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Regulation of an Activate Sludge Wastwater Plant VIA Robust Active Control Design

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ABSTRACT: The main task of this work is related with the design of a class of SISO robust control law for the regulation of substrate concentration (CDO) of an Industrial Activated Sludge Wastewater Plant. The control design is related with an uncertainty estimator (reduced order observer) based Active Control. Departing from the tracking error between the desired and the current substrate concentrations trajectories a control law is designed and the plant is regulated to the corresponding set point of the COD concentration. To be realizable the controller needs model information related with the kinetic term of COD consumption which is provides with a reduced order observer, these coupled structure (observer based controller) is robust against model uncertainties. The performance of the proposed control law is illustrated with numerical simulations employing a mathematical model of an Industrial Activated Sludge Wastewater Plant tuned with industrial data.

Key words: Aerobic Process, Substrate Regulation, Active Control, Uncertainty Estimation, Robust Performance

INTRODUCTION

The Activate Sludge Process (ASP) is the most widely used biological treatment of liquid waste, essentially because it is a cheap technology which can be adapted to any kind of wastewater. In the activated sludge process, a bacterial biomass suspension (the activated sludge) is responsible for the removal of pollutants. Depending on the design and the specific application, an activated sludge wastewater treatment plant can achieve biological nitrogen removal and biological phosphorus removal, plus the removal of organic carbon substances. Many different activated sludge process configurations have evolved during the years: (Jeppsson *et al.*, 1996, Aouaoud *et al.*, 2011, Olsson *et al.*, 2005, Chachuat *et al.*, 2005) provides an exhaustive review on the historical evolution of the activated sludge process. The microorganisms in the activated sludge are mainly bacteria, which can be found also in the raw wastewater incoming into the plant. The composition and the species depend not only on the influent wastewater but also on the design and operation of the wastewater treatment plant. Bacteria constantly need energy in order to grow and to support essential life activities. Growing cells utilize substrate and nutrients located outside the cell membrane for growth and energy in a process. Oxygen is used by microorganisms to oxidize organic matter. Some bacteria can use oxygen either as dissolved oxygen or not: these bacteria are called heterotrophs. They represent the major part of bacteria in activated sludge and use organic carbon in the form of small organic molecules as substrate. Other essential bacteria for the activated sludge process are autotrophs. They can growth only with dissolved oxygen and use inorganic carbon as substrate. To maintain the microbiological population, sludge from the settler is recirculated to the aerated tank. The bacteria growth and particulate inert matter is removed from the process as waste sludge.

For biological processes, several kinds of control strategies have been proposed, adaptive, optimal, H_∞, linearizing and neuro-controllers, (Yoo *et al.*, 2004, Henze *et al.*, 1987, Henze *et al.*, 1995, Henze *et al.*, 1999) they have shown an adequate performance, for a class of bioreacting systems, however, some of them are coupled with optimizing routines or are model based, their main drawbacks are the over-parameterization and lack of robustness under model uncertainties. Recently, an alternative methodology to control systems with high nonlinear behavior, have been applied, this methodology is the Active Control (AC); the controller design is based on the dynamic of the control error *i. e.* the difference between the

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current and the desired trajectory of the system. This methodology has been successfully employed for synchronization of chaotic oscillators, (Isidori, 1995, Ho *et al.,* 2002, Vincent *et al.,* 2005,) but design of explicit controllers with application to regulation of reacting process, at the authors known, have not been studied enough. The realization of the corresponding Active Control law is model based, such that under model uncertainties the standard AC is not applicable. To avoid the problem mentioned above, in this work is proposed an observer based Active Control, where a reduced order observer is designed to provide the corresponding missing information (uncertain terms, related with modeling errors) to the controller and assuring a stable closed-loop behavior.

