NEW RESULTS IN CONTROL SYNTHESIS FOR ELECTROHYDRAULIC SERVOS

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Abstract

This survey presents some recent results of the authors in the field of the control synthesis for electrohydraulic servos. Three are the methodologies of control theory herein considered. Firstly, an integrated methodology of robust control synthesis with antiwindup feedback compensation for linear model of electrohydraulic servo is developed. Secondly, in a strongly nonlinear framework, an integrated fuzzy supervised neurocontrol is proposed. This represents a control strategy which is in fact independent of mathematical model of the systems, thus achieving certain robustness and reducing complexity. At last, the backstepping is used for obtaining of control laws for asymptotic tracking of position or force references in the case of a certain model of an electrohydraulic servo. Conclusive numerical simulations are provided to verify the behaviour of the controlled systems by the proposed control laws.

Keywords: electrohydraulic servo, robust linear control, control saturation, antiwindup compensation, fuzzy supervised neurocontrol, backstepping control, numerical simulation

1 Introduction

Electrohydraulic servos (EHSs) are encountered in most industries where heavy objects are manipulated and large forces or torques at high speeds are exerted. Features such as large processing force and stiffness, high payload capabilities, and good positioning and power to weight ratio, make this type of actuation system appropriate for positioning of aircraft control surfaces (flight controls), high power industrial machinery, position control of military gun turrets and antennas, material handling, construction, agricultural equipment etc.

The usual performance specifications for such applications are high accuracy of reference signals tracking and high bandwidth implying small servo time constants. Because of the complexity of EHS analysis and the nonlinearities in its dynamics, both the design and the control of EHS are still difficult and immature, although various methodologies of the automatic control theory were brought to the proof in this field; from the classical linearization (Blackburn et al, 1960), to the constructive nonlinear control (Sepulchre et al, 1997). In the last twenty years, a large amount of work in hydraulic control systems has been devoted to problems such as: *design of observers* (Ermakov et al, 1986; Panasian, 1986; Ingenbleek and Schwarz, 1993), *modelling and identification* (Jelali and Schwarz, 1995; Jelali and Kroll, 2003), *feedback linearization* (Hahn et al, 1994; Vossoughi and Donath, 1995; Plummer, 1997), *feedback stabilization* (Richard and Outbib, 1995), *high bandwidth control* (Bobrow and Lum, 1996), *sampled-data control* (Kliffken, 1997).

The paper brings together some recent contributions of the authors concerning the developing of new control laws for EHSs. The main concern in the three considered different approaches: linear control, artificial intelligence based control and constructive nonlinear control, is *accuracy of references tracking. Robustness of the controlled system or treatment of control constraint – saturation – were also considered*. As regards last matter, in many applications, particularly in the field of aerospace engineering, actuator saturation is the principal impediment in achieving significant closed-loop performances (Tyan and Bernstein, 1994). The most frequent kind of control constraint for EHS is the physical limitation of current to servovalve torque motor (Fig. 1), and this clearly can not be explicitly taken into account in the framework of various paradigms of control theory, for instance in a linear state feedback synthesis. Usually, the problem is so tackled: the control signals are calculated as if no constraints existed, and then they are simply limited; the procedure might be seriously

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deficient (Frankena and Sivan, 1979).

One of the specific linear control design paradigm that emerged from the 70s is *robust control of a general servomechanism problem* (RSP) (Davison and Goldenberg, 1975). This means that certain system outputs are required to follow (in some specified conditions including disturbance rejection) reference commands of a given class, such as steps, ramps, sinusoids, or polynomial functions of time. The solution of RSP (Davison, 1976) consists of two separate devices: a servocompensator, in fact an internal model of the exogenous dynamics (references and disturbances), and a stabilizing compensator. Thus, a control law (Ursu et al, 1998; Ursu and Ursu, 2001) derived from both the applying of the apparatus of RSP solution in the case of EHSs and introducing of an antireset windup (AW) strategy to counteract the harmful effects of favourised by integral action control saturation, is presented in Section 3. In fact, a sui generis integrated methodology of facing up to nonlinearities and uncertainties of the mathematical models is so obtained.

The main difficulty arising in the design of a control law is due to the strong nonlinearities and uncertainties in process modelling, which make particularly the EHS control problem challenging. Such difficulty can be overcome using *artificial intelligence based synthesis of control law*, which, in the last years, has turned a viable alternative in control design (Wang, 1994; Yen et al, 1995; Ursu et al, 2000). This represents a control strategy that is rather independent of mathematical models of the plants, thus achieving a certain robustness and reducing design complexity. Philosophically, the essential part of intelligent control research was carried out on the same premises as Han's vision on control theory (Han, 1989), which is free of a few fundamental limitations, such as linearity, time invariance, accurate mathematical modelling of plant etc.

Both neural networks and fuzzy logic show great potential for controlling systems that are difficult or impossible to model using traditional techniques. Indeed, the advantages of neural networks are twofold: learning ability and versatile mapping capabilities from input to output. In its turn, the fuzzy set theory provides a suitable tool for the treatment of intrinsic inexactness of the description in a dialectical context.

In the learning optimal process with artificial neural networks, as well as in many other approaches, the risk of surpassing physical control bounds is real. To counteract this risk and not compromise the learning neural network by secondary phenomena as limit cycles, control's chattering and making worse general system's performance, a fuzzy supervised neurocontrol (FSNC) (Ursu et al, 2001) is proposed as AW strategy. Thus, the control will have a switching type structure, which will be clarified in Section 4.

In the early days of nonlinear control theory, most of the concepts were descriptive rather than *constructive* (Sepulchre et al, 1997). Their "feedback activation" began recently, when some local properties were replaced with new concepts applicable to large regions of state space. Thus, a representative example is the concept of Control Lyapunov Function (CLF), whose derivative depends on the control and can be made negative by feedback. For a large class of systems, CLFs can be constructed by backstepping (Krstić et al, 1995). In Section 5, the backstepping approach is employed to successively show the construction of nonlinear control for position and force tracking EHS (Ursu and Popescu, 2003).

An unitary perspective of the three types of control laws is achieved by using common numerical data in mathematical models, whose simulations studies are reported in Section 6.

2 Modelling of the EHSs

Various mathematical models of the EHS will be considered, in connection with the used control strategies. In fact, the mathematical models exhibit a *flexibility property*: to be able to apply a certain mathematical construction, a mathematical model can be often "shaped" to make possible that mathematical construction to apply (Ursu and Ursu, 2002). First, consider the linear time-invariant model of an EHS (Ursu et al, 1994; Ursu et al, 1996), see Fig. 1:

$$\dot{\boldsymbol{x}} = \mathbf{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} + \boldsymbol{E}\omega, \quad y = \boldsymbol{C}\boldsymbol{x}, \quad e = r - y$$

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 \\ -k/m & -f/m & S/m \\ 0 & -S/k_c & -k_{Qp}/k_c \end{bmatrix} \tag{1}$$

$$\boldsymbol{B} = \begin{bmatrix} 0 & 0 & k_{Qu}/k_c \end{bmatrix}^{\mathrm{T}}, \ \boldsymbol{C} = \begin{bmatrix} k_p & 0 & 0 \end{bmatrix}, \ \boldsymbol{E} = [0 \ \ 1 \ \ 0]^{\mathrm{T}}$$

where $\boldsymbol{x} = [x \quad \dot{x} \quad p_1 - p_2]^{\mathrm{T}}$ is the EHS state vector and $k_c := C/(2B)$. As comparison in numerical simulations is taken the mathematical model of an EHS having only a simple position feedback

$$\dot{\boldsymbol{x}} = \mathbf{A}_1 \boldsymbol{x} + \boldsymbol{B} r + \boldsymbol{E}\omega \tag{2}$$

with $\mathbf{A}_1 \equiv \mathbf{A}$, excepting $\mathbf{A}_1(3,1) = -k_{Qu} k_p / k_c$. These models will be used in Section 3. The open loop transfer function derived from Eq. 1 is

$$x = \frac{\dfrac{k_{Qu}}{S} u + \dfrac{m}{S^2}\left(k_c \mathrm{p} + k_{Qp}\right)\omega}{\dfrac{kk_{Qp}}{S^2} + \left(1 + \dfrac{kk_c + fk_{Qp}}{S^2} + \dfrac{2\zeta_h \mathrm{p}}{\omega_h} + \dfrac{\mathrm{p}^2}{\omega_h^2}\right)\mathrm{p}} \tag{3}$$

$$\omega_h = \sqrt{\frac{S^2}{mk_c}} = \sqrt{\frac{2BS^2}{mC}}$$

$$\zeta_h = \frac{k_{Qp}}{S}\sqrt{\frac{m}{k_c}} + \frac{f}{2S}\sqrt{\frac{k_c}{m}}$$

It should be noted the relationship

$$k_{SV} i = k_{SV} k_{mAV} u := k_{Qu} u \tag{4}$$

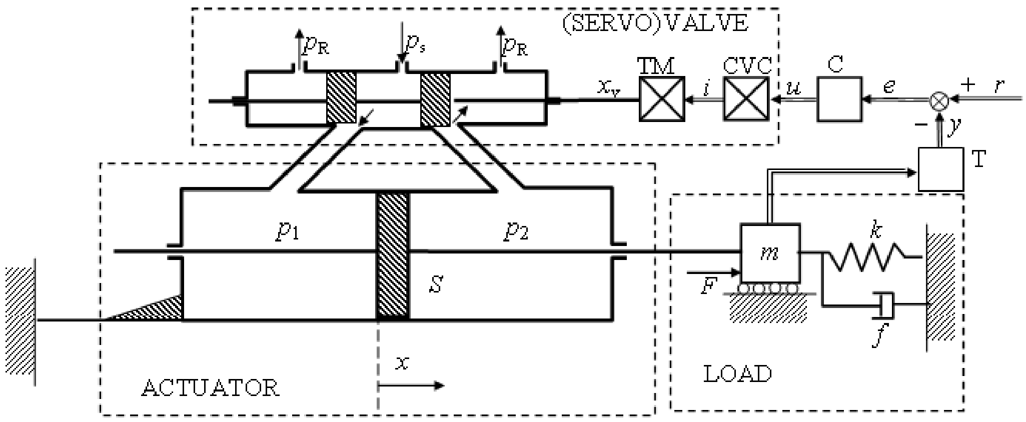

Fig. 1: *Simplified model sketch of an EHS. Legend: T – transducer; C – compensator; CVC – curent- voltage converter; TM – torque motor; here F = mω is load disturbance*

