Robust control of a three phase separator: an LMI approach

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Abstract: This paper presents an $\mathcal{H}_\infty$ approach for a three-phase gravity separator. A switching strategy is applied to chose between two controllers: one to damp oscillatory disturbances in the inflow of the separator, and one for better set-point tracking. The controller selection relies on the inflow disturbance measurement, which is unpractical or unreliable. Therefore, an $\mathcal{H}_2$ observer is designed to estimate the (multiphasic) inflow which in turn is utilized as the controller switching signal. The performance of the proposed strategy is compared to a traditional PI Zone controller normally used in industry. The results demonstrated that the proposed controller outperforms the performance achieved by classical PI Zone controllers allowing a good trade-off between slug attenuation and set-point tracking.

Keywords: Three Phase Separators, Slug Handling, Robust Control, Process Control.

1. INTRODUCTION

In an oil field, the well stream usually consists of a mixture of gas, oil and water, together with impurities. As the economic interest is only in the production of hydrocarbons (oil and gas), there is a need to provide these fields with facilities for the primary processing of fluids. The facilities must split the multiphasic inflow into as pure as possible single phase streams in order to: (*i*) deliver high quality hydrocarbons to post-processing (e.g., inshore refineries); and (*ii*) produce purified water to be discarded in the ocean. To do so, a first rough separation stage can be a gravity separator, which relies on separation by gravitational forces and density differences between the respective phases (Bothamley, 2013).

This work focus on the tree-phase horizontal gravity separators, since they are the ones normally used in oil industry (Thomas, 2001). Active control is necessary to maintain the equipment levels and pressure close to their set-points, which in turn are chosen in a way to maximize oil production and the equipment efficiency. However, disturbances can cause the state variables to vary. The most serious one happens due to the slug flow regime in oil wells and risers, which are characterized by alternating oscillations in the inflows of gas and liquid. Slug control has attracted a great deal of attention in recent decades, see Pedersen et al. (2017a) for a review of slug control methods. Nonetheless, most of the approaches currently suggested handle the slug either on the wells or on the riser.

In this paper, we concentrate in the case where slug suppression controllers in upstream systems are not available or are insufficient, since literature for this situation is rather sparse. Therefore, we aim to design a separator controller to keep the process variables near their optimal set-points, and also damp fluctuations caused by slug flow, sending a more stable flow for downstream processes. Interestingly, there is a trade-off between dampening the flow oscillations and dampening the oscillations in the state variables (oil level, water level and pressure). Thus, the controller must be design accordingly.

The techniques used to tackle this particular situation are usually some form of PID Zone controllers such as Nunes et al. (2005), Mendes et al. (2012); Model Predictive Control (MPC) as suggested by Silveira (2006); or even non-linear MPC (NMPC) as proposed by Mendes et al. (2011), Backi et al. (2018).

We chose to analyze the performance of a robust $\mathcal{H}_\infty$ controller in the separator, given that it was proven to the best model-based linear controller to deal with slug in the wells (Jahanshahi et al., 2012) and in the riser (Pedersen et al., 2017b). This controller is based on the optimal solution of a simple semi-definite programming considering the MIMO (Multiple Inputs and Multiple Outputs) model, thus it is quite advantageous when comparing with the benchmark PID approach. Moreover, constraints on the states and on the control action can be considering on the optimization problem, hence one can easily define different objectives while considering constraints, akin to the MPC strategies. The advantage is that the problem is solved in an offline manner.

For implementation, we test an adaptive $\mathcal{H}_\infty$ strategy. Basically, we use an slug detector to switch between a controller tuned for better reference tracking and another for slug rejection, with the detector being based on the inflow's estimation.

