Comparison of Identification Techniques for a 6-DOF Real Robot and Development of an Intelligent Controller

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1. Introduction

In their beginnings, control systems were developed out of a full knowledge of the mathematical model of the process to be controlled. Nowadays, however, the trend for advanced control systems points to the fact that they can be developed without a previous knowledge of the mathematical model of the system to be controlled, hence leading to advantages and drawbacks at the moment of their application (Craig, 2006). Amongst the most remarkable disadvantages we have the fact that the higher accuracy we ask the controller, the more response delay we have (Ogata, 1996). That is why, if we can get a good enough system description, control systems can be simplified, enhancing their accuracy as well as their speed (Pierro et al., 2008).
Advanced control techniques allow us an accurate control from a system predictor model, as the case of adaptive control techniques by reference model, studied in this chapter. An adaptive control system is a controller capable of modifying system's adjustable parameters generating an acting signal, in order to keep optimum performance independently from environmental modifications. Adaptive control can be represented through the following block diagram:

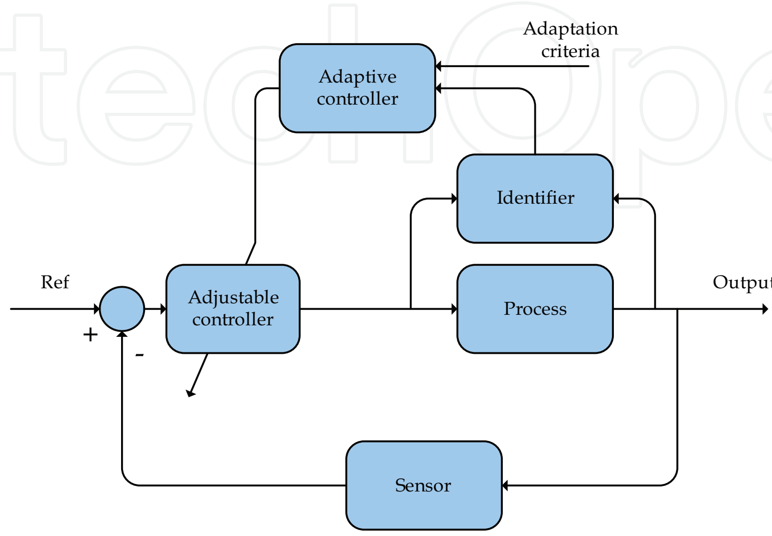


Fig. 1. Adaptive control block diagram

In the scheme we can notice the need of adaptive control for a model that allows to describe the system behavior.
There are several techniques for modeling a system when we have not information about the model, as well as techniques that allows to estimate interesting parameters in a model, approximating it to a specific system. These techniques are known as system identification techniques, which allows to create or approximate specific mathematic models in order to describe, predict or simulate a system (Ljung, 1999).
In the utilization of system identification methods we have to consider the dynamic nature of the system, since there are identification structures for models with linear and non-linear dynamics. Generally speaking, the knowledge of the system's dynamics is a previous or given information, or, in its absence, we can suspect the kind of structure that will describe in a better way the studied system. When starting any identification process, it is necessary to take three basic steps (Ljung, 1999):

1. To carry out an experiment in order to obtain a data set.
2. To choose a model to be adjusted.
3. To select from a set of candidate models a rule by which candidate models can be assessed using the data.

Henceforth, we follow with model estimation; as a general rule, those estimated models use to result acceptable after several iterations, where we must verify if the obtained model is the right one.

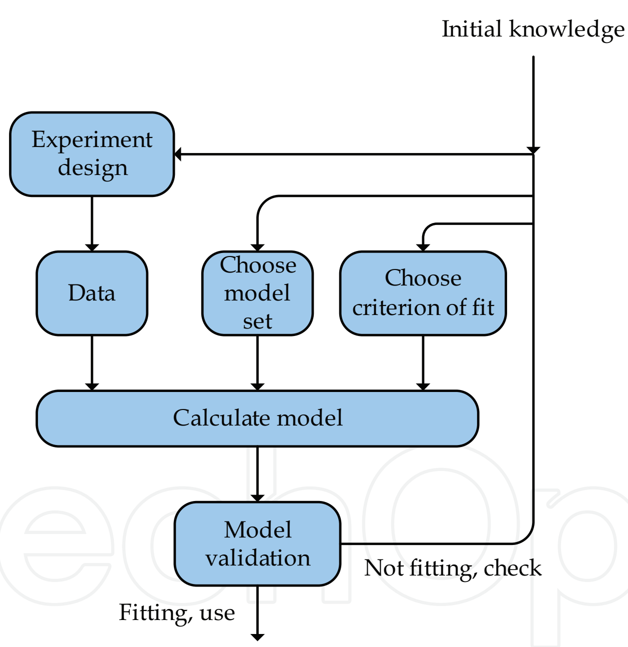


Fig. 2. System identification loop

In this chapter we will review many system identification techniques and adaptive control techniques; both kinds will be applied in the identification and control of a SCARA industrial manipulator. In order to do that, we will obtain a model efficiently representing the dynamics of a SCARA robot, through Hammerstein-Wiener Models. Those models will be verified by implementing several trajectory experiments applied on the system. This identification is carried out in the aim to implement Model Reference Adaptive Control (MRAC), improving in this way the general behavior of the system.

2. Linear system identification

During the modeling process there arise great problems concerning the choice of modelling methods, amongst others. It is here where studies on system identification are centered, basically looking to answer the question How to create the model for a specific system from measured data?

Concerning systems identification, when we talk about a system, we mean a process having inputs and outputs. Observed variables are simply known as outputs. Inputs that can be managed are known as inputs, and other inputs –that only can be measured- are known as measurable perturbations and, finally, there are inputs that cannot be measured, known as non measurable perturbations (Ljung, 1999). In this way, by means of mathematic methods, systems identification tries to model the global behavior of the studied system.

The most important identification techniques are divided into two major groups: linear identification techniques, and non-linear identification techniques. This classification of identification techniques is made because in the real field there are systems that can be approximated to linear or non-linear models.

The most popular system identification linear models family is the Black Box models group. This family of structures covers a total of 32 models. Black Box models base their identification capabilities in parameter adjustment of the polynomials that compose them. Those models are composed by 5 polynomials; depending on which polynomials are employed, it is the model at which the system is approximated to.

The BlackBox model is described in (1).

$$A(q)y(t)=\frac{B(q)}{F(q)}u(t)+\frac{C(q)}{D(q)}e(t) \tag{1}$$

Those polynomials are polynomials in q, that is an operator employed to specify that we are working with a discrete system, since the operator is q=z, corresponding to the operator of the z transform. In this way, the polynomials are defined in (2).

$$\begin{aligned}
&A(q)=a_0+a_1q^{-1}+\cdots+a_{na}q^{-na}\\
&B(q)=b_0+b_1q^{-1}+\cdots+b_{nb}q^{-nb}\\
&C(q)=c_0+c_1q^{-1}+\cdots+c_{nc}q^{-nc}\\
&D(q)=d_0+d_1q^{-1}+\cdots+d_{nd}q^{-nd}\\
&F(q)=f_0+f_1q^{-1}+\cdots+f_{nf}q^{-nf}
\end{aligned} \tag{2}$$

Through the adjustment of each one of the parameters, we achieve the approximation to the studied system. Those adjustable parameters use to be denoted as shown in (3).

$$\theta=[a_0...a_{na} \quad b_0...b_{nb} \quad f_0...f_{nf}] \tag{3}$$

In some cases we observe that system dynamics has delays from input u(t) to output y(t) of n_k samples, therefore, some coefficients of the B(q) polynomial are managed as zero (4).

$$B(q)=b_{nk}q^{-nk}+...+b_{nk+nb-1}q^{-nk-nb-1}=q^{-nk}B'(q) \tag{4}$$

In this way, the generalized model for the case with delays is shown in (5).

$$A(q)y(t)=q_{-nk}\frac{B'(q)}{F(q)}u(t)+\frac{C(q)}{D(q)}e(t) \tag{5}$$

For the sake of simplicity, it is usual to employ nk=1 and the expression shown in (1). Nevertheless, we could always arrive to a general form including the delays by replacing u(t) for u(t-nk+1).
In order to identify the parameters of the model proposed in (1) we employ a predictor with the form:

$$y(t\,|\,\theta)=\frac{D(q)B(q)}{C(q)F(q)}u(t)+\left[1-\frac{D(q)A(q)}{C(q)}\right]y(t) \tag{6}$$

This predictor is compared with the system real output and the error is minimized using some mathematic algorithm, commonly the least square method.
A practical summary of linear Black Box models appears in the scheme shown in fig. 3.

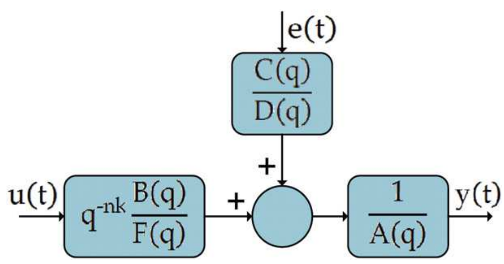


Fig. 3. General structure of linear Black-Box models

As already mentioned, depending on which polynomials are employed in expression (1) a different structure will be chosen. Generally speaking, the most employed structures for systems identification are summarized in table 1.

Employed Polynomials	Name of the model structure
B	FIR (Finite Impulse Response)
AB	ARX
ABC	ARMAX
AC	ARMA
ABD	ARARX
ABCD	ARARMAX
BF	OE (Output Error)
BFCD	BJ (Box-Jenkins)

Table 1. Most popular linear Black-Box models, as a special case of (1)

The model choice will rely on what is intended to be modeled. We will illustrate this situation through an example.

2.1 Example of model selection
Lets consider a DC servomotor having only viscous friction, described in fig. 4.

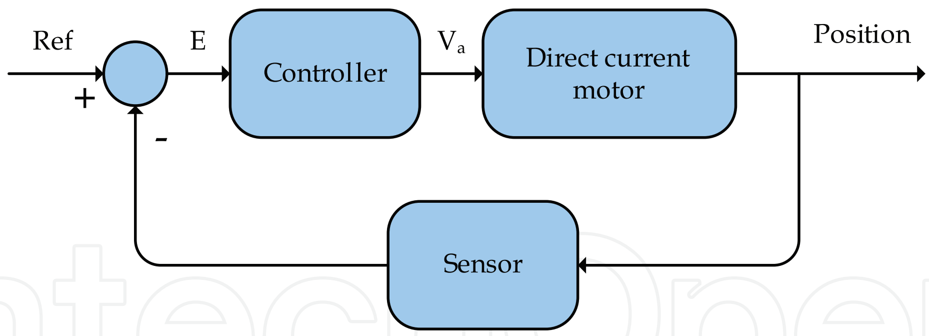


Fig. 4. Servomotor block diagram

The model of a DC motor in the domain of Laplace (Nyzen, 1999) is given by (7):

$$V_a(s)=\frac{1}{nk_m}\left[JLs^3+(JR+fL)s^2+(fR+k_m k_e)s\right]\Theta_m(s) \tag{7}$$

where:

V_a : DC motor input voltage.
R, L, k_e : Electric parameters of the equivalent circuit.
k_m : Motor characteristic torque constant.
n : Geartrain ratio.
F : Viscous friction constant.

