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DYNAMIC ANALISYS AND IDENTIFICATION OF THE MOVABLE NOZZLE USED ON THE BRAZILIAN SATELLITE LAUNCHER

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Abstract. *This paper presents a dynamic system identification of a movable nozzle used in the Brazilian satellite launcher (VLS). This movable nozzle consists of an electrohydraulic actuator that moves a divergent to provide the well-known thrust vector control (TVC). The movable nozzle is attached to the solid propellant by a flexible joint whose angular displacement results in gas flow redirection, responsible for the attitude control of the vehicle. The actuation force is measured by a load cell installed serially with the hydraulic actuator. The main purpose of this work is to investigate the dynamic system behavior of this actuator system. The identification experiment is performed in open loop and two system identification techniques are used to obtain a mathematical representation from experimental data. A linear model is obtained from the DSR_e method , which is a subspace identification algorithm, and a Bouc-Wen model to the nonlinear system dynamics representation, identified using a genetic algorithm. The structure of this model allows to mathematically represent the behavior of hysteretic systems like the flexible joint dynamic in the actuator system investigated in this work. The identified models obtained allow a better understanding of the actuator systems behavior and are useful on new control strategies design for the VLS and hardware-in-the-loop simulations (HWIL).*

Keywords: *Brazilian satellite launcher, movable nozzle, system identification, subspace methods, Bouc-Wen model.*

1. INTRODUCTION

The Brazilian satellite launcher vehicle (VLS) is a rocket used to send sattelites to the Earth orbit. During its flight, the VLS follows a predetermined trajectory using the thrust vector control (TVC) that consists of movable nozzles and electrohydraulic actuators to perform angular displacements on divergent. The Figure 1 presents the VLS and its four stages. Details about this systems are found in Carrijo and Leite Filho (1999), Ramos (2010) and Oliva and Leite Filho (2000).

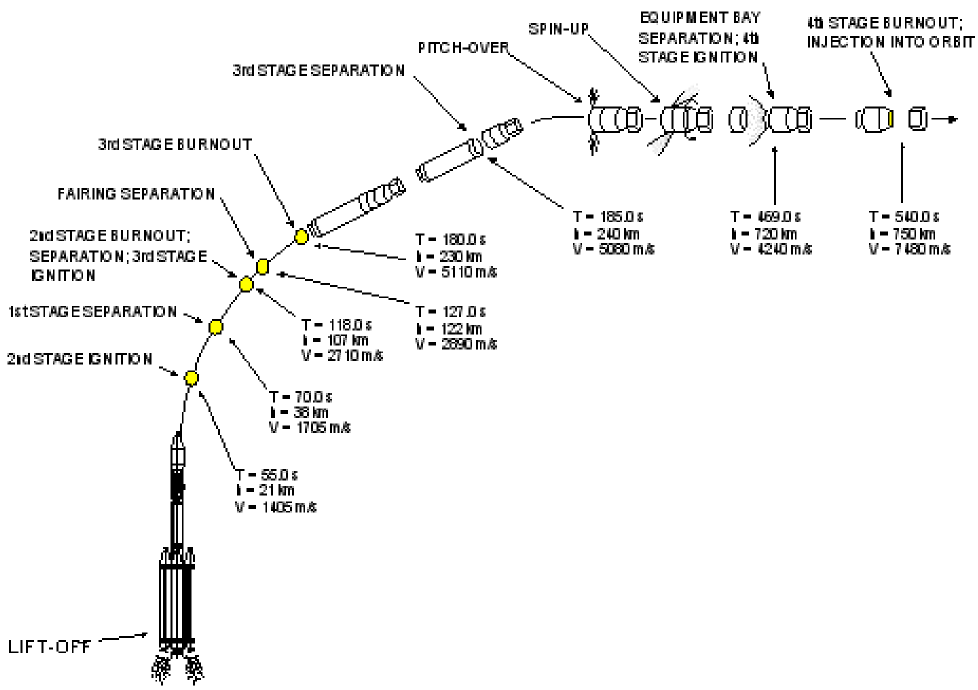

Figure 1. The Sattellite Launcher Vehicle - VLS.

In many cases electrohydraulic actuators are considered linear and are represented dynamically as a simple gain, while in this work the actuation (actuator + nozzle) dynamic system modeling is investigated. Figure 2 presents the movable nozzle, which is a VLS subsystem, to be identified in this work. This subsystem consists of a electrohydraulic actuator that drives a movable mass, resulting in an angular displacement, β. This equipment performs the required the TVC to control the attitude of the vehicle.