An $\mathcal{H}_2$ observer is used as an estimator. It not only provides information regarding inflows to the controller (and to the operator), but also filters measurement noises. The estimator is specially important given the difficulties associated with measuring multiphase flows (Thorn et al., 2013). With a similar objective, an Extended Kalman Filter (EKF) (Backi and Skogestad, 2017) and a non-linear estimator (Mendes et al., 2012) have been used. The $\mathcal{H}_2$ observer is as simple as the aforementioned methods, while also providing hard upper bounds on the estimation errors (and not needing a priori information of covariance matrices). To the authors knowledge, this is the first time an $\mathcal{H}_\infty$ strategy coupled with an $\mathcal{H}_2$ observer has been applied to the three phase separator process.

The remainder of this paper is structured as follows: Section 2 introduces two models to be used as the simulator and as the basis for controller design. The controller itself and the observer are presented in Section 3. Section 4 presents some simulation results. Finally, in Section 5, the paper is closed with some concluding remarks.

2. THREE-PHASE SEPARATOR MODEL

A schematic of the gravity separator is shown in Figure 1. The inflow of water, oil and gas (W_{in}, L_{in}, G_{in}) enters the separator and hits an inlet diverter, which separates the bulk of gas from liquid. Due to this fact, we assume that there are no gas bubbles in the liquid and no liquid droplets in the gas phase. Afterwards, the liquid goes to the separation chamber, of length $C_{CS} = 4.4$ [m], in which a combination of density differences and coalescing parallel plates separates oil from water. The oil goes to the oil chamber where the oil valve (s_l) is used to control the oil level (h_l) and its outflow (L_{out}) behavior. In a similar manner, a water valve (s_w) and a gas valve (s_g) are used to control the water level and outflow $(h_w,\ W_{out})$ and the vessel pressure and gas outflow $(p,\ G_{out})$, respectively.

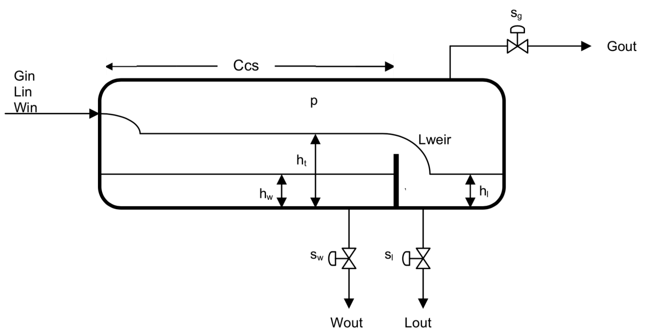

Figure 1. Scheme of a 3-phase separator (Filgueiras, 2005).

The non-linear model that represents the system is fully described in (Filgueiras, 2005). It is the same model used by (Mendes et al., 2012), (Ribeiro et al., 2016) and (Mota Júnior et al., 2020). This model, hereinafter called plant or simulator, will represent the separator during the simulations. The system's main governing equations are:

$$\frac{dh_l}{dt} = \frac{W_{in} + L_{in} - W_{out} - L_{out}}{2C_{C_L}\sqrt{h_l(D - h_l)}} \tag{1}$$

$$\frac{dh_W}{dt} = \frac{W_{in}(1 - Tog \cdot Elw) - W_{out} + L_{in} \cdot Bsw \cdot Ewl}{2C_{Cs}\sqrt{h_W(D - h_W)}} \tag{2}$$

$$\frac{dp}{dt} = \frac{(L_{in} + W_{in} + G_{in} - W_{out} - L_{out} - G_{out}) \cdot p}{V_t - V_{CL} - V_{CS}} \tag{3}$$

with $C_{CL} = 1.0$ [m] being the length of the oil chamber, $D = 1.8$ [m] the separator diameter, Tog the concentration of oil in the water inflow, Elw the efficiency of removal of oil in water, Bsw concentration of water in the oil inflow, Ewl the efficiency of removal of oil in water, V_{C_L} the oil chamber volume, V_{C_S} the separation chamber volume, V_t the total volume.

The model static part, including efficiencies calculations, won't be presented here, but are available in the original thesis (Filgueiras, 2005). The next subsection presents some comments concerning the linear model that is used by our controllers.

