Fault Detection using NLMS Adaptive Filtering for a Wastewater Treatment Process

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***Abstract*—In this paper, a method based on adaptive filtering is proposed for actuator, sensor and toxicity faults detection in a biological wastewater treatment process. Improving water quality in such treatment plants is an important and growing problem so monitoring performance and conditions, optimization and fault diagnosis for biotechnological processes are as important as fault detection. Such detection is performed here using state-parameter estimation where the detection algorithm compares the outputs of an analytical model with those estimated by the normalized least mean square adaptive filter in order to calculate the residual value for each output of the process. Numerical examples are presented in order to illustrate the performance of the proposed method.**

Keywords- wastewater treatment process; adaptive Kalman filter; fault detection; process diagnosis.

I. INTRODUCTION

Improving the quality of waters in the wastewater treatments plants has become more and more important due to the fact that the population is continuously increasing. The environment and especially general population health depends on it. As a result, monitoring performances and conditions, optimization and fault diagnosis for biotechnological processes are novelty topics in the current scientific research.

So far in literature several methods for fault detection and isolation of different types of faults have been proposed [1]-[10]; however, there are limitations in the case of monitoring complex and dynamical processes as Wastewater Treatment Processes (WWTPs).

The main challenge of this work was to propose a simple and fast method to detect different types of faults which can occur in the wastewater treatment process. Subsequently, in order to detect actuator, sensor and biological faults, this paper proposes a method based on adaptive filtering which is monitoring the changes in residuals of the model parameters.

Many adaptive algorithms have been developed over time based on two different approaches, namely the statistical approach and the deterministic approach, each with specific advantages and disadvantages [11] [12]. This paper presents a fault detection algorithm which uses one of the popular Normalized Least Mean Square (NLMS) algorithm for state estimation. This approach proves to be fit for WTTPs since adaptive filtering algorithm has to address the classical compromise between fast convergence/tracking and low misadjustment [13] [14].

The paper structure is the following: Section 2 presents the analytical model of the wastewater treatment process; Section 3 presents the NLMS adaptive filter used to estimate the WWTP outputs; Section 4 presents the fault detection approach and the residuals obtained for sensor, actuator or toxicity faults; Section 5 is dedicated to results and discussion about fault detection performance and the last one highlights the paper's conclusions.

II. THE WASTEWATER TREATMENT PROCESS

The mathematical model of the Wastewater Treatment Process (WWTP) on which this study is based is described by the following equations [7]-[10].

$$\frac{dX}{dt} = \big(\mu(t) - \mu_s(t)\big)X(t) - D(t)(1+r)X(t) + +rD(t)X_r(t) \qquad (1)$$

with:

$$D = \frac{F_{in}}{V} \qquad (2)$$

where:
$X(t)$ – biomass concentration,
$\mu(t)$ – specific growth rate,
$\mu s(t)$ – decay coefficient for biomass,
$D(t)$ – dilution rate is : $D = \frac{F_{in}}{V}$
r – recirculating rate,
$X_r(t)$ – recirculated biomass concentration,
F_{in} – influent flow,
V – bioreactor volume,

$$\frac{dS}{dt} = -\frac{\mu(t) - \mu_S(t)}{Y}X(t) - D(t)(1+r)S(t) + D(t)S_{in} \qquad (3)$$

where:
$S(t)$ – substrate concentration,
Y – yield coefficient,

 ISBN: 978-1-61208-740-5

μ_{max} – maximum specific growth rate,
S_{in} – influent substrate concentration,

$$\frac{dDO}{dt} = -\frac{(1-Y)\left(\mu(t)-\mu_S(t)\right)X(t)}{Y} \cdot 10^3 - D(t)(1+r)DO(t) + +60\alpha W(t)\left(DO_{sat} - DO(t)\right) + D(t)DO_{in} \quad (4)$$

where:
$DO(t)$ – dissolved oxygen concentration,
Do_{ing} – influent dissolved oxygen concentration,
DO_{sat} – saturation value of dissolved oxygen,
$W(t)$ – aeration rate,
α – oxygen transfer rate,

$$\frac{dX_r}{dt} = D_s(t)(1+r)X(t) - D_s(t)(\beta+r)X_r(t) - -0.5D_s(t)(1+\beta)X_r(t) \quad (5)$$

where: D_s is the dilution rate of the sludge

$$D_s = \frac{D \cdot V}{V_s} \quad (6)$$

with V_s – sludge volume and β the rate of the sludge in excess.

