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CONTROL OF PNEUMATIC VALVES WITH FRICTION USING ALGEBRAIC ESTIMATORS

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Abstract. *In this paper we address the problem of friction compensation in a pneumatic control valve. It is proposed a nonlinear control law that uses algebraic estimators in its structure, in order to adapt the controller to the aging of the valve. For that purpose we estimate the valve parameters, including friction, online. The estimators and the controller are validated through simulations*

Keywords: *Algebraic Estimators, Nonlinear Control, Adaptive Control, Logic-Based Control*

1. INTRODUCTION

The control of industrial processes usually is a complex task, due to the number of control loops in the plant, non-linearities, pure delays, backlash among others (Jelali and Huang (2012); Lane Desborough and Miller (2001)). One of these problems is the friction in pneumatic control valves, that may cause oscillations and increase process' variability. It has been assessed that 20% to 30% of the oscillations in industrial processes are due to friction of pneumatic valves (Bialkowski (1992)). Moreover, pneumatic valves are ubiquitous, being fundamental blocks in process industry (Seborg and Mellichamp (2006)). Hence, designing controllers that can maintain their correct functioning is a relevant task from both academic and practical perspectives.

Many control techniques, which provide good performance, rely on the fact that a model for the process is known. Therefore, the knowledge of the valve physical model parameters is desirable. However, altough there are identification methods for estimating these parameters, they are often complicated and they require long periods of time with persistent signals as the process input (Romano and Garcia (2011); Garcia (2008)).

Algebraic estimators are recent (Fliess *et al.* (2002)), nonetheless they have shown good results in simulations and practical applications (Diao *et al.* (2013); Moraes and da Silva (2015)). Those estimators can handle linear and nonlinear phenomena, in a very straightforward manner (Fliess *et al.* (2008)). Unfortunately, algebraic estimators have a very abstract theory that forms a bottleneck for those who are not familiar with differential algebra or operational calculus.

In this paper we address the problem of controlling the position of the valve stem under the effects of friction and stiction. In order to solve this problem we present a controller that uses algebraic estimators in its structure, as well as a switched control logic to better handle the fact that the dynamic model of the stem position is non-smooth, due to friction. We validate our methodology through simulations.

The paper is organized as follows, in section 2, we describe the Karnopp model for the pneumatic valve, and make a few considerations about its approximations. In the sequel, in section 3, we derive the algebraic identifiers and estimators equations, also we describe the identifiability conditions. In section 4, we present a control logic and the structure for the control loop, also we provide the idea of the proof of stability. Afterwards, in section 5, we present the simulations for the parameter identifiers, estimators, and the output of the control loop. Finaly, in section 6, we draw our conclusions and suggest future works.

2. SYSTEM MODEL

In the present paper we will base our calcultions on the Karnoop physical model for stiction (Karnopp (1985)) with the Stribeck correction term. This system modelling is deduced from force-balance equations based on the Newton's second law. In addition we also discarded neglegible terms (Jelali and Huang (2012)), therefore arriving at Eq. (1) below when the stem is moving.

$$m\ddot{x}(t) = -F_v\dot{x}(t) - k_s x(t) - \left(F_c - (F_s - F_c)\, e^{-(\dot{x}(t)/v_s)^2}\right) sign(\dot{x}(t)) + Au(t) \tag{1}$$

Where m is the mass of the moving parts (stem and plug), x is the stem position, F_v is the viscous friction coefficient, F_s is the static friction coefficient, F_c is the Coulomb friction coefficient, v_s is the Stribeck velocity, k_s is the Hooke's law constant of the spring, A is the diaphragm area, and u is the air presure. When the stem is stopped ($\dot{x}$=0), using the notation $F_e = Au - k_s x$ we have two possible situations:

$$m\ddot{x}(t) = \begin{cases} 0 & \text{, if } |F_e(t)| \leq F_s \\ -k_s x(t) + Au(t) + F_s sign(F_e(t)) & \text{, otherwise} \end{cases} \tag{2}$$

In the simulations in section 5. we consider the usual Karnopp model, with dead zone for the velocity as described in (Garcia (2008)). The second condition refers to the valve in the eminence of movement. It should be underlined that this part of the model does not interfere in the dynamics when the valve is in movement ($\dot{x} \neq 0$).

