NEURO-FUZZY CONTROL SYNTHESIS FOR ELECTROHYDRAULIC SERVOS ACTUATING PRIMARY FLIGHT CONTROLS

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Abstract

The objective of this work is to present some theoretical and experimental results concerning the neuro-fuzzy control synthesis as applied to electrohydraulic servos actuating primary flight controls. The control algorithm supposes as component part a neurocontrol designed to minimize a performance criterion. The objective functional supposes a trade-off between the tracking error, the load induced differential pressure in the cylinder's chambers and the control. Whenever the neurocontrol saturates or a certain performance parameter of the system decreases, the scheme of control switches to a feasible and reliable fuzzy logic control. It was thus obtained a Fuzzy Supervised Neuro-Controller (FSNC), with a switching structure, the role of fuzzy control being supervisory – antisaturating and antichattering one. Although the FSNC design does not require of a electrohydraulic servo model, a nonlinear one was considered in numerical simulation.

1 Introduction

This work addresses the problem of theoretical and laboratory test validation for an electrohydraulic motion control system (EHMCS) based on neuro-fuzzy synthesis. The question was partly considered in recent works of the authors [1] – [3]. The EHMCS (Fig. 1) consists firstly of a double effect hydraulic cylinder with $S = 3\times10^{-4}\,\mathrm{m}^2$ piston area and 9.1×10^{-2} m half of piston stroke and an ORSTA TGL33649 electrohydraulic servovalve. The valve is a direct valve, in which a linear motor drives the spool directly according to the input current. The valve has a nominal flow of $40\times10^{-3}\,\mathrm{m}^3/60$ s, at the nominal pressure drop of 70 bar. Secondly, a PC with dual processor Pentium 4 – 2×3.00 GHz – and 1 GB of RAM controls the system through a DAQ PCI 6040E National Instruments. Thirdly, an inductive position transducer Penny & Gilles and two Hottinger Baldwin Messtechnik (HBM) pressure transducers provide the measurement input for DAQ. Finally, the inertial load is simulated by an inertial load simulator and the hydraulic power is supplied by a hydrostatic generator.

Fig. 1. Partial view of the EHCMS.

The EHMCS is in fact a tracking system.

Therefore, for this system the aim of control synthesis is to have a good tracking by the piston position of the specified desired position references introduced as electrical signals by PC. When this control problem is treated in classical manner, a mathematical model of the system must be firstly performed. Secondly, a mathematical procedure of control synthesis must be developed. But, in classical manner, the procedure is dependent of model, and the model is not infallible, and frequently classical control methodologies fail facing to mathematical model complexity. A non-exhaustive mathematical model of the above described system, used in numerical validation of the proposed Fuzzy Supervised Neuro-Controller (FSNC), is the following (see the Nomenclature):

$$
\begin{gathered}
m\ddot{x} + f\,\dot{x} + kx + F + F_{\mathrm{f}} = S(p_1 - p_2) \\
x_{\mathrm{v}} = k_{x_{\mathrm{v}}u}u \\
\dot{p}_1 = \frac{B}{C+Sx}\left\{cW\left|x_{\mathrm{v}}\right|\operatorname{sgn}\left[p_{\mathrm{s}}\left(1+\operatorname{sgn}x_{\mathrm{v}}\right)-2p_1\right]\times \sqrt{\left|p_{\mathrm{s}}(1+\operatorname{sgn}x_{\mathrm{v}})-2p_1\right|/\rho} - S\dot{x}\right\} \\
\dot{p}_2 = \frac{B}{C-Sx}\left\{cW\left|x_{\mathrm{v}}\right|\operatorname{sgn}\left[p_{\mathrm{s}}\left(1-\operatorname{sgn}x_{\mathrm{v}}\right)-2p_2\right]\times \sqrt{\left|p_{\mathrm{s}}(1-\operatorname{sgn}x_{\mathrm{v}})-2p_2\right|/\rho} + S\dot{x}\right\} \\
F_{\mathrm{f}} = \sigma_0 x_{\mathrm{f}} + \sigma_1\dot{x}_{\mathrm{f}} + f_{\mathrm{v}}\dot{x}, \dot{x}_f = \dot{x} - |\dot{x}|x_{\mathrm{f}}/g(\dot{x}) \\
g(\dot{x}) := \left[F_{\mathrm{c}} + (F_{\mathrm{s}} - F_{\mathrm{c}})e^{-(\dot{x}/\mathrm{v}_S)}\right]
\end{gathered}
\tag{1}
$$