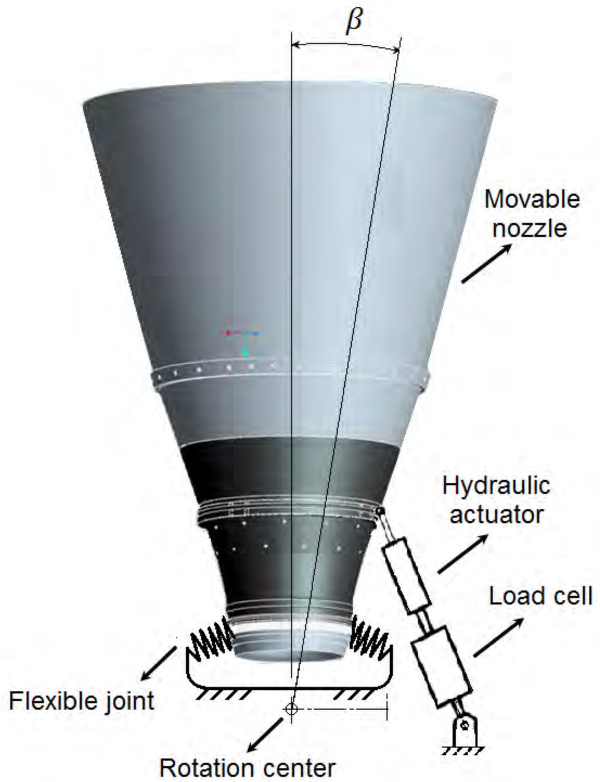

Figure 2. The movable nozzle.

In this context, the identification of the actuator dynamic system consists in a model from input/output experimental data that represents the real dynamic system behavior. The identified model is of great interest mainly for the control system design. The Figure 3 presents a simplified attitude control of the VLS.

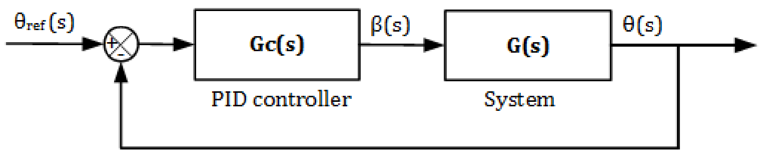

Figure 3. Scheme of the VLS control.

Note that the plant, $G(s)$, appears with the nozzle dynamic. The system input is the angular displacement, $\beta(s)$ and the control variable is the launcher attitude angle, $\theta(s)$.

This paper aims to analyze the dynamic behavior of the movable nozzle used in VLS and determine a mathematical representation for the system. The test bench, at Aeronautic and Space Institute Laboratory, permits to collect data for process identification and integration activities considering several configurations for tests.

1.1 Problem Formulation

The analysis methodology used in this work consists in verifying linear and/or nonlinear system characteristics using experimental data (actuator piston linear displacement and force in the actuator output) taking into account flexible joint dynamic coupled to the system.

The linear and nonlinear identified models allow to insert actuator dynamics (hydraulic actuator assembly + nozzle) that contribute to detail the dynamic equations of the VLS. Such models are of great interest in control system applications and hardware-in-the-loop simulations (HWIL), described in Leite Filho (1999) and Carrijo and Leite Filho (2002),

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because they allow to define control strategies, evaluate the controlled system performance and contribute to VLS Project Engineering Phase.

Concerning the actuation system modeling, one assumes that the electrohydraulic actuators used to move the nozzle provides enough force to angular displace the inertial mass, however, as they require higher speeds of displacement, the presence of dynamic linear inertia associated with the presence of the nozzle and flexible coupling is increased.

The modeling of the actuator system (electrohydraulic actuators + nozzle) is developed using Newton′s Law, and a matching relating model and experimental data is investigated. Figure 4 ilustrates the system configuration to be identified, which the output signal $\mathbf{y}_k$ is the linear displacement of the actuator piston and the input signal $\mathbf{u}_k$ is the actuator force. The variables $\mathbf{w}_k$ and $\mathbf{v}_k$ are, respectively, the process noise and the measurement noise from the sensor.

