ESTIMATION AND COMPENSATION OF DEAD-ZONE INHERENT TO THE ACTUATORS OF INDUSTRIAL PROCESSES

Auciomar C. T. de Cequeira, Marcelo R. B. G. Vale, Daniel G. V. da Fonseca
Laboratory of Automation in Petroleum, Federal University of Rio Grande do Norte, Campus Universitário, Natal, Brazil

Fábio M. U. de Araújo, André L. Maitelli
Department of Computing and Automation, Federal University of Rio Grande do Norte, Natal, Brazil

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Abstract: The oscillations present in control loops can cause damages in industry. Canceling, or even preventing such oscillations, would save up to large amount of dollars. Studies have identified that one of the causes of these oscillations are the nonlinearities present on industrial processes actuators. This paper has the objective to develop a methodology for removal of the harmful effects of nonlinearities. Will be proposed a parameters estimation method to the Hammerstein model, whose nonlinearity is represented by dead-zone. The estimated parameters will be used to construct the inverse model of compensation. A simulated level system was used as test platform. The valve that controls inflow has a dead-zone. Results analysis shows an improvement on system response.

1 INTRODUCTION

Inside industrial process there are hundreds of control loops, which are mainly composed by sensors, actuators, Programmable Logic Control (PLC) and Supervisory Control and Data Acquisition (SCADA). The control efficiency is, therefore, important to ensure a high quality product and low cost production. So, finding and solving control loop problems of a process implies in reject reduction, better product homogeneity, lower production costs and higher rates of production. Even an 1% energy or control efficiency improvement means a huge economy in industrial process, of millions of dollars (Desborough and Miller, 2002).

Several studies related to control loop performance indicate that the majority present deficient behavior, showing oscillations at process output. One of those researches (Desborough and Miller, 2002) evaluated 26 thousand control loops and classified them this way:

- 16% as excellent;
- 16% as acceptable;
- 22% as fair;
- 10% as poor;
- 36% as open loop.

Among the causes for this deficient performance are included bad tune of controllers, wrong process project, the incoming oscillatory perturbations and the nonlinearities of the actuators. And those nonlinearities cause dead-band in actuators as well.

An audit made by a big producer of valves has shown that 30% of the products presented about 4% or more of dead-band and approximately 65% of the valves had a dead-band higher than 2% (FISCHER, 2005). As most of the actions of regulatory control consist of small variations in the order of 1% or less, the control loops would not act effectively in the process for responding to these small variations. For a good performance, it is recommended that the control valve dead-band is about 1% or less (Campos and Teixeira, 2007).

A point to mention is that 20 to 30% of the oscillations in control loops are caused by nonlinearities of the valves (Ulaganathan and Rengaswamy, 2008), among which we can point out the static friction, hysteresis, backlash and dead-zone as the best known. The compensation of the effects of such nonlinearities would help in solving the problem of poor perfor-

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mance of about a quarter of the controllers present in the industry.

The aim of this study is therefore to minimize or cancel the oscillations observed in the outputs of industrial processes, which are caused by dead-zone inherent to the actuators of control loops.

The industrial processes were represented by the Hammerstein model. Inverse models of nonlinearity will be built based on dead-zone parameter estimation. The intention is to make these inverse models capable to compensate the nonlinearity, reducing the oscillations and its harmful effects. It will be proposed a method of parameter estimation for a Hammerstein model that contains as the non-linear part a dead-zone.

2 MATHEMATIC MODELS

This section describes the mathematic models utilized in dead-zone estimation and compensation methodology. This methodology uses the Hammerstein model to represent the industrial processes containing dead-zone. Thereby, the linear part of Hammerstein model is represented by Output Error model and the non-linear part is represented by dead-zone. Besides the Hammerstein model, this section also describes the inverse model for dead-zone compensation. This one will reduce prejudicial effects of nonlinearity.

It should be clear that the mathematic models described in this section are simplified descriptions of real physical phenomena.

2.1 Hammerstein Model

The nonlinear Hammerstein model is composed by a static nonlinearity preceding a linear dynamic (Aguirre, 2007). This model is called block-oriented or block-structured model (Chen, 1995). Thus, both the non-linearity and the dynamics are represented by blocks, as shown in Figure 1. Here, the NL block represents the static nonlinearity function and the L block represents the linear dynamic of modeled process. The signs $u(k)$, $y(k)$ and $e(k)$ are the nonlinearity input, the output and the noise of the system, respectively. The signal $x(k)$ is called internal variable of the Hammerstein model (nonlinearity output and linear dynamic input), and, in general, it cannot be measured, making it difficult to estimate the parameters in the same models.