2.1 Separator Linear Model

The simplified system can be linearized around a operating point, yielding a state space in the form:

$$\begin{cases} \dot{x}(t) = A(\delta(t))x(t) + B_u u(t) + B_w w(t) \\ y(t) = C_y x(t) \end{cases} \tag{4}$$

where $x(t) = [h_W \ \ h_l \ \ p]^T \in \mathbb{R}^3$ is the state vector, $\delta(t)$ is the vector of uncertain parameters, $u(t) = [W_{out} \ \ L_{out} \ \ G_{out}]^T \in \mathbb{R}^3$ is the control signal, $w(t) = [W_{in} \ \ L_{in} \ \ G_{in}]^T \in \mathbb{R}^3$ is the disturbance assumed to be energy bounded, and $y(t) = x(t)$ is the measured output.

The system coefficient takes the form of $A(\delta(t)) = A_0 + \Delta A$, where A_0 represents the nominal system, while $\Delta A \triangleq \sum_{i=1}^{n_\delta} \delta_i A_i$ is the matrix of uncertainty, with A_i representing the uncertainties directions. Also, $\delta(t)$ is within a compact and convex set Δ (Duan and Yu, 2013).

For designing purposes, we disregard the valve's dynamics since they are way faster than the separator's. Three slave PID controllers are used to manipulate the valves $(s_w,\ s_l,\ s_g)$ and maintain the outflows $(W_{out},\ L_{out},\ G_{out})$ at the values defined by the master $\mathcal{H}_\infty$ controller.

Furthermore, parameters such as Bsw and Tog tend to vary with time (Campos et al., 2013). The efficiencies associated with the process also vary and are often not available for measurement. Thus, we decide not consider variations of efficiencies or concentrations directly into our formulation. Instead, we define:

$$\begin{aligned} -0.03 \leq \delta_1 &= \ Tog_i \cdot Elw_i \leq 0.03 \\ -0.03 \leq \delta_2 &= Bsw_i \cdot Ewl_i \leq 0.03 \end{aligned} \tag{5}$$

with the subscript i representing incremental variations around the nominal values of $Bsw = 0.10$ and $Tog = 0.13$. Thus, system (4) is a uncertain time-varying system.

3. CONTROLLER DESIGN

According to Silveira (2006) and Mendes et al. (2012), the most critical objective is damping the oscillations on the water outflow, since it feeds directly into hydrocyclones and these are very sensible to variations. If the flow disturbances are passed to them, its separation efficiency will be severely deteriorated. Conversely, the oil outflow usually goes to a two phase separator, which can be used to damp oil oscillations (Nunes et al., 2010). Thus, a sluggish oil outflow is not too dire. With that in mind, the rest of this section presents the observer and controller design.

3.1 Observer Design

Our approach is a switching strategy between two controllers, one of which offers an optimal solution for operation under normal conditions, and the other aims to damp oscillations on the water outflow. In order to know which controller should be active, the unmeasured disturbances are estimated. To do so, a full-order $\mathcal{H}_2$ state observer is designed. As stated before, it also filters measurements noises.

The observer considers the following augmented system, with $x_o(t)^T = [x(t)^T \ w(t)^T]$:

$$\begin{cases} \dot{x}_o(t) = A_o x_o(t) + B_o u(t) + B_\nu \nu(t) \\ y(t) = C_o x_o(t) + D_\nu \nu(t) \\ z_o(t) = C_{zo} \, x_o(t) \end{cases} \tag{6}$$

$$\text{with} \qquad A_o = \begin{bmatrix} A_0 & B_w \\ 0 & 0 \end{bmatrix}, \quad B_o = \begin{bmatrix} B_u \\ 0 \end{bmatrix}, \quad B_\nu = 0,$$
$$C_o = \begin{bmatrix} I_3 & 0_{3\times3} \end{bmatrix}, \quad D_\nu = I_3, \quad C_{zo} = I_6.$$