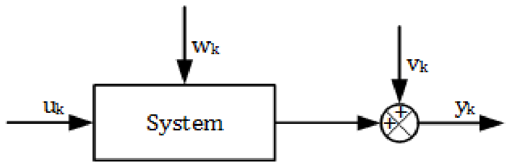

Figure 4. Open loop system: input $\mathbf{u}_k$, output $\mathbf{y}_k$, process noise $\mathbf{w}_k$ and measurement noise $\mathbf{v}_k$.

Identification is performed using two algorithms for system parameters estimation: the first one is a subspace method whose parametric estimations are obtained from the experimental data projection and the second one is an iterative algorithm, which uses the structure of a previously established nonlinear model to get the parameters from the optimization of the prediction error. Thus, this paper is divided into two stages.

In the first stage is considered the nozzle dynamics represented by a 2ªorder model in the form of

$$J\ddot{\beta}(t) + b\dot{\beta}(t) + k\beta(t) = \tau(t) \tag{1}$$

where J is the nozzle inertia, b is the flexible joint damping coefficient and k is flexible joint elastic constant. The identified linear model obtained from the subspace method was chosen as a second order, as

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \mathbf{K}\varepsilon_k \\ \mathbf{y}_k &= \mathbf{C}\mathbf{x}_k + \mathbf{D}\mathbf{u}_k + \varepsilon_k \end{aligned} \tag{2}$$

which $\mathbf{x}_k$ is the system states vector, $\mathbf{u}_k$ is the input vector, $\mathbf{y}_k$ is the output vector and ε_k is the innovation method.

The identification problem consists in determine the model matrices **A**, **B**, **C** and **D** and the Kalman gain **K**.

In the second stage, the parameters J, b e k and the nonlinear model parameters are estimated using a genetic algorithm (GA). The identified model is in form

$$J\ddot{\beta}(t) + b\dot{\beta}(t) + F(t) = \tau(t) \tag{3}$$

where $F(t)$ restauration torque. In the Subsection 3.3 the Bouc-Wen model used for the system dynamic representation will be presented as well as parameters to be estimated.

2. IDENTIFICATION OF DYNAMIC SYSTEMS

The investigation of system dynamics is important for understand and predict the process behavior and, depending on the purpose, improve its characteristics. In practical applications it is usually adopted identification techniques to obtain system models, instead of phenomenological modeling.

In this context, the identification task aims to obtain a mathematical model that explains, at least approximately, the relation of cause and effect between the system input and output, representating their behavior Aguirre (2007).

Generally, system identification methods are classified into two groups: non-parametric and parametric. The non-parametric methods are based, for example, on system transient analysis, correlation analysis, frequency analysis and spectral analysis. In the other hand, parametric methods aim at obtaining a parametric model structure, that is, to find the coefficients that determine the system Aguirre (2007). In this work will be discussed only the parametric identification case.

Several important steps need to be followed in the task of identification in order to achieve a suitable model for the system, among these, most importante tasks are Clavijo (2008):

1. *Experiment design for data collection*;
2. *Adopt a suitable mathematical representation for the system*;
3. *Algorithm choice for model parameters estimation* and

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4. *Model Validation*.

This work aims to determine a mathematical representation for the system dynamics. For this task identification techniques will be adopted which only the system input and system output are used to derive the model.

The Section 3describes the design procedure of the excitation signal and data acquisition for system identification. The mathematical representations used to model the system model are discrete state space and differential equations, whose parametric estimation methods are, respectively, a subspace method and a genetic algorithm.

Subspace methods known in the literature as SIM methods (subspace identification methods), described in Verhaegen and Deprettere (1991), are not iterative methods and are based on linear algebra, being implemented using, for example, the LQ decomposition and singular value decomposition (SVD) as described in Katayama (2005).

Works such as Moor and Overschee (1996) and Clavijo (2008) present two well-known subspaces methods, N4SID (numerical algorithms for subspace state space system identification) and MOESP (multivariable output-error state space model identification algorithm). This work presents another subspace method known as DSR_e (combined deterministic and stochastic system identification and realization), which was proposed by Ruscio (2008). The DSR_e algorithm was implemented in Machado (2013) and is used to identify the mobile nozzle. The performance of this method is as efficient as other methods presented in the literature for modeling dynamic systems.

Genetic algorithms (GA) are search methods, i.e., algorithms based on iterative optimization problem. Works such as Kristinsson and Dumont (1992) presents an identification and control problem using an GA. It is shown that these techniques present a good performance such as a shorter convergence time than PEM methods (prediction error method), however, the computational complexity is still a disadvantage depending on the problem.