Although very simple, this structure may represent several actual physical processes, such as industrial processes with variable gain and control systems

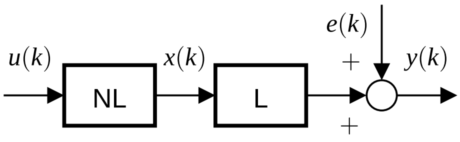


Figure 1: Hammerstein model.

with linear processes and nonlinear actuators (the latter falls within the subject matter in this work). Therefore Hammerstein models are popular in control engineering.

2.2 Output Error Model

There are some mathematical representations that are especially suitable for system identification, using classic algorithms to the estimation of its parameters. Along with the ARX and ARMAX models, the Output Error model is one of the most used structures. In this study, this model represents the linear dynamic of the Hammerstein system (block L of Figure 1) and it is represented in Figure 2. In the same model, it is assumed that the noise disturbs the output in an additive manner, as equations below.

$$y(k) = q^{-d}\frac{B(q)}{A(q)}x(k) + e(k) \tag{1}$$

$$A(q)y(k) = q^{-d}B(q)x(k) + A(q)e(k) \tag{2}$$

$A(q)$ and $B(q)$ are polynomials of order n_a and n_b, respectively, and are defined below. d represents the pure delay system and q^{-1} is the shift operator, so $x(k)q^{-d} = x(k-d)$.

$$A(q) = 1 + a_1q^{-1} + \ldots + a_nq^{-n_a}$$
$$B(q) = b_0 + b_1q^{-1} + \ldots + b_mq^{-n_b}$$

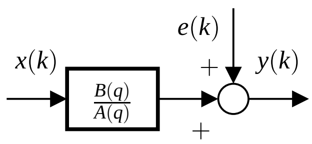


Figure 2: Output Error model.

The Output Error model is much more realistic than the ARX and ARMAX because the modeling of noise does not include the dynamics of the process $1/A(q)$ (Nelles, 2000). So, the parameter estimation task becomes more difficult. As shown in Equation (2), the noise is not white but colored due to the presence of the polynomial $A(q)$. For this reason, the least squares method cannot be used. A non-polarized algorithm should be used so that the estimation is not biased.

The Equation (2) can be rewritten in the form of summations, already introducing the delay in the input signal.

$$y(k) = \sum_{i=0}^{n_b} b_i x(k-d-i) - \sum_{j=1}^{n_a} a_j y(k-j) + \sum_{j=1}^{n_a} a_j e(k-j) + e(k) \quad (3)$$

The signals $y(k)$, $x(k)$ and $e(k)$ are the same as the Hammerstein model (Figure 1), and have been defined previously.

2.3 Dead-zone

The dead-zone is a static nonlinearity with no memory that describes the insensitivity of components for small signals. It can be seen as a static relationship between input and output signals, in which, for a range of input values, there is no answer. Once the output appears, the relationship between input and output is linear.

Figure 3 shows a graphical representation of the dead-zone, where $u(k)$ is the input and $x(k)$ is the output. The limits b_r and b_l represent the range where the output signal remains unchanged, and m_r and m_l indicate the slope of the lines. By definition $b_r > 0$, $b_l < 0$, $m_r > 0$ and $m_l > 0$, and in general, neither the limits nor the slopes are equal.

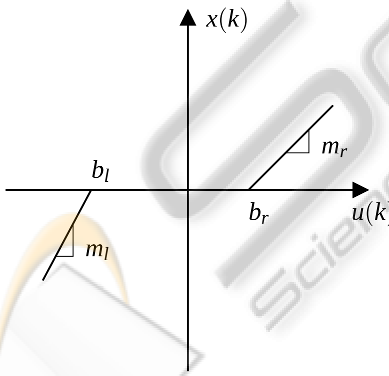


Figure 3: Dead-zone graphic.

