Ammonium Sensor Fault Detection in Wastewater Treatment Plants

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Keywords: Fault Detection, Waste Treatment, Optimal Filtering, Trade-offs.

Abstract: We develop a fault detection strategy for the output ammonium sensor present in wastewater treatment plants. The only assumed measurements are the output ammonium concentration, the aeration of the reactor and the incoming volumetric flow to the plant. The incoming ammonium concentration is not measured, resulting in an important source of uncertainty. We use a IIR model based on Volterra series for predicting the ammonium measurement and we design a fault detector based on a filter applied on the prediction error and a threshold comparator to decide whether the sensor is faulty or not. The faults in the sensor are assumed to produce a slowly decreasing gain due to dirtiness in its surface. The fault detector design is based on the trade-off between fault detection sensitivity and disturbance rejection (due to measurement noise and model uncertainty). The design parameters are based in understandable fault indices: time needed to detect the fault, gain deviation at the time of detection, and poured volume of ammonium until the fault is detected. We use the benchmark BSM1 to validate the results as a common frame in the study of waste water treatment plants.

1 INTRODUCTION

As one of the results of human activity, wastewater must be treated before it returns to the environment. The aim of Wastewater Treatment Plants (WWTPs) is treating and cleaning wastewater to achieve an acceptable healthy state before being returned, being, therefore, crucial agents in an environment-friendly society. One of the critical aspects in its operation is the concentration of ammonium of the treated water. For that purpose, several control strategies have been developed.

One of the most important technologies that enable those control strategies are the ammonium sensors, that allow a tight control of ammonium concentration of the poured water. However, those sensors are not as reliable as would be desirable due to the difficult conditions in which they operate. Quite frequently, wrong measurements provided by faulty ammonium sensors lead to polluted water at the WWTP output. Sudden faults are usually quite easy to detect, as the measurement is suddenly zero or out of range. The most difficult faults are those that produce a slow drift of the measurement due to, for example, a progressive accumulation of dirt in the sensor membranes. The detection of this kind of slow sensor faults is specially difficult because WWTPs are complex non-linear dynamic systems subjected to large disturbances and uncertainties; these systems deal with wide variations of the inlet wastewater, and the biochemical and physical processes that happen in their inside feature limits and saturations. The detection of sensor faults is an active research area in WWTPs in different sensor technologies (Kazemi et al., 2020) and in industrial networked environments (Pinto et al., 2016).

In (Dovzan et al., 2011), a fault detection algorithm is presented for the ammonium sensor of a WWTP, using a Fuzzy prediction model. Several variables are assumed to be measured, including the input ammonium concentration and the dissolved oxygen in the reactors. While the dissolved oxygen is a common measurement in WWTP, the input ammonium concentration is difficult to be measured in practice, because the input water is very dirty. A direct comparison of the prediction error (with no filtering) with a threshold is proposed to detect the fault. This has several drawbacks due to high uncertainties and periodical patterns in the inlet water behavior. Other works as (Nagy-Kiss et al., 2012; García et al., 2017; Behzad et al., 2018; Jia et al., 2018) also use both nonlinear models and nonlinear observers to address the problem of fault detection.

In this work, trying to decouple the model iden-

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Tena, D., Peñarrocha-Alós, I., Sanchis, R. and Moliner-Heredia, R.
Ammonium Sensor Fault Detection in Wastewater Treatment Plants.
DOI: 10.5220/0009875406810688
In *Proceedings of the 17th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2020)*, pages 681-688
ISBN: 978-989-758-442-8

tification problem from the fault detection mechanism design problem, we assume that we have a given model from which we can obtain some characteristic values to validate it. From that starting point, this paper presents a fault detection strategy to detect slow drift type faults of the ammonium sensor in a WWTP. The plant is assumed to be controlled in closed loop using the ammonium measurement, and using the aeration as the control action, as in (Moliner-Heredia et al., 2019). The input flow is also measured, but not the input ammonium concentration since its measurement is difficult due to the dirt of the input water.