Given this EHMCS mathematical embodiment, classical solutions of the control problem *"find control variable u such that tracking error* $\varepsilon(t) := r(t) - k_p x(t) \to 0$ *as* $t \to \infty$ *for specified reference signals* $r(t)$*"* have to facing obvious difficulties. k_p is the position transducer coefficient [V/m]. Our approach in solving this problem belongs to artificial intelligence techniques, which are in fact independent of mathematical model of the system, thus achieving certain robustness and reducing complexity.

2. Neurocontrol

Indeed, artificial intelligence based new approach in the treatment of posed control problem concerns principially an input-output behavioral philosophy of solution. In fact, the mathematical model (1) will herein serve only as illustration of applying the new strategy. In the on line process variant, the mathematical model is naturally substituted by the physical system.

In this and next Sections, the structure of the proposed FSNC is shortly described. The algorithm is composed of a neurocontrol and a fuzzy logic control supervising neurocontrol. As neurocontrol, an unilayered perceptron architecture was used. For this elementary network, two weighting parameters ν_1, ν_2 and a linear combiner generate the neurocontrol

$$u_n = \nu_1 y_1 + \nu_2 y_2 := \nu_1(r - k_p z) + \nu_2(p_1 - p_2) \tag{2}$$

where $r(t)$ – reference input (command [V]). Worthy noting, from EHMCS behavior view point, the input is u and the output is $y = (y_1, y_2)$. From neurocontrol training viewpoint, the system performance is assessed by the cost function, a criterion supposing a trade-off between the first input y_1– tracking error –, the second input component y_2 and the control u

$$J = \frac{1}{2\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\left(q_1 y_1^2(\mathrm{i}) + y_2^2(\mathrm{i}) + q_2 u_{\mathrm{n}}^2(\mathrm{i})\right) := \frac{1}{2\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} J(\mathrm{i}) \tag{3}$$

Consider the on line updating of the weighting vector $\upsilon = [\nu_1 \nu_2]^T$, by the gradient descent learning method [4], in view of cost J reducing

$$
\begin{gathered}
\nu(n+1) = \nu(n) + \Delta\nu(n) \\
\Delta\nu(n) := -\mathrm{diag}(\delta_1, \delta_2)\frac{\partial J}{\partial \nu(n)} = \\
-\mathrm{diag}(\delta_1, \delta_2)\sum_{i=n-N}^{n}\left(\frac{\partial J(i)}{\partial y(i)}\frac{\partial y(i)}{\partial u(i)} + \frac{\partial J(i)}{\partial u(i)}\right)\frac{\partial u(i)}{\partial \nu(i)}
\end{gathered}
\tag{4}
$$

where the matrix $\mathrm{diag}(\delta_1, \delta_2)$ introduces the learning scale vector, $\Delta v(n)$ is the weight vector update and N marks a back memory (of N time steps). The derivatives in (4) require only input-output information about the system. $\partial y(i)/\partial u(i)$ is online approximated by the relationship

$$(y(i)-y(i-1))/(u(i)-u(i-1))$$

The results obtained using this simple unilayered perceptron are very satisfactory.

3. Fuzzy Logic Control And Fuzzy Supervised Neurocontrol

In many applications, particularly in the field of aerospace engineering, actuator saturation is the principal impediment to achieving significant closed-loop performances [5]. In the learning process with artificial neural networks, the risk of control saturation is real. To counteract this risk and not compromise the learning neural network by harmful phenomena as control's chattering and making worse system's performance, FSNC is herein considered as amtiwindup strategy. Thus, the control will have a switching type structure, which will be clarified in the following.