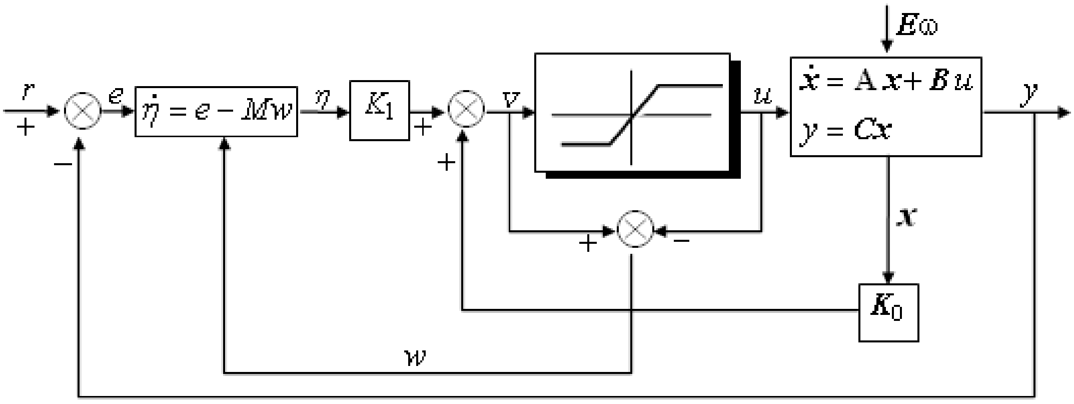

Fig. 2: *The paradigm of the robust servomechanism problem with AW compensation*

Then, in Section 4, the system

$$m\ddot{x} + f\,\dot{x} + k\,x + F + F_{\mathrm{f}} = S\left(p_1 - p_2\right)$$
$$x_{\mathrm{v}} = \lambda\left(r - x\right)$$

$$\dot{p}_1 = \frac{B}{C + Sx}\left\{cW\left|x_{\mathrm{v}}\right|\mathrm{sgn}\left[p_{\mathrm{s}}\left(1 + \mathrm{sgn}\,x_{\mathrm{v}}\right) - 2p_1\right]\cdot \sqrt{\left|p_{\mathrm{s}}(1 + \mathrm{sgn}\,x_{\mathrm{v}}) - 2p_1\right|/\rho} - S\dot{x}\right\}$$
$$\dot{p}_2 = \frac{B}{C - Sx}\left\{cW\left|x_{\mathrm{v}}\right|\mathrm{sgn}\left[p_{\mathrm{s}}\left(1 - \mathrm{sgn}\,x_{\mathrm{v}}\right) - 2p_2\right]\cdot \sqrt{\left|p_{\mathrm{s}}(1 - \mathrm{sgn}\,x_{\mathrm{v}}) - 2p_2\right|/\rho} + S\dot{x}\right\} \quad (5)$$

$$F_{\mathrm{f}} = \sigma_0 x_{\mathrm{f}} + \sigma_1 \dot{x}_{\mathrm{f}} + f_{\mathrm{v}}\dot{x}, \dot{x}_{\mathrm{f}} = \dot{x} - \left|\dot{x}\right| x_{\mathrm{f}} / g\left(\dot{x}\right)$$
$$g\left(\dot{x}\right) := \left[F_{\mathrm{c}} + \left(F_{\mathrm{s}} - F_{\mathrm{c}}\right)e^{-\left(\dot{x}/\mathrm{v}_{\mathrm{s}}\right)}\right]$$

defines a nonlinear model of a mechanohydraulic servo (MHS) (Wang, 1963; Halanay et al, 2004; Mihajlov et al, 2002), taken as comparison term. The control law u for associated EHS will be synthesized by neglecting valve's dynamics; thus, a proportionality law

$$x_{\mathrm{v}} = k_{\mathrm{x_v u}} u \quad (6)$$

will substitute the second equation in Eq. 5.

At last, in Section 5, with the same state vector as in Eq. 1, the first EHS mathematical model used is

$$\dot{x}_1 = x_2,\ \dot{x}_2 = -kx_1/m - fx_2/m + Sx_3/m$$
$$\dot{x}_3 = \frac{1}{k_{\mathrm{c}}}\left(-Sx_2 - k_1 x_3 + cWk_{\mathrm{x_v u}} u\sqrt{\frac{p_{\mathrm{s}} - x_3}{\rho}}\right) \quad (7)$$

for position control law synthesis. Appealing the flexibility property, another mathematical model is considered for force control synthesis, by adding the state variable $x_4 := x_{\mathrm{v}}$

$$\dot{x}_1 = x_2,\ \dot{x}_2 = -kx_1/m - fx_2/m + Sx_3/m$$
$$\dot{x}_3 = \frac{1}{k_{\mathrm{c}}}\left(-Sx_2 - k_1 x_3 + cW\sqrt{\frac{p_{\mathrm{s}} - x_3}{\rho}}x_4\right) \quad (8)$$
$$\dot{x}_4 = \frac{1}{\tau_{\mathrm{SV}}}\left(-x_4 + k_{\mathrm{x_v u}} u\right)$$

As comparison for numerical simulations was taken a simplified mathematical model of a MHS

$$\dot{x}_1 = x_2,\ \dot{x}_2 = -kx_1/m - fx_2/m + Sx_3/m$$
$$\dot{x}_3 = \frac{1}{k_{\mathrm{c}}}\left[-Sx_2 - k_1 x_3 + cW\sqrt{\frac{p_{\mathrm{s}} - x_3}{\rho}}\lambda\left(r - x_1\right)\right] \quad (9)$$

3 A Solution of the Robust Linear EHS Problem with AW Compensation

The control structure of RSP solution, in well-specified conditions, is given by Davison (1976)

$$\boldsymbol{u} = \mathbf{K}_0 \hat{\boldsymbol{x}} + \boldsymbol{K}_1 \boldsymbol{\eta} \tag{10}$$

where $\hat{\boldsymbol{x}}$ is the state vector of a stabilizing compensator and η is the state vector of a servocompensator; K_0 and K_1 are corresponding feedback gains (Fig. 2). By applying this apparatus in the case of EHS's model, an inference was established by Ursu et al (1998): in a large number of cases, the servocompensator designed for *step inputs* represents a good choice

$$\dot{\eta} = e \tag{11}$$

This is in fact an integrator of error signal e.

As for the *stabilizing compensator*, this is not a unique device and may be constructed by using a number of different techniques. To illustrate a *modus operandi*, herein one may consider $\hat{x} \equiv x$, i.e., the stabilizing compensator is simply a direct measurement of the state; so, the control becomes a state feedback for the augmented system comprising the plant (Eq. 1) and the servocompensator (Eq. 11):

$$u = \boldsymbol{K}_0\, \boldsymbol{x} + K_1 \eta \tag{12}$$

Thus, an optimization problem can be stated as an optimal linear quadratic stabilization problem (LQR) for the extended system

$$\begin{bmatrix} \dot{\boldsymbol{x}} \\ \dot{\eta} \end{bmatrix} = \begin{bmatrix} \mathbf{A} & 0 \\ -\boldsymbol{C} & 0 \end{bmatrix} \begin{bmatrix} \boldsymbol{x} \\ \eta \end{bmatrix} + \begin{bmatrix} \boldsymbol{B} \\ 0 \end{bmatrix} u$$
$$y_{\mathrm{q}} = [\mathbf{0} \quad 1] \begin{bmatrix} \boldsymbol{x} \\ \eta \end{bmatrix} \tag{13}$$

with the performance index regarding the quality output y_{q} and the control u

$$J(u) = \int_0^\infty \left(y_{\mathrm{q}}^2 Q_{\mathrm{J}} + u^2 R_{\mathrm{J}} \right) dt \tag{14}$$

where $Q_{\mathrm{J}}, R_{\mathrm{J}}$ are generally weighting matrices. The solution $[\boldsymbol{K}_0 \quad K_1]$ is thus supplied

$$\tilde{\mathbf{X}} \begin{bmatrix} \mathbf{A} & 0 \\ -\boldsymbol{C} & 0 \end{bmatrix} + \begin{bmatrix} \mathbf{A} & 0 \\ -\boldsymbol{C} & 0 \end{bmatrix}^{\mathrm{T}} \tilde{\mathbf{X}} - \tilde{\mathbf{X}} \begin{bmatrix} \boldsymbol{B} \\ 0 \end{bmatrix} R_{\mathrm{J}}^{-1} \begin{bmatrix} \boldsymbol{B} \\ 0 \end{bmatrix}^{\mathrm{T}} \tilde{\mathbf{X}} +$$
$$\begin{bmatrix} \mathbf{0}^{\mathrm{T}} \\ 1 \end{bmatrix} \boldsymbol{Q}_{\mathrm{J}} [\mathbf{0} \quad 1] = \mathbf{0}, \quad [\boldsymbol{K}_0 \quad K_1] = -R_{\mathrm{J}}^{-1} \begin{bmatrix} \boldsymbol{B} \\ 0 \end{bmatrix}^{\mathrm{T}} \tilde{\mathbf{X}} \tag{15}$$