Notice that the measured outputs (y) are the states subject to noise (ν) and z_o is the observer output vector of interest. Moreover, note that no assumptions regarding the inflow dynamics were made. Defining the estimation error as $\tilde{x} := x(t) - \hat{x}(t)$, and the output estimation error as $\tilde{z}_o := z_o(t) - \hat{z}_o(t)$, we obtain:

$$\mathcal{G}_{\nu z_o} : \begin{cases} \dot{\tilde{x}}(t) = (A_o + LC_o)\, \tilde{x}(t) + (B_\nu + LD_\nu)\, \nu(t) \\ \tilde{z}_o(t) = C_{zo} \tilde{x}(t) \end{cases} \tag{7}$$

where $\hat{x}(t)$ and $\hat{z}_o(t)$ are the estimatives, and the gain L is to be designed such that the system $\mathcal{H}_2$ norm is minimized, i.e. $\|\mathcal{G}_{\nu \tilde{z}_o}\|_2 \leq \gamma_3$, with γ_3 as an upper bound for the minimization. We also design L to fix a chosen decay rate of γ_2 for the observer.

Hence, if there exists a matrix $W \in \mathbb{R}^{6\times3}$, and symmetric matrices $P \in \mathbb{R}^6$, $Z \in \mathbb{R}^3$, then problem (8) has a solution $L = P^{-1}W$ that minimizes the effects of $\nu(t)$ on $\tilde{z}_o(t)$ with a fixed decay rate (Duan and Yu, 2013).

$$\begin{aligned} \min_{P,W,Z} \; & \text{trace}\{Z\} \\ \text{s.t.} \; & \begin{bmatrix} Z & \star \\ (PB_\nu + WD_\nu) & P \end{bmatrix} > 0 \\ & \text{He}\{PA_o + WC_o\} + C_{zo}^T C_{zo} < 0 \\ & \text{He}\{PA_o + WC_o\} + 2\gamma_2 P < 0\,, \\ & P > 0. \end{aligned} \tag{8}$$

with $\text{He}\{PA_o + WC_o\} = (PA_o + WC_o) + (PA_o + WC_o)^T$ and $\gamma_3 = \sqrt{trace\{Z\}}$.

For the observer design, the uncertain and unmeasured parameters were disregarded. This is because, after numerous simulations, we noticed that the gain L based on $A_o(\delta(t))$ and A_0 were rather similar. Thus, the correction factor in the observer is robust and the only disadvantage when considering only the nominal case would be the miscalculation of the split ratio of oil and water in the liquid inflow rate.

The optimization problem is setup as a semidefinite programming, as stated in equation (8), in MATLAB. The problem is then solved using Yalmip (Löfberg, 2004) as a parser and Mosek (ApS, 2019) as a solver. There is only one tuning parameter for the observer, which is $\gamma_2 = 0.02$. This value was chosen via trial and error to get a compromise between the observer filtering and estimation capabilities, and its decay rate and dynamics speed.

3.2 Controller Design

Due to the fact that we want to track the optimal set-points during normal operation, one can introduce an augmented state vector, as suggested by Flores et al. (2010). The augmented vector is: $x_a(t)^T = [x(t)^T \ x_c(t)^T]$, with x_c being the states associated with a dynamic compensator such as the one presented below:

$$\{\dot{x}_c(t) = A_c x_c(t) + B_c e(t) \tag{9}$$

The compensator is designed to add integral action to the controller, hence A_c is a matrix of zeros and B_c is an identity matrix. Thus, x_c is just the integral of the tracking errors. The error is defined as $e(t) = r(t) - y(t)$, with $r(t)$ being the desired set-points.