$$\mu(t) = \mu_{max}\frac{S(t)}{K_S+S(t)} \cdot \frac{DO(t)}{K_{DO}+DO(t)} \quad (7)$$

where: K_s is the saturation constant of the substrate and K_{DO} is the saturation constant of dissolved oxygen.

III. Adaptive Filter Using Normalized Least Square (NLMS) Algorithm

As a general note, the adaptive filters are self-adjustable systems which adapt to various conditions and situations therefore are used in a wide range of areas. The common trait of the applications where the adaptive filters provide a good solution is based on minimizing the mean squared error between the filter output and a desired signal.

The filter's parameters are updated using a set of measured data which are used as input for the adaptive filtering algorithm. The algorithm adjusts filter's parameters so that the difference between the input and the output is minimized either statistically or deterministically and these approaches give us applications for modelling, reverse modelling, prediction or interference cancelling.

This paper uses the adaptive filter as a predictor and, in this context, it estimates the current value of the signal $\hat{x}(n)$ based on the past values $x(n-1), x(n-2), \ldots, x(n-N)$. Using the linear combinations of N successive samples of the input signal, the algorithm tries to estimate the output of the desired signal *d(n)*, which is a forward version of the adaptive filter input signal.

The filter is assumed to be finite impulse response (FIR) filter of length L with coefficients $\boldsymbol{w} = (w_1 \ldots w_L)^T$, input signal $\mathbf{x}(n-1) = (x(n-1) \ldots x(n-N))^T$ and output defined by:

$$\hat{x}(n|\mathbf{X}_{n-1}) = \sum_{k=1}^{M} w_k^* \; x(n-1). \quad (8)$$

where $\mathbf{X}_{n-1}$ is a N-dimension for input samples.

The desired signal is:

$$d(n) = x(n) \quad (9)$$

and predicted error is defined by equation:

$$e(n) = x(n) - \hat{x}(n|\mathbf{X}_{n-1}). \quad (10)$$

By minimizing error *e(n)*, an optimal predictive signal input is made.

If NLMS algorithm is used, it can be expressed by the following equation [15]:

$$\hat{\mathbf{w}}(n+1) = \hat{\mathbf{w}}(n) + \mu \mathrm{sgn}(e(n))\, \mathbf{x}(n-1) \quad (11)$$

where μ is the adaptation [15].

IV. Fault Detection Approach

A model-based fault detection approach is proposed in this paper in order to identify anomalies which can occur in the WWTP process. The detection algorithm uses the residual values of each output and by comparing it with a threshold value it can be established when a fault occurs in the system.

As in other studies [9]-[12], the residual $R(k)$ is obtained as a difference between the estimated output $\hat{y}_p(i)$ of the process and the output of the analytical model, $y_m(i)$

$$R(k) = \frac{1}{N}\sum_{i=k-N+1}^{k}(\hat{y}_p(i) - y_m(i))^2 \quad (12)$$

where:
N = number of samples,
R(k) = the value of the residue over the last N samples,
$\hat{y}_p(i)$ - estimated output of the process by the adaptive filter,
$y_m(i)$ – output of the analytical model.