The meaning of the Eq. 11 is obviously: to have a good servo means to have an integral action. But, to have an integral action in Eq. 11 means to have the worst undesirable transients and other stronger harmful secondary saturating effects (Krikelis and Barkas, 1984), particularly the *reset windup phenomenon* (Hanus et al, 1987; Park and Choi, 1993). In fact, when an *on line* closed loop control law such as (10) is implemented, the control saturation can not be evaded by use of an a priori reasoning or designing. Consequently, a variety of so-named *anti-reset-windup* (AW) techniques have been presented lately in the literature for dealing with the actuator limitations. Assuming the conjecture "the performance of the system will be improved as the distances between the equilibrium points of the saturated and unsaturated system become small", the derivation of a compensation matrix M (in peculiar context (11), M is simply scalar; see Fig. 2) is a result of the constraint to make the state of the saturated system arbitrarily close to the state of the unsaturated system, for every time the actuator saturated. The two systems

$$\dot{\boldsymbol{x}} = \mathbf{A}\boldsymbol{x} + \boldsymbol{B}u, \ \boldsymbol{y} = \boldsymbol{C}\boldsymbol{x}, \ u = \mathrm{sat}(v)$$
$$\dot{\eta} = e - M(v - u), \ v = \boldsymbol{K}_0 \boldsymbol{x} + K_1 \eta \tag{16}$$

working in closed-loop, will be analyzed in the absence and also in the presence of saturating actuators (respectively, in the *linear* case $u = v$ and in the *nonlinear* saturating case $u = \mathrm{sat}(v)$). The concatenation of systems in Eq. 16 will give, at equilibrium *stationary* points

$$\begin{bmatrix} x \\ \eta \end{bmatrix}_{\mathrm{stl}} = \begin{bmatrix} \mathbf{A} + BK_0 & BK_1 \\ -C & 0 \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{0} \\ -1 \end{bmatrix} r$$
$$\begin{bmatrix} x_{\mathrm{i}} \\ \eta_{\mathrm{i}} \end{bmatrix}_{\mathrm{stn}} = \begin{bmatrix} \mathbf{A} & \mathbf{0} \\ -C - \mathbf{M}K_0 & -\mathbf{M}K_1 \end{bmatrix}^{-1} \begin{bmatrix} -B\mathrm{sat}_{\mathrm{i}}(v) \\ -\mathbf{M}\mathrm{sat}_{\mathrm{i}}(v) - r \end{bmatrix} \tag{17}$$

The index i marks the situation of v to be inside the linear region, or larger than the upper limit, or smaller than the lower limit of the electrohydraulic actuator. The problem is what value M assures the minimization of the cost J

$$J = \sum_{\mathrm{i}=1}^{2} \left(x_{\mathrm{stl}} - x_{\mathrm{stn,i}} \right)^{\mathrm{T}} \left(x_{\mathrm{stl}} - x_{\mathrm{stn,i}} \right) +$$
$$\sum_{\mathrm{i}=1}^{2} \left(\eta_{\mathrm{stl}} - \eta_{\mathrm{stn,i}} \right)^{\mathrm{T}} \left(\eta_{\mathrm{stl}} - \eta_{\mathrm{stn,i}} \right) \tag{18}$$

The calculus is tedious, but not too difficult; according to general proof given in (Ursu and Ursu, 2001), the solution is

$$M = -\boldsymbol{C}\mathbf{A}^{-1}\boldsymbol{B}(\boldsymbol{K}_0 \mathbf{A}^{-1}\boldsymbol{B} + 1)^{-1} \tag{19}$$

For sake of proof rigor, a positive value a, even if negligible, is necessary in servocompensator's structure

$$\dot{\eta} = a\eta + e \tag{20}$$

4 A Fuzzy Supervised Neurocontrol

Consider an elementary structure of perceptron type, with two weighting parameters v_1, v_2 and a linear combiner giving the neurocontrol

$$u_{\mathrm{n}} = v_1 (r - k_{\mathrm{p}} x) + v_2 k_{\mathrm{v}} \dot{x} := v_1 y_1 + v_2 y_2 \tag{21}$$

In the training, the servo performance is assessed by the cost function, a criterion supposing a trade-off (weights q_1, q_2) between the tracking error y_1, a quasi-energetic component y_2 and neurocontrol u_{n}

$$J = \frac{1}{2n}\sum_{i=1}^{n}\left(q_1 y_1^2(i) + y_2^2(i) + q_2 u_n^2(i)\right) := \frac{1}{2n}\sum_{i=1}^{n} J(i) \qquad (22)$$

The weighting vector $\nu = [\nu_1\ \nu_2]^T$ is updated *online* by the gradient descent learning method (Vemuri, 1993) to reduce the cost J. Consequently, the update is expressed by

$$\nu(n+1) = \nu(n) + \Delta\nu(n)$$

$$\Delta\nu(n) := \mathbf{diag}(\delta_1, \delta_2)\frac{\partial J}{\partial \nu(n)} = -\mathbf{diag}(\delta_1, \delta_2)\times$$

$$\sum_{i=n-L}^{n}\left(\frac{\partial J(i)}{\partial y(i)}\frac{\partial y(i)}{\partial u_n(i)} + \frac{\partial J(i)}{\partial u_n(i)}\right)\frac{\partial u_n(i)}{\partial \nu(i)} \qquad (23)$$

where the matrix $\mathbf{diag}(\delta_1, \delta_2)$ introduces the learning scale vector, $\Delta\nu(n)$ is the weight vector update and L marks a back memory (of L time steps). *The involved derivatives in* Eq. 23 *suppose only input-output information about the system.* $\partial y(i)/\partial u_n(i)$ is approximated online by the ratio

$$\left(y(i) - y(i-1)\right)/\left(u_n(i) - u_n(i-1)\right).$$

To counteract the risk of saturation and achieve the goal of reinforcement learning system, a Fuzzy Supervised Neurocontrol (FSNC) was proposed (Ursu et al, 2001). FSNC switches to a Mamdani type fuzzy logic control when the just described neurocontrol saturated.

Further on, the three standard components of the fuzzy control: fuzzyfier, fuzzy reasoning, and defuzzyfier (Ghazi Zadeh et al, 1997), will be succinctly exemplified. The proposed *fuzzyfier* component converts the crisp input signals

$$l_2(y_{1k}) := \sqrt{\sum_{j=k-2}^{k} y_{1j}^2}, \quad y_{1k},\ y_{2k},\ k = 1, 2, \ldots \qquad (24)$$

into their relevant fuzzy variables (or, equivalently, membership functions) using the following set of linguistic terms: zero (ZE), positive or negative small (PS, NS), positive or negative medium (PM, NM), positive or negative big (PB, NB) (for the sake of simplicity, triangular and singleton type membership functions are chosen, see Fig. 3). l_2 is a norm which computes, over a sliding window with a length of 3 samples, the maximum variation of the tracking error. The insertion of this crisp signal in the fuzzyfier will result in a reduction of fuzzy control switches due to the effects of spurious noise signals (Tzes and Peng, 1997).

The strategy of *fuzzy reasoning* construction embodies herein the idea of a (direct) *proportion between the error signal* y_1 *and the required fuzzy control* u_f. Thus, the fuzzy reasoning engine totals a number of n = 4×7×7 IF, THEN rules, that is the number of the elements of the Cartesian product $A\times B\times C$, A := {ZE; PS; PM; PB}, $B = C$:= {NB; NM; NS; ZE; PS; PM; PB}. These sets are associated with the sets of linguistic terms chosen to define the membership functions for the fuzzy variables $l_2(y_1)$, y_1 and, respectively, y_2. Consequently, the succession of the n rules is the following:

1) IF l_2 (y_1) is ZE and y_2 is PB and y_1 is PB, THEN u_f is PB
2) IF l_2 (y_1) is ZE and y_2 is PB and y_1 is PM, THEN u_f is PM
…
7) IF l_2 (y_1) is ZE and y_2 is PB and y_1 is NB, THEN u_f is NB
8) IF l_2 (y_1) is ZE and y_2 is PM and y_1 is PB, THEN u_f is PB
…
196) IF l_2 (y_1) is PB and y_2 is NB and y_1 is NB, THEN u_f is NB

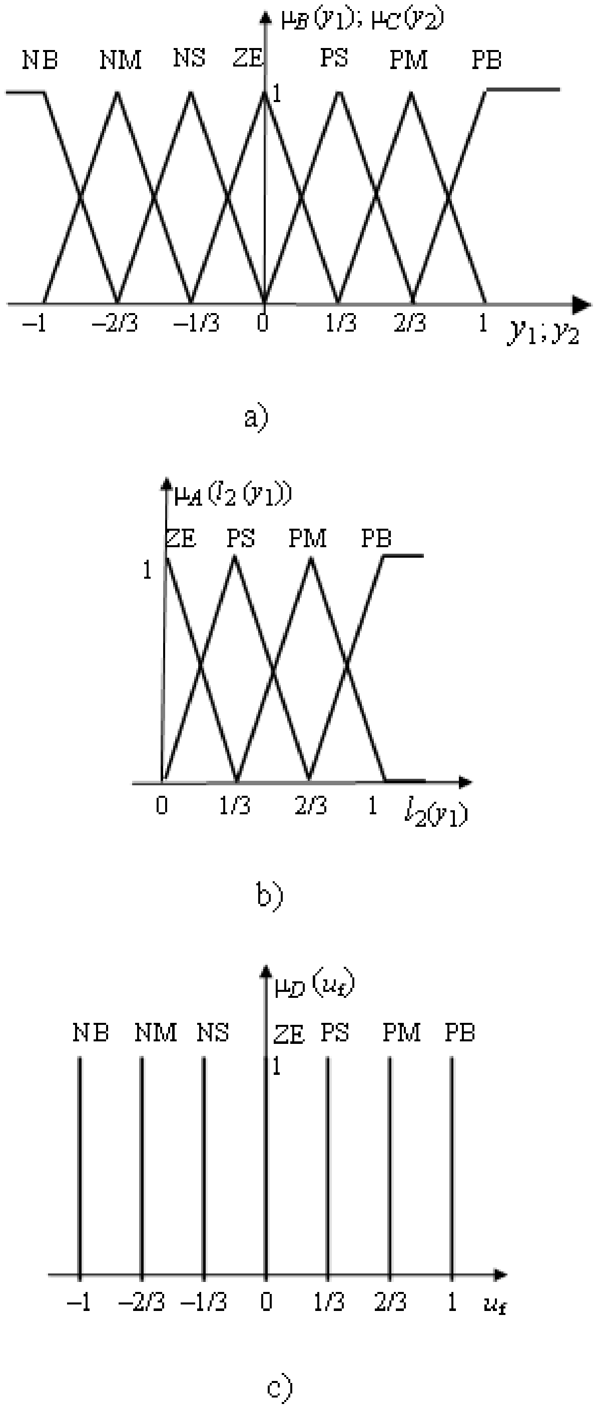

Fig. 3: *Membership functions for: a) scaled input variable y_1, y_2; b) scaled input variable $l_2(y_1)$; c) scaled fuzzy control u_f*