The commonly used Mamdani fuzzy logic control supposes three main components: the fuzzyfier, the fuzzy reasoning, and the defuzzyfier [4]. Herein, the proposed *fuzzyfier* component converts the crisp input signals

$$l_2(y_{1k}) := \sqrt{\sum_{j=k-2}^{k} y_{1j}^2}, y_{1k}, y_{2k}, k = 1,2,... \qquad (5)$$

into their relevant fuzzy variables (or, equivalently, membership functions) using a set of linguistic terms: zero (*ZE*), positive or negative small (*PS*, *NS*), positive or negative medium (*PM*, *NM*), positive or negative big (*PB*, *NB*); thus, fuzzy sets and their pertinent membership functions are produced (for sake of simplicity, triangular and singleton type membership functions are chosen, see Figs. 2, 3). The considered l_2 norm computes, over a sliding window with a length of k 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.

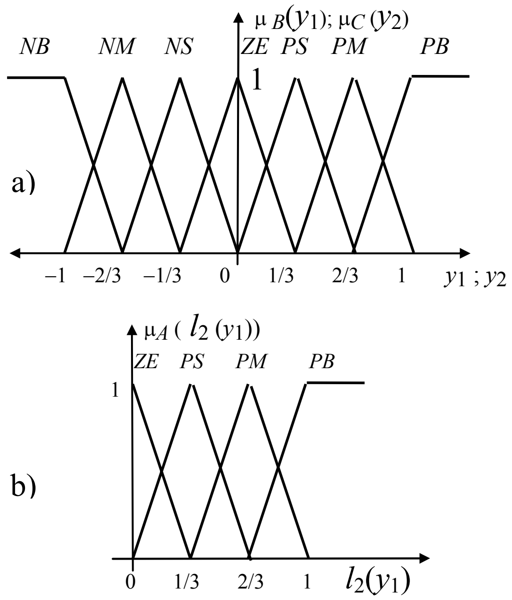

Fig. 2. Triangular membership functions for: a) scaled input variables y_1, y_2 and b) $l_2(y_1)$.

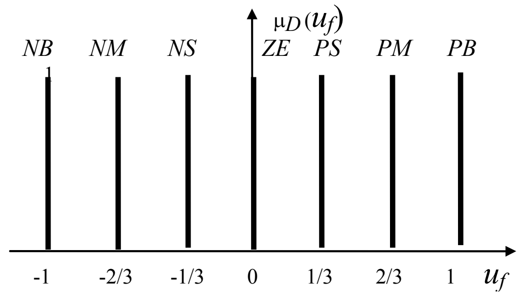

Fig. 3. Singleton membership function for scaled fuzzy control u_f.

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 $n = 4\times7\times7$ 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

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

$$\begin{aligned}&\text{IF } y_{1k} \text{ is } B_i \text{ and } y_{2k} \text{ is } C_i \text{ and } l_2(y_{1k}) \text{ is } A_i,\\ &\qquad \text{THEN } u_{fk} \text{ is } D_i,\ i = 1,2,\ldots, M\end{aligned} \tag{6}$$

(A_i, B, C_i, D_i are linguistic terms belonging to the sets A, B, C, D and $D = B = C$, see Figs. 2, 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 (6) defines a fuzzy set $A_i{\times}B_i{\times}C_i{\times}D_i$ in the input-output Cartesian product space $R_+{\times}R^3$, whose membership function can be defined in the manner

$$\begin{aligned}&\mu_{u_i} =\\ &\min[\mu_{B_i}(y_{1k}), \mu_{C_i}(y_{2k}), \mu_{A_i}(l_2(y_{1k})), \mu_{D_i}(u)],\\ &\qquad i = 1,\ldots, M (k = 1,2,\ldots)\end{aligned} \tag{7}$$

For simplicity, the singleton-type membership function $\mu_D(u)$ of control variable has been preferred; in this case, $\mu_{D_i}(u)$ 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 a formula giving the crisp control u_f [6]:

$$u_f = \sum_{i=1}^{M} \mu_{u_i} u_i^0 \Big/ \sum_{i=1}^{M} \mu_{u_i}\,. \tag{8}$$

The FSNC operates as fuzzy logic control in the case when neurocontrol saturated, or so called l2–norm of tracking error y1 increased. FSNC switches on neurocontrol whenever u_n is not saturating ($|u_n| \le u_{n,max}$) and scaled $l_2(y_1) <$ $l_{2,\,min}$. In the case of fuzzy control operating, the fuzzy neurocontrol u_n is concomitantly updated considering the real acting fuzzy control u_f.