Wastewater engineering represents at present time a subject area of worldwide interest, for reasons of the public health, economic and social issues to which it is closely associate. In particular the wastewater generated by industrial processes is a very important topic for engineering research, from them the petrochemical industry under study produces a wastewater which is generated in the different chemical processes. The wastewater flow produced is about 7000 m^3/d and contains volatile organic carbon's substances classified as toxics like 1,2 dichloroethane, chloroform, benzene, among others volatile compounds, (VOC's). To comply environment legislation (ME, 1997, Igbinosa *et al.,* 2009) is around of 150 mg/L in order to discharge the wastewater treated to the river. One of the main effects on the plant operation are the actual temperature conditions within the bioreactor are 32^{o}C in October-November reaching up to 41^{o}C in August-September. Due to this effect, the microorganism's activity is affected and this must be considered in the dynamic modeling of the system. Some models have been developed to describe the effect of temperature on bacterial growth (Heitzer *et al.,* 1991, Zwieterig *et al.,* 1991). The authors showed that at high temperatures the maximum specific growth rate (μ_{max}) is reduced.
There are several models describing the biological process in the activated sludge plant, the developments in the family proposed by the International Water Association (IWA) represent a major contribute: ASM1, the Activated Sludge Process Model No.1 can be considered as the reference model since this model triggered the general acceptance of the biological process modelling. ASM1 was primarily developed to describe the removal of organic compounds and nitrogen with simultaneous consumption of oxygen and nitrate as electron acceptor. The model, furthermore, aims at yielding a good description of the sludge production. COD (Chemical Oxygen Demand) was adopted as the measure of the concentration of organic matter. ASM2, the Activated Sludge Process Model No.2 extends the capabilities of the ASM1 of the description of bio-phosphorus. ASM2d, the Activated Sludge Process Model No.2d is built on the ASM2 model adding the denitrifying activity of PAOs1 to allow a better description of the dynamics of phosphate and nitrate. ASM3, the Activated Sludge Process Model No.3 was also developed for biological nitrogen removal, with basically the same goal as the ASM1. The major difference between the ASM1 and the ASM3 models is that the latter recognizes the importance of storage polymers in the heterotrophic activated sludge conversion (Henze *et al.,* 1987, Henze *et al.,* 1995, Henze *et al.,* 1999).

MATERIALS & METHODS

For control purposes a mathematical model of an activated sludge process is employed, this model presented in (Aguilar *et al.,* 2005), consider a carbon removal model with an dynamic energy balance to introduce the temperature effects on the maximum specific growth rate, mass transfer coefficient for oxygen (*kla*) and death coefficient (k_d), which were incorporated in the mass balance equations of the process. The temperature effect on the maximum specific growth rate was evaluated with Equation 8, the mass transfer coefficient for the oxygen (*kla*) with Equation 10 which is an empirical function of the air flow (Aguilar *et al.,*2005), the death coefficient (k_d) with Equation 9, the evaporation flux of VOC´s ($K_{ev}S$) is also considered in the COD balance, together with the inactivate biomass $(1-f_n)X$ which contributes to growth the substrate concentration in the bioreactor, all were incorporated in the mass balance equations of the process. The process is described by the following mass balance equations (Raltowsky *et al.,* 2005) , as a first modeling approach of the temperature effect on different parameters is considered introducing an energy balance considering that the metabolic heat generation can be deleted in comparison with the others energy flows. The bioreactor behavior was assumed as completely mixed flow reactor. In the reactor:
Substrate (S) concentration mass balance:

$$\frac{dS}{dt} = \frac{Q_f}{V} S_r - \frac{Q_0}{V} S - \frac{\mu_{max}}{Y} \left(\frac{S}{K_s + S} \right) \left(\frac{C_{O_2}}{K_{OH} + C_{O_2}} \right) X + k_d (1 - f_n) X - K_{ev} S \qquad (1)$$

Biomass (X) concentration mass balance:

$$\frac{dX}{dt} = \frac{Q_r}{V} X_r - \frac{Q_0}{V} X + \frac{\mu_{\max}}{Y}\left(\frac{S}{K_s + S}\right)\left(\frac{C_{O_2}}{K_{OH} + C_{O_2}}\right) X - k_d X \quad (2)$$

Oxygen (C_{O2}) concentration mass balance:

$$\frac{dC_{O_2}}{dt} = \frac{Q_f}{V} C_{O_{2f}} - \frac{Q_0}{V} C_{O_2} - \frac{\mu_{\max}}{Y_{O_2}}\left(\frac{S}{K_s + S}\right)\left(\frac{C_{O_2}}{K_{OH} + C_{O_2}}\right) X - k_L a (C_{O_{2sat}} - C_{O_2}) \quad (3)$$

Energy Balance (T):

$$\frac{dT}{dt} = \frac{Q_0}{V}(T_{in} - T) + \frac{Q_{air}\rho_{air} Cp_{air}}{V\rho C_p}(T_{air} - T) + \frac{h_c A}{V\rho Cp}(T - T_\infty) \quad (4)$$