Let τ be the discrete sampling time. Consider now the three scaled input crisp variables $l_2(y_{1k})$, y_{1k}, and y_{2k}, at each time step t_k = kτ (k = 1, 2,...). Taking into account the two ordinates corresponding in Fig. 3 to each of the three crisp variables, a number of M ≤ 2^3 combinations of three ordinates must be investigated. Having in mind these combinations, a number of M IF..., THEN... rules will operate in the form

$$\text{IF } y_{1k} \text{ is } B_i \text{ and } y_{2k} \text{ is } C_i \text{ and } l_2(y_{1k}) \text{ is } A_i, \quad \text{THEN } u_{fk} \text{ is } D_i, \ i = 1, 2, \ldots, M \tag{25}$$

(A_i, B_i, C_i, D_i are linguistic terms belonging to the sets A, B, C and $D = B = C$, see Fig. 3). The *defuzzyfier* concerns just the transforming of these rules into a mathematical formula giving the output control variable u_f. In terms of fuzzy logic, each rule of (25) defines a fuzzy set $A_i \times B_i \times C_i \times D_i$ in the input-output Cartesian product space $\mathbb{R}_+ \times \mathbb{R}^3$, whose membership function can be defined in the manner

$$\mu_{u_i} = \min\left[\mu_{B_i}(y_{1k}), \mu_{C_i}(y_{2k}), \mu_{A_i}(l_2(y_{1k})), \mu_{D_i}(u_f)\right] \quad i = 1, 2, \ldots, M; \ k = 1, 2, \ldots \tag{26}$$

(other variants, e.g., product instead min, can be chosen). For simplicity, the singleton-type membership function $\mu_D(u_f)$ of fuzzy control variable has been herein preferred; in this case, $\mu_{D_i}(u_f)$ will be replaced by u_i^0, the singleton abscissa. Therefore, using 1) the singleton fuzzyfier for u_f, 2) the center-average type defuzzyfier, and 3) the min inference, the M IF, THEN rules can be transformed, at each time step $k\tau$, into the following formula giving the crisp value of fuzzy control u_f (Wang and Kong, 1994):

$$u_f = \sum_{i=1}^{M} \mu_{u_i} u_i^0 \Big/ \sum_{i=1}^{M} \mu_{u_i} \tag{27}$$

The FSNC operates as fuzzy logic control u_f in the case when neurocontrol u_n saturated, or so called l_2 -norm of tracking error y_1 increased. In the case of fuzzy control operating, the fuzzy neurocontrol u_n is concomitantly updated in the context of the real acting fuzzy control u_f. To obtain the rigor and accuracy of regulated process tracking, fuzzy logic control switches on neurocontrol whenever readjusted neurocontrol u_n is not saturated and scaled norm $l_2(y_1)$ is smaller than a chosen value $l_{2,\min}$. At time t_s, when the switching from fuzzy logic control to neurocontrol occurs, the readjusted weighting vector ν_r will be derived by considering a scale factor u_f / u_n

$$\nu_{1r} = (u_f - \nu_2 y_2) u_f / (u_n y_1), \quad \nu_{2r} = \nu_2 u_f / u_n \tag{28}$$

5 Backstepping Synthesis of Control

Clearly, the system in Eq. 7 is lower triangular, in strict feedback form (Sepulchre et al, 1997) and, therefore, suitable for application of backstepping (Krstić et al, 1995). Assuming known the system's parameters, let introduce the notations

$$e_i = x_i - x_{id}, \quad i = 1, \ldots, 3 \tag{29}$$

where x_{id} stand for the "desired" values of the state variables. So, the control objective is to have the tracking by EHS of a specified x_{1d} position trajectory, in other words, making $e_1 \to 0$.

Proposition 1 (Ursu and Popescu, 2003). *Let k_1, k_2, k_3, ρ_1, ρ_2, ρ_3 be strictly positive tuning parameters. Under the assumption of nonsaturating load ($x_3 < p_s$), the control u given by*

$$u = \frac{k_c\sqrt{\rho}}{\rho_3 c W k_{x_v u}\sqrt{p_s - x_3}} \cdot \left[-\frac{\rho_2 S e_2}{m} + \rho_3\left(\frac{S x_2 + k_1 x_3}{k_c} + \dot{x}_{3d}\right) - k_3 e_3\right] \tag{30}$$

$$x_{3d} = k x_1/S + f x_2/S - \rho_1 m e_1/(\rho_2 S) + m\dot{x}_{2d}/S - m k_2 e_2/(\rho_2 S) \tag{31}$$

$$x_{2d} = \dot{x}_{1d} - k_1 e_1 \tag{32}$$

when applied to Eq. 7, guarantees global asymptotic stability of position tracking error $e_1 = x_1 - x_{1d}$.

Let note that the mathematical model (Eq. 7) involves a conjecture: *a chosen positive u does not change its sign, in transitory regime, when various positive references x_{1d} are claimed to be tracked*; otherwise, the model should contain the term $\sqrt{p_s - x_3 \operatorname{sgn} u}$ and the backstepping cannot works in the described manner. This technical difficulty can be evaded by introducing a new state variable, the valve displacement.

Let now consider the case of force control. It can be easily verified inspecting the system (Eq. 7) that the internal states x_1 and x_2, as described by the first two equations in (Eq. 7), are stable. On the other hand, the output of interest in force control is, of course, the pressure. At this point, an idea of partitioning the state system (Eq. 7) into two subsystems − a first one internal stable, and a second one taken as framework of control synthesis − will be introduced. The internal stable system is the subsystem of the first two equations, with "perturbation term" Sx_3/m. Then, if it is not necessary to stabilize the states x_1, x_2, a backstepping procedure cannot be applied only about x_3 oneself. In these circumstances, the system (Eq. 7) will be completed by adding an equation of first order for the dynamics of the valve displacement $x_v := x_4$: so, the control will be constructed on the last two equations of the system (Eq. 8) and then will be certified by proof as ensuring the stability and tracking performance of the whole system. Summarizing, the obtained result is given in the following.

Proposition 2 (Ursu and Popescu, 2003). *Let k_3, k_4, ρ_3, ρ_4 be strictly positive tuning parameters. Under the assumption of a nonsaturating load ($x_3 < p_s$), the control u given by*

$$u = \frac{\tau_{SV}}{\rho_4 k_{x_v u}}\left[\frac{-\rho_3 c W e_3\sqrt{p_a - x_3}}{k_c\sqrt{\rho}} + \rho_4\left(\frac{x_4}{\tau_{SV}} + \dot{x}_{4d}\right) - k_4 e_4\right] \tag{33}$$

$$x_{4\mathrm{d}} = \frac{k_\mathrm{c}\sqrt{\rho}}{cW\sqrt{p_\mathrm{s} - x_3}}\left(\frac{Sx_2 + k_1 x_3}{k_\mathrm{c}} + \dot{x}_{3\mathrm{d}} - k_3 e_3\right) \qquad (34)$$

when applied to (Eq. 8), guarantees global asymptotic stability of pressure (force) tracking error $e_3 = x_3 - x_{3d}$.

6 Numerical Simulations Results

The aforedescribed control laws were brought to the proof in numerical simulations of the EHSs mathematical models, having as reference the parameters corresponding to the MHS included in the aileron chain of military jet IAR 99, namely: $m = 30$ Kg, $f = 300$ Ns/m, $k = 10^5$ N/m, $x_\mathrm{M} = 0.03$ m, $k_\mathrm{Qp} = 0.523\cdot10^{-12}\mathrm{m}^5/(\mathrm{Ns})$, $\rho = 850\ \mathrm{kg/m}^3$, $S = 10^{-3}\mathrm{m}^2$, $p_\mathrm{s} = 21\cdot10^6\ \mathrm{N/m}^2$, $B = 6\cdot10^8\ \mathrm{N/m}^2$, $\lambda = 2/3$, $c = 0.63$. Thus, the hydraulic drive is defined by natural frequency ω_h = 1154.7 rad/s and damping ratio ς_h = 0.058. An equivalent rectangular valve port with $W = 0.0005$ m and $x_\mathrm{vM} = 0.0017$ m was considered, supplying a maximal flow $Q_\mathrm{M} = 10^{-4}\ \mathrm{m}^3/\mathrm{s}$ and a maximal piston velocity $\dot{x}_\mathrm{M} = 0.1$ m/s. The flow control valve associated to all EHSs mathematical model has the rated current $I = \pm20$ mA. Bounds for references r are ±10 V; control saturation means valve spool displacement saturation. k_v was embedded on ν_2 and k_p was taken 10/0.03 V/m. Then, $k_\mathrm{SV} = 5\times10^{-6}$ m^3/smA, $k_{\mathrm{x_v u}} = x_\mathrm{vM}/10$m/V additionally $k_\mathrm{Qu} = 10^{-5}$ m^3/sV and, finally, $k_\mathrm{mAV} = 2$ mA/V.