Aiming to simplify notation and for identifiability purposes, that will be explained at subsection 3.2 we will define $a = -\frac{F_v}{m}$, $b = -\frac{k_s}{m}$, $c = \frac{A}{m}$, $k = -\frac{F_c}{m}$, and $\gamma = -\frac{F_s - F_c}{m}$.

$$\ddot{x}(t) = -a\dot{x}(t) - bx(t) + \left(k - \gamma e^{-(\dot{x}(t)/v_s)^2}\right) sign(\dot{x}(t)) + cu(t) \tag{3}$$

It should be remarked that, at high velocities, $|\dot{x}| \gg v_s$, the Stribeck term vanishes. Consequently the system model can be well approximated by Eq. (4). More than that, this approximation is widely used in the literature (Garcia (2008); Romano and Garcia (2008)), since the Stribeck effect is often neglegible.

$$\ddot{x}(t) = a\dot{x}(t) + bx(t) + ksign(\dot{x}(t)) + cu(t) \tag{4}$$

3. ONLINE ALGEBRAIC IDENTIFICATION AND ESTIMATION

3.1 Identification of the Model Parameters

In this section we will assume that the high velocity condition is satisfied, also that $\dot{x}$ is positive, in order to make the $sign$ function disapear from the left hand side in Eq. (4). One can then rewrite the approximate model using Yosida's operational calculus (Yosida (2012)) notation, hence obtaining the following Eq. (5).

$$s^2 X - sx(0) - \dot{x}(0) = asX - ax(0) + bX + k\frac{1}{s} + cU \tag{5}$$

Multiplying both sides by s and differentiating with respect to s three times in order to cancel the effects of the constant disturbance and the effects of the initial conditions we arrive at the equation:

$$\frac{d^3(s^3X)}{ds^3} = a\frac{d^3(s^2X)}{ds^3} + b\frac{d^3(sX)}{ds^3} + c\frac{d^3(sU)}{ds^3} \tag{6}$$

At last we multiply both side by s^{-4} in order to avoid any time derivatives and filter the signals involved.

$$\begin{aligned} \frac{1}{s}\frac{d^3X}{ds^3} + \frac{9}{s^2}\frac{d^2X}{ds^2} + \frac{18}{s^3}\frac{dX}{ds} + \frac{6}{s^4}X = a\left(\frac{1}{s^2}\frac{d^3X}{ds^3} + \frac{6}{s^3}\frac{d^2X}{ds^2} + \frac{6}{s^4}\frac{dX}{ds}\right) \\ +b\left(\frac{1}{s^3}\frac{d^3X}{ds^3} + \frac{1}{s^4}\frac{d^2X}{ds^2}\right) + c\left(\frac{1}{s^3}\frac{d^3U}{ds^3} + \frac{1}{s^4}\frac{d^2U}{ds^2}\right) \end{aligned} \tag{7}$$

We now can rewrite Eq. (7) in time domain as:

$$q_1(t) = ap_{11}(t) + bp_{12}(t) + cp_{13}(t) \tag{8}$$

Where:

$$q_1(t) = \int_0^t (-\sigma_1^3 x(\sigma_1))d\sigma_1 + 9\int_0^t \int_0^{\sigma_1} (\sigma_2^2 x(\sigma_2))d\sigma_2 d\sigma_1 + 18\int_0^t \int_0^{\sigma_1} \int_0^{\sigma_2} (-\sigma_3 x(\sigma_3))d\sigma_3 d\sigma_2 d\sigma_1 \\ + 6\int_0^t \int_0^{\sigma_1} \int_0^{\sigma_2} \int_0^{\sigma_3} (x(\sigma_4))d\sigma_4 d\sigma_3 d\sigma_2 d\sigma_1 \tag{9}$$

$$p_{11}(t) = \int_0^t \int_0^{\sigma_1} (-\sigma_2^3 x(\sigma_2))d\sigma_2 d\sigma_1 + 6\int_0^t \int_0^{\sigma_1} \int_0^{\sigma_2} (-\sigma_3^2 x(\sigma_3))d\sigma_3 d\sigma_2 d\sigma_1 \\ + 6\int_0^t \int_0^{\sigma_1} \int_0^{\sigma_2} \int_0^{\sigma_3} (-\sigma_4 x(\sigma_4))d\sigma_4 d\sigma_3 d\sigma_2 d\sigma_1 \tag{10}$$