In the settler

$$\frac{d\gamma_{x,r}}{dt} = \frac{Q_u}{V_s} X_r - \frac{Q_0}{V_s} X \quad (5)$$

Here:

$$Q_0 = Q_f + Q_r \quad (6)$$

$$Q_u = Q_w + Q_r \quad (7)$$

and
Where:
A = Transport area (m^2)
t = time (d)
h_c = heat transfer coefficient
Q_f = influent flow rate (m^3/d)
Q_r = recycle flow rate (m^3/d)
Q_W = waste flow rate (m^3/d)
Q_{air} = air flow rate (m^3/d)
S_f = COD concentration in the influent (mg/L)
S = COD concentration in the reactor (mg/L)
X = biomass concentration in the reactor (mg/L)
X_r = biomass concentration in the settler (mg/L)
C_{O2f} = dissolved oxygen concentration in the influent (mg/L)
C_{O2} = dissolved oxygen concentration in the reactor (mg/L)
C_{O2sat} = dissolved oxygen saturation concentration (mg/L)
μ = specific growth rate (d^{-1})
μ_{max} = maximum specific growth rate (d^{-1})
$\mu_{max} = b^2 (T-285)^2\{1-\exp[c(T-330.5)]\}^2$

b= 0.05 ($K^{-1} h^{-0.5}$)
c= 0.005 (K^{-1})
T= water temperature (°C)

K_s = 30 mg/L (substrate saturation coefficient)
K_{OH} = 0.2 mg/L (substrate saturation coefficient)
k_d = death coefficient (d^{-1})

$$k_d = k_{d\,20} 1.05^{(T-20)} \quad (8)$$

k_{d20}=0.03 d^{-1}= death coefficient at 20°C
$Y_{x/s}$ = 0.67 = yield coefficient (mg biomass produced/mg COD consumed)
Y_{O2} = 2.03 = yield oxygen coefficient (mg biomass produced /mg O_2 consumed)
kla = mass transfer coefficient (d^{-1})

$$kla = kla_{20} 1.02^{(T-20)} \quad (9)$$

kla_{20} = mass transfer coefficient at 20°C (d^{-1})
T = wastewater temperature in the reactor (°C)
V = 15000 m^3 (reactor volume)
V_S = 750 m^3 (settler volume)
ρ = density (g/cm^3)
Cp = Heat Capacity (kcal/g °C)

A suitable solution to the wastewater treatment plant is the development of adequate information systems to control and supervise the process. However, a closer look at the current operation of wastewater treatment plant reveals that automation is still minimal even if in the scientific community and in process industries the importance of automation and control in these processes has been recognized in the last years. Several reasons for this lack in wastewater treatment plant can be found: i) the insight in the process is still marginal, ii) reliable technologies are still unsatisfactory or not existing, iii) the possibilities to act on the process are still inapt or insufficient and, most importantly, iv) wastewater treatment plant is considered as a non-profit industry. Automation has been considered costly and has not been part of the process design.

For the control of aerobic wastewater plant, several strategies have been proposed, considering several input-output selections and SISO and MIMO control structures (Aguilar *et al.*, 2001, González *et al.*, 2001) In this work is considered a SISO control structure, for sake of simplicity, to show how the active control (AC) can be implemented, following the pair of control and controlled variables proposed in (Aguilar *et al.*, 2005); the COD (substrate) concentration is considered as the controlled measured output (*y*). The COD is the amount of oxygen required to oxidize, by chemical means, organic carbon compounds completely to CO_2 and H_2O and it is measured is routinely made in industrial operation, the corresponding control input (*u*) is related with the input flow, which affect the input substrate concentration rate. With the above, let us to analyze the following subsystem related with the substrate mass balance equation:

$$\frac{dS}{dt} = \frac{Q_f}{V} S_r - \frac{Q_O}{V} S - \vartheta \qquad (10)$$

With:

$$\vartheta = \frac{\mu_{max}}{Y}\left(\frac{S}{K_s + S}\right)\left(\frac{C_{O_2}}{K_{OH} + C_{O_2}}\right) X + (1 - f_n) X - K_{ev} S$$

, as the total COD consumption rate.