Throughout this section, the presented figures from numerical studies are considered as representative for the control laws working. The models of references (*chosen not to saturate ab initio the valve*) and load disturbance were

$$\begin{gathered} r = x_\mathrm{vM}k_\mathrm{p}\ \ [\mathrm{V}] \\ r = x_\mathrm{vM}k_\mathrm{p}\left[0.5\sin(2\pi\times2t) + 0.1\sin(2\pi\times5t)\right] \\ [\mathrm{V}] \\ F = 2000\sin(2\pi\times0.8t)\ \ [\mathrm{N}] := m\,\omega(t) \end{gathered} \qquad (35)$$

Figure 4 shows some results obtained on the linear, simple position feedback, system (Eq. 2) (Figs. 4a and 4d, left), and on the linear system (Eq. 1), by applying robust linear control solution (Eq. 12), without anti-windup compensation (Fig. 4b, 4c) and 4d right). The desired piston displacement r/k_p is herein depicted. Obviously, a simple position feedback cannot successfully face up to load disturbance (Fig. 4a and 4d left); on the contrary, good tracking performance and load disturbance robustness emphasizes the system with two compensators (Eq. 12). The vector high gain (specific to LQR problem)

$$[\mathrm{K}_0\ \ \mathrm{K}_1] = [5796.1\ \ 3.8216\ \ 0.7557\ \ -10^6] \qquad (36)$$

corresponds to weighting values $Q_\mathrm{J} = 10^5$ and $R_\mathrm{J} = 10^{-7}$, whose choice requires a trial and error process. Discrete type integration procedure supposed a constant control on the sampling period τ. Worthy noting is the influence of τ on the control saturation (Fig. 4c).

Further on, the benefit of the AW compensation is illustrated by Fig. 5. The system depicted as linear in Fig. 4 is subjected to control constraint in Fig. 5a, 5b. In the left side of Fig. 5a, the harmful effect of saturation is clearly present in an uncompensated system; in the right side, one can see *the remarkable efficiency of AW compensation strategy developed in Section 3*. Fig. 5b shows control evolutions associated to Fig. 5a. Similarly, Fig. 5c and 5d represent the case of a relaxed control synthesis, obtained by choosing $Q_\mathrm{J} = 10^5$ and $R_\mathrm{J} = 10^{-8}$ ($[K_0\ \ K_1] = [14075\ \ 8.08\ \ 1.1\ \ -3.16\times10^6]$). Spectacular chattering (in the left sides, for saturated and uncompensated system) and antichattering (in the right sides, for saturated and compensated system) effects are proved.

Neuro-fuzzy control u_nf, as result of switching between optimal neurocontrol u_n and antisaturation fuzzy control u_f, is represented by case studies in Fig. 6 (model without internal friction F_f) and 7 (model containing internal friction F_f). The back memory was L = 1. For step reference, scaled variables y_1, y_2 and $l_2(y_1)$ were obtained by dividing respectively with maximal values $k_\mathrm{p}x_\mathrm{vM}$, $k_\mathrm{v}\dot{x}_\mathrm{M}$ and $\sqrt{3}k_\mathrm{p}x_\mathrm{vM}$; one proceeds similarly for sinusoidal combination reference (but rigor of these scalations is not too important). Switching parameter $l_{2,\min} = 1/3$ was chosen. LuGre model of internal friction F_f is defined by $f_\mathrm{v} = 60$ Ns/m, $\sigma_0 = 12\cdot10^5$ N/m, $\sigma_1 = 300$ Ns/m, $v_\mathrm{s} = 0.1$ m/s, $F_\mathrm{c} = 100$ N (Ursu, 1984), $F_\mathrm{s} = 120$ N and graphs of evolutions are depicted in Fig. 8. In processing numerical experiments, the system operation is restricted to the noncavitation regime, i.e., $p_\mathrm{s} \geq p_\mathrm{i} > 0$, i = 1,2.

The following set was tuned in a trial and error type process: initial weighting vector $\nu = [100\ \ 1]$, learning rates $[\delta_1\ \ \delta_2] = [5\cdot10^{-2}\ \ 10^{-4}]$ and weights $[q_1\ \ q_2] = [300\ \ 0.1]$ (by using physical units daN and cm in simulation). *Better tracking performance of EHS in comparison with MHS is pointed out*: for sinusoidal combination reference, actual load displacement x is virtually superposed on desired load displacement r/k_p. On the other hand, MHS tracking property is affected by some dephasage. Worthy of note, *the presence of a strong nonlinear component as internal friction F_f doesn't influences behaviour of the two systems*.

As it was pointed out, the objective of backstepping synthesized control is to have the EHS tracking of the specified $x_{1\mathrm{d}}(t)$ position or $x_{3\mathrm{d}}(t)$ pressure references. Such references can be described as

$$x_\mathrm{id}(t) = x_\mathrm{is}\left(1 - e^{-t/t_\mathrm{id}}\right),\ \mathrm{i} = 1 \text{ or } 3 \qquad (37)$$

which is associated with the time response of a first order systems to step input: x_is stand for desired stationary value of the states x_1, respectively x_3, and t_id stand for desired time constants.

The supplementary parameter appearing in equations (7) is $k_\mathrm{l} = 5/210$ cm^5/(daN·s) (however, herein with negligible influence in system's behaviour). As reference point of the numerical simulations was taken the MHS system (Eq. 9). To have in this servo a concrete term of comparison for position control technique, $r = 0.17/\lambda = 0.255$ cm was chosen.

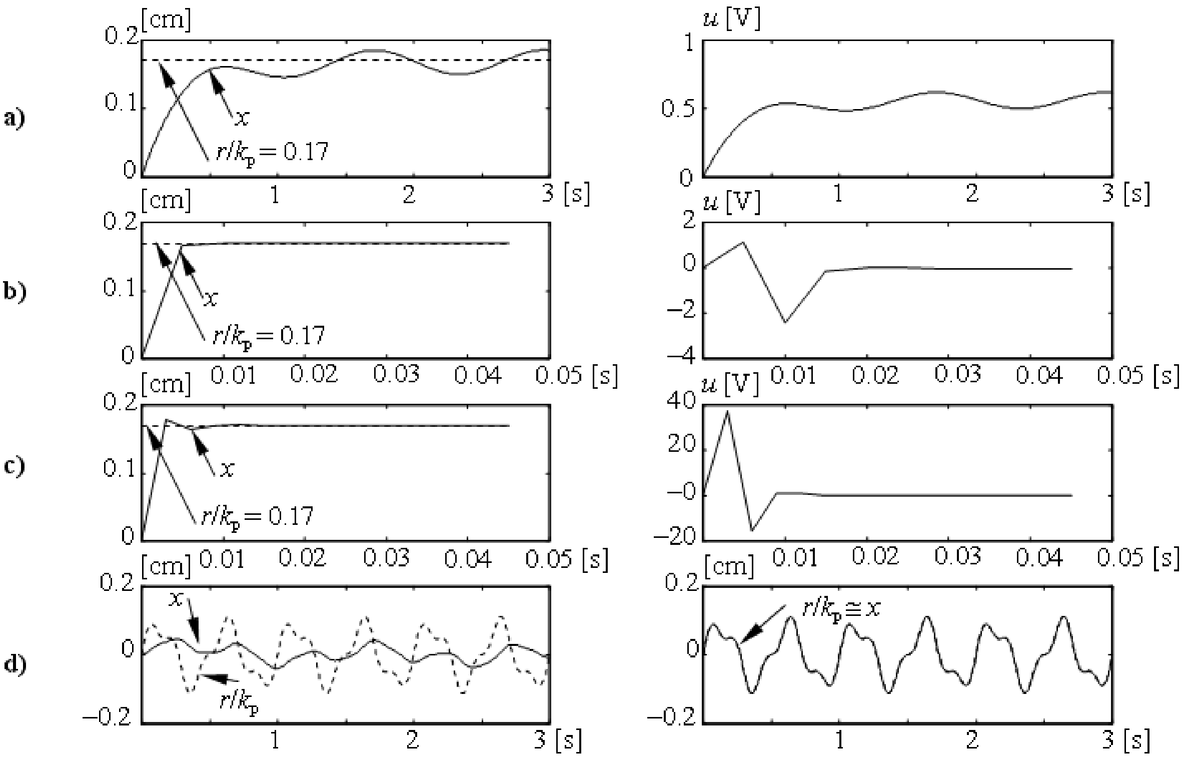

Fig. 4: *Solution of the robust linear EHS problem. Desired (r/k_p = 0.17 cm) and actual (x) piston displacements. a) case of a simple position feedback servo, 0.005 s sampling step; b) robust EHS, 0.005 s sampling step; c) robust EHS, 0.003 s sampling step; d) comparison between simple position feedback servo (left) and robust EHS (right), sinusoidal combination reference, 0.005 s integration step*