The concatenation of equation (4) and equation (9) leads to the following augmented dynamics:

$$\begin{cases} \dot{x}_a(t) = A_a(\delta) x_a(t) + B_{ua} u(t) + B_{wa} w(t) + B_r r(t) \\ z_a(t) = C_{za} x_a(t) + D_{ua} u(t) \end{cases} \tag{10}$$

$$\text{with} \qquad A_a(\delta) = \begin{bmatrix} A(\delta(t)) & 0 \\ -B_c C_y & A_c \end{bmatrix}, \; B_{ua} = \begin{bmatrix} B_u \\ 0 \end{bmatrix},$$
$$B_{wa} = \begin{bmatrix} B_w \\ 0 \end{bmatrix}, \; B_r = \begin{bmatrix} 0 \\ B_c \end{bmatrix}. \tag{11}$$

In order to design a state-feedback $u(t) = K_1 x(t) + K_2 x_c(t)$, we consider the following auxiliary system:

$$\mathcal{G}_{wz_a} : \begin{cases} \dot{x}_a(t) = (A_a(\delta) + B_{ua} K_a)\, x_a(t) + B_{wa} w(t) \\ z_a(t) = (C_{za} + D_{ua} K_a)\, x_a(t) \end{cases} \tag{12}$$

with $K_a = [K_1 \ K_2]$ being designed in order to ensure that $\|\mathcal{G}_{wz_a}\|_\infty \leq \gamma_1$, where $\gamma_1 > 0$ is an admissible level of $\mathcal{H}_\infty$ performance (Duan and Yu, 2013).

The variable $z_a(t)$ is an auxiliary variable in which the effects of the disturbances $w(t)$ should be minimized. Since we want to minimize its effects on the states, while at the same time avoid oscillations on the outflows, z_a is:

$$z_a(t) = \begin{bmatrix} x_a(t) \\ u(t) \end{bmatrix}, \quad C_{za} = \begin{bmatrix} \alpha_s \\ 0_{3\times6} \end{bmatrix}, \quad D_{ua} = \begin{bmatrix} 0_{6\times3} \\ \alpha_u \end{bmatrix}. \tag{13}$$

with $\alpha_s > 0$ and $\alpha_u > 0$ as diagonal matrices to adjust the importance between states and control effort. The objective here is dual-fold: we adjust these matrices to get a good compromise between tracking levels and damp the water outflow oscillations, and also to get a trade-off between transient response and control effort. The aim is to get a somewhat more conservative controller to avoid saturation on the valves.

Notice that the vessel's pressure must always be around its set-point, since both high and low pressures can damage the compressor unit (separator's subsequent system). We assume that such unit has an inlet drum to help deal with variations on the gas outflow, thus the pressure is the bigger concern.

In summary, we consider the system (12) with the uncertainty being represented by equation (5). If there exists a matrix $W_a \in \mathbb{R}^{3\times 6}$ and a symmetric matrix $Q_a \in \mathbb{R}^6$, then problem (14) has a solution $K_a = W_a Q_a^{-1}$ that guarantees that the closed loop system is quadratically stable while minimizing the effects of $w(t)$ on $z_a(t)$ within a desired pole region. Our feedback design can be posed by the following optimization problem:

$$\begin{aligned} &\min_{Q_a, W_a} \gamma_1 \\ &\text{s.t.} \begin{bmatrix} \Gamma(Q_a, W_a) & \star & \star \\ B_{wa}^T & -\gamma_1 I_3 & \star \\ C_{za}Q_a + D_{ua}W_a & D_{wa} & -\gamma_1 I_9 \end{bmatrix} < 0, \ \forall \delta \in \Delta_E \\ &\qquad \iota \otimes Q_a + M \otimes (A_a(\delta)Q_a + B_{ua}W_a) + ... \\ &\qquad M^T \otimes (A_a(\delta)Q_a + B_{ua}W_a)^T < 0, \ \forall \delta \in \Delta_E \\ &\quad Q_a > 0. \end{aligned} \tag{14}$$

with $\Gamma(Q_a, W_a) = A_a(\delta)Q_a + B_{ua}W_a + (A_aQ_a(\delta) + B_{ua}W_a)^T$, $\otimes$ being the kronecker product, and Δ_E representing the vertices of polytope $\mathbf{\Delta}$.

The interest reader may refer to Duan and Yu (2013) for proof regarding the conditions presented in problem (14).