Analytically, the dead-zone can be written as follows:

$$x(k) = \begin{cases} m_r\,[u(k)-b_r], & \text{if } u(k) \geq b_r \\ 0, & \text{if } b_l < u(k) < b_r \\ m_l\,[u(k)-b_l], & \text{if } u(k) \leq b_l \end{cases} \quad (4)$$

One way to write the behavior of the dead-zone so that it is linear in the parameters is:

$$x(k) = X_r(k) m_r\,[u(k)-b_r] + X_l(k) m_l\,[u(k)-b_l] \quad (5)$$

where $X_r(k)$ and $X_l(k)$ are auxiliary functions that take the value 0 (zero) or 1 (one) according to the following conditions:

$$X_r(k) = \begin{cases} 1, & \text{if } u(k) \geq b_r \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

$$X_l(k) = \begin{cases} 1, & \text{if } u(k) \leq b_l \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

2.4 Inverse Model for Dead-zone Compensation

It is known that the nonlinearities are among the key factors that limit the static and dynamic performance of control systems, preventing high precisions when using linear controllers. In order to cancel the harmful effects generated by the dead-zone, it is proposed to implement its inverse model.

The Figure 4 shows the structure used in this work for the cancellation of this nonlinearity. The inverse nonlinearity (INL block) was allocated before the nonlinearity (NL block) to cancel out its effects. When implemented with the real parameters, such compensation cancels completely the effects of dead-zone. Therefore, if the dead-zone is fully compensated, the input signal $u_c(k)$ must be equal to the signal $x(k)$.

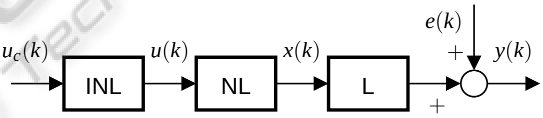


Figure 4: Block diagram of nonlinearity compensation.

The graphical relationship between the input signal $u_c(k)$ and output signal $u(k)$ is shown in Figure 5.

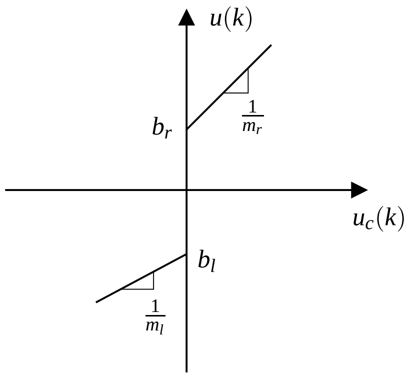


Figure 5: Graphic of dead-zone inverse compensation.

The dead-zone inverse model is represented by Equation 8. The parameters b_r, b_l, m_r and m_l are the same used in modeling of dead-zone.

$$u(k) = \begin{cases} \frac{1}{m_r}\left[u_c(k) + m_r b_r\right], & \text{if } u_c(k) > 0 \\ 0, & \text{if } u_c(k) = 0 \\ \frac{1}{m_l}\left[u_c(k) + m_l b_l\right], & \text{if } u_c(k) < 0 \end{cases} \quad (8)$$

For a linear parameterization of inverse compensation, we have:

$$\begin{aligned} u(k) = \chi_r(k)\frac{1}{m_r}\left[u_c(k) + m_r b_r\right] \\ +\chi_l(k)\frac{1}{m_l}\left[u_c(k) + m_l b_l\right] \end{aligned} \quad (9)$$

where $\chi_r(k)$ and $\chi_l(k)$ are auxiliary functions defined as:

$$\chi_r(k) = \begin{cases} 1, & \text{if } u_c(k) > 0 \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

$$\chi_l(k) = \begin{cases} 1, & \text{if } u_c(k) < 0 \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

The inverse model equation is similar to the dead-zone model. The variables m_r, m_l, b_r and b_l have the same meaning of Equation (5). The difference lies in the definition of auxiliary functions $\chi_r(k)$ and $\chi_l(k)$.

To check the accuracy of the inverse model, in other words, to conclude that $x(k) = u_c(k)$, three situations will be analyzed: $u_c(k) > 0$, $u_c(k) < 0$ and $u_c(k) = 0$. For this proof, the function of the inverse of the dead-zone will be called $ZI(\cdot)$.

Lemma 1. *(Dead-zone Inverse) when implemented with real parameters m_r, m_l, b_l and b_r, the dead-zone inverse* (8) *cancels the effect of dead-zone* (4), *that is*

$$u(k) = ZI(u_c(k)) \Rightarrow x(k) = u_c(k), \forall k \geq 0.$$

Proof. Suppose $u_c(k) > 0$. For $u_c(k) > 0$, the auxiliary function $\chi_r(k)$ (10) will be equal to 1 and $\chi_l(k)$ (11) will take value 0. Therefore, $u(k)$ (9) will be:

$$u(k) = \frac{1}{m_r}\left[u_c(k) + m_r b_r\right] = \frac{u_c(k)}{m_r} + b_r \quad (12)$$

As it was admitted that $u_c(k) > 0$, and by definition $m_r > 0$, the portion $\frac{u_c(k)}{m_r}$ is also positive. So, $u(k) > b_r$. The auxiliary function $X_r(k)$ (6) will take value 1, while $X_l(k)$ (7) will be 0. Substituting (12) in (5) with the appropriate values of the auxiliary functions we have:

$$x(k) = m_r\left(\frac{u_c(k)}{m_r} + b_r - b_r\right) \quad (13)$$

Making the simplifications, we conclude that $x(k) = u_c(k)$.