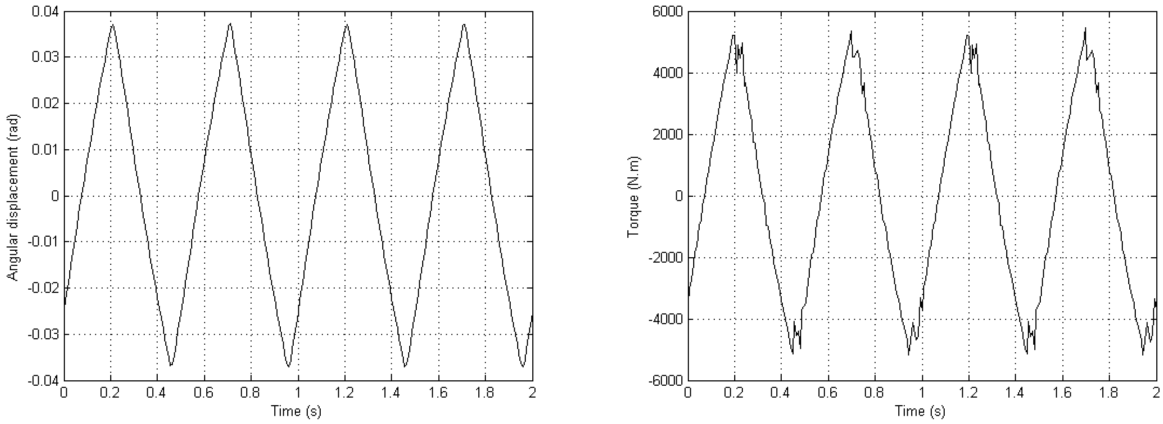
In Yao and Sethares (1994) is also presented the problem of parameter estimation, treating the case of nonlinear models and in Charalampakis and Koumousis (2008) is presented a hybrid evolutionary algorithm for estimating hysteretic systems. In this work, we chose the genetic algorithm to obtain the parameters of the nonlinear model adopted for representing the mobile nozzle, but it is possible to obtain such parameters using the Levenberg-Marquardt method, described in Marquardt (1963), for example.

This work aims to determine a mathematical representation for the system dynamics. For this task will be used system identification techniques, which only input and output of the system are used to derive the model.

3. IDENTIFICATION OF THE ACTUATION DYNAMIC SYSTEM

Experiments were performed with the system in order to evaluate the dynamic behavior from the collected data. The presence of the flexible joint effects in the system response (measured signal by the load cell) may be observed by varying the period of the excitation signal in order to make the system response slower or faster.

To ease the verification of such influence, this work presents the input and output of the system, as shown in Figure 5. According to the torque signal, shown in Figure 5(b), it is evidente the elastic behavior of the system due to the flexible.



(a) Output signal, displacement (rad).

(b) Input signal, torque (N.m).

Figure 5. Input and output system data.

From the experimental data collected, the hysteresis curve of the system was drawn as shown in Figure 6. It is observed that the curve is very narrow, which indicates that around the point of operation of the movable nozzle where it has been made experiments, the hysteresis behavior of the flexible joint is not high, but it is of interest that it be taken into consideration on the VLS dynamic system modeling.