Note that the term contains the COD kinetic rate, the non-activate biomass and the volatile substrate. Now, it is proposed a desired COD closed-loop trajectory as follows:

$$\frac{dy_d}{dt} = -\alpha\left(y_d - y_{sp}\right) \qquad (11)$$

This desired output trajectory allows reaching the corresponding set point y_{sp} asymptotically with a convergence rate given by the parameter α.

Now, defining the control error as:

$$e = S - S_d = y - y_d \qquad (12)$$

then,

$$\dot{e} = \alpha\left(y_d - y_{sp}\right) - \vartheta(\circ) - \frac{Q_O}{V} y + u(t) \qquad (13)$$

from the above, the following controller is proposed, applying the AC methodology:

$$u(t) = \frac{Q_f}{V} S_f = \alpha\, y_{sp} + \vartheta(\circ) + \zeta(t) \qquad (14)$$

such that this controller provides the following closed-loop structure of the control error dynamic:

$$\dot{e} = \alpha\, y_d - \frac{Q_O}{V} y + \zeta(t) \qquad (15)$$

or in alternative form:

$$\dot{e} = -\frac{Q_O}{V} e + \left(\alpha - \frac{Q_O}{V}\right) y_d + \zeta(t) \qquad (16)$$

the exogenous function ζ is chosen such that it can provide a stable behavior to the control error trajectory, in accordance with the following structure:

$$\zeta(t) = -\left(\alpha - \frac{Q_O}{V}\right) y_d - 1 \qquad (17)$$

Note that the control input depends of the nonlinear term $\vartheta(\circ)$, consequently the controller is realizable if only if the nonlinear term is known, which is an important drawback for the standard AC implementation when modeling errors are present.

One the major bottlenecks in the application of computer monitoring and control for biological process is the lack of reliable, sterilizable and robust sensors for the on-line measurements of process key variables, such as biomass, precursors, product concentrations and consumption rates. Several attempts to quantify the above variables have been employed, some of them are optical techniques, electrochemical detection and by viscosity, filtration and fluorescence methods (Schuler and Schmidt, 1992), but these approaches frequently do not properly address the most important industrial problems and necessities. To tackled the problem mentioned above, several estimation techniques for bioprocess have been developed, these techniques are often named soft-sensors some of them are based on balancing technique, this approach is adequate for steady-state operation, however it become unstable when dynamic and corrupted measured are presents (Dochain and Vanrolleghem, 2001); on other hand filtering (observing) theory where extended Kalman filters, nonlinear Luenberger observers, sliding-mode, high gain and so on have been successfully employed (Alvarez *et al.*, 2005). Considering our particular case, the state variable to be regulated is directly the measures output of the system, i. e. the COD concentration such that, a reduced order observer to infer the uncertain term $\vartheta(\circ)$ is proposed as follows (Alvarez *et al.*, 1999):

$$\frac{d\hat{\vartheta}}{dt} = \tau\left(\vartheta_{obs} - \hat{\vartheta}\right) \qquad (18)$$

Where τ is the observer gain, $\hat{\vartheta}$ is the estimate of the uncertain term and the observed uncertainty ϑ_{obs} is obtained by solving the mass balance equation, in accordance with the next equation:

$$\vartheta_{obs} = -\frac{dy}{dt} + \frac{Q_f}{V} S_f - \frac{Q_O}{V} y \qquad (19)$$

As it can be seen, the structure of the proposed observer includes the derivative of the COD concentration, which must be calculated in order to obtain estimates of the reaction rate. However, the synthesis of derivators is a difficult task; moreover if the concentration measurements are noisy the synthesis could be impossible. In order to avoid this situation the following change of variable is proposed:

$$\Theta = \hat{\vartheta} + \tau y \qquad (20)$$

Producing an uncertainty observer with the following structure:

$$\frac{d\,\Theta}{dt} = \tau\left(\frac{Q_f}{V} S_f - \frac{Q_O}{V} y - \hat{\vartheta}\right) \qquad (21)$$

