Implementation of AWBT Compensation using ANN

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Abstract: - For approaching the problem of Anti-Windup Bumpless Transfer (AWBT), in this work, a method for implementation of compensation schemes using Artificial Neuronal Networks (ANN) is presented. Using this technique, the saturated signal of control is obtained via a neuronal inverse model. Thus, the saturation measurement problem or the use of actuator models is avoided; and the compensation is guaranteed, spite of the changes in the saturation levels; this is, it is not necessary to specify the saturation levels to priori.

Key-Words: - Actuator Saturation. Anti-Windup. Compensation-based Control. Artificial Neural Networks.

1 Introduction

In general, the controlled industrial processes present the actuator saturation problem. In control theory that restriction is denominated the bounded control problem, which leads to consider methods and technics that allow the practical installation of control systems.

On the other hand, the control systems can operate in multiple environments and with multiple objectives. Each specific situation defines the operation mode, which can require a commutation of the controller. The modes commutation is the substitution in the plant inputs, considering that the controller output is replaced by another.

As a result of substitutions and limitations, the plant inputs will be different to the controller's output. When this happens, the controller outputs don't drive the plant appropriately and the controller's states will be strongly updated, [6, 8]. This effect is called Wind-Up. In global terms, the wind-up is one inconsistency among the control input to the process and the internal states of the controller. The adverse effect of the wind-up is a significant performance deterioration, overshots and even inestability, [8, 3].

The wind-up problem can be handled by means of compensation where, in a first stage, it is designed the control system without taking into account the restrictions; and in a second stage, some compensation scheme is looked for, with the purpose of minimizing the effect of the limitations and commutations. The last outlined focus has been denominated the *anti-windup bumpless transfer problem* (AWBT), [6].

A general framework for the AWBT problem has been shown in [6]. The development is based on the paradigm of designing a linear controller, which ignores the non linear inputs and incorporate AWBT compensation to minimize those adverse effects due to any non linearity in the control input.

In all the cases of solution for the AWBT problem by compensation, it is required of one residual signal obtained between the controller's output and the nonlinear output of the actuator, [2, 3, 5, 6, 8, 15]. The measuring of such a residual constitutes an additional problem, from the point of view of the installation of the selected compensation scheme, since it is not always possible to obtain, [2]. This generates a limitation for the possibility of installing the compensation scheme, and more particularly in the cascade control systems, [10].

So, it is fundamental to obtain a measure of the residual, which in many cases is difficult to achieve and demands the use of actuator models, [2, 6]. The use of models has the difficulty of not generating the appropriate residuals for changes in the saturation levels of actuators, [11].

On the other hand, for solving the reconstruction problem or estimating actuator output, some techniques have been presented. In [11] fault detection and isolation filters are used, which have the inconvenience of demanding hard conditions for distinguishing multiple saturations. Another method consists on using process inverse models for reconstructing the inputs (in this case, the actuator output), with the inconvenience of requiring the process output derivatives, [13].

In this same order of ideas, Artificial Neural Networks (ANN) have shown an excellent capability for reconstructing signals, [1]. This capability responds to its relative functionality for modeling input-output relations. The benefits of the ANN-based inverse models, where is not necessary the use process outputs derivatives, has allowed the application of this schemes for diverse problems as: fault detection, [12]; PID auto-tuning control, [14].

The ANN capability for emulating inverse models will be applied in this work for estimating the actuator output signal in order to be able to implant compensation schemes for the AWBT problem. The work has been structured as follows: Next, several techniques for the AWBT compensation problem will be presented. Then, a brief introduction concerning the use of the ANN for signals reconstruction is explained. In the same section, the employment of ANN is shown for implanting compensation schemes. Next, an illustrative example is presented and, finally, there will be presented some conclusions.