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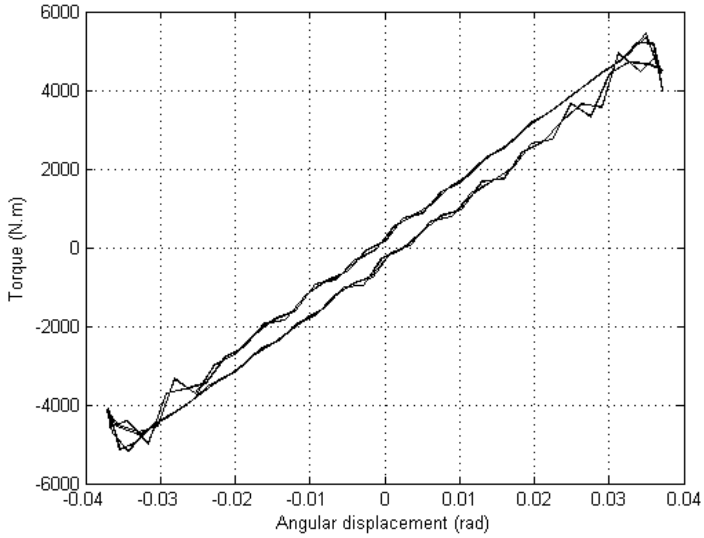
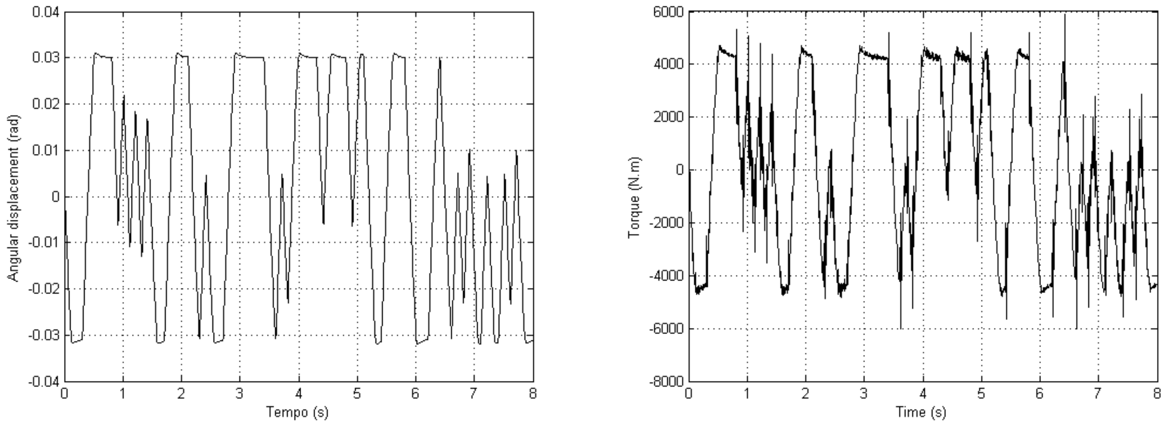


Figure 6. Hysteresis curve obtained from experimental data.

3.1 Project of the excitation signal used for identification

The excitation signal used to identify the system dynamics is a pseudo-random binary signal (PRBS), designed in a way that the switching time of the amplitude of the signal is compatible with the system time constant estimated by experimental test, according to the Figure 7(b). The figure has been enlarged for better visualization.



(a) Output signal, displacement (rad).

(b) Excitation signal, torque (N.m).

Figure 7. Experimental data used for identification.

The system was excited within the range of operation [-3°, 3°] for which the controllers were designed. Data were collected for $59.8s$ at $2.5kHz$ with a sampling period of $0.4ms$, which is 20 times larger than the time constant of the system.

In order to reduce the amount of samples to minimize the computational effort of identification algorithms, but without loss of confidence, it was taken decimation measurements, with a new sampling period $T_s = 0.008s$. This resulted in a number of samples $N = 7476$.

3.2 Identification of a linear model

The DSR_e method was applied for system identification and the discrete model obtained using the SIM method is

$$\begin{aligned} \mathbf{x}_{k+1} &= \begin{bmatrix} 0.2839 & 0.8327 \end{bmatrix} \mathbf{x}_k + 10^{-5} \times \begin{bmatrix} -0.1990 \\ -0.9051 \end{bmatrix} \mathbf{u}_k + \begin{bmatrix} -0.2721 \\ 0.1283 \end{bmatrix} \varepsilon_k \\ \mathbf{y}_k &= \begin{bmatrix} -0.9351 & 0.0320 \end{bmatrix} \mathbf{x}_k + 10^{-5} \times \begin{bmatrix} 3.6652 \end{bmatrix} \mathbf{u}_k \end{aligned} \quad (4)$$

Given the discrete state-space models obtained by the applied identification methods, it was convenient to convert them to transfer function models, in order to evaluate the values of inertia, friction and elastic constant related to the Equation (1).

The identified model transfer function is

$$G_m(s) = \frac{0.03971}{s^2 + 14.95s + 5694} \tag{5}$$

which frequency response is presented in the Figure 8.