Suppose that $u_c(k) < 0$. For $u_c(k) < 0$, the auxiliary function $\chi_r(k)$ (10) will be equal to 0 and $\chi_l(k)$ (11) will take value 1. As a result, $u(k)$ (9) will be:

$$u(k) = \frac{u_c(k) + m_l b_l}{m_l} = \frac{u_c(k)}{m_l} + b_l \quad (14)$$

As it was admitted that $u_c(k) < 0$, and by definition $m_l > 0$, the portion $\frac{u_c(k)}{m_r}$ will be negative. So, $u(k) < b_l$. The auxiliary function $X_r(k)$ (6) will take value 0 while $X_l(k)$ (7) will be equal to 1. Substituting (14) in (5) with the appropriate values of the auxiliary functions we have:

$$x(k) = m_l\left(\frac{u_c(k)}{m_l} + b_l - b_l\right) \quad (15)$$

Making the simplifications, we conclude that $x(k) = u_c(k)$.

Suppose that $u_c(k) = 0$. For $u_c(k) = 0$, the auxiliary functions $\chi_r(k)$ (10) and $\chi_l(k)$ (11) are equal to 0 and the signal $u(k)$ will take value 0 too. Since, by definition, $b_r > 0$ and $b_l < 0$, the signal $u(k)$ will be $b_l < u(k) < b_r$, and according to Equation (4) the signal $x(k) = 0$. Therefore, $x(k) = u_c(k)$. □

3 PARAMETER ESTIMATION METHODOLOGY

There is a lot of work in literature regarding the identification of the Hammerstein model. Many works require that the nonlinearity is approximated by a static and continuous function, usually a polynomial. The convergence is guaranteed. However, in the case of this paper, the nonlinearity is represented by discontinuous models.

The methodology proposed here is based on (Vörös, 1997, 2003). The author developed an iterative (Vörös, 1997) and recursive (Vörös, 2003) method to estimate parameters of the Hammerstein model with discontinuous nonlinearities. He relates the problem of identification because of the impossibility of measuring the internal variable of the Hammerstein model. Instead of measuring this variable, its estimate is used based on the estimated parameters in the previous step of the recursion. There is no proof of convergence for this identification method of Hammerstein with internal variable estimation. However, it is satisfactory for most practical applications (Vörös, 2006).

There are certain situations that the least squares method is polarized or tendentious. One of these situations occur when the noise or error in the regression equation is not white, which is the case of the

Output Error models. To solve the problem of polarization, non-polarized estimators must be used, like: extended least squares, generalized least squares, instrumental variables estimator (Aguirre, 2007). The method chosen for this study was the recursive instrumental variables estimation (RIV) with forgetting factor. The equations that are utilized in this estimation method are written below (Ljung, 1987):

$$K(k+1) = \frac{P(k)z(k+1)}{\lambda + \phi^T(k+1)P(k)z(k+1)} \quad (16)$$

$$P(k+1) = \frac{1}{\lambda}\left[P(k) - K(k+1)\phi^T(k+1)P(k)\right] \quad (17)$$

$$\hat{y}(k+1) = \phi^T(k+1)\hat{\theta}(k) \quad (18)$$

$$\hat{\theta}(k+1) = \hat{\theta}(k) + K(k+1)\left[y(k+1) - \hat{y}(k+1)\right] \quad (19)$$

where K is the estimator gain calculated from the covariance matrix P, $\hat{y}$ is the estimated value of system output y, $\hat{\theta}$ is the vector of estimated parameters, ϕ is the vector of regressors, z is the vector of instrumental variables and λ is the forgetting factor.