In the literature, many papers about control of WWTP, as (Zeng and Liu, 2015), (Revollar et al., 2016; Revollar et al., 2015; Revollar et al., 2017), are based on the model that the Benchmark Simulation Model n^{o}1 offers (see(Alex et al., 2008)). In this paper, the BSM1 model is used to simulate the behavior of a WWTP and to test the developed fault detection algorithm. Some other works try to make the control tolerant to different faults (Nagy-Kiss et al., 2015).

The proposed fault detection strategy compares the ammonium output concentration measurement and a prediction of this variable. This prediction is based on a relatively simple non-linear Volterra model with two inputs: the aeration and the input flow. The error (difference between measurement and prediction) is low pass filtered to reject the fluctuations due to the daily and weekly patterns of input ammonium concentration and the input flow. The paper studies the relation between the filter time constant, the time needed to detect a fault and the deviation of the measurements at the detection time, leading to the selection of the filter that minimizes the volume of poured ammonium that is out of control.

The paper is structured as follows. First, the problem of ammonium sensor fault detection in WWTP is described. Then the prediction model used is detailed. The fault detection algorithm is then developed, followed by extensive simulation results to test the validity of the approach. Finally, some conclusions are summarized.

2 PROBLEM STATEMENT

This paper deals with the problem of detecting slow drift type faults in the output ammonium concentration sensor in waste water treatment plants, in which the output ammonium is controlled in closed loop using that ammonium sensor as output measurement, and the aeration as control action. We have used a realistic simulation model of the WWTP to test the fault detection algorithm. This model is the widely known Benchmark Simulation Model nº 1 (BSM1) (Alex et al., 2008). This model describes the behavior of a biological reactor with two non-aerated compartments followed by three aerated compartments. The equations that regulate this reactor come from the Activated Sludge Model nº 1 (ASM1, see (Henze et al., 1987)). The BSM1 also describes the behavior of the secondary clarifier. An explanation of these equations can be found in (Vilanova et al., 2017).

As it can be seen in Figure 1, inlet wastewater (Q_i) enters the bioreactor and crosses all the compartments. In the meanwhile, bacteria stored in the reactor treat the wastewater, eliminating some components and generating some others. In the last compartment, there is a bifurcation, where some of the flow (Q_{int}) is recycled back to the first compartment, and the other part flows to the secondary clarifier (Q_f). Here, wastewater is subjected to a settling process, and the flow is yet divided into the effluent (Q_e), which may be dumped directly into the river, and the underflow (Q_u), which is rich in particulate components. This flow is partially purged to eliminate some of these particles, which results in the generation of sludge (Q_w). The rest of the flow (Q_r) is also recycled back to the first compartment of the biological reactor.

The differential equations that model the BSM1 use 13 different internal states for each compartment, which correspond with 12 components and a measure of alkalinity. In this paper, due to the recent improvements in the field of ammonium sensors, we have chosen the ammonium concentration in the effluent flow ($S_{NH,e}$) as the measured variable. In correspondence with the BSM1 example, the oxygen transfer coefficient in the fifth compartment (k_La_5) is the main controllable input. A controller (denoted by C in Figure 2) is assumed to be operating in closed loop, measuring the output ammonium, and modifying the aeration (the oxygen transfer coefficient) in order to pour the water with a given prescribed ammonium concentration. The control algorithm is not relevant for this paper, but we assume that the closed loop behavior is stable.

The fault of the sensor to be detected is assumed to be a slow negative ramp variation of the sensor gain (K, being equal to 1 in normal conditions), which presents progressively smaller measurements, lower than the real output concentration, i.e., $K < 1$. This kind of fault is more difficult to detect that a step like fault, specially in this process since it has very complex non-linear dynamics. There is also an important uncertainty in the ammonium concentration of the input flow, which is not measured (denoted as disturbance d in Figure 2). Note that the controller only

