensitive to others. For the case of a single sensor fault in the ith sensor, Eq. (7) becomes

$$\boldsymbol{e}(t) = \boldsymbol{e}^*(t) = \boldsymbol{b}_i f_i(t) \tag{8}$$

where $\boldsymbol{b}_i$ is the ith column of matrix $\boldsymbol{B}$ which represents the fault direction. By pre-multiplying a transformation matrix $\boldsymbol{W}$ to $\boldsymbol{e}(t)$, we can generate the following structured residuals $\boldsymbol{r}(t)$

$$\boldsymbol{r}(t) = \boldsymbol{We}(t) = b_i f_i(t) \tag{9}$$

where the matrix $\boldsymbol{W}$ is designed so that each element of $\boldsymbol{r}(t)$ is insensitive to one particular sensor fault and sensitive to the other faults. Choose w_i such that $\boldsymbol{r}_i(t)$ is insensitive to the ith sensor fault but most sensitive to the others. Mathematically, this is equivalent to

$$\max_{w_i} \sum_{j \neq i} \frac{(w_i^T \boldsymbol{b}_\mathrm{j})^2}{\|\boldsymbol{b}_\mathrm{j}\|^2} \tag{10}$$

Geometrically, w_i is chosen to be orthogonal to b_i while minimising its angle to other fault directions b_j. To reduce false alarms, an exponential weighted moving average (EWMA) is applied to the structured residual, the filtered structured residual (FSR).

$$\bar{r}_i(t) = \gamma \bar{r}_i(t-1) + (1-\gamma) r_i(t) \tag{11}$$

After a set of structured residuals has been generated, a decision about which sensor fails has to be made. Qin and Li (1999) suggested four types of fault identification indices: (1) identification index based on exponential weighted moving average (EWMA) filtered structured residuals (I_{FSR}), (2) generalized likelihood ratio (GLR), (3) cumulative sum of residuals (CSR) and (4) cumulative variances index (CVI). For the identification index based on the EWMA-filtered structured residuals (I_{FSR}), all structured residuals, $I^i_{FSR}(t)$ $(i = 1, 2, \ldots, n)$, are smaller than one under normal conditions. Under the condition of sensor i being faulty, the structured residual of the sensor i, $I^i_{FSR}(t)$, remains smaller than one while the other structured residuals, $I^j_{FSR}(t)$, become larger than one.

$$I^i_{FSR}(t) = \frac{\bar{r}_i^2}{\boldsymbol{w}_i^T \boldsymbol{R}_e \boldsymbol{w}_i \chi^2_\alpha(1)} \tag{12}$$

where $\bar{r}_i$ is the EWMA-filtered structured residual, w_i is the transformation matrix, $\boldsymbol{R}_e$ is the covariance matrix of the residual, $\chi(1)$ is the chi-square distribution with one degree of freedom, and α is the confidence level. If a sensor i is faulty, $r_i^2(t)$ is not affected by the fault due to the specific structuring of the residuals in the SRAMS-method, whereas otherwise the residuals $r_j^2(t)$ will increase significantly since their sensitivity to sensor i is maximised. On the other hand, a normalised cumulative variance index (CVI), which is sensitive to a variance change such as found in a precision degradation fault, is calculated as follows:

$$I^i_{CVI}(t) = \frac{V^i_{sum}(t)}{w_i^T \boldsymbol{R}_e w_i \chi^2_\alpha(t - t_f)} = \frac{\sum_{k=t_f}^{t} (r_i(k) - \hat{\mu}_{ij})}{w_i^T \boldsymbol{R}_e \boldsymbol{w}_i \chi^2_\alpha(t - t_f)}, \qquad i = 1, 2, \cdots, n \tag{13}$$

where $V^i_{sum}(t)$ is the cumulative variance, μ_{ij} is the estimated mean change after a fault, $\chi(t\text{-}t_f)$ is the chi-square distribution with t-t_f degree of freedom and t_f is the fault detection time. If sensor i is faulty, $I^i_{CVI}(t)$ will be less than one but other $I^i_{CVI}(t)$ are larger than one (Qin and Li, 1999).

The first three indices are similar in the sense that they are designed to filter high frequency noise by a moving average, a forgetting factor approach, whereas the last index is sensitive to variance-type of faults (Dunia *et al.*, 1996). We selected the FSR and CVI indices, which are used to detect the change of the mean and the variance. On the other hand, it is important to isolate sensor faults from process changes or disturbances. If sensor fault indices detect a faulty situation and all structured residuals are affected, it is likely to be a process change or a disturbance.