It is important to remark that in the model shown in (7) it is included the phenomenon of friction in the joint driven by the servomotor, but only considering the linear part representing such phenomenon, without including the non-linear parts present in classic friction models, like the static friction one (Makkar, 2005).

Assuming an ideal sensor and a proportional integral controller, as shown in (8):

$$V_a(s)=k_p\left(1+\frac{k_I}{s}\right)E(s) \tag{8}$$

Linking equations (7) and (8) we have the equation that models the position with respect to the servomotor input voltage:

$$(r_1s^4+r_2s^3+r_3s^2+r_{41}s+r_5)\Theta(s)=(r_4s+r_5)U(s) \tag{9}$$

where:

$r_1=\frac{JL}{nk_a}$

$r_2=\frac{(JR+fL)}{nk_a}$

$r_3=\frac{(fR+k_m k_e)}{nk_a}$

$r_4=k_p$

$r_5=k_p k_I$

Using Euler's backward method, shown in (10), we can discretize (9), having:

$$s=\frac{1-z^{-1}}{T} \tag{10}$$

where:
T: Sample time.

$$\left[\frac{r_1'}{r_5'}z^{-4}+\frac{r_2'}{r_5'}z^{-3}+\frac{r_3'}{r_5'}z^{-2}+\frac{r_4'}{r_5'}z^{-1}+1\right]\Theta(z)=\left[\frac{r_6'}{r_5'}z^{-1}+\frac{r_7'}{r_5'}\right]U(z) \tag{11}$$

where:

$$r_1'=\frac{JL}{nk_aT^3}$$

$$r_2'=\frac{3JL}{nk_aT^3}+\frac{(JR+fL)}{nk_aT^2}$$

$$r_3'=\frac{-3JL}{nk_aT^3}-\frac{2(JR+fL)}{nk_aT^2}-\frac{(fR+k_mk_e)}{nk_aT}$$

$$r_4'=\frac{JL}{nk_aT^3}+\frac{(JR+fL)}{nk_aT^2}+k_p$$

$$r_5'=k_p$$

The model (11) can be represented and approximated through a linear Black-Box model of the ARX kind. This model only has A and B polynomials, therefore it can be a good linear approximation for a simplified servomotor, considering an A polynomial of order 3 and a B polynomial of order 1, as shown in (12) (Santander et al., 2010).

$$\left[A_3q^{-3}+A_2q^{-2}+A_1q^{-1}+1\right]y(t)=B(q)u(t)+e(t) \tag{12}$$

Assuming zero error, the model in (12) can be simply written as:

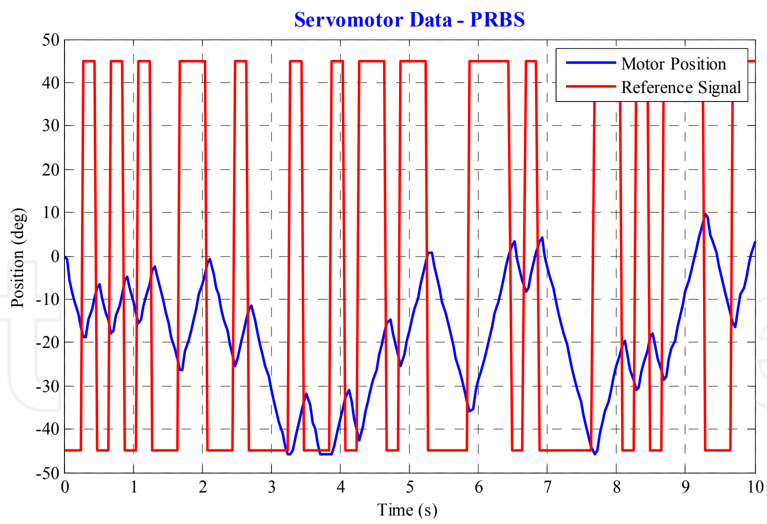
$$\left[A_3q^{-3}+A_2q^{-2}+A_1q^{-1}+1\right]y(t)=B(q)u(t) \tag{13}$$

2.2 Choice of excitation signal

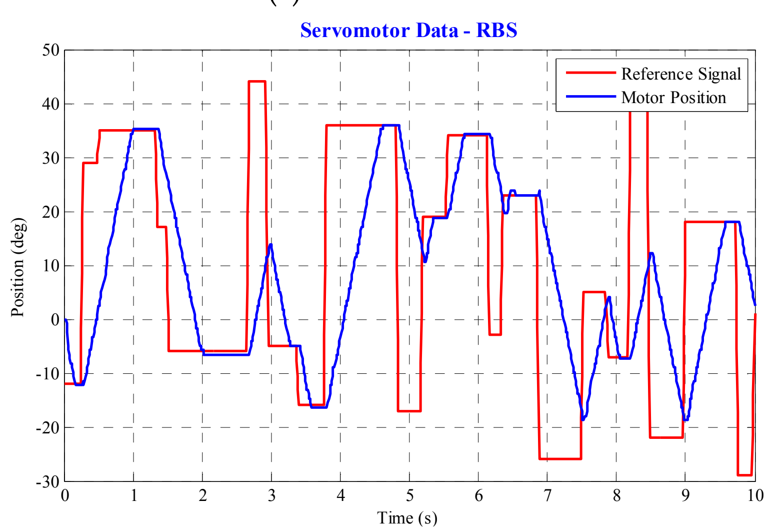
In order to obtain a model describing in an efficient way a given system, we must take into account the applied excitation signal, since it will permit a better tracking of the behavior we desire to describe.

Lets consider again the example of a servomotor, in (13) it is clear that it can be described with an ARX model, but the choice of the signal that can capture in a better way its dynamics it's not a trivial issue, generally depending of the system behavior, and without clear rules to follow. For this example we carry out the identification process using three different excitation signals: PRBS (Pseudo Random Binary Signal), RBS (Random Binary Signal), and GCPS (Growing Constant Pulses Signal) (Santander et al., 2010).

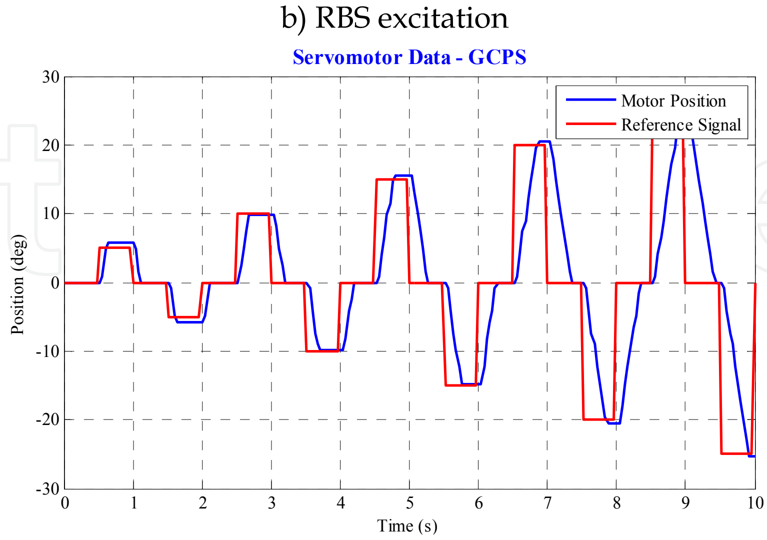
Using excitation signals we can get the adjustment of A and B polynomials for each one of the cases presented in fig. 5, those models are then validated using a smooth trajectory –as shown in fig.6- and model errors are calculated using (14). Results are summarized in table 2.



(a) PRBS excitation



b) RBS excitation



c) GCPS excitation

Fig. 5. HITEC HS-475HB servomotor data, with PRBS, RBS and GCPS excitations, respectively

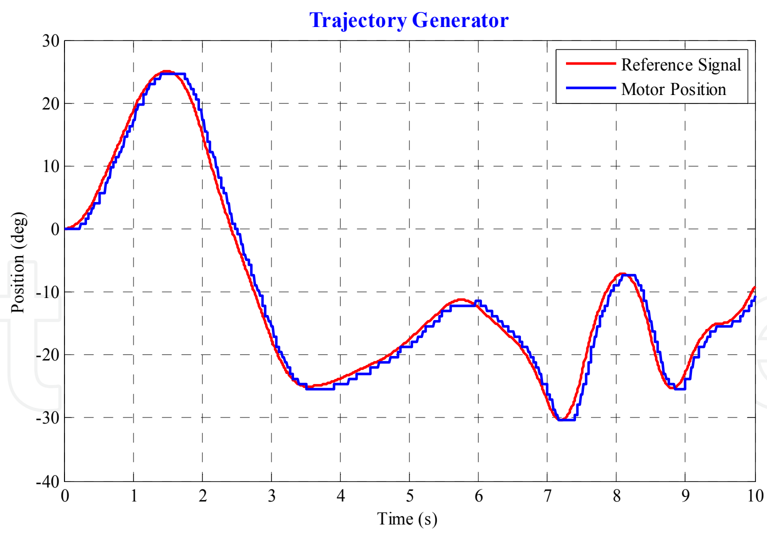


Fig. 6. Servomotor response when applying a smooth trajectory

$$error\% = \sqrt{\frac{\sum_{i=1}^{n}(o_i - p_i)^2}{\sum_{i=1}^{n} o_i^{\,2}}} \tag{12}$$

where:
o_i: Motor observed values.
p_i: Predicted or identified values.

Signal	error %
PRBS	193.611%
RBS	29.968%
GCPS	16.475%

Table 2. Approximated ARX models verification results

We must remark that, for the specific case of the studied servomotor, the best excitation signal for servomotor identification is GCPS (Santander et al., 2010).