Note that with equations (20) and (21) the uncertain term can be expressed finally as:

$$\hat{\vartheta} = \Theta - \tau y \qquad (22)$$

As can be seen this estimation methodology only depends of measured variables, consequently is completely realizable. Now, for the realization of the robust (non ideal) AC, the estimate of the uncertain term determinate above is coupled to the ideal AC to produce:

$$u(t) = \alpha\, y_{sp} + \hat{\vartheta}(\circ) + \zeta(t) \qquad (23)$$

Note that the above no ideal controller can recover its ideal properties if the estimation error $e_1 = \vartheta_{obs} - \hat{\vartheta}$ tends to zero, to prove this, let us consider the convergence analysis of the proposed observer, departing of the unknown dynamic of the uncertain term:

$$\frac{d\,\vartheta}{dt} = \Phi(\circ) \qquad (24)$$

The Equation 18 is an asymptotic proportional reduced observer for the system given by Equation 24, where $\tau > 0$, determines the desired convergence rate of the observer, if the following assumptions are satisfied:

There exist τ and $N \in \Re^+$ such that:

A1 the dynamic of the uncertain term is bounded i. e.

$$\|\Phi(\circ)\| \le N$$

A2

$$\lim_{t \to t_0}\left\|\exp\left(-\int_0^t \tau\, d\sigma\right)\right\| = 0 \quad with\ t_0\ l\arg e\ enough$$

Considering the above equation (24), the dynamic of the estimation error is defined as:

$$\dot{e}_1 + \tau e_1 = \Phi(\circ) \qquad (25)$$

Solving it renders:

$$e_1 = e_{10}\exp(-\tau t) + \int_0^t \exp(-\tau t)\exp(\tau\sigma)\Phi(\circ)\,d\sigma \qquad (26)$$

where e_{10} is the initial condition of the estimation error. Taking norms of the equations (26) the following inequality arises:

$$0 \le \lim_{t\to t_0}\|e_1\| \le \|e_{10}\| \lim_{t\to t_0}\left[\left\|\exp\left(-\tau\int dt\right)\right\|\right] + \frac{\lim_{t\to t_0}\left[\int_0^t \|\exp(\tau\sigma)\Phi(\circ)\,d\sigma\|\right]}{\lim_{t\to t_0}\left\|\exp\left(\int \tau\, dt\right)\right\|} \qquad (27)$$

From **A1** and **A2:**

$$0 \le \lim_{t\to t_0}\|e_1(t)\| \le \frac{\lim_{t\to t_0}\left[N\int_0^t \left\|\int \exp(\tau\sigma)\,d\sigma\right\|\right]}{\lim_{t\to t_0}\left\|\exp\left(\int \tau dt\right)\right\|}$$

The above equation means that the $\frac{\infty}{\infty}$ case of uniform L´höpital´s rule can be applied as follows:

$$0 \le \lim_{t\to t_0}\|e_1(t)\| \le \lim_{t\to t_0}\frac{N\left\|\exp\left(\int \tau\, dt\right)\right\|}{\left\|\exp\left(\int \tau\, dt\right)\right\|\|\tau\|} = \lim_{t\to t_0}\frac{N}{\|\tau\|}$$

in the limit, when $t \to t_0$:

$$|e_1| \le \frac{N}{\|\tau\|} \to 0 \qquad (28)$$

RESULTS & DISCUSSION

The mathematical model was validated with the COD data obtained from the wastewater treatment plant which was in operation during a year, from October 2002 to September 2003 as presented previously in (Maqueda *et al.*, 2005). For simulation purposes a step disturbance in the recycle flow Q_r is considered from 525 mg/l to 551 mg/l, besides other step disturbance on the oxygen concentration at reactor input is also considered, from 3 mg/l to 2 mg/l. A commercial PI controller is simulated for comparison purposes, the tuning of the PI control's gains were done via input-output response with a step disturbance in the control input, which yields the following parameters: the steady-state gain K = 2.8 mg d/Lm^3; the characteristic time π= 7 days; the proportional control gain K_p = 1.5 d^{-1} and the integral time τ_I = 7 d, these values were obtained applying IMC tuning rules (Rivera *et al.*,1986) . For the robust AC controller the convergence rate α = 10 d^{-1} and the observer gain τ= 1 d^{-1} were considered. Fig. 1 is related with the concentrations space portrait, note that the controller lead the COD concentration to the required set point (150 mg/l) with a biomass of 4200 mg/l and the dissolved oxygen is around 0.4 mg/l, which is the closed-loop steady-state. Fig. 2 shows the closed-loop time evolution of the COD concentration, can be observed an asymptotic stable behavior of the COD trajectory to the former set point which is reached in 12 days for the proposed controller, this settling time can be reduced with a more large value of the parameter α, in order to improve the convergence rate. The PI controller needs 47 days to reach the corresponding set point. Fig. 3 is related with the closed-loop performance of the control output (COD concentration) when disturbances arrive, the proposed AC controller has a faster response in comparison with the PI controller. The control input behavior can be seen in Fig. 4, note that the robust AC controller show a faster response, the PI controller acts lowly, not great control effort is needed to comply with