Sensor fault identification and reconstruction

After a fault is detected, it is important to identify its source and apply the necessary corrective actions to eliminate the abnormal condition. The procedure to restore normal conditions by applying a corrective change in the data is called data reconstruction. Logically, the procedure for identifying a fault by reconstruction for a given type of faults is called data identification via reconstruction. Reconstruction of the normal data from faulty measurements also leads to the estimation of the fault magnitude. Therefore, fault reconstruction is presented first, followed by fault identification (Qin and Li, 2001). Since the sensor fault direction has been identified, the best reconstruction can be used to estimate the sensor fault magnitude $f_i(t)$ by minimizing the effect of the fault on $e(t)$ in the direction Ξ_i, that is,

$$J = \|e^*(t)\|^2 = \|e(t) - B\Xi_i f_i(t)\|^2 \tag{14}$$

A least square solution to this problem leads to

$$\hat{f}_i(t) = (B\Xi_i)^+ e(t) \tag{15}$$

where $(\cdot)^+$ is the Moore–Penrose pseudo inverse. The task of sensor reconstruction is to estimate the normal values x^* by eliminating the effect of a fault f_i. A reconstructed value $\mathbf{x}_i$ is calculated by correcting the effect of a fault on the process data $\mathbf{x}$:

$$\mathbf{x}_i = \mathbf{x} - B\Xi_i\hat{f}_i(t) \tag{16}$$

where $\hat{f}_i$ is an estimate of the actual fault magnitude f_i along the SRAMS direction. The reconstructed value ($\mathbf{x}_i$) can then be used in the monitoring and prediction models instead of the actual faulty measurements (Qin and Li, 2001).

Results and discussion

Labscale SHARON reactor

A lab-scale SHARON reactor was constructed in the BIOMATH lab (Van Hulle *et al.*, 2005). The reactor is a 2l continuously stirred tank reactor (CSTR) without biomass retention. The pump flow rate of the synthetic influent determines both the hydraulic residence time and the sludge residence time (SRT), since both residence times are equal and defined as the ratio of the volume to the flow rate. The reactor is aerated through a pumice stone using air from a compressor (1 bar over pressure) and the controlled operating temperature is 35°C. In the reactor, the dissolved oxygen (DO) and pH are measured. The pH is controlled through Labview software by addition of acid (HCl) and base ($NaHCO_3$). The data used for the sensor validation were collected in the steady-state operation period and consist of 10 variables: (1) HRT, (2) influent ammonium, (3) influent bicarbonate:ammonium ratio, (4) dissolved oxygen (DO), (5) pH, (6–7) dosage rates of base and acid, and (8–10) daily measurements of ammonia, nitrite and nitrate in the effluent.

We built a process model ***B*** using PCA with two principal components and designed a matrix ***W*** with SRAMS. Filtered SPE and FSR are used to detect the sensor faults and two indices of I_{FSR} and cumulative variance index (CVI) with the 95% confidence level are monitored to identify faulty sensors. Four types of sensor faults, including bias, drift, complete failure and precision degradation, are introduced at time t_f, where the abnormal condition is caused by single and multiple sensor failures. The remaining measurements are used to reconstruct the faulty sensor based on the redundancy of the measurements. Table 1 summarises the four types of abnormal conditions detected and lists fault time and detection time. In order to reduce false alarms due to dynamic transients, an EWMA filter with a coefficient of $r = 0.90$ was applied to generate the FSRs for all four faulty cases. The CVI index is calculated based on the unfiltered structured residuals with a moving window of five samples considering the hydraulic retention time.

A bias $f(t) = 2.0$, which causes a shift in the measurement with a retained trend, is artificially introduced to the measurement of the DO sensor at $t_f = 50$. Figure 1 shows the sensor fault identification and reconstruction results. The sensor bias fault is detected in the SPE plot with a quite long delay but is effectively detected in the FSRs within a relatively short time. To make the detailed identification, two indices of I_{FSR} and CVI are shown in sub-plots (c) and (d) in the left pane, where a value above one indicates faulty situations. The FSR can correctly identify the faulty sensor, namely sensor 4 (DO), as the corresponding FSR is below the confidence limit, whereas CVI shows false identification results of normal sensors since the CVI-method is not designed for bias fault identification. In the right pane of Figure 1, the reconstructed sensor signal indicates that the difference between normal and reconstructed sensor data is relatively small and can be replaced in the faulty data. These reconstructed data allow the quality of the real data to

Table 1 Summary of four fault scenarios and the detection results

	Bias	Drift	Complete failure	Precision degradation
Faulty sensor	DO	DO	pH	DO
Fault expression	$f_1(t) = b$	$f_2(t) = a(t - t_f)$	$x_3(t) = c$	$f_4(t) = n(0,\sigma^2)$
Fault size	$\mathrm{DO}(t) + 2.0$	$\mathrm{DO}(t) + 0.3{*}t$	$\mathrm{pH}(t_f) + 1.0$	$\mathrm{DO}(t) + n(0, 2^2)$
Fault time (t_f)	50	50	50	50
Detection time ($\hat{t}_f$)	53	52	52	54

be checked by looking at the difference. The estimated fault size shows that this is a bias and how large the fault is.