2 Control for AWBT Compensation problem

In summary, for the solution of the AWBT problem by means of compensation the developed techniques are the following ones:

1. Anti-reset: This technique refers to the calculation, tracking and readjustment of the integral action in PID controllers, [2].
2. Conditional integration: The idea of this method is to stop the integration action just when the saturation appear, [2].
3. Internal Model control (IMC): Using IMC, the restrictions of the actuator don't cause any stability problem, since the restricted control signal is handled by the plant and by the model, [3, 6, 8].
4. The Conditioning Technique: This technique was formulated as an extension of the returning calculation method, [5, 8].
5. Observer Based method: An observer is incorporated in the controller structure, and it operates only when there is saturation for effects of correcting the possible uncertainties, [3, 8].

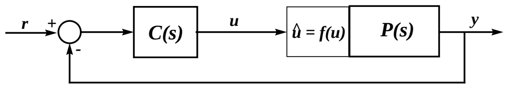

Figure 1: Control System with Saturation of Actuators.

We consider the unified framework for AWBT compensation design, [6]. Let us consider a linear system given by:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t); \end{aligned} \tag{1}$$

where $x \in \mathbb{R}^n$ are the states, $u \in \mathbb{R}^p$ are the controls and $y \in \mathbb{R}^q$ are the outputs. The matrices A, B, C have appropriate dimensions.

The AWBT compensation problem is formulated from the Fig. 1, where, due to the limitations and/or substitutions, a non linearity appears among the the controller's output and the effective process input. The effective control input $\hat{u}(t)$ is a non linear function of the controller's output $u(t)$.

$$\hat{u}(t) = f(u)$$

In the case of actuator saturation, each of the input elements of the controls vector is applied to the process through the non linearity

$$\hat{u}_i(t) = \begin{cases} u_{i_{min}} & \text{si} \quad u(t) < u_{i_{min}} \\ u(t) & \text{si} \quad u_{i_{min}} \leq u(t) \leq u_{i_{max}} \\ u_{i_{max}} & \text{si} \quad u(t) > u_{i_{max}}, \quad i = 1, 2, \ldots, p \end{cases} \tag{2}$$

Regarding the substitutions when the control is selected from a controllers' set using a mechanism of min-max selectors, this results in a dead area non linearity, [7].

The controller $C(s)$, which we will represented by

$$C(s) = \left(\begin{array}{c|c} F & G \\ \hline H & R \end{array} \right) = H(sI - F)^{-1}G + R, \tag{3}$$

with a left coprime factoring described by

$$C(s) = N(s)^{-1}M(s); \tag{4}$$

is designed without considering the non linearities and with the stabilization and execution goals fixed according to certain performance criteria.

In the ideal case, it doesn't exist limit for the effective process input and then $\hat{u}(t) = u(t)$. Under the presence of the not linearity $f(u)$, the system in closed loop can be represented in a two ports configuration like the one shown in Fig. 2. There, ω represents all the external in-

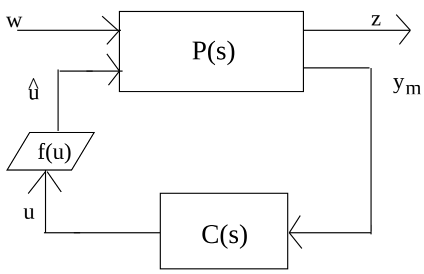

Figure 2: Control Problem with non linearity.

puts as as the setpoints, interferences and noises; z are the controlled outputs and y_m is the measured outputs for the controller's $C(s)$ that allows to complete the pre-established objectives. In that representation, the process $P(s)$ will be conformed by

$$P(s) = \begin{pmatrix} P_{11}(s) & P_{12}(s) \\ P_{21}(s) & P_{22}(s) \end{pmatrix} \tag{5}$$

In the ideal case, the synthesis of $C(s)$ can be reached by means of robust control tools. Under the $f(u)$ presence, that non linearity can become an uncertainty and then apply the robust control techniques, [9].