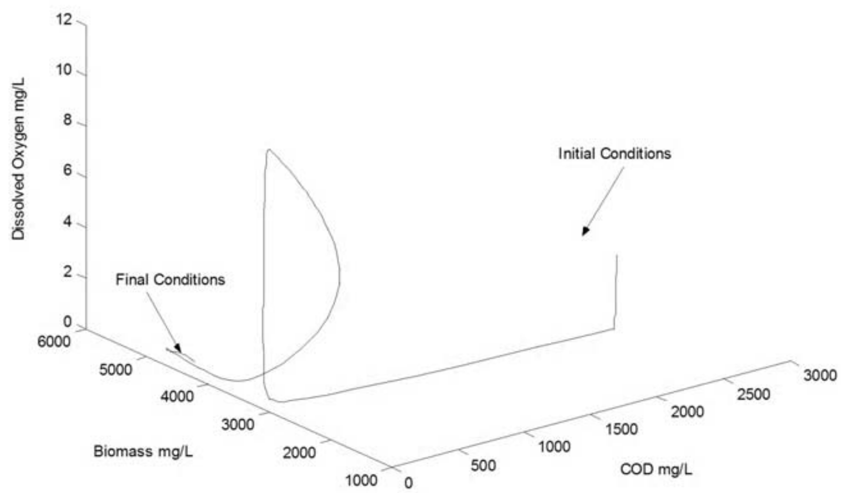

Fig. 1. Closed-loop steady-state phase portrait

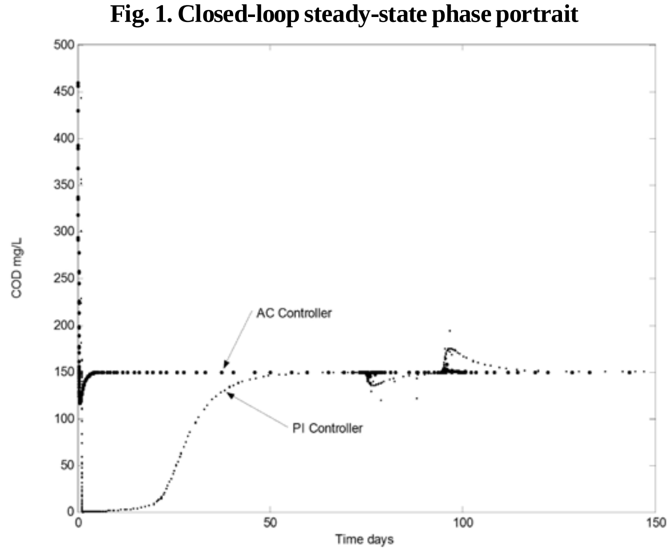

Fig. 2. Closed-loop performance of the COD with the proposed controller

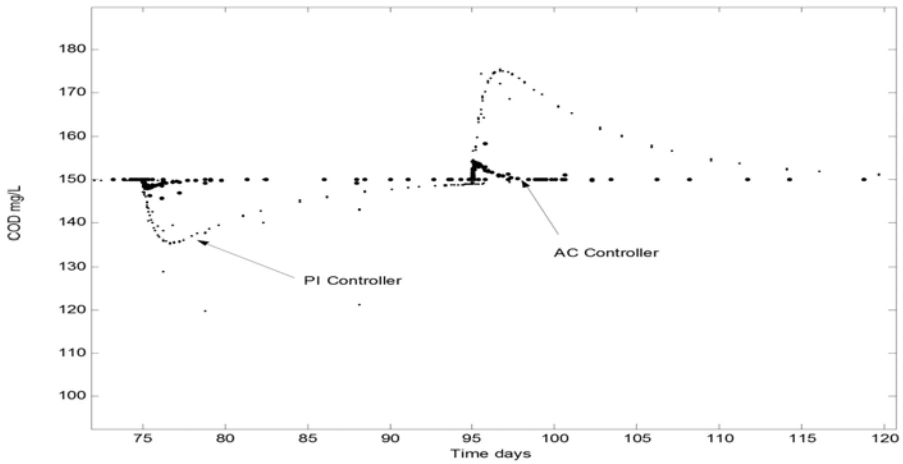

Fig. 3. Closed-loop performance of the COD against disturbances

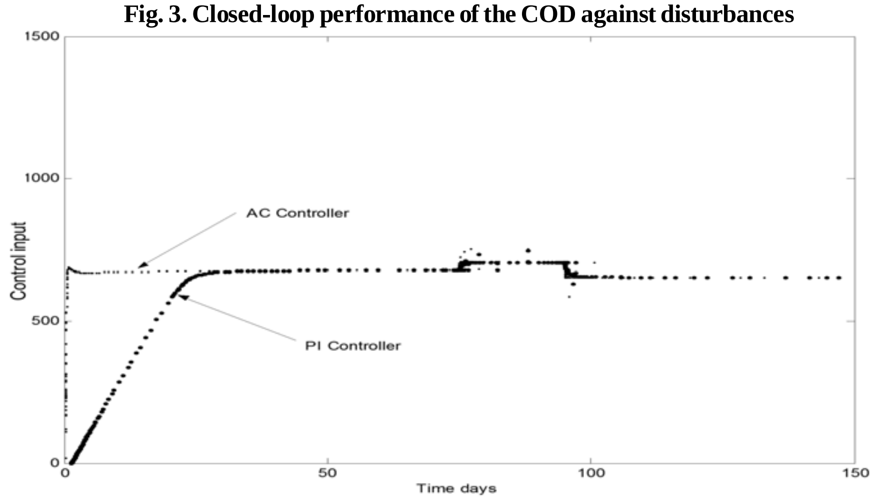

Fig. 4. Closed-loop performance of the system input (Input Flow m^3/days) with proposed controller

the regulation task and finally Fig. 5 shows the closed-loop performance of the reduced order observer, note a satisfactory performance of the proposed estimation methodology, this occurs because the proposed methodology is able to regulated the process into more wide operating region given its nonlinear properties and the low parameters dependence, which helps to avoid tuning issues.