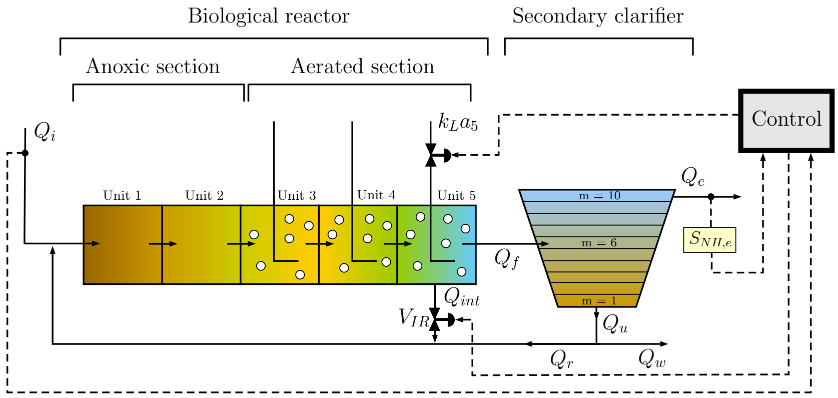

Figure 1: BSM1 Model Adaptation.

knows the concentration given by the sensor, not its real value. The fact that the sensor shows lower values than the real concentration makes the controller to actuate in such a way that the real ammonium may be over the desired constraints.

The proposed fault detection strategy is based on a predictor that estimates the value of the output ammonium, using as input data the input flow and the control action (the oxygen transfer coefficient). The error (difference between measurement and prediction) is evaluated to conclude if a fault occurs in the sensor. In the following sections we explain in detail the prediction model and the fault detection mechanism.

3 PREDICTION MODEL

We propose a simple infinite impulse response (IIR) non-linear model based on Volterra series to compute the prediction of the output ammonium concentration, at 1 minute sampling period. The inputs of the model are the input flow (Q) and the control action (u, the oxygen transfer coefficient), and its output is the WWTP output ammonium concentration (y). The equation (1) shows the structure of the proposed model:

$$\begin{aligned} \hat{y}[k] &= y_0 + \sum_{i=1}^{n} a_i \hat{y}[k-i] + \sum_{i=1}^{m} b_i u[k-i] + \\ &+ \sum_{i=1}^{m} c_i u[k-i]^2 + \sum_{i=1}^{m} d_i Q[k-i] + \\ &+ \sum_{i=1}^{m} e_i Q[k-i]^2 + \sum_{i=1}^{m} f_i Q[k-i]u[k-i] \quad (1) \end{aligned}$$

The model is linear in the parameters (y_0, $a_i, \ldots, f_i$), and they are obtained through least squares identification from simulated data without sensor fault. The simulations are run with the BSM1 model and the included input flow data. Several models can be used to predict the value of the sensor, as well as identification techniques. In this work, we focus on the problem of detecting a fault on the sensor from a given model (the one presented here or another one) by means of filtering the estimation error and defining a threshold. This threshold is computed taking into account that the predicted values have some error due to both modelling errors and sensor noises, and the filtered error takes into account its effect on the ability to detect faults.

4 FAULT DETECTION MECHANISM

The fault detection strategy consists of low pass filtering the error between the measurement of ammonium and the prediction given by equation (1) and then compare it with a given threshold at each period k. Figure 2 shows the complete detection diagram.

We propose to use a low pass filter because there are modeling errors and important uncertainties that have a quasi periodical shape, mainly daily and weekly variations of the incoming water ammonium concentration. This means that, in absence of sensor faults, the error will have an important quasi periodic variation that should be filtered to get a smoother signal. On the other hand, the modeling error produces a bias in the error signal, i.e. the average is not zero. Note that the identification of the parameters in (1) with a least squares method does not guarantee a zero mean estimation error.

The proposed filter is detailed in equation (2), in which $y[k]$ is the measurement at period k and $\tilde{y}_f[k]$ is the filtered error. Filter time constant τ is defined in minutes.

$$\tilde{y}_f[k] = e^{-\frac{1}{\tau}} \tilde{y}_f[k-1] + (1 - e^{-\frac{1}{\tau}})(y[k] - \hat{y}[k]) \quad (2)$$