3.1 Equations Development

The vector of instrumental variables was chosen so that the estimated system output $\hat{y}$ and the system input u were utilized. The equation can be seen below.

$$\begin{aligned} z(k) = \Big[&\hat{y}(k-1) \cdots \hat{y}(k-n_a), \\ &u(k-d) \cdots u(k-d-n_b)\Big] \end{aligned} \quad (20)$$

Substituting Equation (5) in Equation (3) we have equation (21), which describes the total behavior of the system with its both linear and non-linear characteristics.

$$\begin{aligned} y(k) = \sum_{i=0}^{n_b} b_i \Big\{ &X_r(k-d-i)m_r\left[u(k-d-i) - b_r\right] \\ &+ X_l(k-d-i)m_l\left[u(k-d-i) - b_l\right] \Big\} \\ &- \sum_{j=1}^{n_a} a_j y(k-j) + \sum_{j=1}^{n_a} a_j e(k-j) + e(k) \end{aligned} \quad (21)$$

It is observed that, if we multiply the coefficients b_i by the term in braces, there will be a number of parameters like $n_a + 4(n_b+1)$ to be estimated, besides, they are connected to each other ($b_i m_r$, $b_i m_r b_r$, for example). To avoid this large amount of parameters, the key term separation principle was used (Vörös, 1995). In this new formulation, the internal variable $b_0 x(k-d)$ is separated from the others, which generated the following equation, with the number of parameters equals to $n_a + n_b + 4$:

$$\begin{aligned} y(k) = b_0 \Big\{ &X_r(k-d)m_r\left[u(k-d) - b_r\right] \\ &+ X_l(k-d)m_l\left[u(k-d) - b_l\right] \Big\} \\ &+ \sum_{i=1}^{n_b} b_i x(k-d-i) - \sum_{j=1}^{n_a} a_j y(k-j) \\ &+ \sum_{j=1}^{n_a} a_j e(k-j) + e(k) \end{aligned} \quad (22)$$

For Equation (22), the vector of regressors and the vector of parameters can be respectively defined such as:

$$\begin{aligned} \phi^T(k) = \Big[&-y(k-1), \ldots, -y(k-n_a), \\ &X_r(k-d)u(k-d), -X_r(k-d), \\ &X_l(k-d)u(k-d), -X_l(k-d), \\ &x(k-d-1), \ldots, x(k-d-n_b)\Big] \end{aligned} \quad (23)$$

$$\begin{aligned} \theta^T = \Big[&a_1, \ldots, a_{n_a}, b_0 m_r, b_0 m_r b_r, \\ &b_0 m_l, b_0 m_l b_l, b_1, \ldots, b_{n_b}\Big] \end{aligned} \quad (24)$$

The internal variables $x(k-d-1), \ldots, x(k-d-n_b)$ cannot be measured directly. Estimates of their values will be used, based on the parameters of the previous step of the recursive estimation. In other words, the estimated values of m_r , b_r, m_l and b_l will be used in Equation (5) for the construction of the regressors $x(k-d-1), \ldots, x(k-d-n_b)$.

The dead-zone parameters are estimated with b_0. To obtain the separated values, it is necessary to know the parameter b_0. For this, it was admitted that the plant gain is known. By the final value theorem (Nelles, 2000):

$$\frac{\sum_{i=0}^{n_b} b_i}{1 + \sum_{j=1}^{n_a} a_j} = K_p \quad (25)$$

where K_p is the plant gain. So, b_0 is:

$$b_0 = -\sum_{i=1}^{n_b} b_i + K_p\left(1 + \sum_{j=1}^{n_a} a_j\right) \quad (26)$$

We can conclude that, in order to discover the separated value of each dead-zone parameter, simply perform the following divisions:

$$\begin{aligned} m_r &= b_0 m_r / b_0 \\ b_r &= b_0 m_r b_r / b_0 m_r \\ m_l &= b_0 m_l / b_0 \\ b_l &= b_0 m_l b_l / b_0 m_l \end{aligned}$$

Although all parameters are estimated, these last four parameters are the ones used to construct the inverse model of compensation.

4 TEST PLATFORM

The testing process is a level system in which we want to control tank height and it can be seen in Figure 6. It consists of an incompressible fluid reservoir having a flow input q_{in} controlled by a pneumatic valve that has an associated nonlinearity, and a flow output q_{out} dependent on the height.

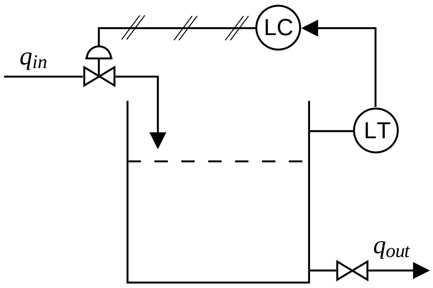


Figure 6: Level system.