Inside the general framework presented in [6], The AWBT problem involves the design of $\hat{C}(s)$ based on the two ports diagram shown in Fig. 3. $\hat{C}(s)$ constitutes the AWBT compensated ver-

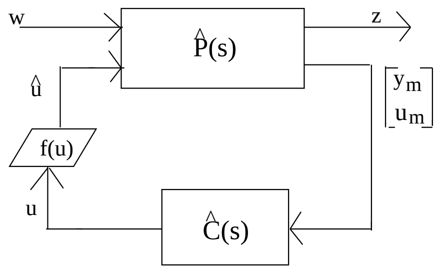

Figure 3: The AWBT Problem.

sion of $C(s)$ and the increased plant corresponds to

$$\hat{P}(s) = \begin{pmatrix} P_{11}(s) & P_{12}(s) \\ P_{21}(s) & P_{22}(s) \\ 0 & P_{32}(s) \end{pmatrix} \tag{6}$$

Since $\hat{u}(t)$ does not provides information of the generic non linearity $f(u)$, and it is used as feedback for the compensation synthesis, it is fundamental to measure it or to estimate it, which constitutes an additional problem because of the difficulty for determining the appropriate value. Based on the requirement of $\hat{u}(t)$ in the compensation techniques for the AWBT problem, inside the general framework u_m represents a measure or estimation of this plant input.

$$u_m = P_{32}\hat{u}. \tag{7}$$

In our proposal, the u_m estimation is obtained using an ANN based inverse model, which allows the reconstruction of that signal. In terms of two matrix parameters H_1 y H_2, a parametrization of all the controllers $\hat{C}(s)$ with AWBT that satisfy certain criteria of admissibility defined appropriately corresponds to, [6]:

$$\hat{C}(s) = (M(s) \quad I - N(s)), \tag{8}$$

with

$$M(s) = \left(\begin{array}{c|c} F - H_1 H & G - H_1 R \\ \hline H_2 H & H_2 R \end{array} \right) \tag{9}$$

$$N(s) = \left(\begin{array}{c|c} F - H_1 H & -H_1 \\ \hline H_2 H & H_2 \end{array} \right) \tag{10}$$

where H_2 is a invertible matrix and, it is assumed that $F - H_1H$ has stable eigenvalues. Then, using the selection of H_1 and H_2, ll the time invariant linear AWBT compensation schemes are particular cases of this parametrization.

3 ANN and Inverse Models

Artificial neural networks (ANN) constitute a branch of the Artificial Intelligence. With this technique is looked the emulation of the operation of the Biological Neural networks in the relative thing to the learning and processing of information. Their applications include: systems modeling and identification, simulation, Processes control, prediction, fault handling, patterns recognition, medical diagnosis, virtual sensors design , etc., [1]. In this context, for signals patterns recognition or their reconstruction in dynamical systems, there are widely used the inverse models, which allow to generate estimation of the input signals from the outputs ones. The capabilities of ANN for reconstructing signals patterns, particularly, using inverse models, has the advantage of avoiding stability requirements and the employment of process outputs derivatives, [12].

4 Generation of the u_m signal using ANN

The AWBT compensation schemes, use a measurement or an estimation of $\hat{u}$, which is denominated u_m. In the practice, the main difficulty is obtaining such a value, [11]. A first estimation of $\hat{u}$ can be obtained using a model for the actuator non linearity represented by $f(u)$. From the implementation point of view, the model will generate the estimated value to be used in the calculation of the compensation, just as it is illustrated in Fig. 4. The estimated value, in this case, will be $u_m = P_{32}(s)u_1$. The problem, in this case, is when it happens changes in the non linear characterization of the actuator, and it is not reflected in an immediate way in the model, and those changes are not reflected in the control and the deterioration behavior can be obtained again; this mean that the compensation doesn't have effect. When there exists difficulty for obtaining a model of the non linearities, it should be consider techniques that allow to determine a estimation of $\hat{u}$ through the available signals. This is the case of signals reconstruction using inverse models based-on ANN.