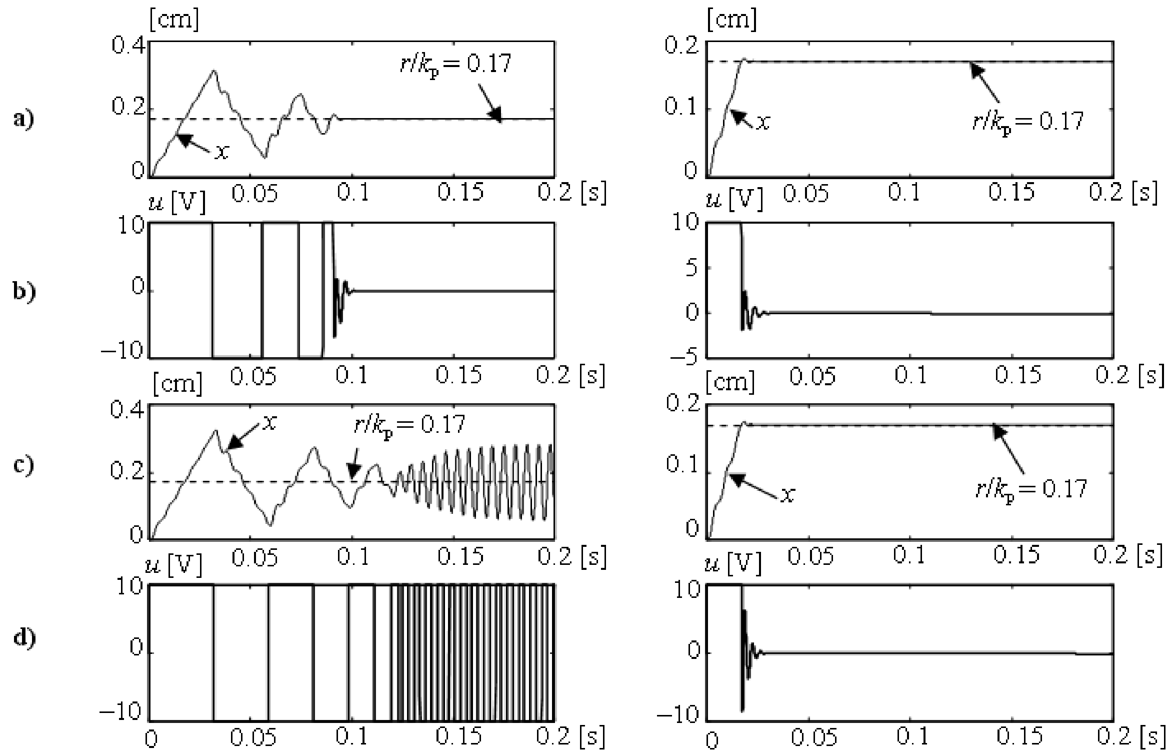

Fig. 5: *Solution of the robust nonlinear EHS problem with AW compensation. Desired (r/k_p = 0.17) and actual (x) piston displacements. a) left side – saturated and uncompensated system, right side – saturated and compensated system, step response evolutions; b) control variables associated to case a); c) and d), similar case studies for an relaxed control synthesis*

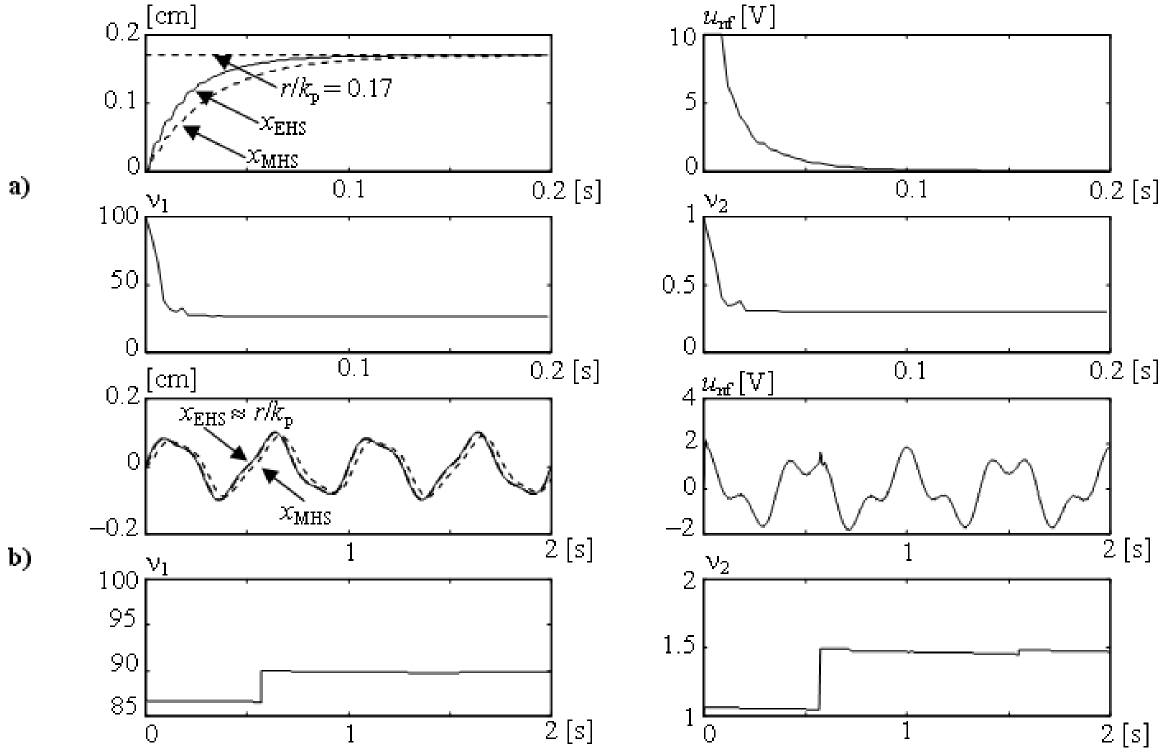

Fig. 6: *Neuro-fuzzy controlled EHS, $F_f = 0$, comparison with MHS. Desired (r/k_p) and actual (x) piston displacements. a) step reference; b) sinusoidal combination reference*

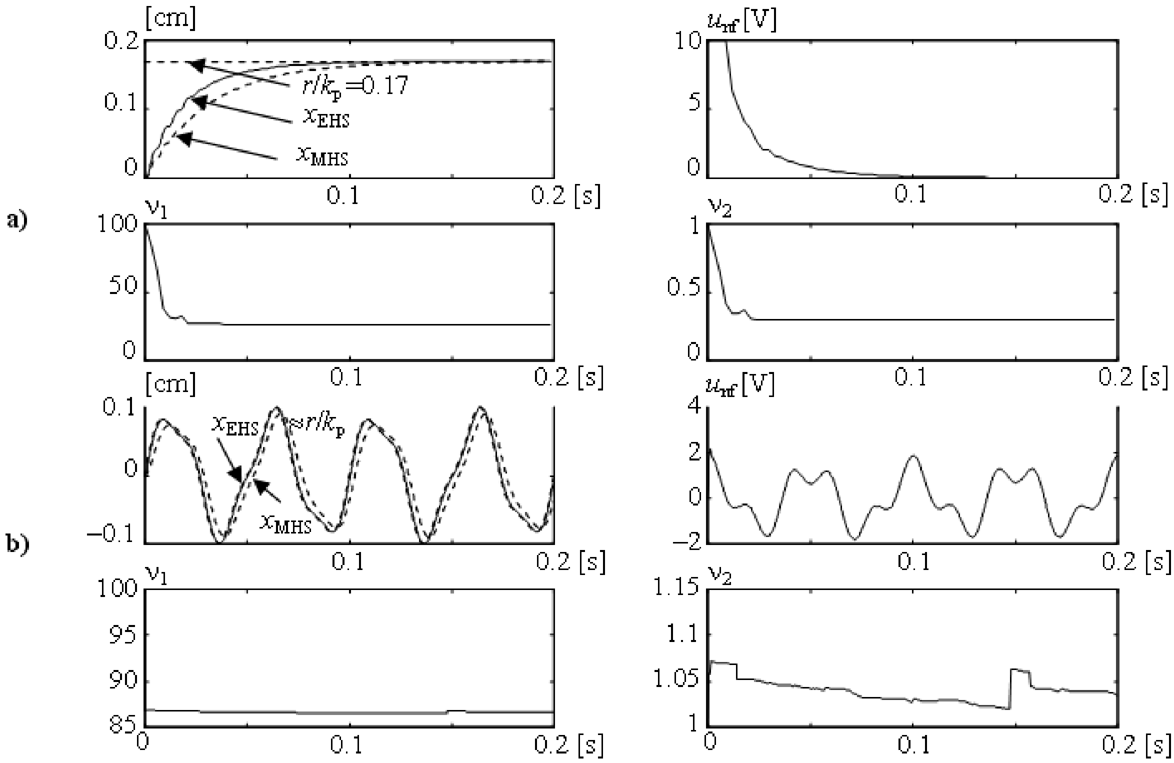

Fig. 7: *Neuro-fuzzy controlled EHS, $F_f \neq 0$, comparison with MHS. Desired (r/k_p) and actual (x) piston displacements. a) step reference; b) sinusoidal combination reference*

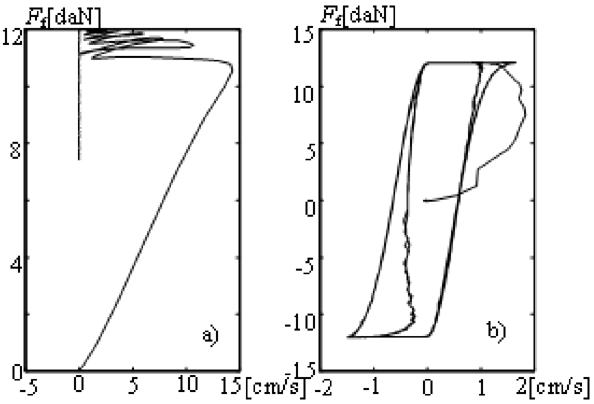

Fig. 8: *LuGre model of friction: a) step reference case; b) sinusoidal combination reference case*