3. Wiener-Hammerstein models

The main objective of this chapter is the control of a SCARA robot, therefore we will focus on finding models that describe efficiently the dynamic behavior of robotic manipulators. It is important to notice that robot dynamic models are highly non-linear, due to the different coupling of their links, and also because of opposition to their movement, that is, friction. That is why approximation with linear methods is not enough for a SCARA robot, and therefore it is necessary to explore other options providing an efficient modeling of the robot. Amongst current and most valid options applied to robots, we find studies carried out for parameter estimation of direct dynamic models, using the non-linear function obtained by means of Lagrange-Euler or Newton-Euler methods (Gautier et al., 2008), (Olsen & Petersen, 2001). Even if the models obtained for describing robot dynamics are highly accurate, they require a vast amount of calculations and measurement of robot interesting variables, at least the measurement of torque applied on each robot link. But what happens when the studied system have not sensors for torque measurement? It is necessary the implementation of such system? Next we will review a modeling option that does not require this kind of sensors.

There is a great variety of methods for non-linear identification, covering many different points of view. Up to date, the application of any method is totally arbitrary: some methods that work with very good predictions in some cases, are completely useless in other cases. The non-linear identification techniques we will review now are the Wiener-Hammerstein models.

It is common to find systems whose dynamics can be properly described by linear systems, although having static nonlinearities from the input and/or output. These nonlinearities can be caused by phenomena like saturation, or others. In the studied case, the SCARA robot actuators are DC motors subject to friction forces, with highly non-linear characteristics, so it is a good option to apply this kind of models.

We talk about Hammerstein models when the static nonlinearity is found in the input, and Wiener models when the static nonlinearity is in the output, as shown here:

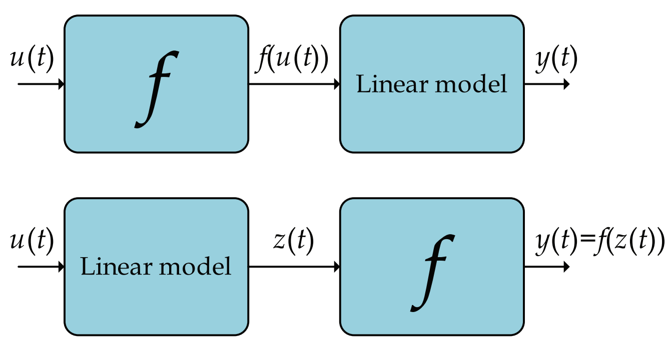


Fig. 7. Upper diagram: Hammerstein Model, Lower diagram: Wiener Model

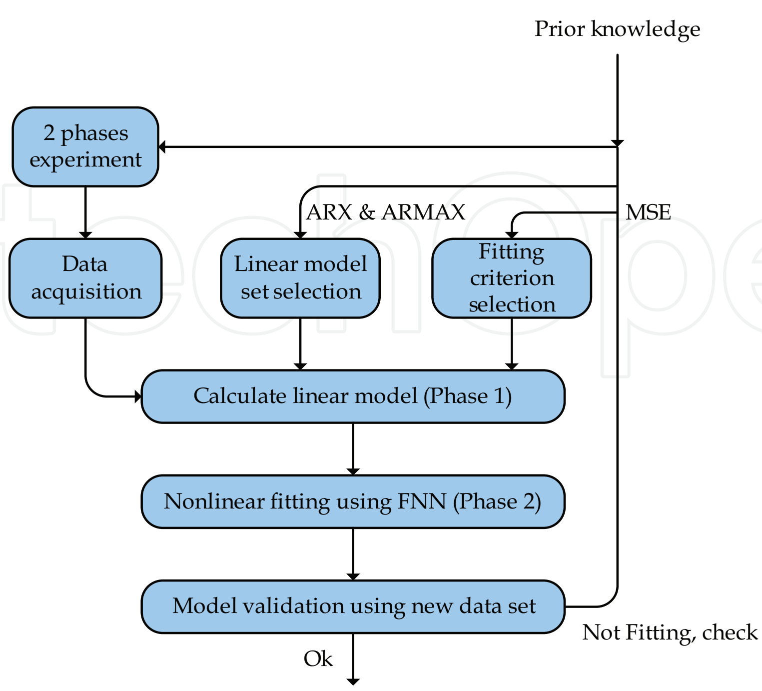


Fig. 8. System identification loop for Hammerstein-Wiener models

Function *f* presented in the model can be parameterized in terms of the physical parameters that compose it, like saturation level, or also in terms of another non-linear functions. In this way, if we assume a linear model G, the output predictor will be:

$$\hat{y}(t \mid \theta, \eta) = G(q, \theta) f(u(t), \eta) \tag{14}$$

For the case of modeling of the linear part we can use Black Box linear models, described in the previous section. The non-linear function employed for modeling can be any non-linear function that models and contributes to the improvement of the model. The most employed ones are: neural networks, fuzzy functions, tree partitioning, and others.
It is important to have in mind the kind of signal employed for function adjustment, since it must capture the system's nonlinear dynamics. It is advisable to employ a set of at least 10 chained independent trajectories for such identification (Gautier et al., 2008).
For the identification through Hammerstein-Wiener models we created a scheme that particularizes the general scheme of identification loop shown in fig. 2; in this scheme, Hammerstein-Wiener models are considered as the predetermined models to be employed.

4. Adaptive control

System identification and parameter estimation are vital steps in most control applications, as well as adaptive controllers by reference models and self-tuning controllers (Kasim, 2003). Adaptive control techniques can be divided mainly in two groups: Adaptive controllers by reference models (MRAC) and Self-tuning regulators (STR) (Rodríguez & Lopéz, 1996). The MRACs try to find, for a defined input signal, a closed-loop behavior given by the reference model. The STRs try to reach optimum control, subject to a kind of controller, getting information about the process and its signals. The advantages of the MRACs lie in their quick adaptation to a defined input, and in the simplicity of the stability treatment using non-linear systems stability theory. The STRs have the advantage of adapting to any case, particularly to non-measurable perturbations, having at the same time a modular structure, making it possible block programming. In the proposed work we decided to develop adaptive control by model of reference.
The most popular scheme of adaptive control is shown in fig. 9.

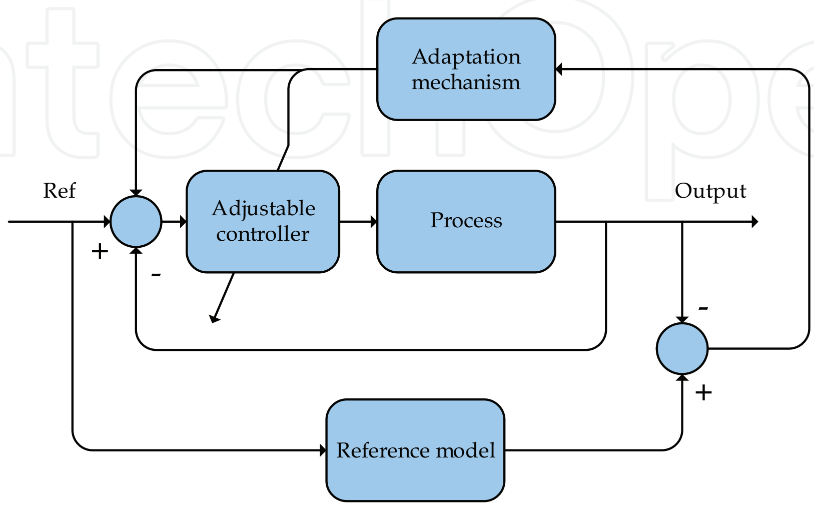


Fig. 9. MRAC scheme

One of the most important parts shown in the scheme in fig. 9 is the adaptation law. Generally speaking, adaptation laws employ Lyapunov's stability theory and Popov's hyperstability theory.

4.1 Adaptive control design

The method presented below is based in the utilization of sensibility models, so parameters can be adapted in the right way. The method deduction starts by setting the actuation index. Given a reference model Gref and an adjustable system Gadj(û), which we desire to follow the model for getting zero or minimum error in case or perturbations, we define:

$$J=\frac{1}{2}\int e^2 dt \ ; \ e=y_m - y_a \tag{15}$$

where:
y_m: Motor observed values.
y_a: Predicted or identified values.
û: Adjustable parameters.
By using the optimization rule by gradient, we obtain the adaptation rule:

$$\Delta\hat{u}(e,t)=-K\mathrm{grad}(J)=-K\frac{\partial J}{\partial \hat{u}} \tag{16}$$

The variation of the adjustable parameter with respect to time will be:

$$\dot{\hat{u}}=\frac{\partial \hat{u}}{dt}=-K\frac{\partial}{\partial t}\left(\frac{\partial J}{\partial \hat{u}}\right) \tag{17}$$

Assuming a slow variation of the adaptation law:

$$\dot{\hat{u}}=\frac{\partial \hat{u}}{dt}=-K\frac{\partial}{\partial \hat{u}}\left(\frac{\partial J}{\partial t}\right)=-K\frac{\partial}{\partial \hat{u}}\left(\frac{1}{2}e^2\right)=-Ke\frac{\partial e}{\partial \hat{u}} \tag{18}$$

The adaptation rule presented in 18, is known as the MIT adaptation rule (Whitetaker et al., 1958).

$$\frac{\partial e}{\partial \hat{u}}=\frac{\partial(y_m-y_a)}{\partial \hat{u}}=\frac{\partial y_a}{\partial \hat{u}} \tag{19}$$

The partial derivative of y_a with respect to û is the sensibility of the adjustable system with respect to the parameter. In this case, the sensibility function is proportional to y_m, leading 19 to:

$$\dot{\hat{u}}=-Key_m \tag{20}$$

This rule has been very popular, although having some disadvantages we should take in consideration:

- When adjusting several parameters, it is required a great number of sensibility functions.
- The adaptation gain controls the adaptation speed: if it's too high, it can cause system unstability, and if it's too low, the adaptation will be slow.
- To obtain a good behavior between speed and stability, studies must be carried out through simulation.

5. Description of SCARA robot model

Next, we will make a brief description of the system on which identification and adaptive control techniques previously explained will be theoretically and practically applied. This system is a SCARA (Selective Compliant Assembly Robot Arm) robot with 6 DOF (Degree Of Freedom), whose construction is a cheap solution for design and implementation of this kind of systems, and that was developed by students of the Department of Electric Engineering of the Universidad de Santiago de Chile, for teaching and research purposes.