The detection efficiency is obtained through the binary signal E which is generated by using a OR function described below:

$$E(i) = \begin{cases} 1 \; if R(i) > \varepsilon_X || R(i) > \varepsilon_S || R(i) > \varepsilon_{DO} || R(i) > \varepsilon_{X_r} \\ 0 \; else \end{cases} \quad (13)$$

This function detects a fault even if the selected threshold is not exceeded by the residual value on a particular output. It is necessary for the residuals to exceed at least one time one of the four thresholds in order to correctly detect the presence of a fault in the process.

A. Fault detection scheme

As presented in [7]-[10] the input parameter DO_{in} is considered to be constant. The fault detection scheme is shown in Figure 1. A model of the supervised process, in this case an analytical model, is used to provide the same evolution of the output as the process outputs if the same values of the inputs are applied. The model outputs are compared with the estimated outputs of the NLMS adaptive filter in order to generate the residuals.

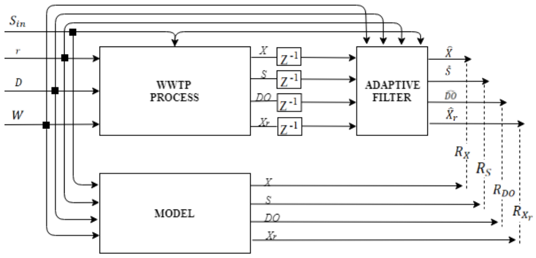

Figure 1. The fault detection scheme

B. *Fault detection parameters*

As several other studies presented [7]-[10], the algorithm's decision parameters are:

- sensibility threshold value ε which is compared with the residual value R in order to establish if the conditions of a fault occurrence are met.

- number of samples N, on which the residual value, R is obtained.

C. *Method validation by numerical simulations*

Several experiments were carried on in order to find the optimal values for the parameters N and ε and to achieve the best performances of the detection approach.

1) *Fault of the recirculation pump*

The deviations caused by the recirculation pump fault can be seen in Figure 2. When this actuator fault occurs in the process, the recirculation rate value becomes zero ($r = 0$ when $N_t \in [3500, 3899]$). The residuals are obtained for each output of the system when $N = 10, N = 20, N = 40$.

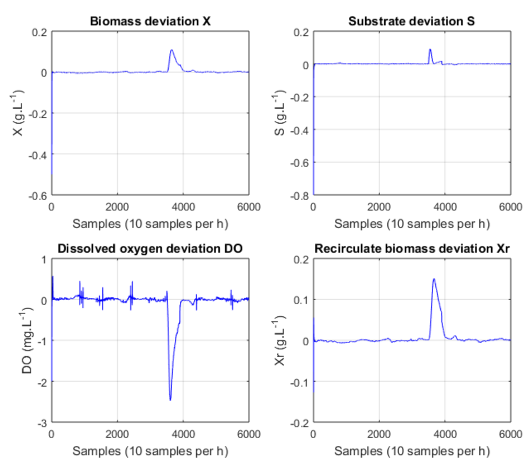

Figure 2. The outputs, X, S, DO, X_r deviations caused by the recirculation pump fault ($X = 0$ over 3500 to 3899 samples)

Figures 3 – 5 show the residuals obtained in both cases, when the system operates in normal conditions (the residual values are close to zero) and when the recirculation pump fails around sample no. 3500 (the residual value is increasing due to process output deviation caused by the pump malfunction).

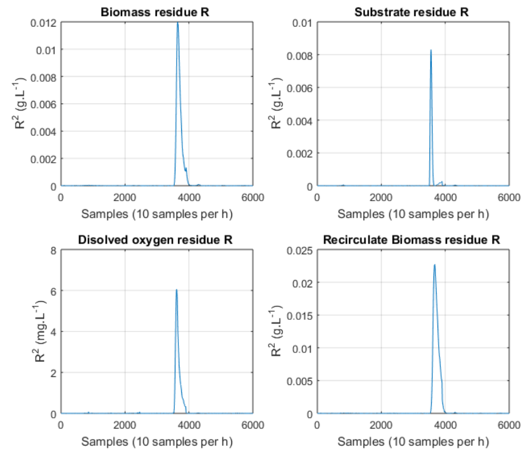

Figure 3. The residue, R for partial fault of the recirculation pump when $N = 10$