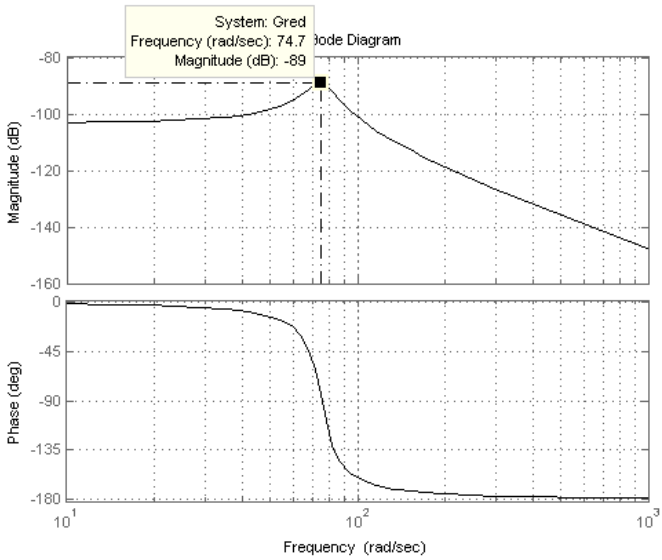


Figure 8. Identified linear model frequency response: magnitude and phase, respectively.

According to the figure, the ressonance frequency is $f_r = 11.88Hz$, the natural frequency is approximately $f_n = 15.39Hz$, with structural damping $\zeta = 0.0971$.

3.3 Identification of a nonlinear model: Bouc-Wen model

The equation of motion adopted to express the behavior of the movable nozzle is given by Equation (3), which parameters J, b, k and a are the inertia of the nozzle, the damping coefficient, the elastic constant of the flexible joint, already defined in Subsection 1.1and, according to the Bouc-Wen model, $F(t)$ is the restoring torque that is given by

$$F(t) = ak\beta(t) + (1-a)kz(t) = \tau(t) \tag{6}$$

where a is the ratio of post-yield to pre-yield (elastic) stiffness and $z(t)$ represents the hysteresis component of the system (adimensional parameter) represented by the following nonlinear differential equation with the initial condition $z(0) = 0$,

$$\dot{z}(t) = A\dot{x}(t) - |z(t)|^n[\gamma sign(x\dot{(t)}z(t))]\dot{x}(t) \tag{7}$$

and the last value of $z(t)$ is given by

$$z_{MAX} = \frac{A}{\overline{\beta} + \gamma}^{\frac{1}{n}} \tag{8}$$

where the adimensionals parameters A, $\overline{\beta}$, γ e n control the behavior of the model, which can be understood as two springs connected in parallel as shown in Figure 9.

The Elastic Postyielding Spring represents the purely elastic behavior of the system (linear) given by the term $ak\beta(t)$ of $F(t)$ and the nonlinear term, $(1-a)kz(t)$, which represents the Hysterectic Spring.

The graph $F \times u$ shown in Figure 9 illustrates these two responces (elastic and hysteretic) according to the inclination of the asymptotes for each of the responces of the system.

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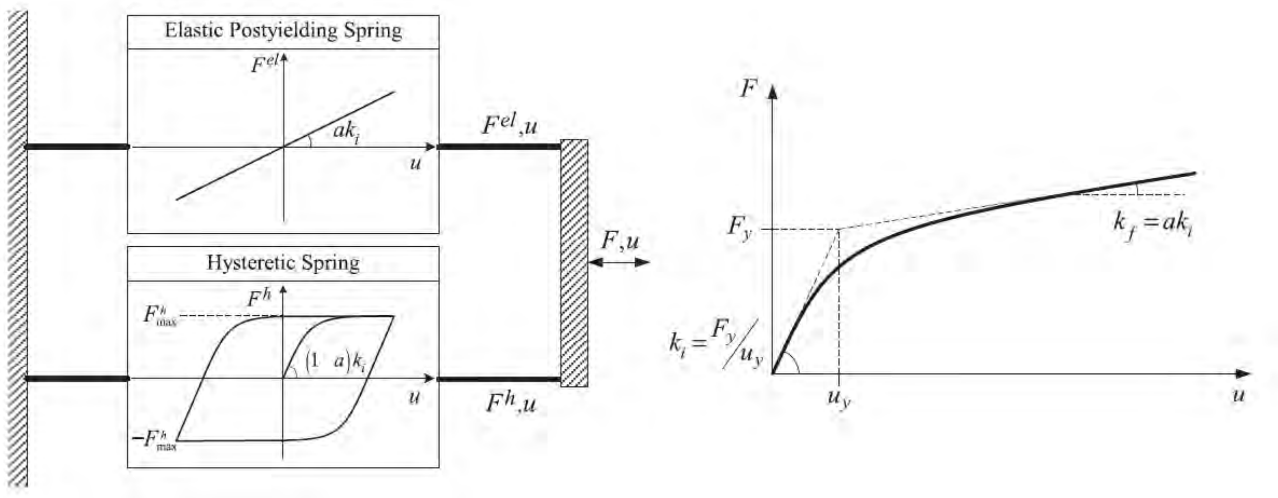

Figure 9. Bouc-Wen model represented by Charalampakis and Koumousis (2008).