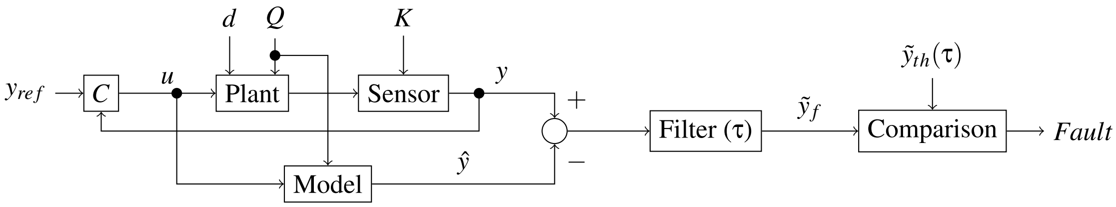

Figure 2: Fault detection mechanism (y_{ref}: ammonium reference, u: aeration, d: disturbances, Q: input flow, K: sensor gain, y: measured ammonium, $\hat{y}$: estimated ammonium, $\tilde{y}_f$: filtered estimation error, $\tilde{y}_{th}$: threshold).

The detection logic (3) is simply a comparison of this filtered error with a threshold $\tilde{y}_{th}$.

$$\begin{cases} \text{if } |\tilde{y}_f[k]| > \tilde{y}_{th}: & \text{fault,} \\ \text{otherwise}: & \text{no fault.} \end{cases} \tag{3}$$

This threshold must be defined from fault free data to avoid false alarms (or more precisely to reach a given low rate of false alarms), filtering these data (i.e., estimation error) from a sufficient large time window (the one needed to stabilize the behavior of the filtered data for the chosen time constant) and computing its maximum value, i.e.,

$$\tilde{y}_{th} = \max_{k \in [1,N]} |m_s \tilde{y}_f[k]|, \tag{4}$$

where m_s is a security margin ($m_s \geq 1$) to avoid false alarms in the case that errors are different in other operation points or control situations. Obviously, this threshold is a function of the filter time constant (the higher the time constant, the lower the threshold). However, it does not converge to zero; it has a lower bound because of the inherent bias in the error signal due to modeling errors.

We define the detection time (t_d) as the time elapsed since the gain of the sensor starts the descent until our filtered prediction error reaches the threshold. The time constant of the filter (τ) affects the value of the threshold as well as the evolution of the filtered signal, and, therefore, affects the achieved detection time as well as the value of the fault (the gain in the sensor due to dirty) at the instant of detection.

If we assume a slowly varying ramp like fault, a very high value of τ will lead to a threshold close to the lower bound determined by the error bias and the filtered error will change very slowly because of the high τ what, altogether, will cause a high detection time. On the other hand, a very low value of τ will also lead to a high detection time because of the high value of the corresponding threshold.

Thus, we can find an intermediate value of τ that minimizes the detection time or other interesting indices that measure the performance of the fault detector. As the ammonium sensor is used to control the concentration of ammonium that is poured and it

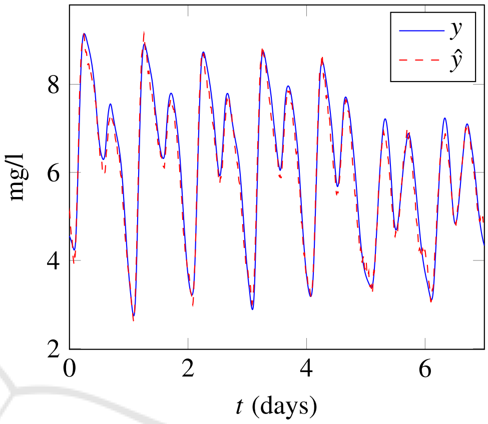

Figure 3: Measured ammonium and its estimation during one week.

must be under control to avoid environmental or legal problems, a good performance index can be the amount of poured ammonium that is over the legally allowed concentration, between the time of fault appearance and the instant of detection of the fault.

5 SIMULATION RESULTS

In this section we present the proposed algorithm results applied to data from the BSM1. First, we have excited the system with the inlet flow included in the BMS1 and several random operations on the control action that keep the ammonium between a certain operation range and excite sufficiently the plant to perform an identification. Then, we extract a data set to apply least squares and to get the model parameters, and another data set to validate the model predictions. Figure 3 shows the measured ammonium and the estimated one during a particular week in the validation set.