The first constraint is the proper $\mathcal{H}_\infty$ problem, and the second one defines a strip-type LMI region that restricts the closed-loop eigenvalues to have their real part between -10^{-8} and -10^{-2}. This region is defined by:

$$\iota = 2\begin{bmatrix} 10^{-8} & 0 \\ 0 & 10^{-2} \end{bmatrix}, \quad M = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \tag{15}$$

This desired pole region allows the closed-loop to be as slow as necessary, however it caps the eigenvalues maximum values to make sure that our observer is at least 10 times faster than our controller while also avoiding a K_a that is too large. Large gains may lead to aggressive control action, and we want to steer clear of valve saturation. Alternatively, one may consider the constraints on the outputs and control action directly on the $\mathcal{H}_\infty$ formulation, see Yu et al. (2015) for instance.

Yet again, the optimization problem is setup as a semidefinite programming, as stated in equation (14), in MATLAB. The problem is then solved using Yalmip and Mosek. The controller weights for sluggish regime are $\alpha_s = \text{diag}(1, 1, 1, 10^{-3}, 10^{-2}, 1)$ and $\alpha_u = \text{diag}(10^4, 10, 1)$. For normal operation, their values are $\alpha_s = \text{diag}(1,\ 1,\ 1,\ 0.1,\ 0.1,\ 1)$ and $\alpha_u = \text{diag}(10^3,\ 10^3,\ 10^2)$.

Under normal operation, the values of α_u are chosen to get an acceptable trade-off between outputs and control action and based on the magnitude difference between them. The weighting regarding the states associated with the tracking error (x_c) are also chosen to get a less aggressive controller.

During the sluggish flow, our tuning punishes big variations on the water outflow while also allowing the water level to vary. There are multiple choices of weights to achieve oscillations damping, this particular one was chosen because it provides the biggest damp factor.

3.3 Slug Detector

The slug detector uses the inflow estimations to detect oscillations in the vessel's disturbances. The detector applied here was developed in Mendes et al. (2012) and it is based on the calculation of the moving average standard deviation of the estimated disturbance data. If the standard deviation is less than a pre-established limit, it means that the inflows are approximately constant, if the standard deviation exceeds this limit, the detector will indicate the presence of sluggish flow.

As for the tuning parameters, the window size is 250 samples (taken at each 10 seconds), which is roughly equal to the period of the oscillations. The limits are set at 0.01 on the water and oil outflows and 0.09 at the gas inflow. Note that, unlike the original one, this slug detector does not predict slugs. It only detects oscillations in order to trigger a switch between the aforementioned controllers.

Moreover, in order to get a smoother transition between the two controllers, the switching mechanism interpolates between the gains using a convex combination of them: $K = (1-\eta)K_{slug} + \eta K_{nonslug}$, with $\eta \in [0\ 1]$. The variable η is a function of the filtered disturbance detector. Its value is based on the approached presented in Steindal et al. (2019). Moreover, as suggested by (Cheong and Safonov, 2009), the states x_c are reset to get a bumpless transfer.

4. SIMULATION RESULTS

In this section, several simulation results are presented, which demonstrate the capabilities of the proposed strategy. To illustrate its advantages, the results are compared to a PI Zone controller similar to the one used in Mendes et al. (2012) and Nunes et al. (2005). All the controllers are design in the continuous domain, since our master controller is implemented in a digital manner (i.e. in a computer or digital PLC), and the non-linear plant simulator is solved with an ode45 solver.

4.1 Optimization results

Based on the controller weights previously discussed, the state-feedback gain is obtained by solving problem (14).

The problem yields, for the sluggish regime, the feedback gain presented in equation (16).

$$K_a = \begin{bmatrix} 0.0023 & 0 & 0 & -0 & 0 & 0 \\ -0.0022 & 0.1437 & 0.0414 & 0 & -0.0010 & -0.0378 \\ 0.0010 & 0.3029 & 0.0809 & -0 & 0.0007 & -0.7640 \end{bmatrix} \tag{16}$$

Note that column four, associated with the tracking error in the water level, has zero values. Thus, the slug rejection controller allows the water level to vary around the original operational point in order to damp the oscillations.