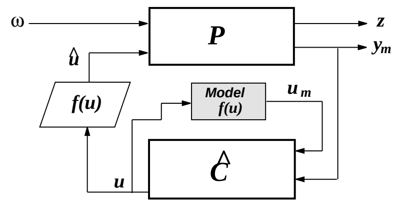

Figure 4: Implementation of AWBT compensation through of non-linear model.

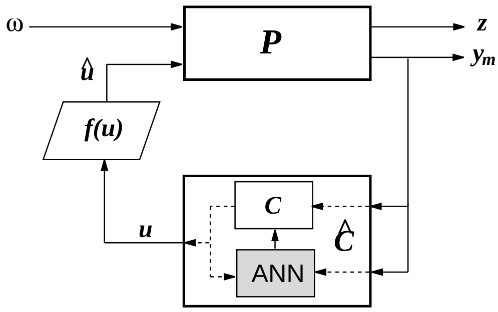

Figure 5: Implementation of AWBT compensation using Neuronal Inverse Models.

Let us consider the dynamic system (1). Applying an ANN based inverse model, it can be achieved a estimation of the effective plant input, which is represented by the signal u_m, necessary for the compensation.

5 Illustrative Example

Let consider the linearized system for a batch unstable reactor described by, [4]:

$$\dot{x} = \begin{pmatrix} 1.3800 & -0.2077 & 6.7150 & -5.6760 \\ -0.5814 & -4.2900 & 0 & 0.6750 \\ 1.0670 & 4.2730 & -6.6540 & 5.8930 \\ 0.0480 & 4.2730 & 1.3430 & -2.1040 \end{pmatrix} x + \begin{pmatrix} 0 & 0 \\ 5.6790 & 0 \\ 1.1360 & -3.1460 \\ 1.1360 & 0 \end{pmatrix} u;$$

$$y = \begin{pmatrix} 1 & 0 & 1 & -1 \\ 0 & 1 & 0 & 0 \end{pmatrix} x.$$

In this case it is supposed that the actuators are saturated in the following limits:

$$u_{1_{min}} = 0, \quad u_{1_{max}} = 3, \quad u_{2_{min}} = 0, \quad u_{2_{max}} = 18.85$$

Based on the design methodology for compensation, a stabilizing controller is built for tracking an step signal. This controller is a multivariable PI given for:

$$C(s) = \left(\begin{array}{c|c} 0 & K_i \\ \hline \mathbb{I} & K_p \end{array} \right),$$

where

$$K_p = \begin{pmatrix} 0 & 2 \\ -2.5 & 0 \end{pmatrix}, \qquad K_i = \begin{pmatrix} 0 & 2 \\ -2.8 & 0 \end{pmatrix}.$$

The compensation is given using the *windup anti-reset technique*, [2], where the resulting controller is:

$$\hat{C}(s) = \left(\begin{array}{c|cc} 0 & K_i & -K_r \\ \hline \mathbb{I} & \multicolumn{2}{c}{K_p} \end{array} \right)$$

where K_r is the feedback gain for the difference among u and $\hat{u}$. Particularly, there is selected the following gain :

$$K_r = \begin{pmatrix} 0.5 & 0 \\ 0 & 0.5 \end{pmatrix}.$$

Based on Section 4 an ANN based inverse model has been designed, for estimating u_m, with the following characteristic:

- Four inputs corresponding to the two inputs of control and to the two outputs of the system.
- Two outputs corresponding to the actuator outputs.
- 15 nodes and a hidden layer are selected for the structure of the ANN.

The ANN was trained using the backpropagation algorithm, and the validation and verification phases are given in order to guarantee the generalization capabilities of the ANN based inverse model.

The simulations for the system without saturation, with saturation but without compensation, and with saturation and having compensation are shown in the following figures.