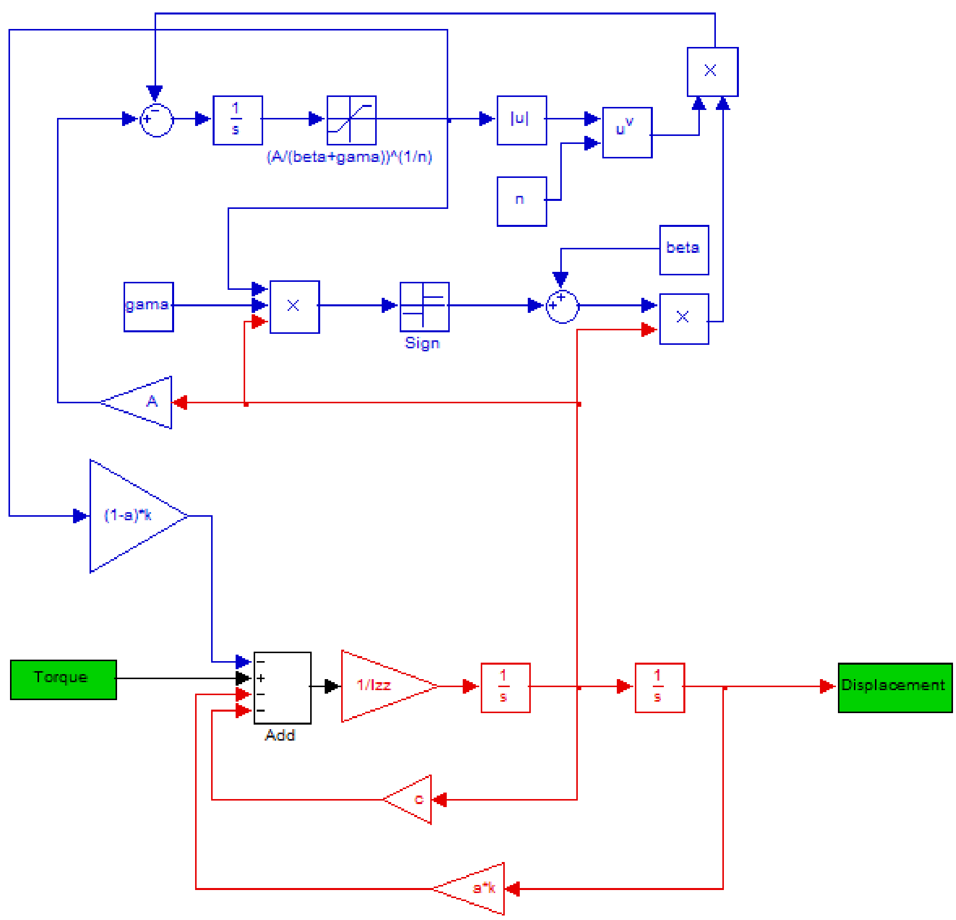

Figure 10. SIMULINK diagram: Bouc-Wen model.

The Figure 10 presents the SIMULINK block diagram of the Bouc-Wen model used to represent the system and whose parameters are estimated using an GA. The block **Torque** is the system input variable and the block **Displacement** is the output variable.

The parametric estimation method used in this work is a genetic algorithm, with cost function minimizes the prediction error between the measured output and the predicted output obtained from simulation of the model shown in Figure 10. The complete Bouc-Wen model with parameters estimated by the GA is

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$$\begin{aligned} 22,92\ddot{\beta}(t) + 422,25\dot{\beta}(t) + 5,94 \times 10^4\beta + 2,38 \times 10^5 z(t) &= \tau(t) \\ \dot{z}(t) &= 0,35\dot{x(t)} - |z(t)|^{0,99}[1,86 sign(\dot{x(t)}z(t))]\dot{x(t)} \end{aligned} \quad (9)$$

The linear and nonlinear model identified parameters are summarized in Table 1. The parameters value of inertia and elastic constant obtained in this work are in accordance with the parameters obtained by an earlier experiment conducted at the Institute with qualified units, that are about $21.9Kg.m^2$ and $5.5 \times 10^5 N/m$ for unstressed and equipped units with carbon protection.

Table 1. Identified parameters of the models.