The valve is a pneumatic actuator of fluid flow control and has associated dynamics (Wigren, 1993). It was assumed that it has linear opening characteristics and the model can be seen as follows:

$$G_v(s) = \frac{25}{s^2+5s+25} \tag{27}$$

The reservoir contains incompressible fluid and it is classically found in literature. The model used here is a linearization of a more complex model (Ikonen and Najim, 2002), and its transfer function is:

$$G_t(s) = \frac{2}{s+0,9} \tag{28}$$

The continuous model of the entire system, considering the transport delay of $d = 3$, is:

$$G(s) = \frac{50e^{-0,3}}{s^3+5,9s^2+29,5s+22,5} \tag{29}$$

The discrete model of the level system using a zero-order hold and a discretization time of 0,1s is:

$$G(z) = z^{-3}\,\frac{0,00713z^2+0,02441z+0,0053}{z^3-2,328z^2+1,899z-0,5543} \tag{30}$$

5 SIMULATION AND RESULTS

References generated in the process and the measurements of tank height are expressed in percentage. As a excitation sign the PRS (pseudo random signal) was used within a range of values averaging 50% and varying uniformly from 45 to 55% being the chosen values kept constant in a minimum of 10 sampling periods. The forgetting factor was kept constant during the first 2000 sampling periods having a value of 0,995, and after this time, it changed exponentially to 1, according to Equation (31), with $\lambda_0 = 0,995$.

$$\lambda(k) = \lambda_0\lambda(k-1) + (1-\lambda_0) \tag{31}$$

The noise was considered as a white additive one, with average zero and Gaussian variance of 0, 03. The initial values of the parameter vector θ were 10^{-3} and covariance matrix P was initialized as a diagonal matrix whose elements were equal to 10^6.

In order to quantify the efficiency of controls with and without compensation, two metrics of performance evaluation were implemented (Goodhart et al., 1991). The first one considers the variance of the control signal,

$$\varepsilon_1 = \frac{\sum\left(u(k) - \frac{\sum u(k)}{N}\right)^2}{N} \tag{32}$$

and the second metric evaluates the deviation of the process output regarding the reference according to the integral absolute error (IAE),

$$\varepsilon_2 = \frac{\sum|r(k)-y(k)|}{N} \tag{33}$$

N being the number of samples.

The evaluations were divided into 3 tracks. In the first one, the reference is kept constant at a value of 50% from 1 to 60s. At the 10s instant, a -10 amplitude disturbance occurs and ceases to exist at the 40s instant. In track 2, the reference is changed to 49% at 60s, and at 80s, in the last track, it is changed to 51%.

The block diagram for the estimation process can be seen in Figure 7. Block E represents the generator of excitation signal PRS, NL block represents the dead-zone nonlinearity, blocks A and T are respectively the dynamics of the valve and tank and represent the linear part of the Hammerstein model. The RIV estimation method with the presence of the forgetting factor is represented by block M.

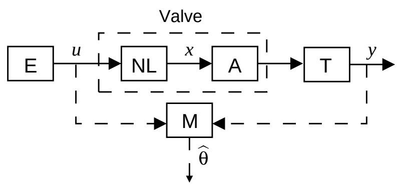


Figure 7: Block diagram of the level system estimation.

The block diagram of the compensation is shown in Figure 8. Block C represents a PI controller, which was tuned empirically so that, for the level system without the presence of nonlinearities, the plant response would behave without a large overshoot and with no regime error (less than 2%). Mathematical manipulations were made so that a control signal equals to zero would correspond to a level of 50%. Block INL represents the inverse nonlinearity, and was allocated before its respective nonlinearity. The others blocks have the same meanings described above.

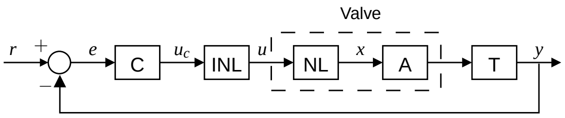


Figure 8: Block diagram of the level system with nonlinearity compensation.

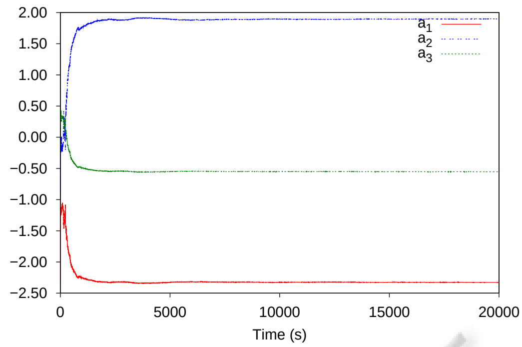
The dead-zone in the actuator of this process was built with the following parameters: $m_r = 3$, $m_l = 3$, $b_r = 1$ and $b_l = -1$. The graphics containing the parameters estimation results of linear dynamics and dead-zone can be seen in Figure 9. The parameter values obtained at the end of the recursive estimation process are shown in Table 1. The actual values of each one are also in Table 1 for comparison.