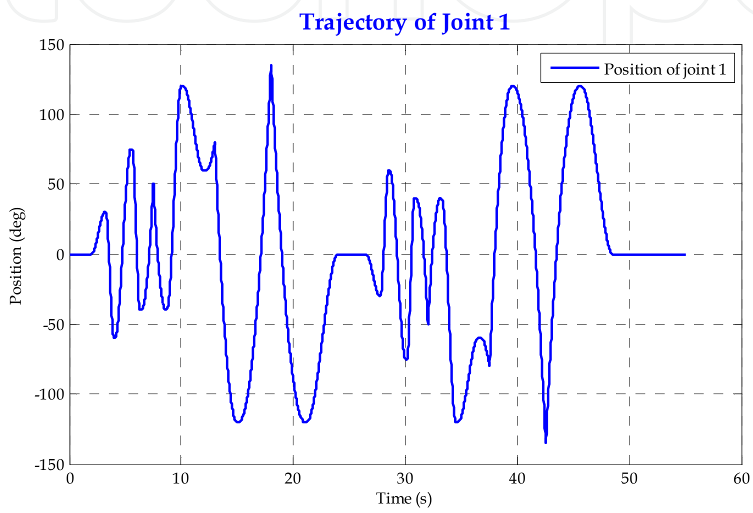
Fig. 10. Real employed SCARA system

The first three joints of this system are driven by DC motors controlled by signals provided by an interface implemented through the utilization of MatLab/Simulink software, and the other three joints are driven by servomotors. The SCARA system has an encoder in each one of the main joints, letting angular position readings for the first two rotational joints, and linear position readings for its prismatic joint, permitting the positioning of objects in space. The employed encoders were specifically designed and manufactured for this particular purpose. The last three actuators, located in the end of the robot's kinematic open chain, permit the driving of a clamp able to orientate objects in space. This clamp is endowed with pressure sensors in the tips.

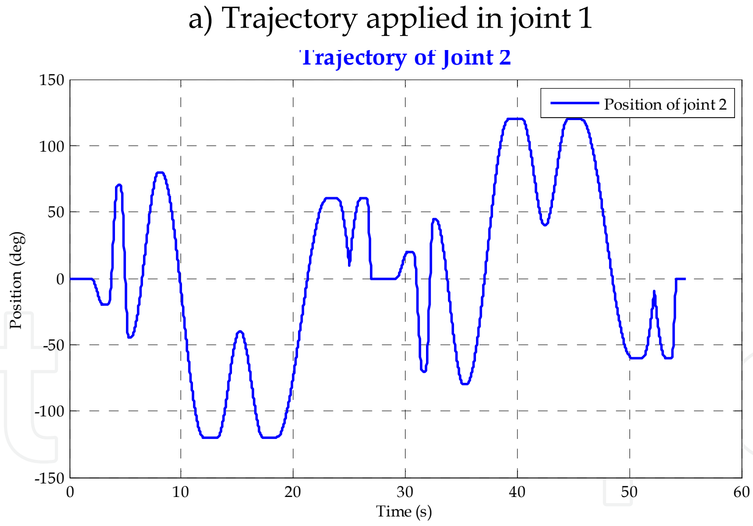
It is important to remark that this robot, besides the non-linearities inherent to this kind of system, poses additional control challenges, due to mechanical building imperfections. One of the most important problems is the difference between absolute values of the torques required for rotate in either way each one of the first two joints, because of mechanical imperfections in the employed gear trains. Due to this, the rotation speeds to the left or right of those joints are not equal to the absolute values of the applied torques. That is why this system poses additional control challenges, compared with other SCARA robots currently available in the market, since for achieving a good performance, in theoretical and practical ways, it is necessary to investigate, develop and implement control algorithms allowing to obtain better intelligent controllers.

6. Hammerstein-Wiener models applied to the SCARA system

For the application of identification techniques it is necessary to gather data that capture the robot dynamics, requiring the concatenation of at least 10 different trajectories, so the identification process can be developed with a proper and sufficient amount of information. That is why excitation trajectories are generated and applied combining different dynamics, in order to obtain a good identification of the studied system (Janot et al., 2007), (Gautier et al., 2008), (Olsen & Petersen, 2001). The trajectories employed in this process are generated out of an interpolation or third degree, being known the final and initial position, and the initial and final times of the two first joints of the studied system. We look for capturing the non-linear dynamics of the robot, considering its total work range, from -135° to 135° for each joint. In order to capture the dynamics of the system's non-linear behavior, sudden changes in rotation way and speed are produced, and for doing that, 10 different trajectories are concatenated, as shown in fig. 11.



a) Trajectory applied in joint 1



b) Trajectory applied in joint 2

Fig. 11. Trajectories applied in joints 1 and 2, respectively

The major dynamic complexities of this robot are found in its two first joints, therefore, the process of parameter identification is carried out on these joints only.

6.1 Linear models

Using data from the application of trajectories for both joints, black-box linear models for describing the system dynamics are proposed. In this regard, the following scheme is used:

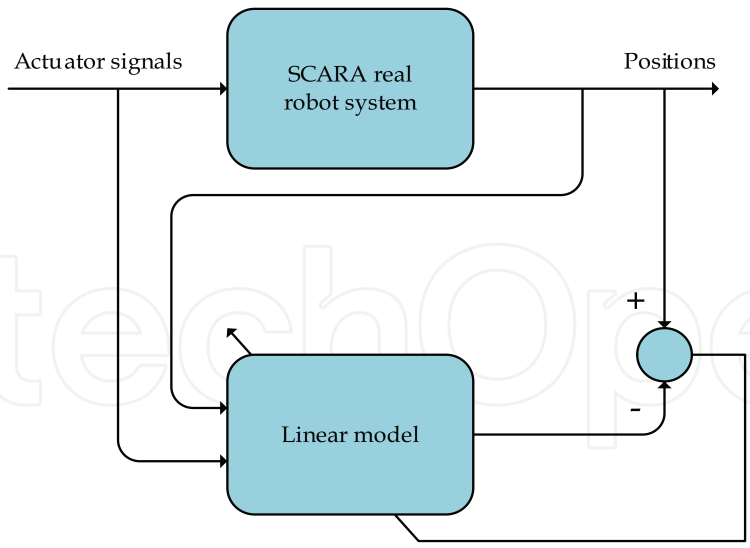
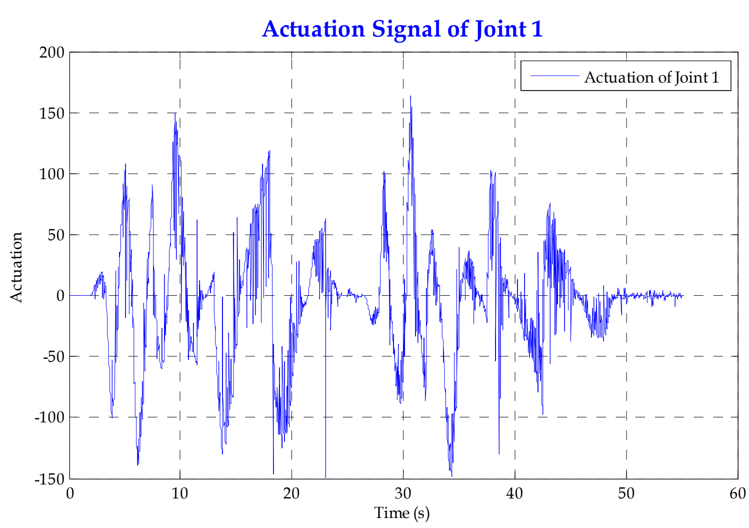
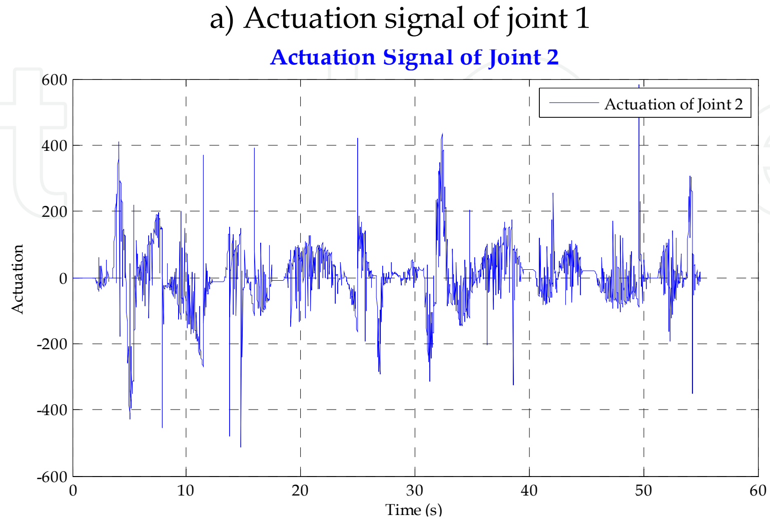


Fig. 12. Linear model adjustment scheme



a) Actuation signal of joint 1

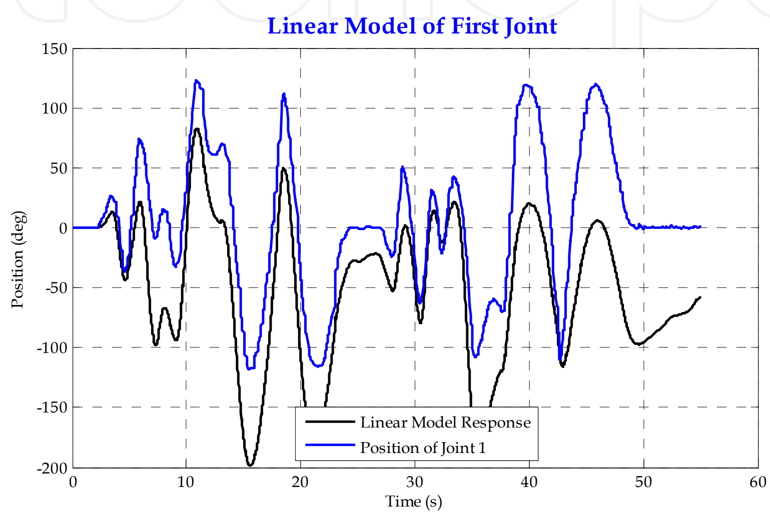


b) Actuation signal of joint 2

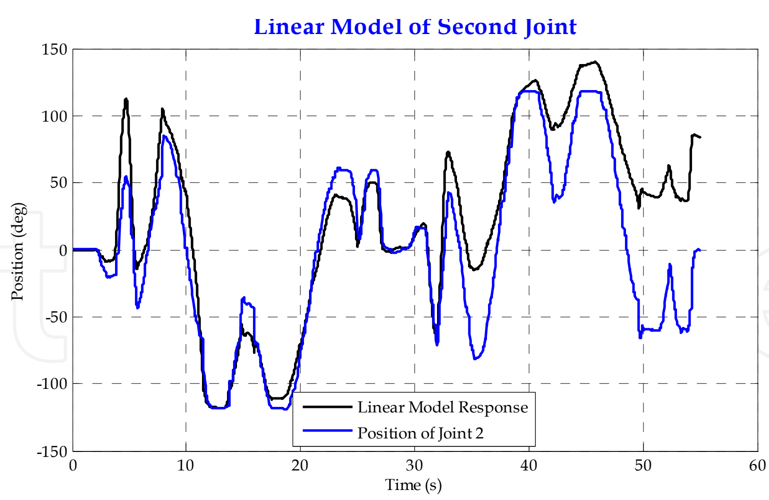
Fig. 13. SCARA robot actuator signals applied

The actuator signals applied to the SCARA robot for the trajectories shown in fig. 11 are used as input for adjusting the parameters of the polynomials in different linear models. The actuator signals are shown in fig. 13.