The second fault type considered here (see Figure 2) was generated by introducing a drift into the sensor measurements of DO at $t_f = 50$. Similar to the case of sensor bias described above, good fault identification results were obtained for this sensor fault. The reconstructed sensor signal indicates that the difference between the normal and the reconstructed sensor trajectory is relatively large with an increasing offset. The estimated fault size indicates that this is a drift fault, causing FSR to be more effective than CVI.

Figure 3 shows the fault identification results of a precision degradation type fault in the DO sensor. The FSR can detect this fault more effectively than the SPE plot. Since

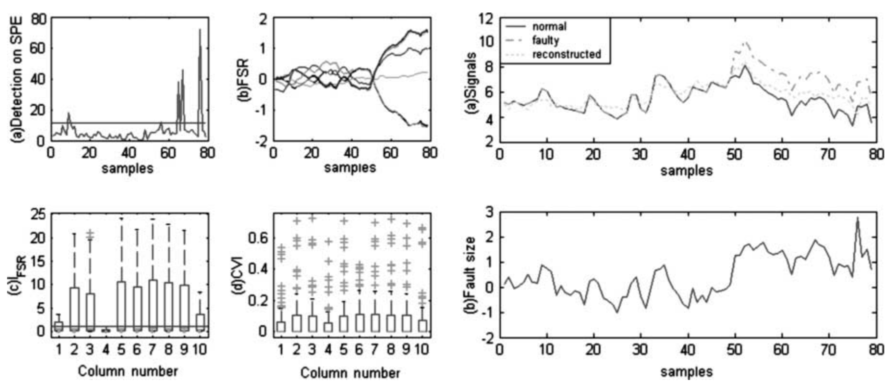

Figure 1 (Left) Sensor fault detection and identification of DO sensor bias (a) SPE plot, (b) FSR, (c) I_{FSR}, (d) CVI, (Right) Sensor reconstruction of DO sensor bias (a) normal, faulty and reconstructed signals, (b) fault size

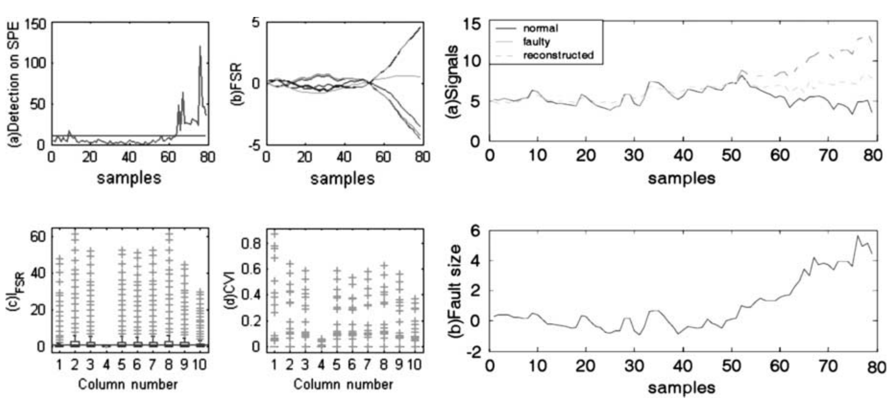

Figure 2 (Left) Sensor fault detection and identification of DO sensor drift (a) SPE plot, (b) FSR, (c) I_{FSR}, (d) CVI, (Right) Sensor reconstruction of DO sensor drift (a) normal, faulty and reconstructed signals, (b) fault size

this is a variance change, both I_{FSR} and CVI have smallest values for the fourth sensor (DO) identifying the correct sensor fault. The estimated fault size indicates that this is a fault related to a variance change.

Multiple sensor fault case

We also tested the method for multiple sensor fault identification, where more than one sensor is simultaneously faulty. As a simple case study, we applied the SRAMS method to three nitrogen output variables, ammonium nitrogen (NH_4-N), nitrite (NO_2-N), and nitrate (NO_3-N) since there is enough redundancy between these three variables from the stoichiometric reactions to reconstruct their values. Faulty data were simulated by introducing precision degradation of NH_4 and NO_2 sensors at $t_f = 50$. The sensor validation and reconstruction results are shown in Figure 4. SPE and FSR allow the detection and identification of the precision degradation of these two sensors. Similar to the results of Qin and Li (1999), it was shown that CVI is most sensitive to variance changes. I_{FSR} showed false identification of a fault in the third sensor (NO_3-N). In summary, as Qin and Li (2001) previously showed, the unique index may not identify all kinds of faults but combined indices can help identify the faulty sensors and fault types.