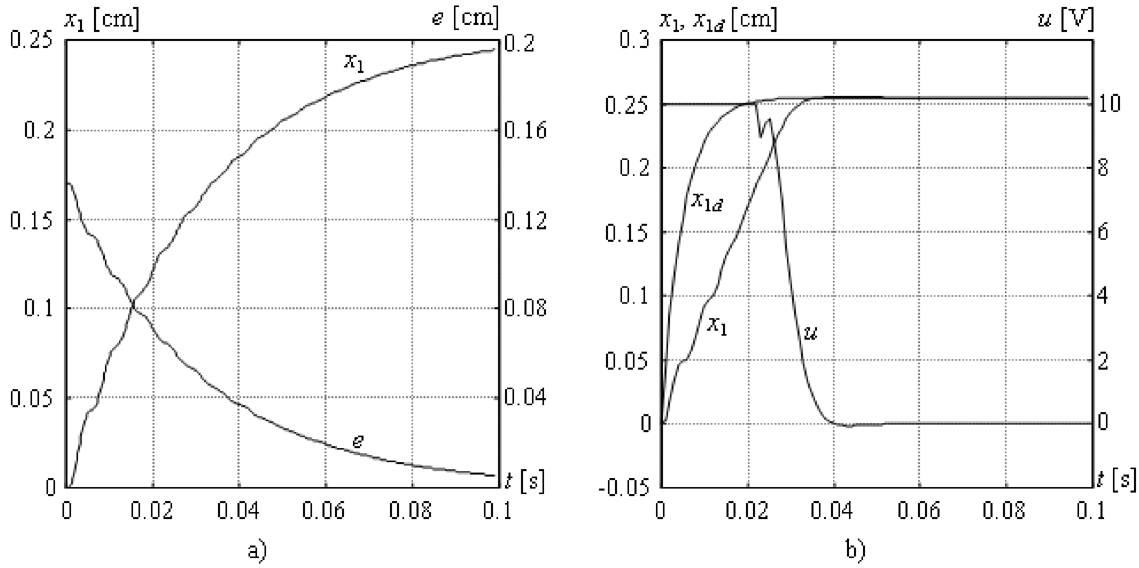

Fig. 9: *Comparison between the step input tracking: a) MHS case: $\tau_a \cong 0.0337$ s; b) EHS case with backstepping position control: $\tau_a \cong 0.0205$ s*

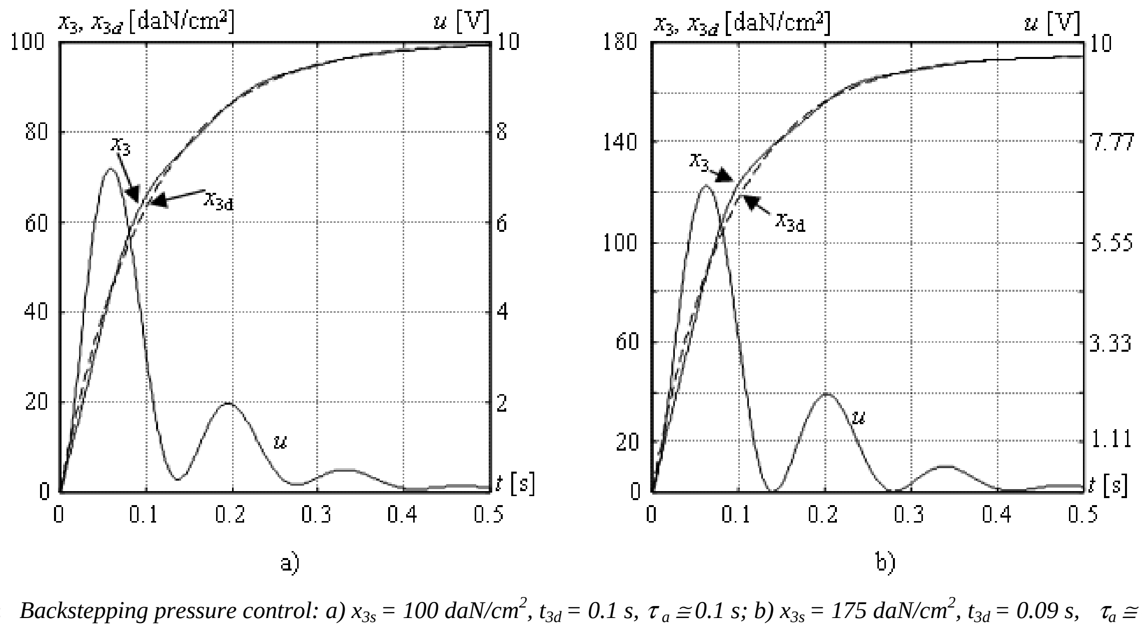

Fig. 10: *Backstepping pressure control: a) x_{3s} = 100 daN/cm^2, t_{3d} = 0.1 s, $\tau_a \cong 0.1$ s; b) x_{3s} = 175 daN/cm^2, t_{3d} = 0.09 s, $\tau_a \cong 0.09$ s*

Therefore, having this reference, the entire valve port is in fact open to flow passing and, consequently, the resulting time constant, *in accordance with experimental data* (Ursu, 1984) characterizes the best step input tracking with the MHS "passive" system: $\tau_a \cong 0.0337$ s (Fig. 9a), where the error signal $e := \lambda(r - x_1)$ is represented; initial error: $e_0 = 0.17$ cm). *An evidently better tracking of step references is ensured by backstepping position control synthesis*. The values of the tuning parameters were: $\rho_1 = 400$; $\rho_2 = 0.01$ s^2; $\rho_3 = 1$ cm^6·daN^{-2}; $k_1 = 400$ s^{-1}; $k_2 = 4$ s; $k_3 = 400$ cm^6·daN^{-2}·s^{-1}. *The control objective*, in terms of desired position reference $x_{1s} = 0.255$ cm and $t_{1d} = 0.01$ s, *is accomplished with faster time constant* $\tau_a \cong 0.0205$ s (Fig. 9b). The transient regime is stable, irrespective of stationary regime value x_{1s} and t_{1d}; however, the designer must be attentive to control saturation. To counteract this effect, special antiwindup strategies can be applied.

Similar conclusions are valid in the case of backstepping force control (Fig. 10). The tuning parameters were: $\rho_3 = 10^{-10}$; $\rho_4 = 1$ daN^2·cm^{-6}; $k_3 = 1000$ s^{-1}; $k_4 = 800$ daN^2·cm^{-6}·s^{-1}. The time constant of the valve was $\tau_{SV} = 1/573$ s. The desired control objective, in terms of pressure reference $x_{3s} = 100$ daN/cm^2 and $t_{3d} = 0.1$ s is accomplished with good time constant $\tau_a \cong 0.1$ s (Fig. 10a) and $\tau \cong 0.09$ s when x_{3s} and t_{3d} were chosen 175 daN/cm^2 and, respectively, 0.09 s (Fig. 10b). Herein, according to expectation, increased $k_{x,u}$ gains were necessary: 0.34 cm/V and 0.85 cm/V (Fig. 10a), and, respectively, 10b. *The significance of result consists in obtaining a simple technique to convert a position control into a force control, without major hard cost: only a change in spool valve device is involved*.

It can be seen that the state variables x_1, in the first case, and x_3, in the second case, come very close to the desired x_{1d} and, respectively, x_{3d}, values.

Integration procedure supposed using zero-order-hold control paradigm in all cases. excepting the case of the robust servomechanism with AW compensation described in Section 3, where a variable step routine specific to continuous time systems was used. In the case of FSNC, τ was chosen 0.003 s; in the case of backstepping, τ was chosen 0.003 s (Fig. 9) and 0.001 s (Fig. 10).

7 Conclusion

This survey paper presents some recent results in control law synthesis for electrohydraulic servos, covering modern and postmodern (Zhou et al, 1996) ages in the field.

Firstly, the two results described in Section 3, the integral action as general internal model and associated AW strategy can be viewed as an integrated linear robust methodology as against the general nonlinearities of the EHS. This assertion is based on the following inference: 1) the equations governing the movement of the load actuated by an EHS, strongly nonlinear (Wang, 1963), can be correctly linearized (Ursu et al, 1994) only in the presence of small inputs; 2) thus, invoking the paradigm of sampled data systems (Åström and Wittenmark, 1974), the response of a system to (small) step inputs is representative, having in view the procedure of sampling general reference signals; 3) thus, only control saturation nonlinearity remains to be counteracted.

Secondly, the paper proposes in Section 4 an integrated, switching type, fuzzy supervised neurocontrol for an EHS. This represents a control strategy which is in fact independent of mathematical model of the systems, thus achieving certain robustness and reducing complexity.

Finally, applying the flexibility property of mathematical models, the backstepping technique was used in Section 5 to provide two control laws that ensure asymptotic tracking of given position and, respectively, force references. A future work will prove this approach is itself flexible enough to also ensure robustness properties to controlled system.

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Nomenclature

Acronymes:

EHS – electrohydraulic servo
MHS – mechanohydraulic servo
FSNC – fuzzy supervised neurocontrol
AW – antiwindup
LQR – Linear Quadratic Regulator

Variables:

$x(t)$	EHS or MHS load displacement (defined from the center of the actuator cylinde	[m])
$p_i(t)$	actuator cylinder pressures (i = 1, 2)	[N/m^2]
$e(t)$	error signal	[V]
$y(t)$	measured output [V], here the same with the regulated output of EHS	[V]
$r(t)$	reference input (command) ([V], for EHS; [m], for MHS)	
$\omega(t)$	load disturbance	[m/s^2]

$u(t)$	control, that is, valve input voltage	[V]
$i(t)$	driving current to valve torque motor	[mA]
$x_v(t)$	valve spool displacement relatively to its sleeve, defined from the valve's neutral position	[m]
$x_f(t)$	internal friction state variable	[m]
$\eta(t)$	state variable of the integrator type servocompensator	[V· s]
$F_f(t)$	internal friction force due to the tight sealing [N]	
$F(t)$	load disturbance	

Load parameters:

m	total mass of piston and load referred to piston	[Kg]
k	load spring gradient	[N/m]
f	viscous damping coefficient of load	[Ns/m]