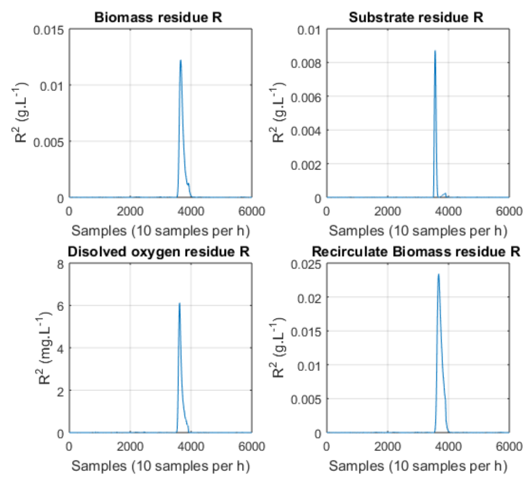

Figure 4. The residue, R for partial fault of the recirculation pump when $N = 20$

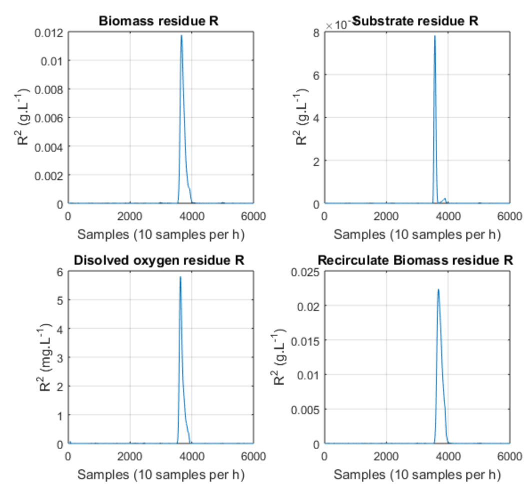

Figure 5. The residue, R for partial fault of the recirculation pump when $N = 40$

2) Fault of the biomass sensor

In general, a WWTP plant is equipped with many important sensors for monitoring the process performances and conditions [1]. Here, a fault of the biomass sensor is simulated over 400 samples. The output deviations caused by this fault are shown in Figure 6. As previously, the residuals R are generated for each output of the process when $N = 10, N = 20, N = 40$.

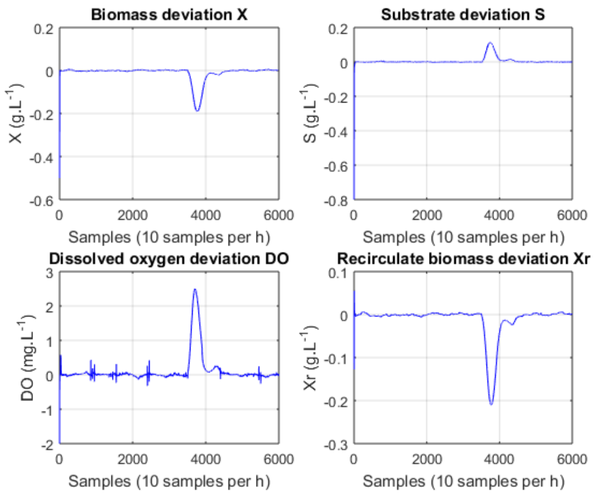

Figure 6. The outputs, X, S, DO, X_r deviations caused by the biomass sensor fault ($X = 0$ over 3500 to 3899 samples)