For normal operation, the feedback gain is presented in equation (17).

$$K_a = \begin{bmatrix} 0.0327 & 0.0070 & 0.0032 & -0.0001 & -0.0001 & -0.0002 \\ -0.0306 & 0.0143 & 0.0037 & 0.0001 & -0.0001 & -0.0001 \\ -0.0015 & -0.0103 & 0.0063 & 0.0000 & 0.0002 & -0.0097 \end{bmatrix} \tag{17}$$

Note that the closed-loop is stable for both gains. Finally, notice that a compromise between the two controllers would yield a gain for normal conditions which also damp oscillations on the water outflows (although not as much as the proposed approach). Thus, if it's not possible to use the slug detector nor the $\mathcal{H}_2$ filter, it would still be possible to apply a similar $\mathcal{H}_\infty$ controller.

The observer gain comes from the optimization problem (8), which yields

$$L = \begin{bmatrix} -0.0400 & -0.0000 & 0.0000 \\ -0.0000 & -0.0400 & 0.0000 \\ 0.0000 & 0.0000 & -0.0400 \\ -0.0069 & 0.0002 & 0.0000 \\ 0.0069 & -0.0015 & -0.0000 \\ 0.0000 & 0.0013 & -0.0006 \end{bmatrix} \quad (18)$$

The optimization problem yields an upper bound of $\gamma_3 = 0.35$, which roughly means that the noise effects will be cut by a third. It is possible to get an even smaller γ_3, i.e. a better filter, however we chose a more conservative one due to our control strategy, which uses a convex combination of the controllers when the switching happens and is also plague by uncertainties.

4.2 Simulation results

The simulation test has a duration of 22.5 hours, and it is subject to both normal and sluggish flow regimes. The test was initialized at steady state with $x(0) = [0.4332,\ 0.496,\ 9.479]^T$, inflows of $w(0) = [0.0133,\ 0.0167,\ 0.13]^T$. The rest of the parameters are taken from (Filgueiras, 2005).

At the beginning of the simulation, we applied a slug flow disturbance on the system and maintain such flow for around 16 hours. At t = 19.5 hours, the fluid's characteristics change, being represented by $Tog_i = -0.02$ and at t = 21 hours a step on the inflow rate is applied. Finally, we also change the oil level set-point, at t = 22.5 hours to check if the controller successfully tracks the new reference.

Figure 2 shows the inflows estimations compared to the real inflows. We can see that the $\mathcal{H}_2$ observer can approximate the inflows with small errors, thus it can be used to identify the sluggish regime. During this flow, there is a small estimation error due to variations on the separation efficiency (which varies with the inflow's oscillations) and due to noise. Also notice that once the Tog_i changes, the observer also misjudge the split flow ratio, believing that the oil inflow rate is smaller and the water inflow higher than their real counterparts. Notice that the estimator perceives the step change on the real inflows, but the misestimation due to Tog_i continues until the test end.

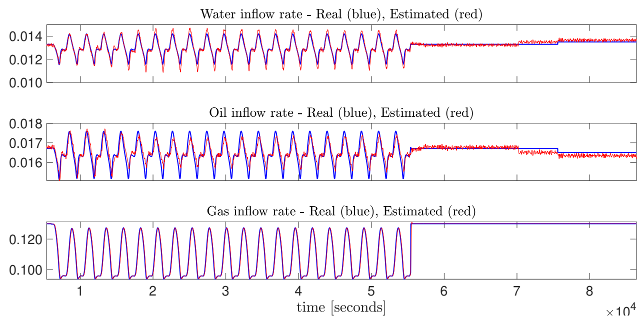

Figure 2. Estimate inflows (red) and real values (blue).

As previously stated, small variations on the efficiencies or concentrations are not critical, because the main purpose of the observer is to know if slug is presented or not.