To select the most appropriate linear model for the identification of the different joints of the system under study, the model used in Example 2.1 can't be used, since it is highly complex and there is too much parameters uncertainty. Model selection and order of polynomials is done by selecting the simulation tests that best fits. Keep in mind that the linear model fit doesn't need to be too accurate, since this is used as part of a nonlinear model named Hammerstein-Wiener model.



a) Linear model performance for joint 1



b) Linear model performance for joint 2

Fig. 14. Linear models performance for joints 1 and 2, respectively

To create linear models, actuator signals in both joints are used as inputs, and the joint position as a reference signal. For joint 1, the linear model that best fits is an ARMAX with A polynomial of order 3, the B polynomials of orders 4 and 2 respectively, and finally a C polynomial of order 2. The fitting percentage is 52.82%. For joint 2, the linear model that best fits is an ARX, with A polynomial of order 4, and B polynomials of order 5. The percentage fit of this model is 41.41%. Both models used a first order delay for the first actuator entry and a second order delay for the second actuator. The responses of both models are shown in the figure 14.

6.2 Hammerstein-Wiener models

From the previous linear models, the proposed nonlinear model can be completed. The realization of this model uses the following scheme:

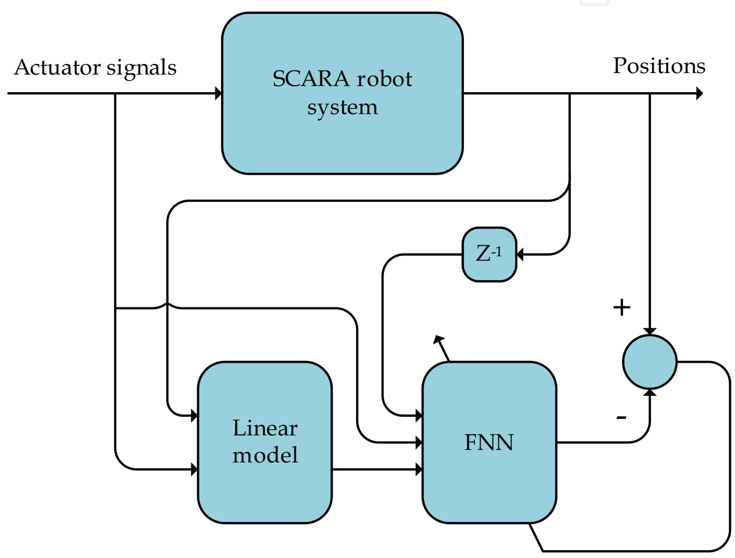
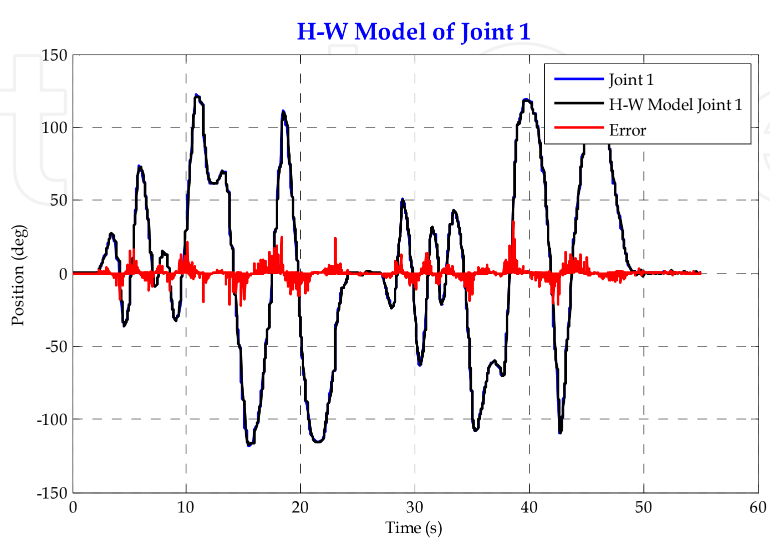
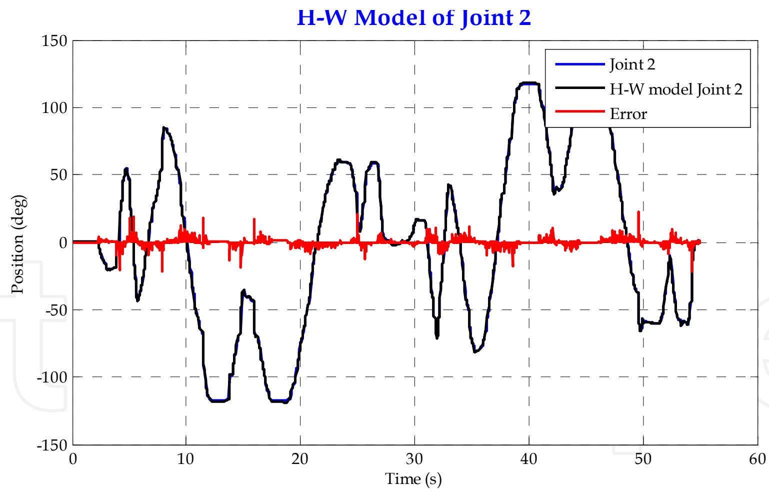


Fig. 15. Hammerstein-Wiener models fitting scheme

The nonlinear functions used are three-layered Feed forward Neural Networks (FNN). The FNN training results that correct the Hammerstein-Wiener model are shown below:



a) Hammerstein-Wiener model response for both joint 1



b) Hammerstein-Wiener model response for both joint 2

Fig. 16. Hammerstein-Wiener model response for both joints

6.3 Model implementation

The implementation of the obtained models is performed using MatLab/Simulink software, due to its simplicity in creating simulations, and in the fact that the studied robot is controlled through an interface created in it. The model implemented is the following:

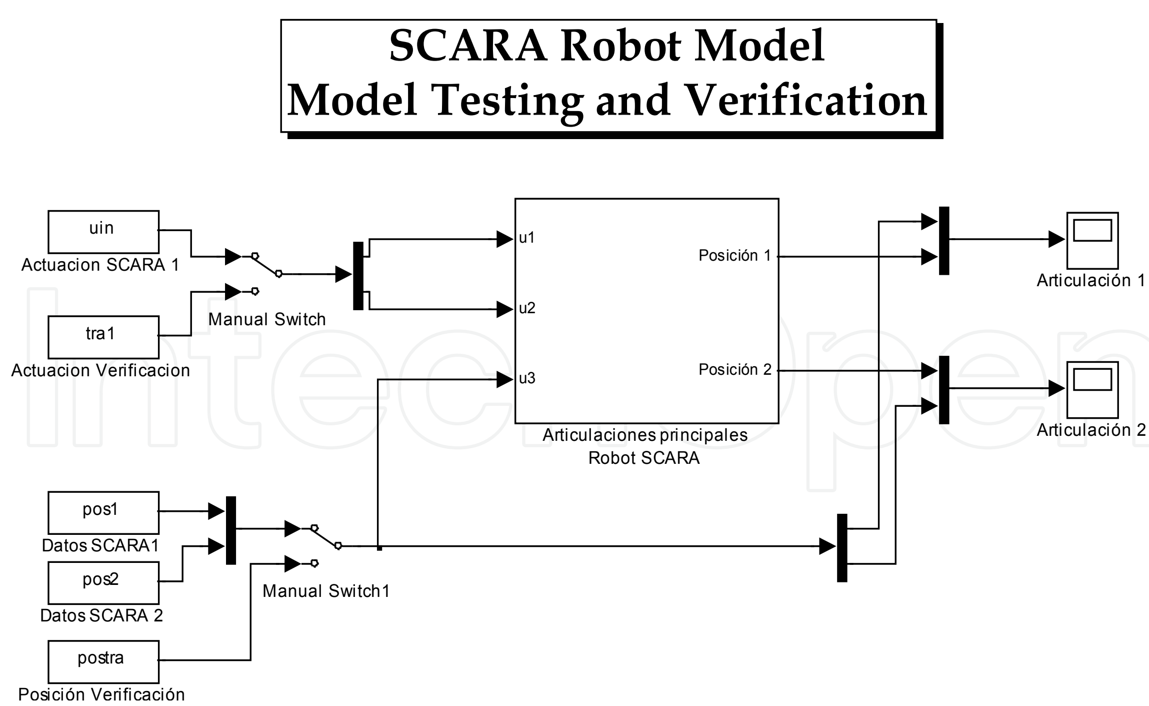


Fig. 17. Implemented model in MatLab/Simulink

The specific identification model is shown in figure 18.