The estimation error (difference between measured and estimated ammonium) has some random behavior and a significant periodical pattern due to the daily and weekly variations of the inlet flow. Figure 4 shows the frequency spectrum of the estimation error showing the important peaks that appear in the

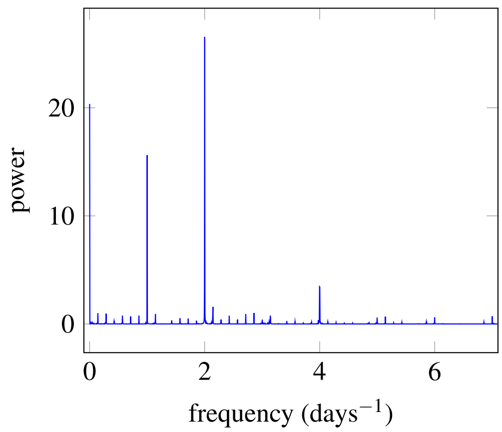

Figure 4: Frequency spectrum of the estimation error, showing the high effect of periodical disturbances.

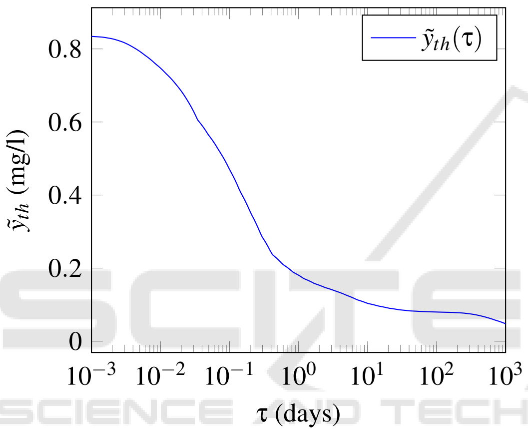

Figure 5: Computed threshold with fault-free data with different time constants.

frequency related with one week and their harmonics, and in the frequency related with one day and their harmonics.

We have filtered the fault free estimation error with several time constants, obtaining the thresholds (4) with $m_s = 2$. Figure 5 exhibits the relation between the filter time constant τ and the threshold obtained. There is a maximum threshold of 0.83 mg/l for fast filtering and a minimum threshold of 0.047 mg/l for slow filtering (related with the mean estimation error of the proposed model).

Then, we have simulated several ramp faults in the BSM1 benchmark. For that, we have modified the output ammonium concentration measurement multiplying it by a time varying gain that starts initially in 1 and then has a constant decay. Since that measurement is used in the control algorithm, the fault implies that real ammonium concentration does not track the reference of the controller (it is higher than the ammonium reference). We have simulated gains with

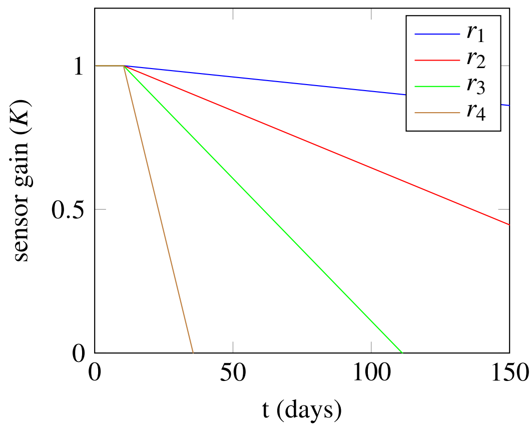

Figure 6: Sensor gain evolution for the four simulated scenarios.

4 decay ratios: $r_1 = 0.7\%$, $r_2 = 2.8\%$, $r_3 = 7\%$ and $r_4 = 28\%$ per week. Figure 6 shows the different time varying gains simulated.

Then, we apply comparison (3) to the obtained faulty signals for different time constants (τ) of the filter. Figure 7 shows the filtered estimation error for time constants of 0.02, 1, 10 and 120 days (0.02 days $\approx$ 30 min) under the fault with the lower gain decay r_1, and the corresponding computed threshold by filtering fault free data with that time constant. We see that for low values of the time constants (i.e., practically no filtering), the threshold is high and that implies a large detection time. For high values of the time constant, the absolute filtered error changes very slowly and that also generates a large detection time. For intermediate time constants we obtain lower detection times.