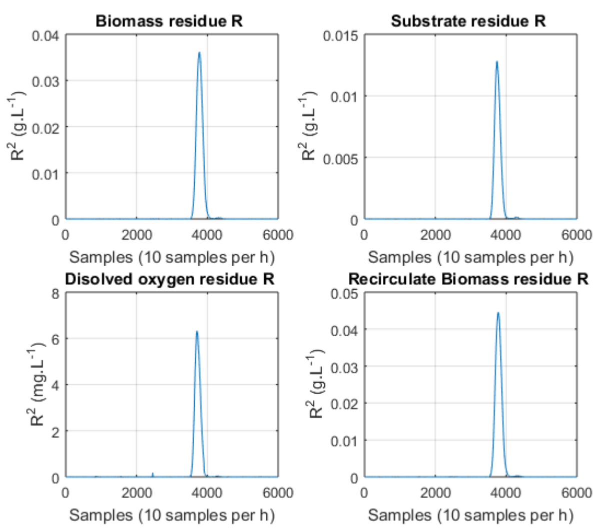

Figure 7. The residue, R for toxicity fault when $N = 10$

From Figures 7 – 9, it can be observed that the residual value R is big compared with the process and the measurement noise. So, in this case, tweaking N value to a smaller size will avoid generating false alarms.

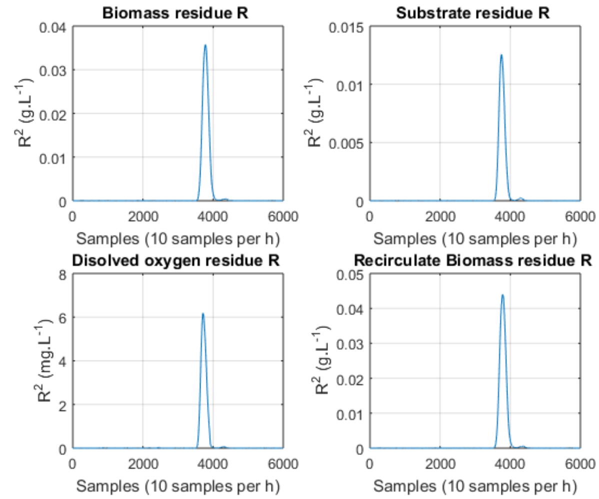

Figure 8. The residue, R for toxicity fault when $N = 20$

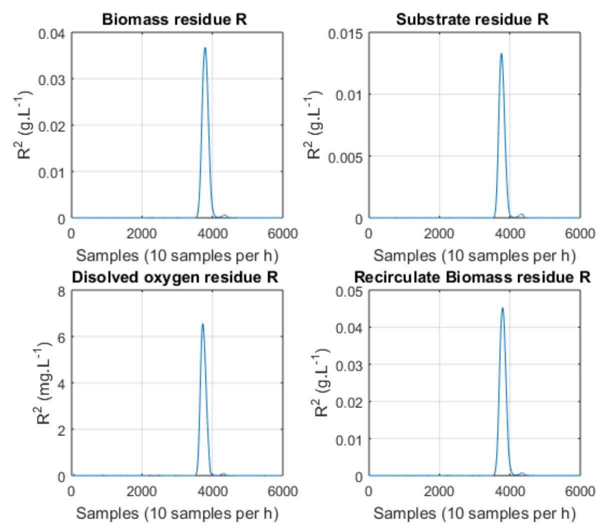

Figure 9. The residue, R for toxicity fault when $N = 40$

3) Toxicity shock fault

A fault caused by a toxic shock suffered by the microorganism's culture, presented in Figure 10, was simulated by reducing the value of the maximum specific growth rate μ_{max} by half, over $N_t \in [3500, 3899]$). Figure 11 – 13, shows the residual values at different iterations of parameter N ($N = 10, N = 20$ and $N = 40$).

Simulation results show that depending on the value of N, the measurement and process noise is reduced, which could cause a lower value of the threshold and a possible increasing of the detection time. Therefore, a compromise must be made when choosing the detection parameters in order to achieve good results.