$$p_{12}(t) = \int_0^t \int_0^{\sigma_1} \int_0^{\sigma_2} (-\sigma_3^3 x(\sigma_3))d\sigma_3 d\sigma_2 d\sigma_1 + 3\int_0^t \int_0^{\sigma_1} \int_0^{\sigma_2} \int_0^{\sigma_3} (\sigma_4^2 x(\sigma_4))d\sigma_4 d\sigma_3 d\sigma_2 d\sigma_1 \tag{11}$$

$$p_{13}(t) = \int_0^t \int_0^{\sigma_1} \int_0^{\sigma_2} (-\sigma_3^3 u(\sigma_3))d\sigma_3 d\sigma_2 d\sigma_1 + 3\int_0^t \int_0^{\sigma_1} \int_0^{\sigma_2} \int_0^{\sigma_3} (\sigma_4^2 u(\sigma_4))d\sigma_4 d\sigma_3 d\sigma_2 d\sigma_1 \tag{12}$$

Finally, integrating Eq. (8) once and twice in order to reach the following system of equations:

$$\begin{pmatrix} p_{11}(t) & p_{12}(t) & p_{13}(t) \\ p_{21}(t) & p_{22}(t) & p_{23}(t) \\ p_{31}(t) & p_{32}(t) & p_{33}(t) \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix} = \begin{pmatrix} q_1(t) \\ q_2(t) \\ q_3(t) \end{pmatrix} \tag{13}$$

Where:

$$p_{21}(t) = \int_0^t p_{11}(\sigma_1)d\sigma_1; \quad p_{31}(t) = \int_0^t p_{21}(\sigma_1)d\sigma_1 \tag{14}$$

$$p_{22}(t) = \int_0^t p_{12}(\sigma_1)d\sigma_1; \quad p_{32}(t) = \int_0^t p_{22}(\sigma_1)d\sigma_1 \tag{15}$$

$$p_{23}(t) = \int_0^t p_{13}(\sigma_1)d\sigma_1; \quad p_{33}(t) = \int_0^t p_{23}(\sigma_1)d\sigma_1 \tag{16}$$

3.2 Identifiability

In this subsection we address the identifibility problem for the algebraic identification procedure presented in the last subsection. To ensure that our model is identifiable we need to impose conditions on the input signal, such that the determinant of the matrix on the left hand side in Eq. (13) is different from zero. Fortunately, as proved in (Fliess and Sira–Ramírez (2003)), almost every input signal will work. However a few remarks must be made, because a constant input, which would correspond to setpoint regulation, does not provide the necessary conditions.

To see that a constant input in fact does not verify those conditions one just have to look at Eq. (6) and notice that if $u(t)$ was constant, then the term that multiplies the parameter c would be equal to zero. Therefore the term $p_{13}(t)$ would also be zero, which implies our claim. An input that circunvents this difficulty is proposed in section 4.

Furthermore, we defined the constants a, b, c, k, and γ, in section 2.claiming that it would be important for the identifiability. This is the case, because if we had not done so the system of Eq. (13) would be overparametrized (Fliess and Sira-Ramírez (2007)).

3.3 Friction Estimation

Friction estimation is achieved using algebraic derivative estimators described in (Fliess *et al.* (2008); Zehetner *et al.* (2007)). Their main advantages are that they are non-assymptotic and that they do not require the knowledge of the model. Hence, they are independent from the algebraic identifiers outputs.

One should notice that a function that is n times differentiable has a Taylor polynomial expansion up to order n, and can be approximated by Eq. (17) below (Hirsch (1997)).

$$x(t) \approx \sum_{i=0}^{n} x^{(i)}(0)\frac{t^i}{i!} \tag{17}$$

Therefore, using an apposite procedure to that of the subsection 3.1 one can construct an algebraic estimator for the term that multiplies the i-th power in Eq. (17). Building this estimator, by its turn, is equivalent to constructing an estimador for $x^{(i)}(0)$. Hence, using this estimate only for a short period of time should bare consistent results. Nonetheless, since these estimators have no dynamics, the instant $t = 0$ can be chosen arbitrarily. Thus, these estimators can be reinitialized as often as possible, achieving very good estimates. Also, to shorten the notation we will write $a_i = x^{(i)}(0)$.