Figure 8 shows the obtained detection times t_d for the four simulated gain decays with time constants from 10^{-3} days (i.e., 1.4 min) to 10^3 days. We see that for time constants between 0.4 days to 10 days we have a different minimum detection time for each situation. Figure 9 shows the value of the simulated sensor gain reduction at the time of detection for each explored time constant.

In a real application we do not know a priori which will be the real decay for the faulty sensor, so we cannot directly decide an optimum value for the time constant from the analysis of detection time and the value of the gain at that instant. In order to decide a filtering time constant that gives good results in all cases, we analyze now the poured volume of ammonium that is out of the control specifications in each situation; this can be computed as the integral of the product between real ammonium concentration and the flow during the time from fault appearance until fault detection. That value is proportional to the prod-

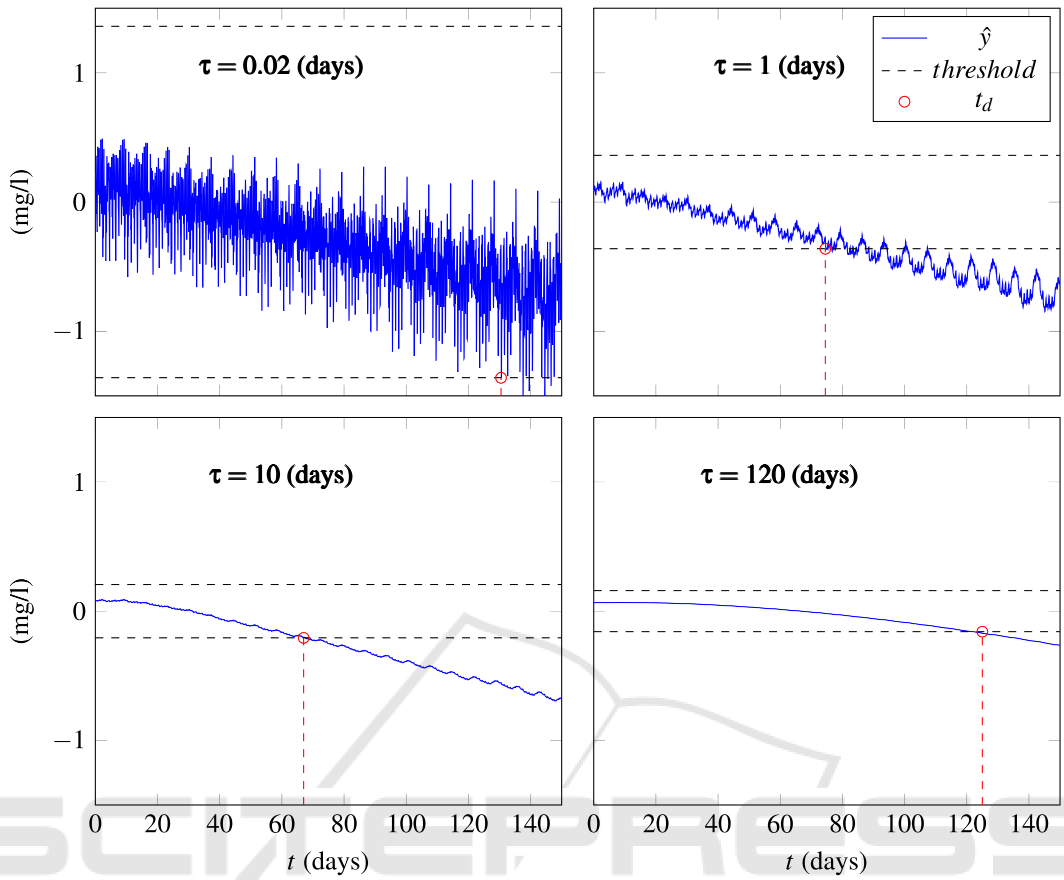

Figure 7: Filtered error and threshold for different time constants in the experiment with lower gain decay rate (r_1). Fault starts at $t = 10$ days.