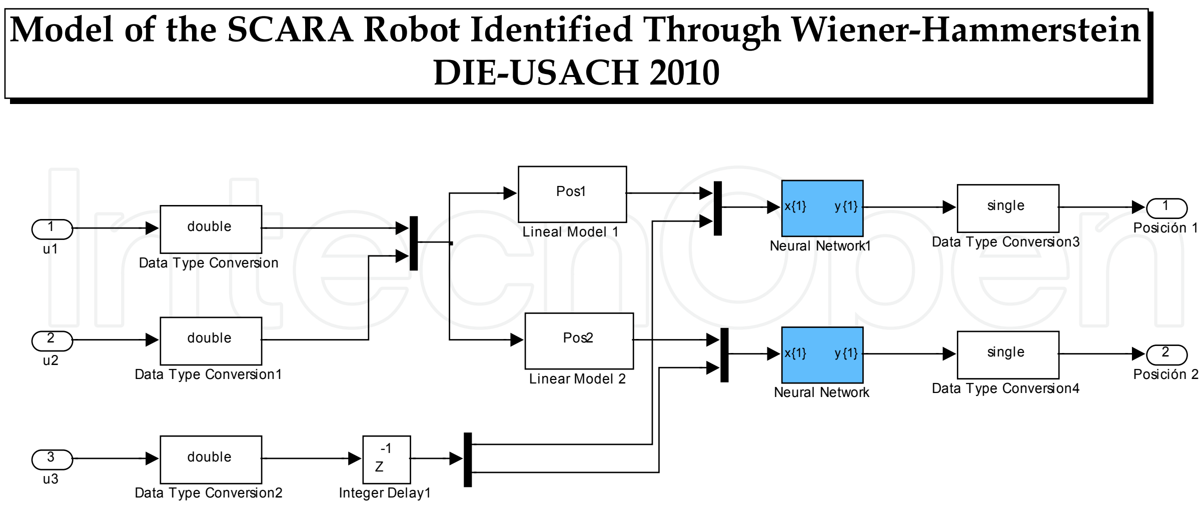


Fig. 18. Hammerstein-Wiener Model

6.4 Model validation

To ensure that the model obtained is a good representation of the joints of the SCARA system, another experiment is performed using a path different from that used for fitting, which allows evaluating the system behavior. The validation, implementing 3 different experiments, was carried out on-line. The scheme implemented in MatLab/Simulink used for controlling the SCARA robot and verifying the created model is shown below:

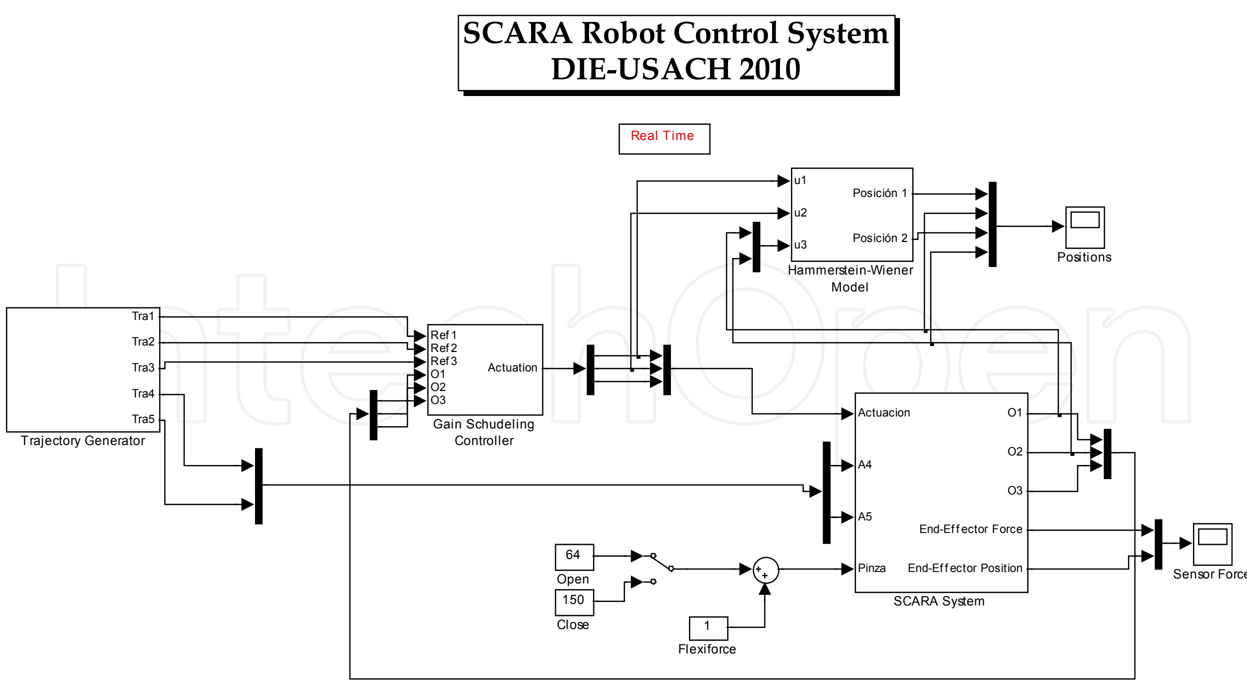


Fig. 19. Implemented control system

For the first verification experiment, we applied a trajectory to the first joint, keeping fixed the second joint.

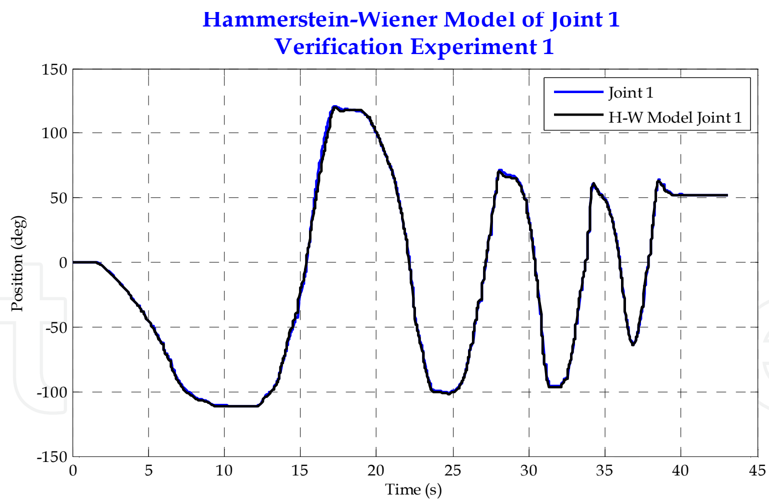


Fig. 20. Joint 1 verification; experiment 1

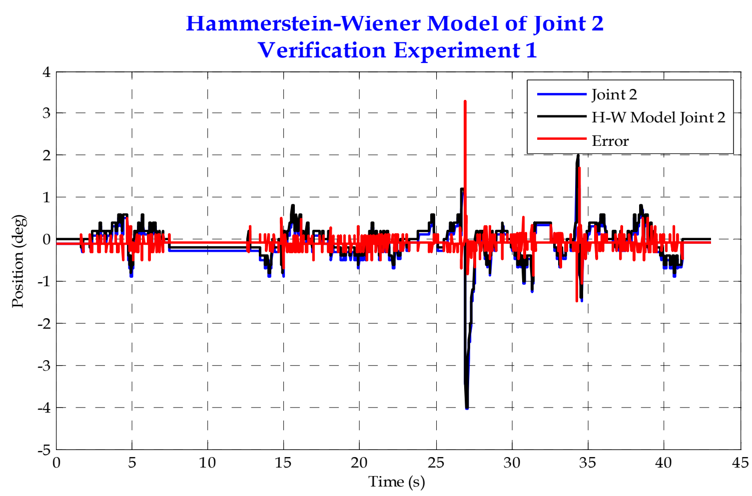


Fig. 21. Joint 2 verification; experiment 1

For the second experiment, we applied different trajectories to both joints, the verifications are shown next:

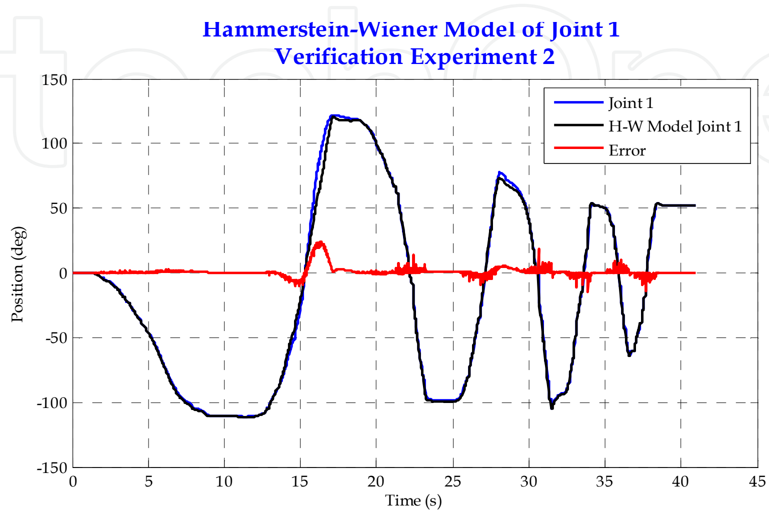


Fig. 22. Joint 1 verification; experiment 2

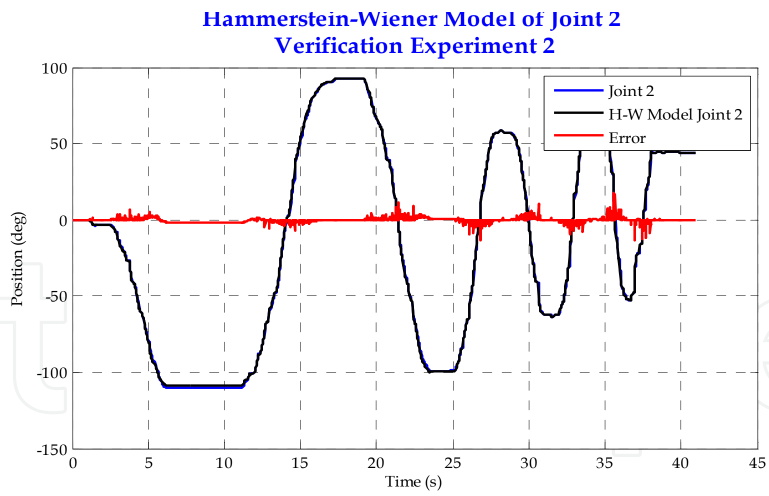


Fig. 23. Joint 2 verification; experiment 2

Finally, in order to carry out a most exigent test to the created model, we applied a PRBS signal as reference for the robot to be followed in its second joint, and a normal trajectory in the first joint. The results are shown below:

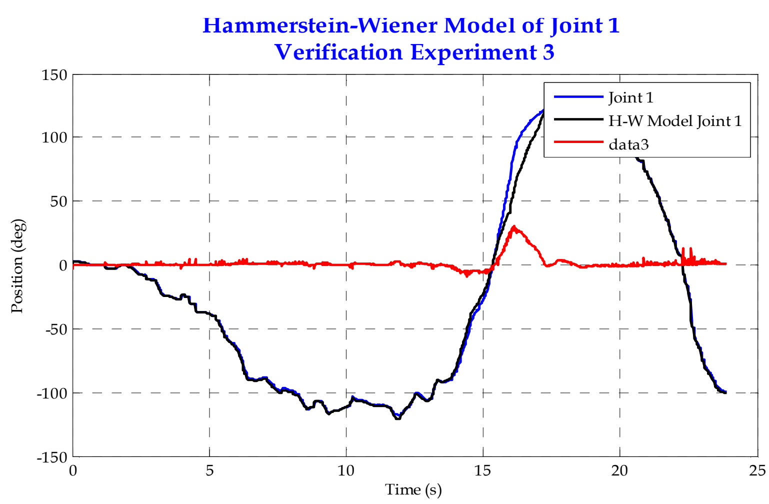


Fig. 24. Joint 1 verification; experiment 3

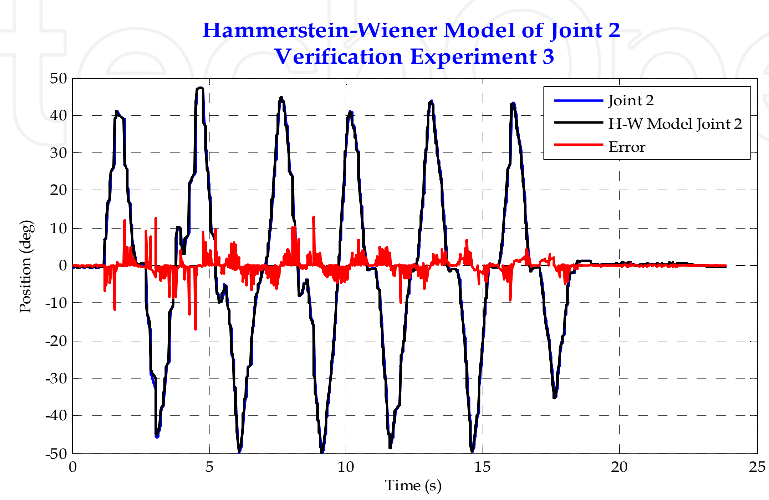


Fig. 25. Joint 2 verification; experiment 3

7. MRAC implementation

For the implementation of MRAC we will employ the sensibility theory presented in eq. 20. The implementation of such controller, using MatLab/Simulink software, is shown below:

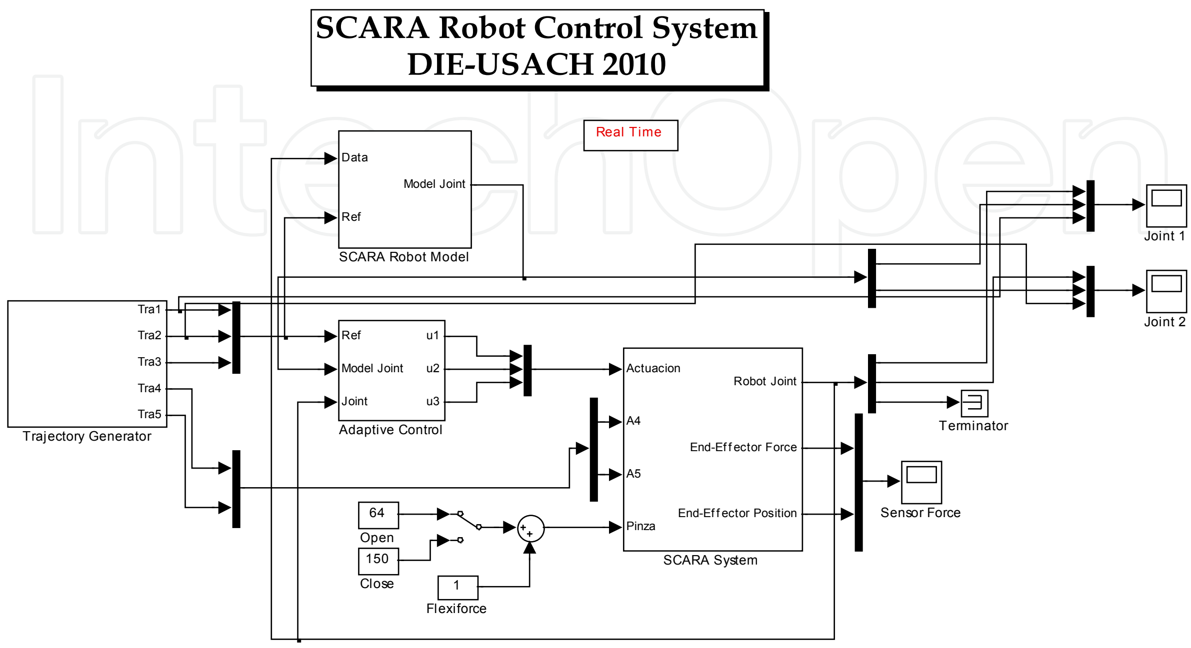


Fig. 26. MRAC Implementation

For the implementation of the sensibility theory we created three adaptation law blocks. Adaptive control makes parameter adjustment of a classic PID controller, as shown in the next figure:

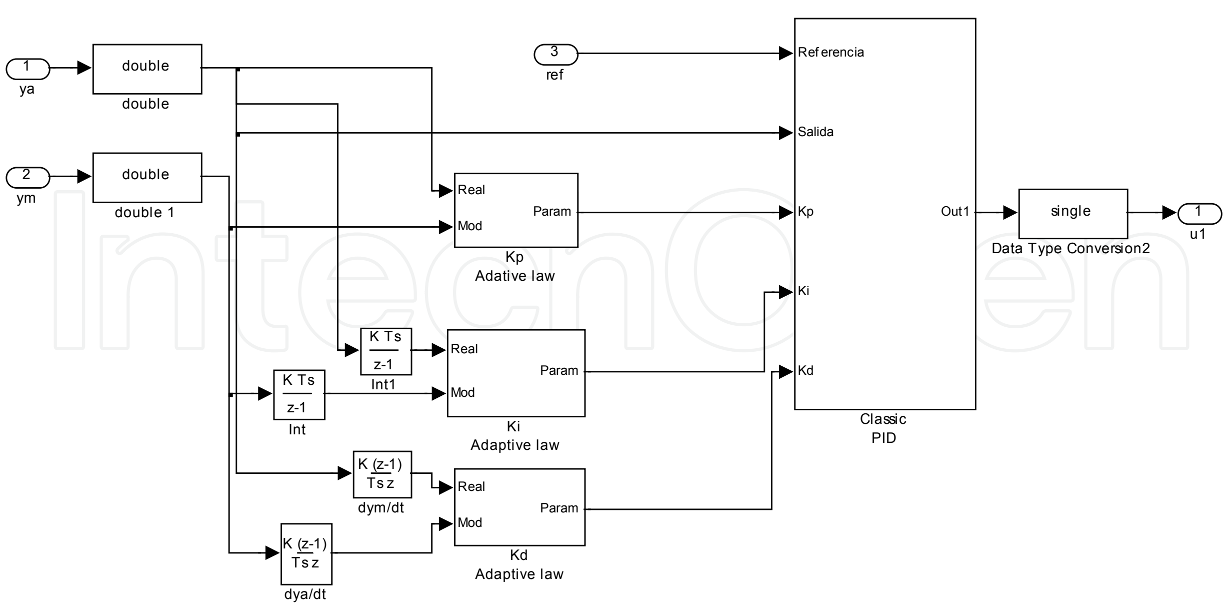


Fig. 27. Adaptive Controller

The adaptation laws were built accordingly to (Espinoza, 2009), and are shown in the figure below:

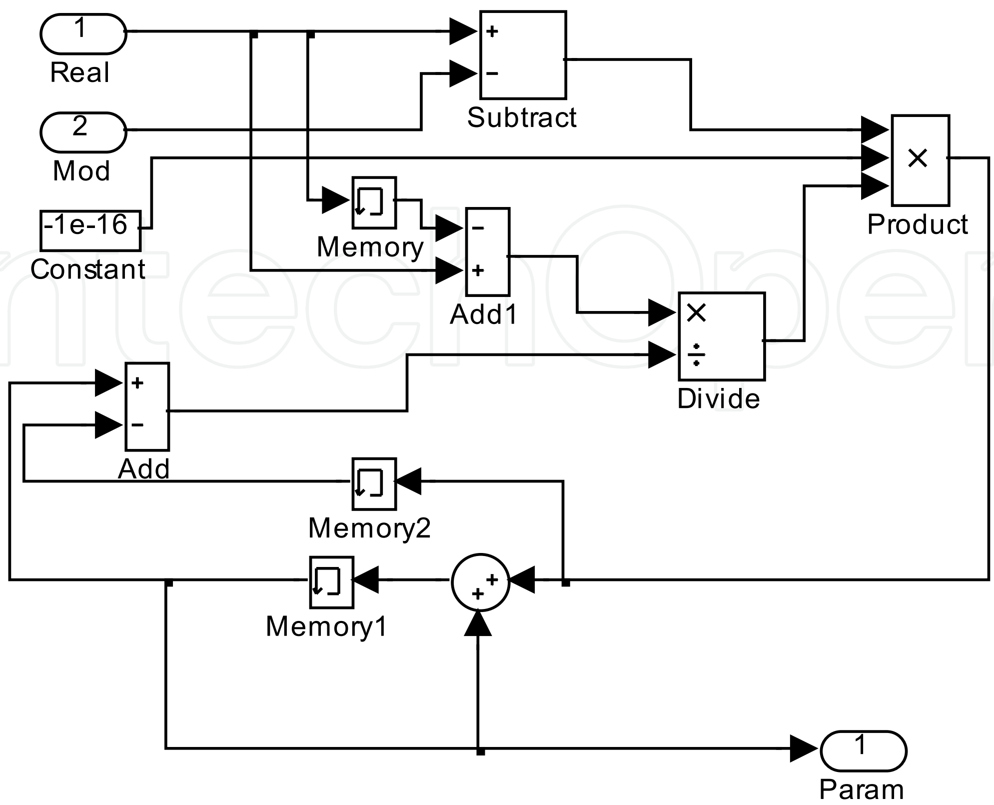


Fig. 28. Adaptive law

7.1 Results

Applying a step of 50° for the first joint and of -50° for the second joint, we obtain the following response of the system with adaptive controller:

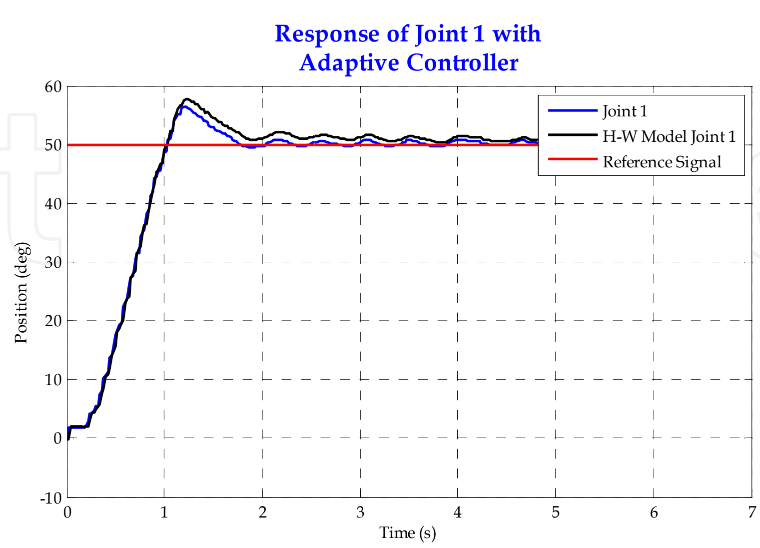


Fig. 29. Response to step, joint 1

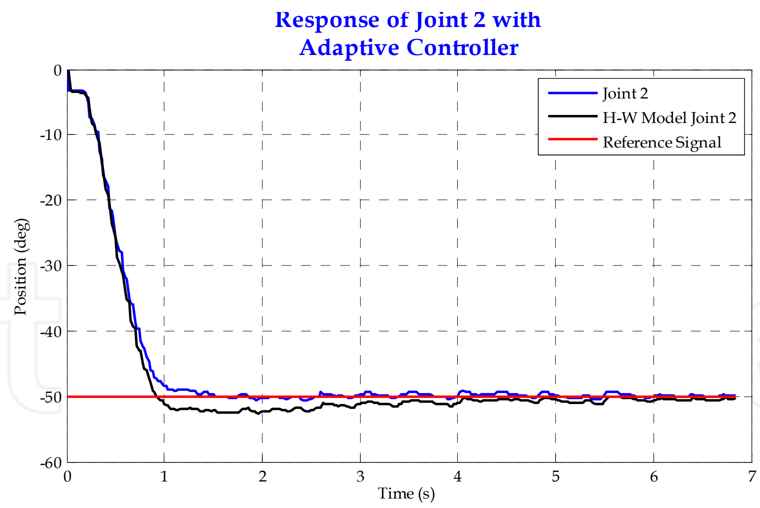


Fig. 30. Response to step, joint 2

Finally, we apply a trajectory for verifying the result obtained with the implemented controller.

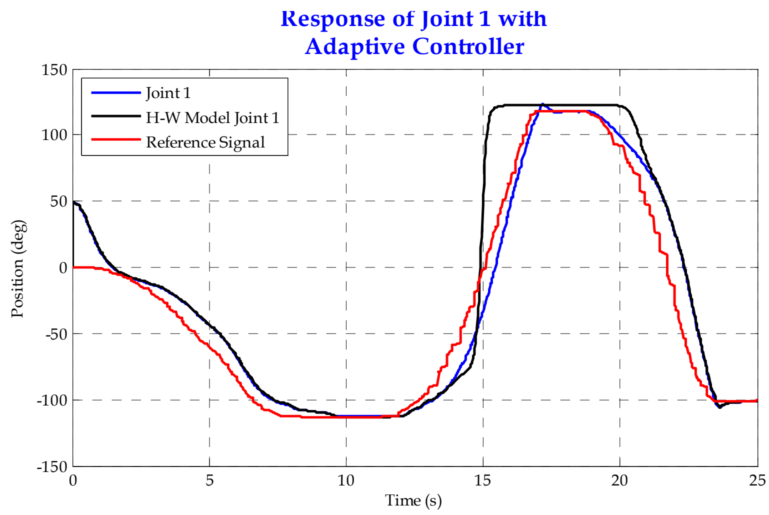


Fig. 31. Response of joint 1 to a trajectory

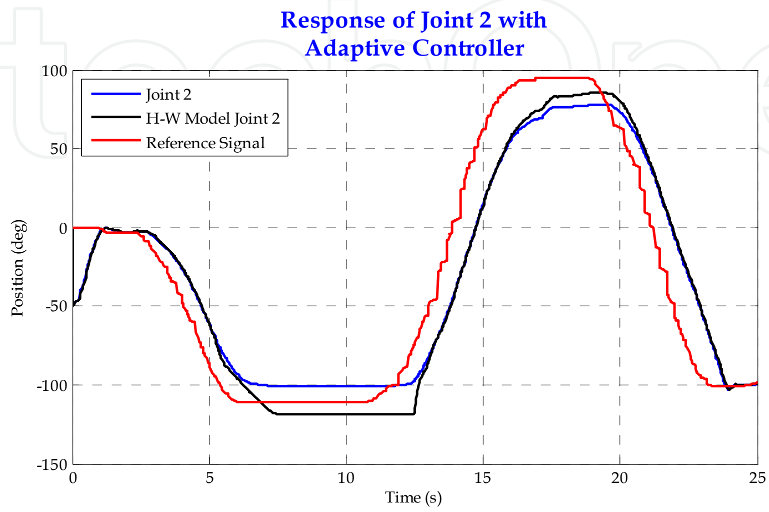


Fig. 32. Response of joint 2 to a trajectory

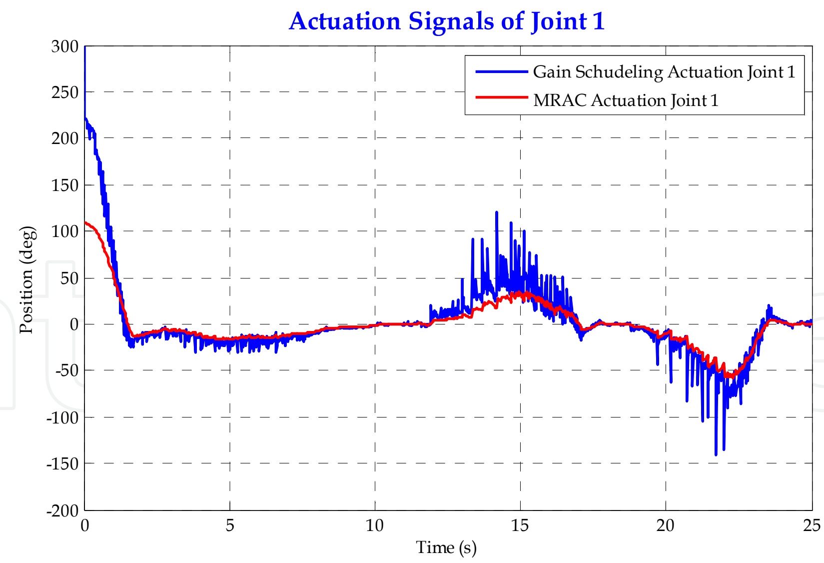


Fig. 33. Actuation signals of joint 1

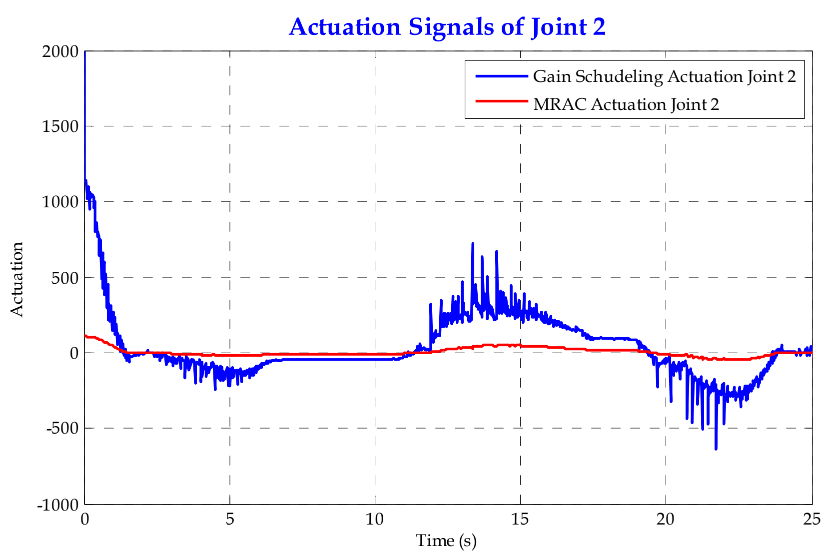


Fig. 34. Actuation signals of joint 2

8. Conclusions

Through the application of Hammerstein-Wiener models we can identify efficiently the dynamics of a real manipulator robot. For the application of those models, it is only necessary to know the position output of each joint and the robot's actuation signal.

We propose a new particular identification loop for Hammerstein-Wiener models, shown schematically in fig. 8, where we consider ARX or ARMAX linear models and a non-linear part composed by FNN. It is important to notice that for non-linear cases, the choice of linear model and the FNN configuration is obtained thanks to experimental developments, choosing the models better describing the studied system, from a set of identified models.

From the verification carried out for the obtained Hammerstein-Wiener models, we conclude that those models can capture the non-linear dynamics of the system; nevertheless, those models present little errors when more exigent trajectories are applied to the system,

as in the case of PRBS trajectory (see fig. 25), due to the fact that the dynamics of the first two links is coupled, therefore, sudden movements in a joint cause unidentified perturbations in the adjacent joint.
An adaptive controller has been successfully implemented in a real system. Although we can notice some flaws in the identified model of the real robotic system, the adaptive controller follows closely the behavior of the model (see figs. 28 and 29). A remarkable aspect is that actuation signals obtained employing the adaptive controller are smoother than the ones obtained with the Gain Scheduling controller implemented first in the robotic system, both for the applied trajectories (see figs. 31 and 32), and their respective actuation signals (see figs. 33 and 34). The smoothing of actuation signals in both joints, as the case obtained in this work, leads to a decrease of oscillations in the joints, lower material fatigue and, therefore, a lower energy consumption for the robotic system.

9. Acknowledgements

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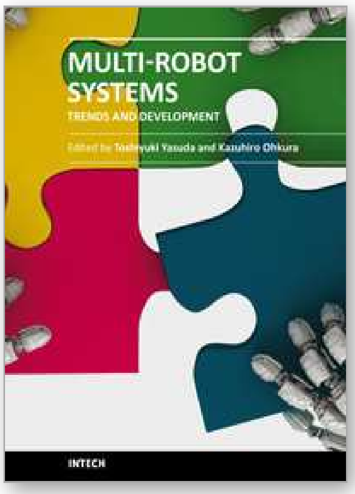

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