CONCLUSION

A mathematical model of an Activated Sludge Wastewater Plant is developed and corroborate with industrial COD and operating data with good results. This model is employed as a *virtual* process where the total COD (substrate) consumption rate is supposed uncertain (unknown). To avoid the problem of the modeling errors a reduced order observer is proposed, the information generated by the observer is coupled with an Active Control law, such that a robust structure against modeling error is achieved. Numerical simulations illustrate the satisfactory performance of the observer based AC law.

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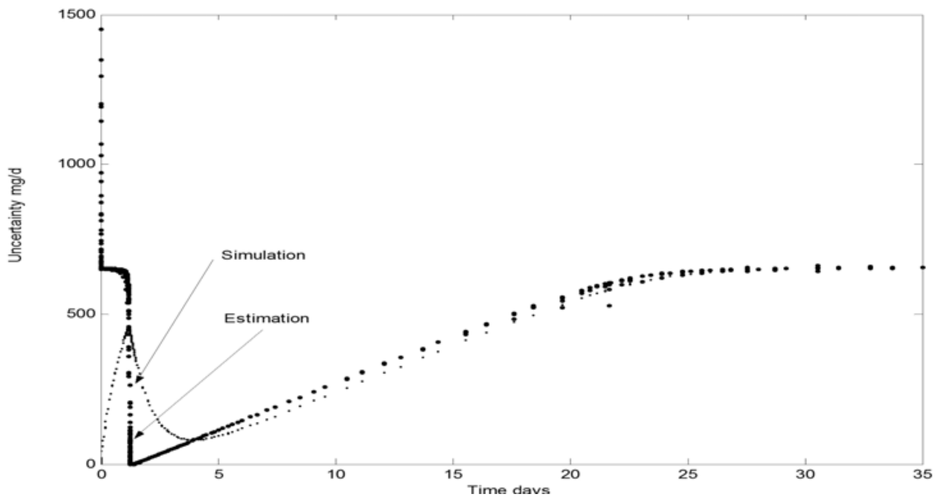

Fig. 5. Closed-loop uncertainty observer performance

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