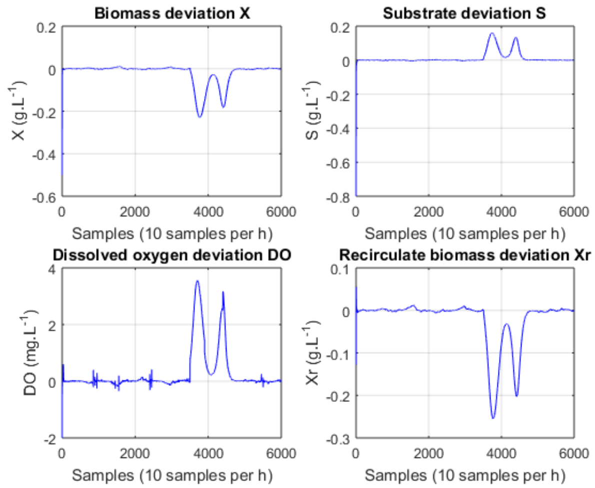

Figure 10. The outputs, X, S, DO, X_r deviations caused by the toxicity fault ($\mu_{max}/2$ over 3500 to 3899 samples)

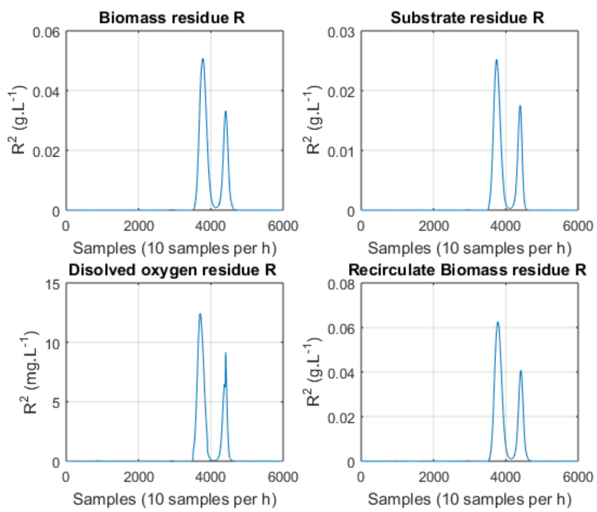

Figure 11. The residue, R for toxicity fault when $N = 10$

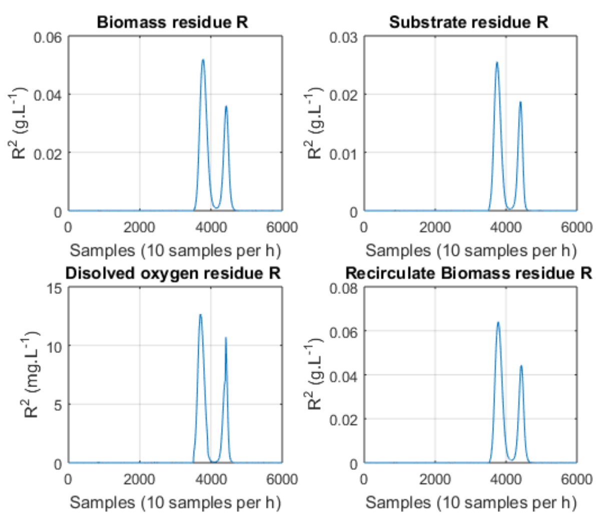

Figure 12. The residue, R for toxicity fault when $N = 20$

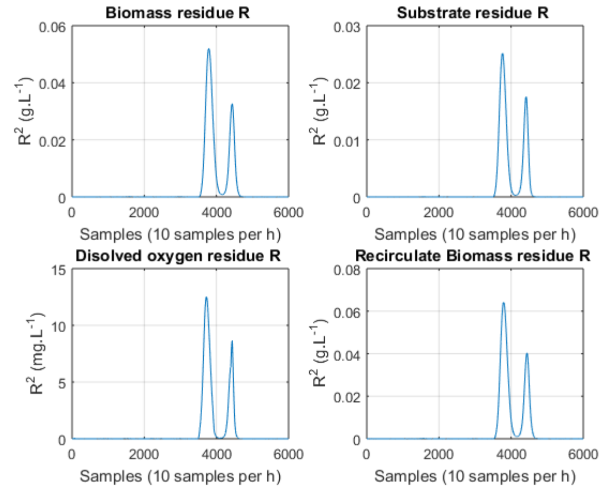

Figure 13. The residue, R for toxicity fault when $N = 40$

V. RESULTS AND DISCUSSION

In all the previously presented cases of simulated faults the value of N is set to 10, which corresponds to the criteria of choosing the detection parameters described in section IV. Also the sensibility thresholds for each output are: $\varepsilon_X = 4 \cdot 10^{-4}$, $\varepsilon_S = 2 \cdot 10^{-4}$, $\varepsilon_{DO} = 0.1$, $\varepsilon_{X_r} = 5.5 \cdot 10^{-4}$.

Further, the detection efficiency E (Figures 14 – 17) is obtained for all types of faults analyzed in the previous section: recirculation pump fault, biomass sensor fault and toxicity fault.

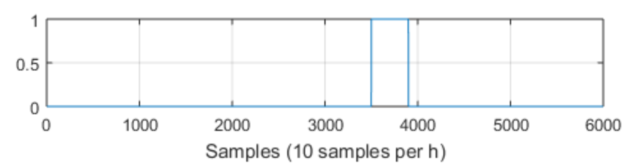

Figure 14. Fault simulated over $N_t \in [3500, 3899]$

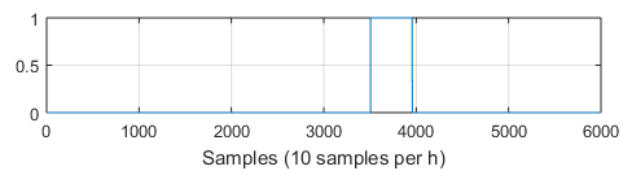

Figure 15. Alarm signal for recirculation pump fault detection (detection over $N_t \in [3506, 3958]$, after ~36 min)

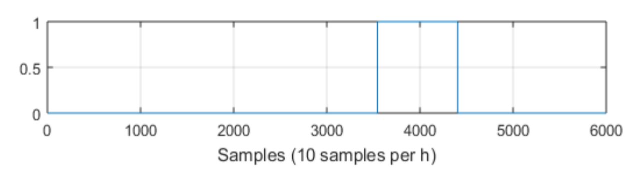

Figure 16. Alarm signal for biomass sensor fault detection (detection over $N_t \in [3543, 4405]$, after $\sim 4h$)