Analyzing the estimation graphics, it is observed that all the parameters have converged up to 7500s, the last ones being the coefficients of the polynomial $B(q)$. The values obtained in the estimation process are shown in Table 1, and have small errors (the biggest errors are in the order of 10^{-2}) in relation to the real values. The algorithm showed good convergence for the noise presence.

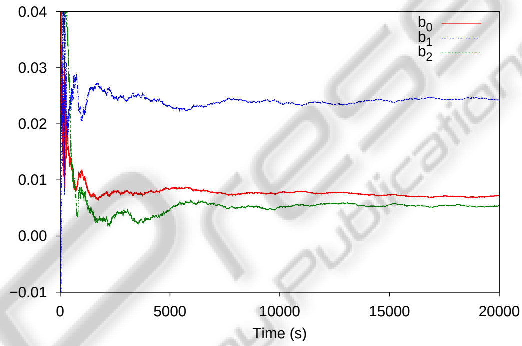
Table 1: Parameters of level system with dead-zone.

Parameters	Estimated Value	Real Value
a_1	-2.3271	-2.328
a_2	1.8968	1.899
a_3	-0.55309	-0.5543
b_0	0.00718	0.00713
b_1	0.02424	0.02441
b_2	0.00542	0.0053
m_r	3.0256	3
m_l	2.993	3
b_r	1.0214	1
b_l	-0.99561	-1

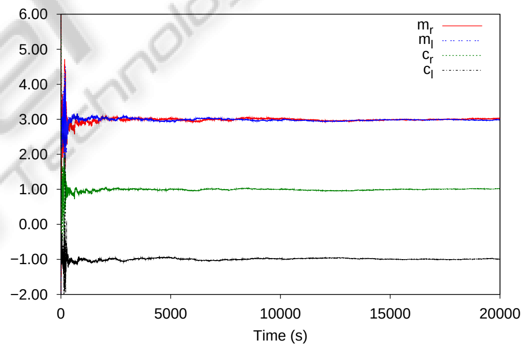
The controller was empirically tuned to $k_p = 0.5$ and $k_i = 0.7$. Figure 10 contains the graphics of plant level output for the linear case, that is, without the presence of dead-zone. Figures 11 and 12 represent,



(a) Polynomial $A(q)$.



(b) Polynomial $B(q)$.



(c) Dead-zone.

Figure 9: Parameter estimation of level system with dead-zone.

respectively, the cases of plant output with the presence of dead-zone with and without the compensator block. The control signals for these last two cases are shown in Figure 13.

For track 1, the control without compensation was rather oscillatory during the existence of the disturbance (10 to 40s) with the tank level ranging approximately from 45 to 55%. After the disturbance, the level returned to the reference and remained without oscillations. This was due to mathematical manipulations that keep the reservoir level by 50% for a valve input signal equal to zero. In tracks 2 and 3 the reference is changed respectively to 49 and 51%. In these two tracks, it is observed the existence of oscillations maintained in the output with amplitude around the reference of ±1%. As for the control with compensation, the behavior of the plant output is very similar to the case where there is not the dead-zone presence. Thereby, and according to Table 2, the control with compensation had better IAE indices (ε_2) for the 3 tracks compared to the control without compensation.

Table 2 also shows the index ε_1 of control signal variance evaluation for the two cases with the presence of dead-zone. Note that, in the case with compensation, the inverse nonlinearity (INL block) output was considered as control signal, and not the output of PI controller. Based on the graphic of Figure 13, the control signal with the inverse nonlinearity is more aggressive in relation to the sign of pure PI control for the dead-zone region. This is caused by the discontinuity present in the graphic of the inverse dead-zone (see Figure 5) around de zero point. Whenever the PI output inverts its sign (from positive to negative or vice versa), a jump in the output compensation occurs. Even with this discontinuity, the control with compensation had a smaller variance in its signal to the 3 tracks of the evaluation.

Table 2: Metrics for performance evaluation of nonlinear system with and without compensation.