EHS parameters:

p_s	supply pressure to valve	[N/m^2]
$p_R \approx 0$	return pressure	
S	actuator piston area	[m^2]
x_M	half of piston stroke	[m]
C	semivolume of oil under compression in both cylinder chambers $C = S \times x_M$	[m^3]
B	bulk modulus of oil	[N/m^2]
k_{Qp}	flow-pressure gain	[m^5/(N·s)]
k_{Qu}	flow-voltage gain	[m^3/(V·s)]
k_p	position transducer coefficient	[V/m]
k_v	velocity scale factor	[V×s/m]
k_{SV}	flow-current gain	[m^3/(mA·s)]
k_{mAV}	current-voltage gain	[mA/V]
$k_{x_v u}$	valve displacement-voltage gain	[m/V]
W	area gradient of valve [m^2/m], or valve port width	[m]
x_{vM}	length of rectangular valve port	[m]
$\dot{x}_M$	maximal (no load) piston velocity	
Q_M	maximal flow (no load flow rate)	
τ_{SV}	time constant of valve	[s]
τ_a	actual time constant of hydraulic drive	[s]
k_l	leakage coefficient	[m^5/(N·s)]
c	valve discharge coefficient	
λ	kinematic feedbak coefficient of MHS	
ρ	oil density	[kg/m^3]
ω_h	hydraulic drive natural frequency	[rad/s]
ς_h	hydraulic drive damping ratio	

Cylinder internal friction parameters:

σ_0	stifness coefficient	[N/m]
σ_1	damping coefficient	[Ns/m]
f_v	viscous friction coefficient	[Ns/m]
v_s	Stribeck velocity	[m/s]
F_s	static friction	[N]
F_c	Coulomb friction	[N]

Other notations:

k_v	scale factor in neurocontrol synthesis
τ	discrete sampling time
$\mathrm{sgn}(\cdot)$	signum function
$\mathrm{sat}(\cdot)$	saturation function
t	time variable [s]
p	= d/dt Laplace operator[1/s]
$\dot{f}$	derivative of function f with respect to time t
[M]^T	the transpose of matrix [M]

References

Åström, K. J. and **Wittenmark, B.** 1974. *Computer controlled systems. Theory and design*. Prentice-Hall, Englewood Cliffs, NJ.

Blackburn, J. E., Shearer, J. L. and **Reethof, G.** 1960. *Fluid power control*. Tech. Press of Massachusetts Institute of Technology and Wiley, New York.

Bobrow, J. E. and **Lum, K.** 1996. Adaptive, high band-width control of a hydraulic actuator, *Transactions of the ASME, Journal of Dynamic Systems, Measurements and Control*, 118, December, pp. 714–720.

Davison, E. J. and **Goldenberg, A.** 1975. Robust control of a general servomechanism problem: the servocompensator. *Automatica*, 11, pp. 461-471.

Davison, E. J. 1976. The robust control of a servomechanism problem for linear time-invariant multivariable system. *IEEE Transactions on Automatic Control*, 21, pp. 25-34.

Ermakov, S. A., **Klaptsova, T. S.** and **Smirnov, G. G.** 1986. Synthesis of electrohydraulic tracking systems with observers (in Russian), *Pnevmatika i Gidravlika*. 12, Moskow, Mashinostroenie, pp. 45–54.

Frankena , J. F. and **Sivan , R.** 1979. A nonlinear optimal control law for linear systems. *International Journal of Control*, 30, pp. 159-178.

Ghazi Zadeh, A., Fahim, A. M. and **El-Gindy, M.** 1997. Neural network and fuzzy logic applications to vehicle systems: literature survey. *International Journal of Vehicle Design*, 18, pp. 132-193.

Hahn, H., Piepenbrink, A. and **Leimbach, K.-D.** 1994. Input-output linearization control of an electro servohydraulic actuator. *Proceeding of 3rd IEEE Conference on Control Applications*, Glasgow, pp. 995-1000.

Halanay, A., Safta, C. A., Ursu, I. and **Ursu, F.** 2004. Stability of equilibria in a four–dimensional nonlinear model of a hydraulic servomechanism. *Journal of Engineering Mathematics*, 49, pp. 391–406.

Han, J. 1989. Control theory: it is a theory of model or control? *Systems Science and Mathematical Sciences*, 9, pp. 328–335.

Hanus, R., Kinnaert, M. and **Henrotte, J.-L.** 1987. Conditioning technique: a general antiwindup and bumpless transfer method. *Automatica*, 23, pp. 729-739.

Ingenbleek, R. and **Schwarz, H.** 1993. A nonlinear discrete-time observer based control scheme and its application to hydraulic drives. *Proceedings of* 2nd *European Control Conference*, Groningen, the Netherlands, July, pp. 215–219.

Jelali, M. and **Schwarz, H.** 1995. Continuos-time identification of hydraulic servo-drive nonlinear models. *Proceedings of* 3rd *European Control Conference*, 3, Rome, Italy, pp. 1545-1549.

Jelali, M. and **Kroll, A.** 2003. *Hydraulic servo-systems*. Springer Verlag, Berlin.

Kliffken, M. G. 1997 Robust sampled-data control of hydraulic flight control actuators, 5th *Scandinavian International Conference on Fluid Power, SICFP'97*, Linköping, Sweden, May 28-30.

Krikelis, N. J. and **Barkas, S. K.** 1984, Design of tracking systems subject to actuator saturation. *International Journal of Control*, 39, 4, pp. 667-682.

Krstić, M., Kanellakopoulos, I. and **Kokotović, P.** 1995. *Nonlinear and adaptive control design,* Wiley and Sons, New York.

Mihajlov, M., Nikolić, V. and **Antić, D.** 2002. Position control of an electro-hydraulic servo system using sliding mode control enhanced by fuzzy PI controller. *Facta Universitas. Series: Mechanical Engineering*, 1, pp. 1217-1230.

Panasian, H. V. 1986. Reduced order observers applied to state and parameter estimation of hydromechanical servoactuators. *Journal of Guidance, Control and Dynamics*, 9, pp. 249–251.

Park, J. K. and **Choi, C.-H.** 1993. A compensation method for improving the performance of multi variable control systems with saturating actuators. *Control-Theory and Advanced Technology*, 9, pp. 305-322.

Plummer, A. R. 1997. Feedback linearization for acceleration control of electrohydraulic actuators. *Proceedings of the Institution of Mechanical Engineers*, 211, Part 1, pp. 395–406.

Richard, E. and **Outbib, R.** 1995. Feedback stabilization of an electrohydraulic system. *Proceedings of* 3rd *European Control Conference*, Rome, Italy, September, pp. 330–334.

Sepulchre, R., Janković, M. and **Kokotović, P.** 1997. *Constructive nonlinear control*, Springer-Verlag, London.

Tyan, F. and **Bernstein, S.** 1994. Antiwindup compensator synthesis for systems with saturating actuators. *Proc. of 33rd Conference on Decision and Control*, Lake Buena Vista, FL, pp. 150-155.

Tzes, A. and **Peng, P.-Y.** 1997. Fuzzy neural network control for DC-motor micromaneuvering. *Transactions of the ASME, Journal of Dynamic Systems, Measurement and Control*, 119, pp. 312-315.

Ursu, I. 1984. Theoretical and experimental data concerning qualification testing and flight clearance for aircraft servomechanism SMHR. *National Institute for Scientific and Technical Creation – INCREST Report*, N-5303, Bucharest.

Ursu, I., Popescu, F., Vladimirescu, M. and **Costin, R.** 1994. On some linearization methods of the generalized flow rate characteristic of the hydraulic servomechanism. *Revue Roumaine des Sciences Technique, Série de Mécanique Appliquée*, 39, pp. 207-217.

Ursu, I., Vladimirescu, M. and **Ursu, F.** 1996. About aeroservoelasticity criteria for electrohydraulic servo-mechanisms synthesis. *Proceedings of ICAS'* 96, Sorrento, Italy, pp. 2335-2344.

Ursu, I., Tecuceanu, G., Ursu, F., Sireteanu, T. and **Vladimirescu, M.** 1998. *Aircraft Engineering and Aerospace Technology,* 70, 4, pp. 259–264.

Ursu, I., Ursu F., Sireteanu, T. and **Stammers, C. W.** 2000. Artificial intelligence based synthesis of semiactive suspension systems. *Shock and Vibration Digest*, 32, pp. 3-10.

Ursu, I., Ursu, F. and **Iorga, L.** 2001. Neuro-fuzzy synthesis of flight controls electrohydraulic servo. *Aircraft Engineering and Aerospace Technology*, 73, pp. 465-471.

Ursu, F. and **Ursu, I.** 2001. Robust synthesis with antiwindup compensation for electrohydraulic servoactuating primary flight controls. *Preprints of the* 15th *IFAC Symposium on Automatic Control in Aerospace*, Bologna-Forli, September, 2–7, pp. 197-202.

Ursu, I. and **Ursu, F.** 2002. *Active and semiactive control.* Romanian Academy Publishing House, Bucharest.

Ursu, I. and **Popescu, F.** 2003. Nonlinear control synthesis for position and force electrohydraulic servos. *Proceedings of the Romanian Academy*, Series A, 4, 2, pp. 115–120.

Vemuri, V. 1993. Artificial neural networks in control applications. In *Advances in Computers*, edited by M. C. Yovits, Academic Press, 36, pp. 203-332.

Vossoughi, G. and **Donath, M.** 1995. Dynamic feedback linearization for electrohydraulically actuated control systems. *Transactions of the ASME, Journal of Dynamic Systems, Measurements and Control*, 117, December, pp. 468–477.

Zhou, K. Doyle, J. K. and **Glover, K.** 1996. *Robust and optimal control*, Prentice Hall, New Jersey.

Yen, J., Langari, R. and **Zadeh, L. A.** Eds. 1995. *Industrial applications of fuzzy control and intelligent systems*. New York, IEEE Press.

Wang, L. 1994. *Adaptive fuzzy systems and control – design and stability analysis*, Englewood Cliffs, New Jersey, Prentice Hall.

Wang, P. K. C. 1963. Analytical design of electrohydraulic servomechanism with near time-optimal response. *IEEE Transactions on Automatic Control AC-8*, pp. 15-27.

Wang, L-X. and **Kong, H.** 1994. Combining mathematical model and heuristics into controllers: an adaptive fuzzy control approach. *Proceedings of the 33rd IEEE Conference on Decision and Control*, Buena Vista, Florida, December 14-16, 4, pp. 4122-4127.

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