Since we want to approximate the first derivative of the stem position, we have to consider that the function x is at least three times differentiable, a fact that is true for every open neighborhood far from the line $\dot{x} = 0$. Furthermore, consider the second order Taylor polynomial of x around zero, which exists by the previous assumption on the differentiability.

$$x(t) = a_0 + a_1 t + a_2\frac{t^2}{2!} \tag{18}$$

Our derivative estimate is the term a_1. In order to obtain it we perform a similar procedure as in the subsection 3.1 . Hence we apply the operator $s^{-3}\frac{d}{ds}s^{-1}\frac{d}{ds}s^3$ to obtain the following derivative estimator:

$$a_1 = -\frac{12}{t^4}\int_0^t (3t^2 - 16t\tau + 15\tau^2)x(\tau)d\tau \tag{19}$$

For the second order derivative estimator we will consider the third order Taylor polynomial expansion around zero.

$$x(t) = a_0 + a_1 t + a_2\frac{t^2}{2!} + a_3\frac{t^3}{3!} \tag{20}$$

This time we will apply the operator $s^{-4}\frac{d^2}{ds^2}s^{-1}\frac{d}{ds}s^4$ in order to estimate a_2. After these calculations we end up with the following estimator.

$$a_2 = \frac{120}{t^6}\int_0^t (4t^3 - 45t^2\tau + 108t\tau^2 - 70\tau^3)x(\tau)d\tau \tag{21}$$

It is then straightforward to derive a friction estimator from Eq. (4). For the validity region of the approximation, one can isolate the friction term and use both the parameters identified and the derivatives estimates in order to estimate the friction. Considering that $\dot{x}(t) > 0$, then we arrive at the following estimator:

$$k_e = \ddot{x}_e(t) + a_e\dot{x}_e(t) + b_e x_e(t) - c_e u(t) \tag{22}$$

From this point on, all the parameters with subscript e, such as a_e, b_e, c_e, and k_e denote parameter estimates, at the example a, b, c, and k respectively. Also, for the real system one has to consider the measurement noise. Therefore, the subscripts are necessary.

4. CONTROL LAW

The control law proposed here does not discuss the problem of controlling the flow of fluids going through the valve, but solely the problem of controlling the stem position. Therefore, we consider that our system is part of a larger control system, which encompases an external controller for the flow. This can be seen in figure 1. Where θ_e represents the estimated parameters, r is the reference signal that we wish to track, u is the control input, y is the system output, and the η_i, $i = 1, 2, 3$ variables are external signals sent by the supervisory system in order to switch the identifier on and off.

The proposed control law makes the following reasonable assumptions: the reference signal r sent by the signal generator is kept constant during the system's transient regime, the identification procedure is hold on for a window large enough to ensure the convergence of the identifiers (Fliess and Sira-Ramírez (2007)), the system dynamics is given by Eq. (1).

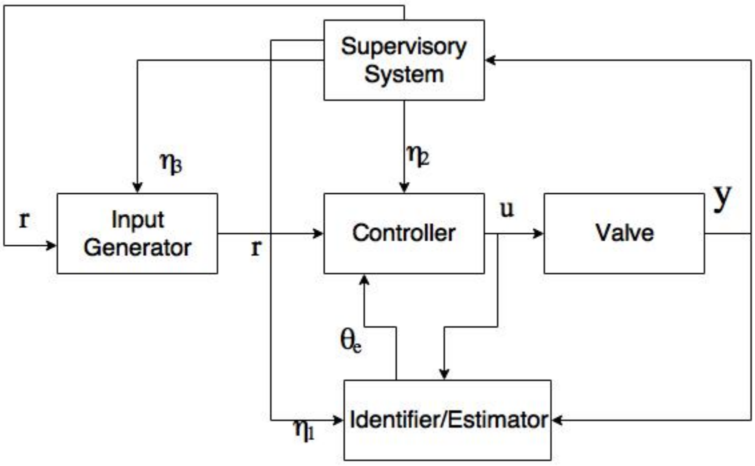


Figure 1. Block Diagram for the Control System

4.1 Control Logic

The control logic is divided in 4 different states. It involves both an identification phase and controlled phases. Denote by Δr the difference between the last value of r and the current one, keeping this difference until the next change of reference happens, η represents the external signals η_i, sent by the supervisory system in order to start the identification. The reason to define Δr is that if its value is positive (resp. negative), then the velocity of the stem will be positive (resp. negative) if we depart from the transient regime.