Track	With Comp.		Without Comp.	
	ε_1	ε_2	ε_1	ε_2
1	3.0574	1.7683	2.4786	0.3696
2	0.1242	0.3722	0.0492	0.2028
3	0.1201	0.4188	0.0547	0.2439

6 CONCLUSIONS

In this work, it was developed a method of estimation and compensation of dead-zone that is present in the actuators of various industrial processes. It was used, as a testing process, a simulation of a level tank, which has a valve with a dead-zone to control the input flow.

First it was developed an estimation method of parameters for a Hammerstein model, in which the nonlinear part is represented by dead-zone. As linear dynamic, the Output Error model was used, which is a more complex model and the estimation task becomes more difficult when compared to the estimation of ARX and ARMAX models, because the noise is much more influential in the process. The method used the key term separation principle, reducing the number of parameters to be estimated.

In practice, the process operator defines the duration and type of measures that can be collected from the process. In fact, large variations in the excitation signal are very useful in identifying systems. However, they are not often allowed by the operators. Then, the identification should be made using normal operation data.

After being estimated, the parameters that make up the dead-zone were used to construct the inverse model of compensation. In general, the controller with compensation was more aggressive than the control without compensation during the dead-zone region. However, the plant output is much less oscillating in the compensated case. Performance metrics

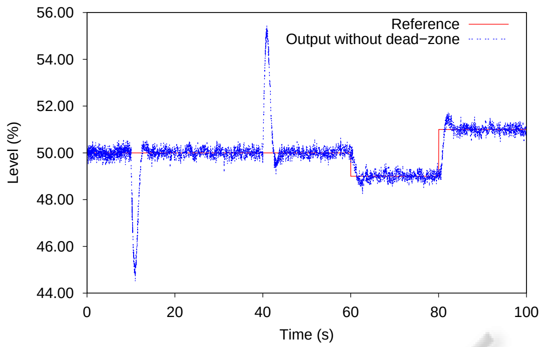


Figure 10: Plant output without dead-zone.

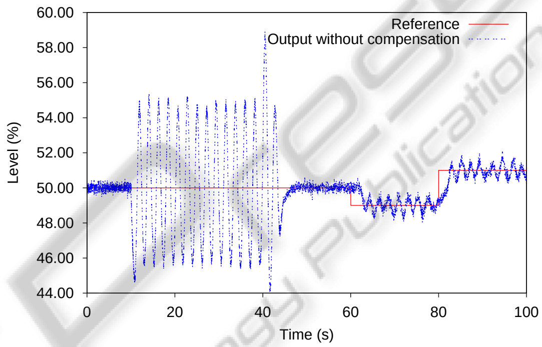


Figure 11: Plant output with dead-zone and without compensation.

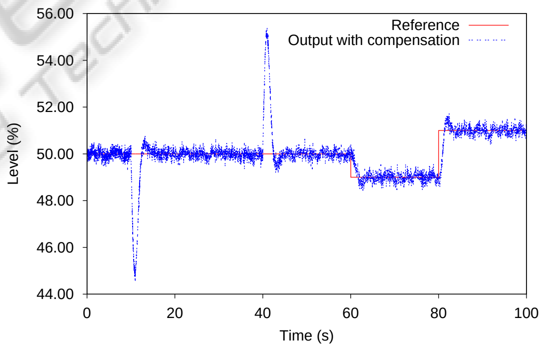


Figure 12: Plant output with dead-zone and with compensation.

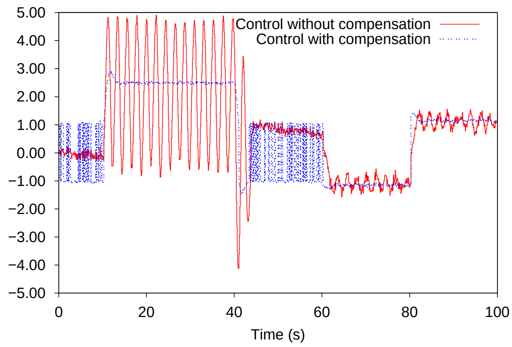


Figure 13: Control signals for the nonlinear system.

quantify the control actions and the error at the plant response. Therefore, the purpose of minimizing or even canceling the oscillations was achieved.

The estimation and compensation techniques developed here can be applied to any industrial plant that is represented according to Hammerstein model, which has the dead-zone as nonlinearity.

It is intended, as future work, to estimate and compensate the backlash nonlinearity. In addition, we intend to implement the proposal in a Programmable Logic Controller (PLC). This will bring this work to a possible application in the real world.

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