Based on these results, we applied the proposed switching strategy and compare it with the benchmark PI Zone presented in (Nunes et al., 2005). In this PI, the water and oil levels have a band of 0.2m. Its tuning parameters inside and out of the zone are presented in table 1.

Table 1. PI Tuning parameters.

	Inside Zone		Out of Zone	
Variables	Kc	Ti	Kc	Ti
hw	0.001	125	0.1	50
hl	0.01	125	0.02	50
p	0.03	125	0.03	50

Figure 3 shows the obtained responses of process variables with their respective set points. Figure 4 shows the input and output flow rates.

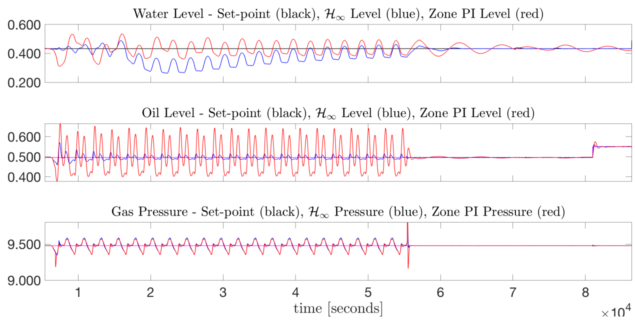

Figure 3. Closed-loop performance. Behavior of process variables using the proposed controller (blue) and the PI Zone (red).

In Figure 3, the main difference between the dynamic behaviors is that the $\mathcal{H}_\infty$ does not cause the oil level to oscillate. Moreover, when the sluggish regime ends, our controller is less oscillatory than the PI in the water level control loop. The pressure control is pretty much the same for both approaches. Note that both controllers manage to maintain the levels within the save zone (with band of ± 0.2m the initial level), however only the PI directly considers such zone.

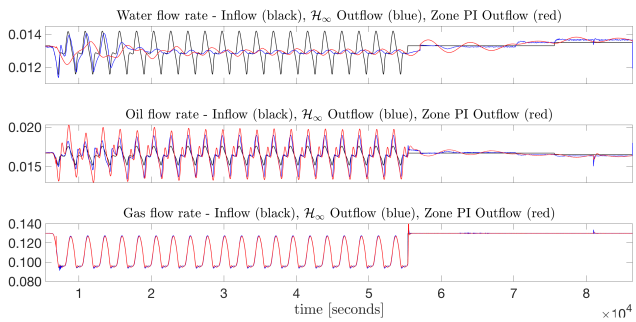

Figure 4. Closed-loop performance. Behavior of input (black) and output flow rates using the proposed controller (blue) and the PI Zone (red).

In Figure 4, we can see that both controllers attenuate the disturbances in the water outflow. However, the proposed strategy yields an outflow that has oscillations 8.72 times smaller than in the inflow against a 5.4 damp factor from the PI Zone.

Regarding the oil outflows, both controllers amplify the oscillations in the oil output flow rate. This was expected, since variations on the water level induces variations on the weir between the separation and oil chamber, which in turn causes a disturbance to the oil level. This weir disturbance added to the inflow disturbance causes higher oscillations on the oil output flow rate. Nevertheless, note that, even though an improvement regarding the oil outflow rate was not one of the objectives, the proposed controller yields smaller oscillations than the benchmark approach.

5. CONCLUSION

In this paper, we presented an $\mathcal{H}_\infty$ based switching control strategy for the attenuation of the effects of sluggish inflow disturbances on the state and the manipulated variables of a three phase separator. Even though the process has nonlinear and complex dynamics, a controller based on a simple linear model of the plant was enough for the controller design. The proposed approach performs better than a benchmark PI Zone controller in all the simulated scenarios. Particularly, the proposed strategy allows better damping of the oscillating disturbances and also better performance in steady conditions, with smaller steady-state conditions. Future work includes studies with a refined version of the proposed strategy with anti-windup action and control/states constraints on the optimization problem.

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