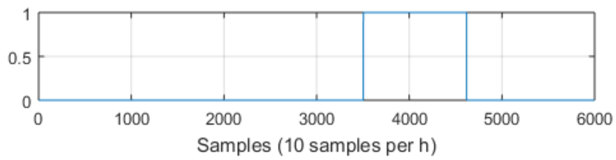

Figure 17. Alarm signal for toxicity fault detection (detection over $N_t \in [3504, 4619]$, after ~24 min)

The best detection time of the proposed algorithm was obtained in the case of toxicity fault, after approximately 24 minutes.

The fault detection algorithm simulation was run on a computer having the following specifications: Intel Core i3-6100U with 2.30GHz, 4 GB RAM memory and 500GB SSD. The detection performances are displayed in approximately 30 seconds.

VI. CONCLUSIONS

This paper proposes a model-based fault detection method for a wastewater treatment process. The detection algorithm compares the outputs of the analytical model with the ones estimated by the NLMS adaptive filter in order to calculate the residual value for each output of the process.

The alarm decision, occurring when a fault appears in the system, is enabled based on the detection parameters values (threshold ε and number of samples N). The results obtained are promising when compared with other studies [1] [2] and [8] [9] presenting aspects of sensor and actuator faults detection in WWTP.

Moreover, this paper analyses the case of a toxicity shock fault detection that could damage the microorganism's culture and cause erraticism in these types of biotechnological processes.

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