- In state S_0, the system is started, the purposes of this state are to allow the practicioner to start the process with any desired input, and to avoid any indeterminations in the value of Δr.
- In state S_1, which is triggered by $\Delta r > 0$ and $\eta \neq 0$, we apply the control law given by:

$$u = \frac{r(t) - b_e k_e}{c_e} \tag{23}$$

- In state S_2, which is triggered if $\Delta r < 0$ and $\eta \neq 0$, we apply the control law given by:

$$u = \frac{r(t) + b_e k_e}{c_e} \tag{24}$$

- In state S_3, which is triggered if $\eta = 0$, is the state where the identification happens. Hence we apply an input that ensures identifiability, in our case we have chosen

$$r(t) = \alpha 1(t) + \beta sin(\omega t), \tag{25}$$

  where α is a constant greater than F_s/A, $1(t)$ is the step function, $\beta > 0$ is a small parameter chosen by the practicioner, and ω is a small positive number to avoid high frequency oscillations. The reason for the sinusoidal term is only to circunvent the lost of identifiability pointed out in subsection 3.2, which would occur if we only applied the step function, and the motive for $\alpha > F_s/A$ is that it ensures that the system will start moving.

One should notice that the parameter α from the identification phase, can be chosen, in some cases, as an educated guess to approximate the control u from the controlled phase, reducing the loss in performance during the identification phase. All these rules can be synthetized in the figure 2. Also, one should remark that the typical poles for the uncontrolled system are usually fast, hence there is no need for their replacement.

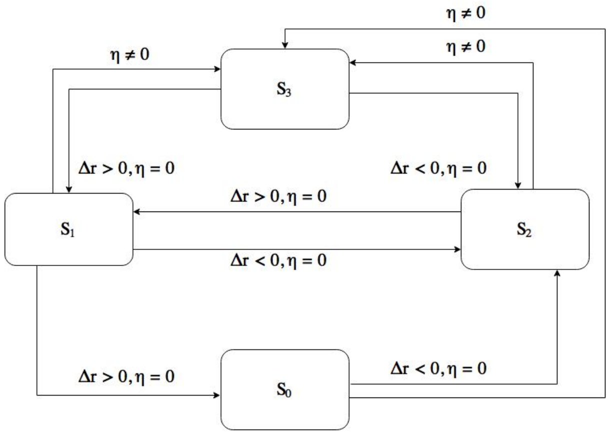


Figure 2. State Machine for the Control Law

4.2 Stability and Performance

In this section we will only consider the stability and performance of the system while in the states S_1 and S_2, since they are the states at which the controller is actually trying to solve the output regulation problem. Also in the remaining of this subsection we will consider that we are at S_1, since for S_2 is analogous. Therefore, we will make the following change of coordinates in Eq. (1), $y = x + r$, and assume that r is a function constant by parts, which is what one should expect in practice, then $\dot{y} = \dot{x}$. Also assuming that the coefficients found by the identifier are correct, we arrive, after a few manipulations, at:

$$\begin{aligned} &\ddot{y}(t) = -a\dot{y}(t) - by(t) - \gamma e^{-(\dot{y}/v_s)^2} \\ &y(0) = y_0, \quad \dot{y}(0) = \dot{y}_0 \end{aligned} \tag{26}$$

Now, consider the following system:

$$\begin{aligned} &\ddot{z}(t) = -a\dot{z}(t) - bz(t) - \gamma \\ &z(0) = y_0, \quad \dot{z}(0) = \dot{y}_0 \end{aligned} \tag{27}$$

It is straaightforward to see that, $e^{-(\dot{y}/v_s)^2} \leq 1$, hence, defining $e = y - z$:

$$\begin{aligned} &\ddot{e}(t) + a\dot{e}(t) + be(t) = \gamma(1 - e^{-(\dot{y}/v_s)^2}) \leq \gamma \\ &e(0) = 0, \quad \dot{e}(0) = 0 \end{aligned} \tag{28}$$

Considering then $\ddot{e}(t) + a\dot{e}(t) + be(t) \leq \gamma$, and unsing Bellman-Gronwall lemma, plus a few results in linear systems (Sontag (2013)), we have that the error is bounded. Nonetheless, z in Eq. (27) is also bounded, completing the proof by the triangle inequality. One should also notice that if the Stribeck term is neglegible, then the steady state error is also neglegible, in fact it can be proved that the error is bounded linearly by the value of γ. Also, a proof considering small mismatches between the estimated parameters and the real ones follows similar lines as those presented in this paragraph.