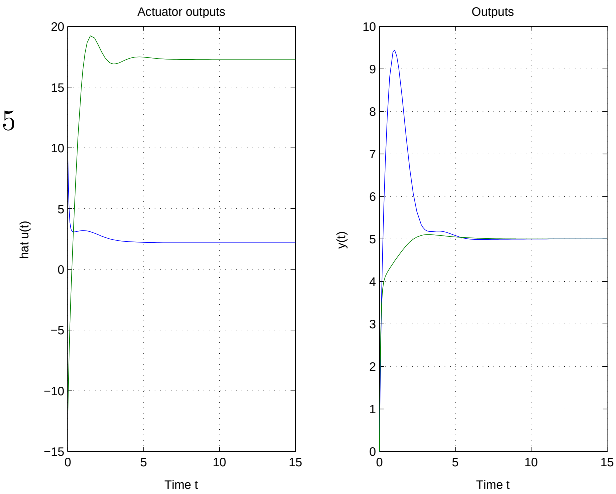

Figure 6: System responses without saturation case.

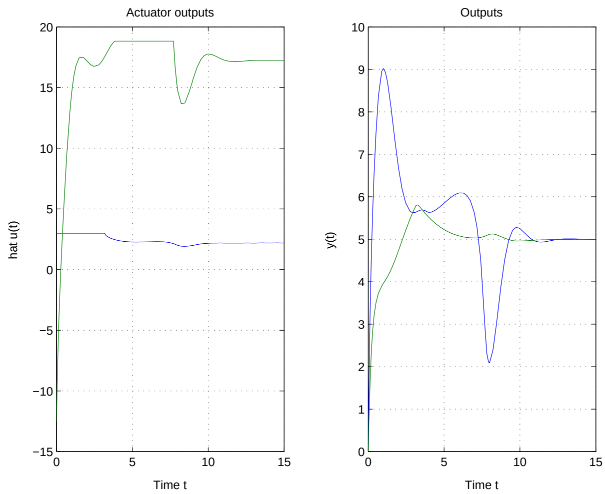

Figure 7: System responses with saturation and without compensation.

It can be noticed from Fig. 7 the saturation effect in the output of the system. A deterioration meaning in the behavior is observed with relationship to the case without saturation, Fig. 6. Through the compensation, Fig. 8, it is able to improve the behavior from the system in a similar way to the case without saturation. Any change on the saturation levels, the mechanism of detection (neuronal inverse model) allows an immediate upgrade for finding the necessary compensation.

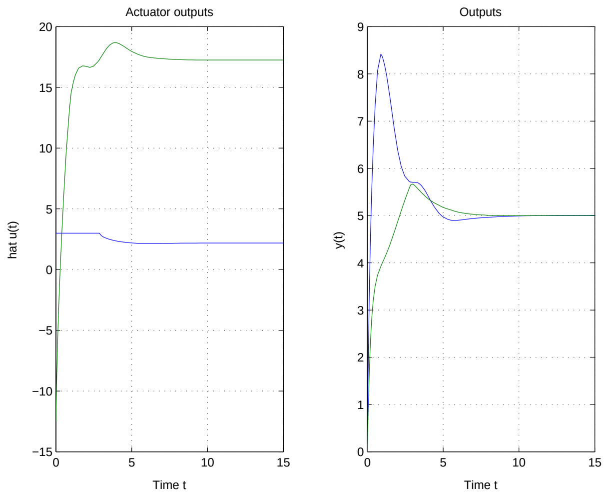

Figure 8: System responses with compensation windup anti-rese.

6 Conclusion

Based on the Artificial Neural Networks inverse models, it has been presented a technique for implanting compensation methods for the actuator saturation problem in linear systems. The inverse models, built using artificial neural networks, allows to generate an estimation for the output signal of the actuator, which is necessary for the compensation. This technique has the advantage that any change in the non linear characteristics of the actuator are recognized and used for the compensation in an immediate way.

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