Parameters	J	b	k	a	A	β	γ	n
Linear model	25.18	376.53	1.43×10^5	-	-	-	-	-
Nonlinear model	22.92	422.25	2.97×10^5	0.20	0.35	0.93	1.86	0.99

The Figure 11 presents the hysteresis curve for both the identified models of the movable nozzle in this work. It is observed that both models can track the experimental data.

The nonlinear model shows slightly better performance for the case considered, where the best predictions were obtained by the Bouc-Wen model as shown in Figure 12(b).

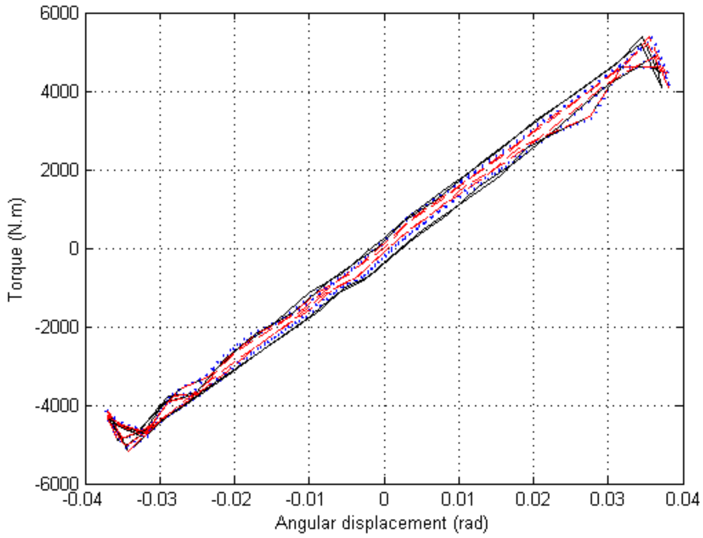

Figure 11. Histeresis curve: (–) experimental data, (- -) linear model and (:) nonlinear model.

4. CONCLUSIONS

This work presented a real plant modeling using two different techniques of dynamic system identification. The parameters of the linear model, described by discrete state space model, were estimated using a subspace method and a model based on the Bouc-Wen structure with aid of a GA. The linear model obtained, presents the nozzle inertia, the flexible joint damping coefficient and the flexible joint elastic constant coherent and are of very interest for control system designs, either useful for pass-band analysis associated to the movable nozzle system actuator. At the other hand, the parameters estimation of the nonlinear model is of interest for analysis to the behavior of the actuator when the flexible joint is present. Thus, this work is considered as reference to other detailed studies involving the control system design, mainly knowing that, with the model at hand, is possible to define a process of validation to the controller, based on the closed loop performance.

5. ACKNOWLEDGMENTS

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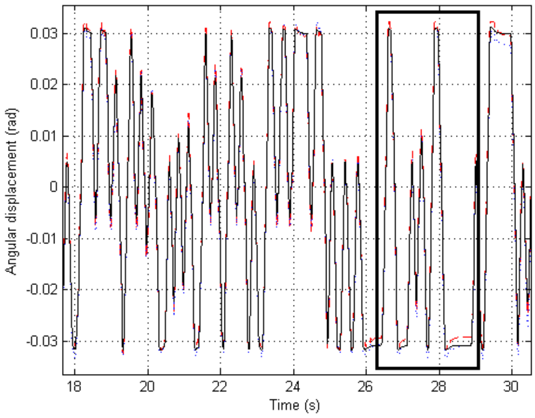
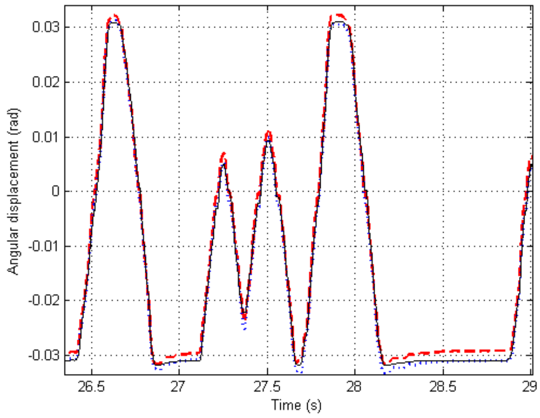


(a)



(b)

Figure 12. Validation of the models (output predictions of the identified models): (a) (–) measured output, (- -) output prediction of the linear model and (:) output prediction of the nonlinear model and (b) Figure 12(a) expanded.

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