5. COMPUTATIONAL PROCEDURE

In this section we considered the parameters values as being $m = 1.3608$kg, $A = 0.0645\ m^2$, $F_c = 1.4234 \cdot 10^3$N, $F_v = 612.944$N, $F_s = 284.6862$N, $k_s = 5.2538 \cdot 10^4$N, $v_s = 2.54 \cdot 10^{-4}$m/s. Also, the output value was converted from meters to p.u.. Furthermore, the dead zone for $|\dot{x}|$, from the Karnopp model, was chosen to be $0.6 v_s$ as suggested by (Garcia (2008)). These parameter values were obtained previously through experiments with the pneumatic control valve at the Laboratory of Automation and Control from the Polytechnique School of the University of São Paulo.

5.1 Identifier

In order to explain how the identifier calculations were performed in the simulations, we will exemplify how to implement them through the calculation of the term $p_{12}(t)$. Because the other terms are computed in a similar fashion we omit their expressions in this text and refer to the article (Fliess and Sira-Ramírez (2007)) for further clarifications.

$$\dot{\pi}_1(t) = 3t^2 x \tag{29}$$

$$\dot{\pi}_2(t) = -t^3 x + \pi_1 \tag{30}$$

$$\dot{\pi}_3(t) = \pi_2(t) \tag{31}$$

$$\dot{\pi}_4(t) = \pi_3(t) \tag{32}$$

$$p_{12}(t) = \pi_4(t) \tag{33}$$

Basically we rewrote the integrals as a time-varying linear system realization, where the input is x, the states are π_i, with $i = 1, \cdots, 4$, and p_{12} is the output.

The simulations were performed using the model from Eq. (1), to account for the Stribeck effect. Also, the output of the process was affected by an additive high frequency noise modeled by a sinusoidal function with frequency 10^5 Hz, and amplitude 0.01 p.u.. All the simulations used fixed steps of size $T_s = 10^{-5}$, with the solver running the Dorman-Prince method (edo8). The system remains in the identification state S_3 for the first 0.8s, and afterwards it moves to state S_1. The signal applied during the identification state was chosen to be $u = 1.92sin(t) + 6.4$. One should also sotice that the graphs only begin after a brief time, in our case 0.4 s, due to numerical issues (Fliess *et al.* (2008)).

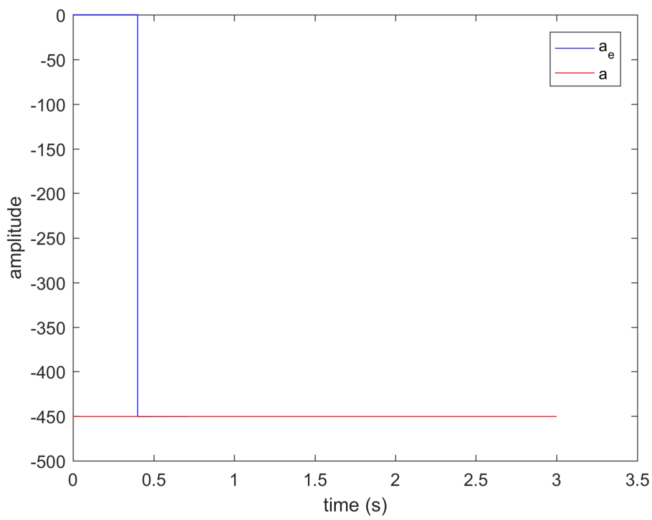


Figure 3. Comparison between a_e and a

As can be seen from the figures 3,4, and 5, the identified parameters are good estimates for the true ones. Any mismatch between the real values and the estimated ones cannot be percieved in the pictures.

5.2 Friction Estimation

To implement the derivative estimators we proceed in a similar fashion as in the paper (Zehetner *et al.* (2007)). Hence, we approximate the integral by a trapezoidal rule and generate a time-varying FIR filter of length N, with input x. In order to implement this filter we must keep the last N samples of the stem position x stored.

The length of the filters used in the simulations was 500 each, and the simulations were performed with fixed step size of $T_s = 10^{-5}$, and using the Dorman-Prince method (edo8). Furthermore, the output of the process was affected by an additive high frequency noise modeled by a sinusoidal function with frequency 10^5 Hz, and amplitude 0.01 p.u.. The system performs the friction estimation while in state S_3, which occurs at the first 0.8s. One should notice that we keep the final value of k_e as our estimate, but some other option could have been made. Also, experiments show that chosing any other value inside the blue region from 0.4s to 0.8s would give similar results.