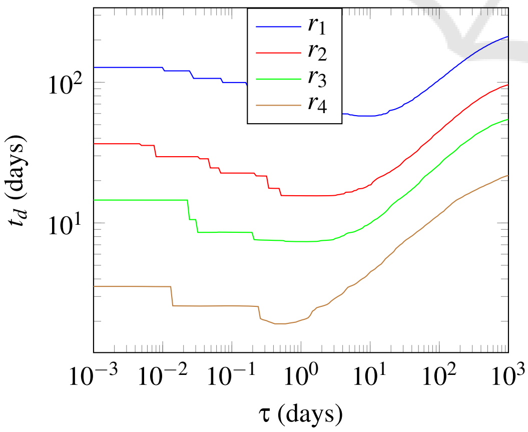

Figure 8: Achieved detection time for different experiments and time constants.

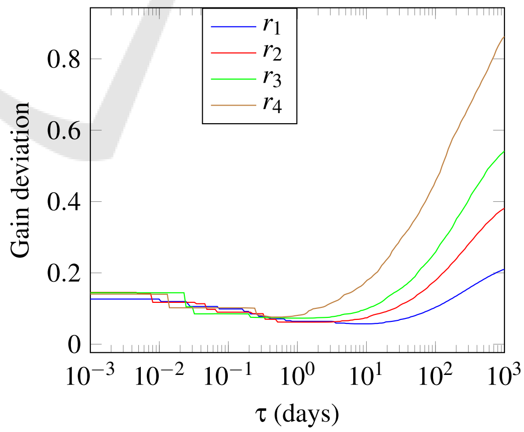

Figure 9: Sensor gain deviation at the time of detection with different time constants.

uct between detection time and simulated sensor gain reduction at the time of detection (figures 8 and 9).

Figure 10 shows that value, evincing that the minimum values for each of the simulated sensor gain decays are closer (in terms of τ) than the ones for the detection time. We have also included in the figure the average of the poured ammonium for the four simulated scenarios. The conclusion is that time constants in the range [1,10] days are a good choice to minimize the estimated poured volume.

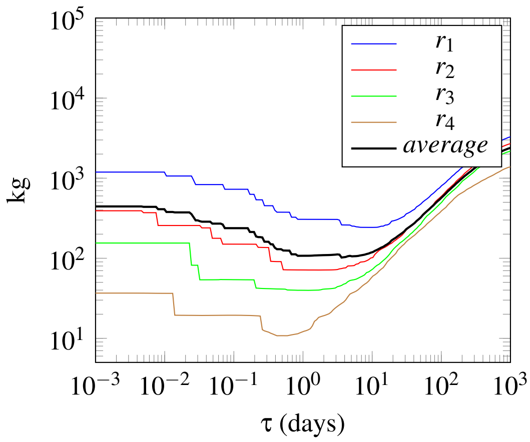

Figure 10: Estimated ammonium mass that is out of specification until the detection of the fault.

6 CONCLUSIONS

A fault detection strategy has been proposed to detect faults in the output ammonium sensor of waste water treatment plants. The plant is assumed to be operated in closed loop by a controller that measures the ammonium, and changes the aeration of the reactor. The faults are assumed to be a slow drift of the measurement. The only signals that are assumed to be measured are the ammonium sensor, the aeration and the incoming volumetric water flow. The input ammonium concentration is not measured. The BSM1 model is used to simulate the behavior of the plant and validate the proposal.

The fault detection scheme is based on a prediction model that predicts the output ammonium, and the comparison of the filtered prediction error with a threshold. The predictor is based on a Volterra series based IIR model, whose parameters are obtained through least squares identification.

Despite the modeling errors that produce a bias in the prediction error, plus the important uncertainty in the input ammonium concentration, that follows a quasi periodic daily and weekly pattern, the proposed fault detector detects the slow varying fault. The paper shows that the detection time depends on the time constant of the filter, and concludes that there is an optimum value that minimizes the fault detection time for a given sensor drift. This optimum value depends on the magnitude of the fault, so we have proposed to use the constant time that minimizes the estimated poured volume of ammonium out of control specifications for the range of proposed faults. Future research lines come from studying the behavior of our proposal in other scenarios as rainy days or storms.

ACKNOWLEDGEMENTS

Supported by MICINN project number TEC2015-69155-R from the Spanish government, Universitat Jaume I (UJI-B2018-39) and the grant ACIF/2018/245 from Generalitat Valenciana.

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