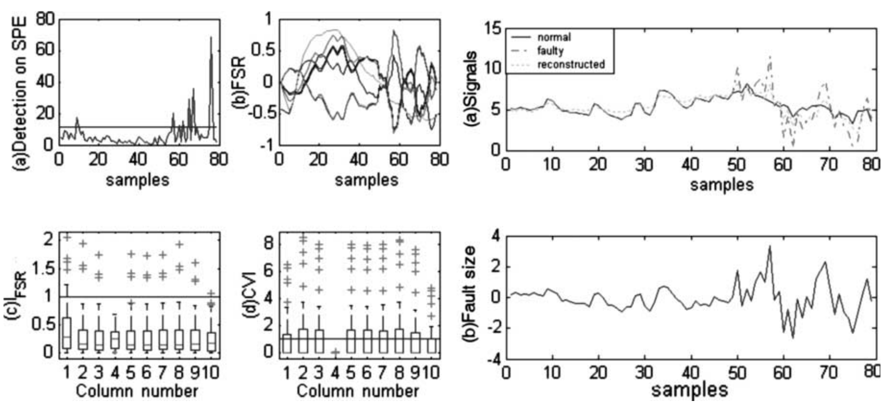

Figure 3 (Left) Sensor fault detection and identification of the precision degradation of the DO sensor (a) SPE plot, (b) FSR, (c) I_{FSR}, (d) CVI, (Right) Sensor reconstruction of the precision degradation of DO sensor, (a) normal, faulty and reconstructed signals, (b) fault size

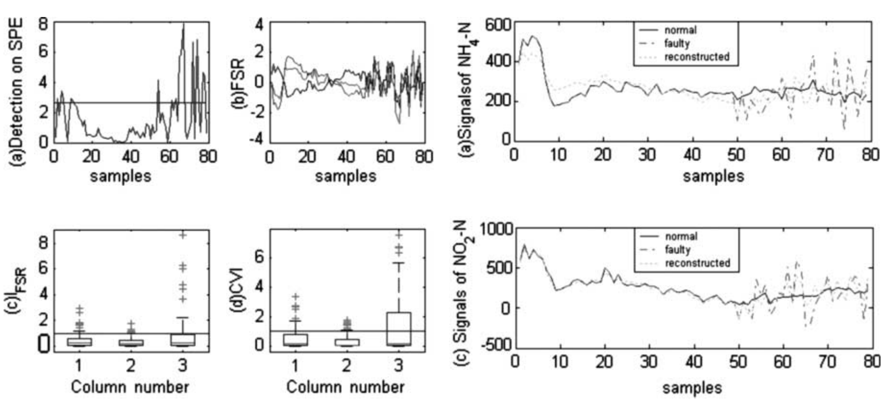

Figure 4 (Left) Sensor fault detection and identification of multiple faults, the precision degradation of NH_4 and NO_2 sensors (a) SPE plot, (b) FSR, (c) I_{FSR}, (d) CVI, (Right) Sensor reconstruction of the precision degradation (a) NH_4, (b)NO_2

In this paper, only uncontrolled variables were subjected to sensor validation. Otherwise, any errors related to controlled variables will be transferred to the manipulated variables during the sensor validation procedure. This may distort the sensor identification method. If the controlled variables are used in sensor validation, it should be pointed out that the success of sensor validation under feedback control relies on the fact that sensor fault detection is achieved faster than the time constant of the feedback control loop. If the faults are not significantly faster than the closed loop process dynamics, the feedback must be rigorously considered in the sensor validation model. On the other hand, the integration of control performance monitoring and process monitoring could lead to further fault discrimination among process faults, sensor faults and control performance-induced upsets (Pranatyasto and Qin, 2001).

Conclusions

A sensor validation method is used to detect and identify single and multiple sensor faults and to reconcile the failed sensor values in the SHARON process. Faulty sensors were identified by tracking the filtered structured residuals and other indices against confidence limits. The estimated fault magnitude allowed the generation of a reconstructed sensor value, which can be used to develop more reliable prediction models. Also, the proposed sensor validation method can be easily used for sensor surveillance of other continuously measuring sensors and analysers. However, since it is difficult to reconstruct an uncorrelated variable from other variables, uncorrelated variables should be excluded from this procedure when one uses the redundancy-based sensor value reconstruction. We are currently developing a real-time sustainable sensor validation system for WWTP.

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