From figure 5.2 and figure 5.2 we observe that the first derivative estimator performed well, however the second order derivative performance, although satisfactory for controlling the system, is very noisy.

In addition, the estimate for the friction term k_e, was estimated using Eq. (22). For this reason, the noise that

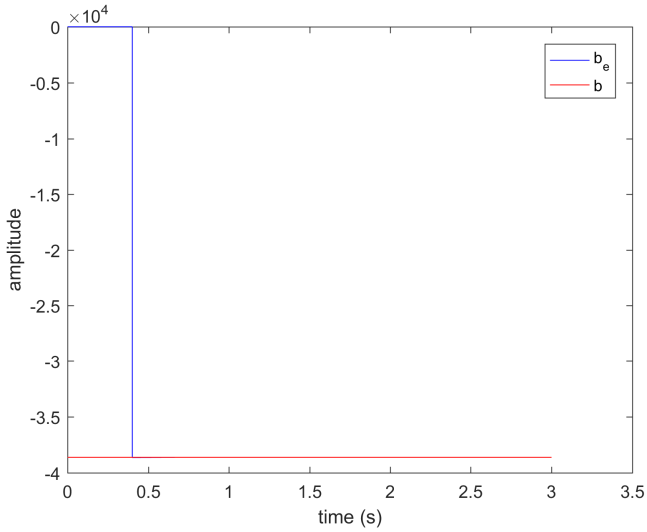


Figure 4. Comparison between b_e and b

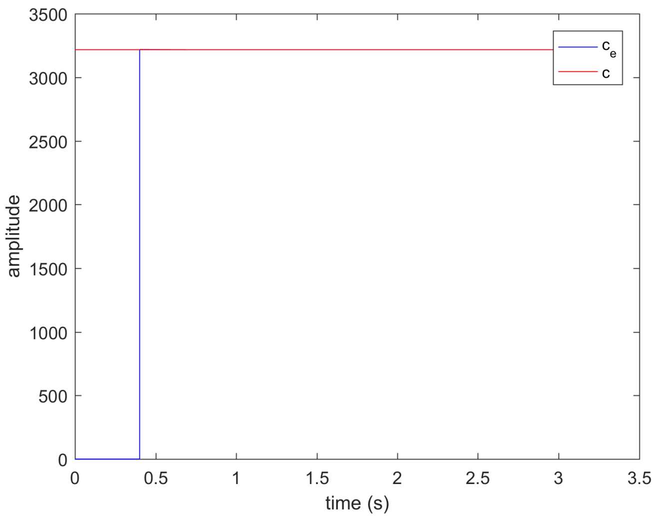
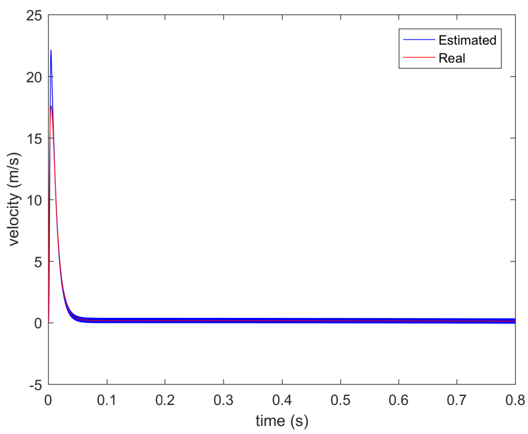
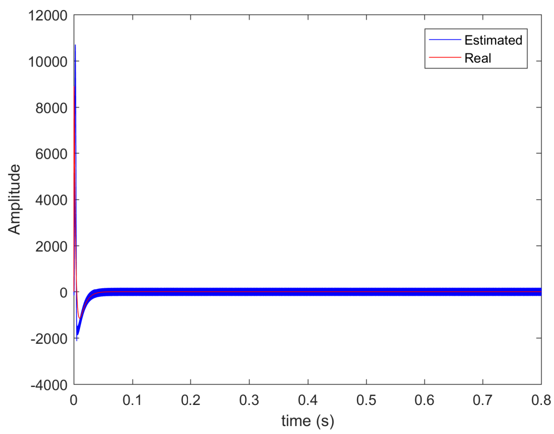


Figure 5. Comparison between c_e and c



(a) Velocity



(b) Acceleration

affects both the velocity estimator and the acceleration diminish the quality of our estimate for k_e. However, it does not compromise significantly the controller performance as shown in subsection 5.3

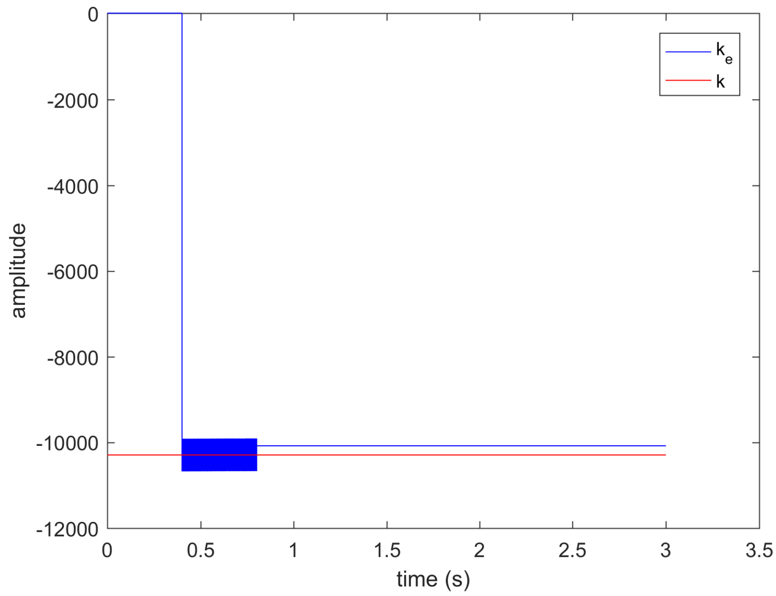


Figure 6. Comparison between k_e and k

5.3 System Performance

In this subsection the simulations were performed with fixed step size of $T_s = 10^{-5}$, and using the Dorman-Prince (edo8). We modeled the additive measurement high frequency noise at the output of the process as a sinusoidal function with frequency 10^5 Hz, and amplitude 0.01 p.u.. This simulations refer to the states S_1, which starts at 0.8s, and S_2, which starts at 1.8s. Our goal was to demonstrate the controller going through all states in the simulations.

In the conditions described, we achieved a steady state error smaller than 0.01 p.u. between the system's output and the reference we wanted to track. One should notice that our tracking error is smaller than the amplitude of the measurement noise.

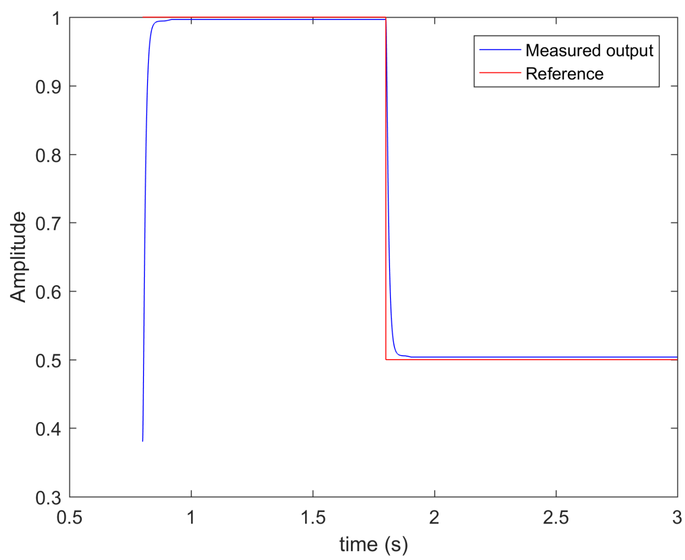


Figure 7. Output Regulation Performance

6. CONCLUSION

In the present paper we addressed the problem of controlling a pneumatic valve with friction using algebraic identifiers and estimators for the system's parameters and the Coulomb friction. We obtained the equations for the identifiers, as well as explained how to implement them. Also, we described the procedure to obtain the derivative estimators.

Furthermore, we simulated the pneumatic valve under the influence of the controller and the prameter estimates. Both the identifiers and the friction estimator performed well even in the presence of high frequency noise, altough the former had a much better performance in comparison to the later. Moreover, the controlled system's performance obtained was considerably more than satisfactory for the noise conditions imposed.

As future research directions, investigations will be held with the goal of finding manners of reducing the sampling frequency in order to be able to embed the algorithm in a dedicated microcontroller. Also, we wish to find manners to reduce the noise in the estimate k_e, aiming to improve our result.

7. ACKNOWLEDGEMENTS

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