4. Numerical simulations

The aforementioned FSNC was applied in simulation studies of the systems similar to (1) [1]–[3]. Despite of such model complexity, the simulation studies performed in the cited references attest good tracking performance, both in the presence of step and sinusoidal combination type signals r. The parameters used in simulations correspond to the mechanohydraulic servo (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_M = 0.03 m, ρ = 850 kg/m^3, $S = 10^{-3}$m^2, $p_s = 21{\times}10^6$ N/m^2, $k_{Qp} = 0.523{\times}10^{-12}$m^5/(Ns), $B = 6{\times}10^8$ N/m^2, c = 0.63. An equivalent rectangular valve port with W = 0.0005 m and x_{vM} = 0.0017 m was considered, supplying a maximal flow $Q_M = 10^{-4}$ m^3/s and a maximal piston velocity $\dot{x}_M = 0.1$ m/s.

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 Figs. 4 (model without internal friction F_f) and 5 (model containing internal friction F_f); see also [3], where a quasi-energetic component $y_2 = \nu_2 k_v \dot{x}$ was considered in performance criterion. The back memory L = 1. For step reference, scaled variables y_1, y_2 and $l_2(y_1)$ were obtained by dividing respectively by

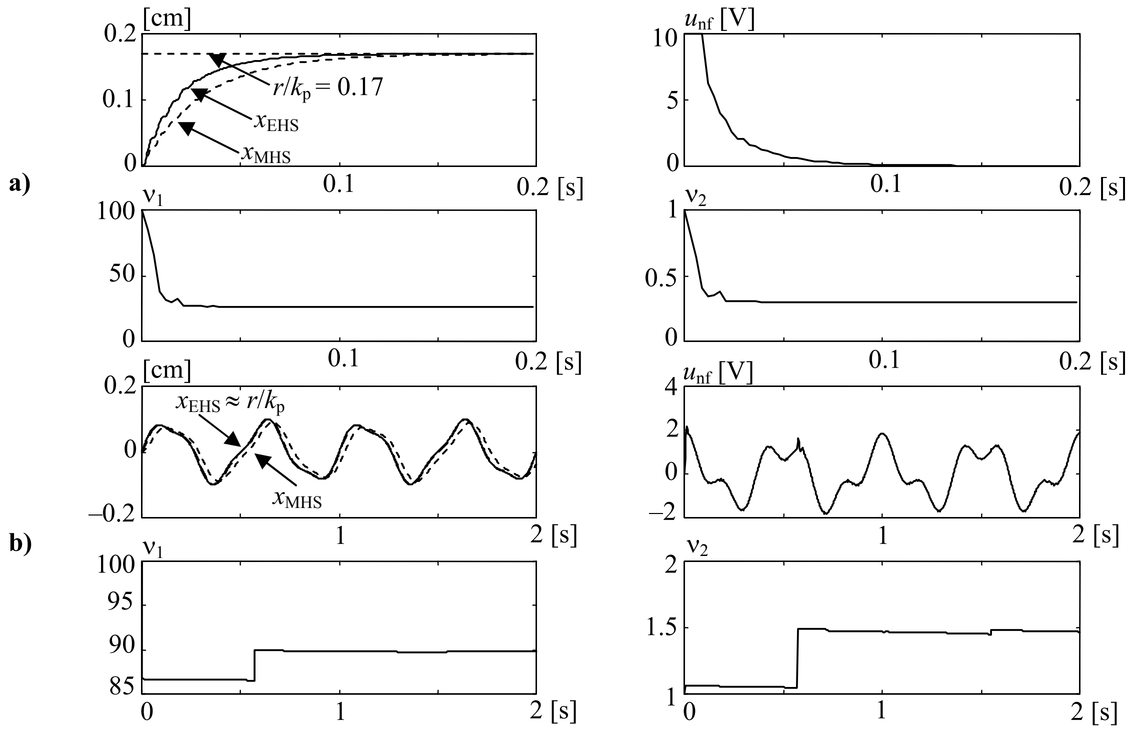

Fig. 4. Neuro-fuzzy controlled EHS, $F_f = 0$, comparison with MHS. Desired (r/k_p) and actual (x) piston displacements. a) step reference; b) sinusoidal combination reference.

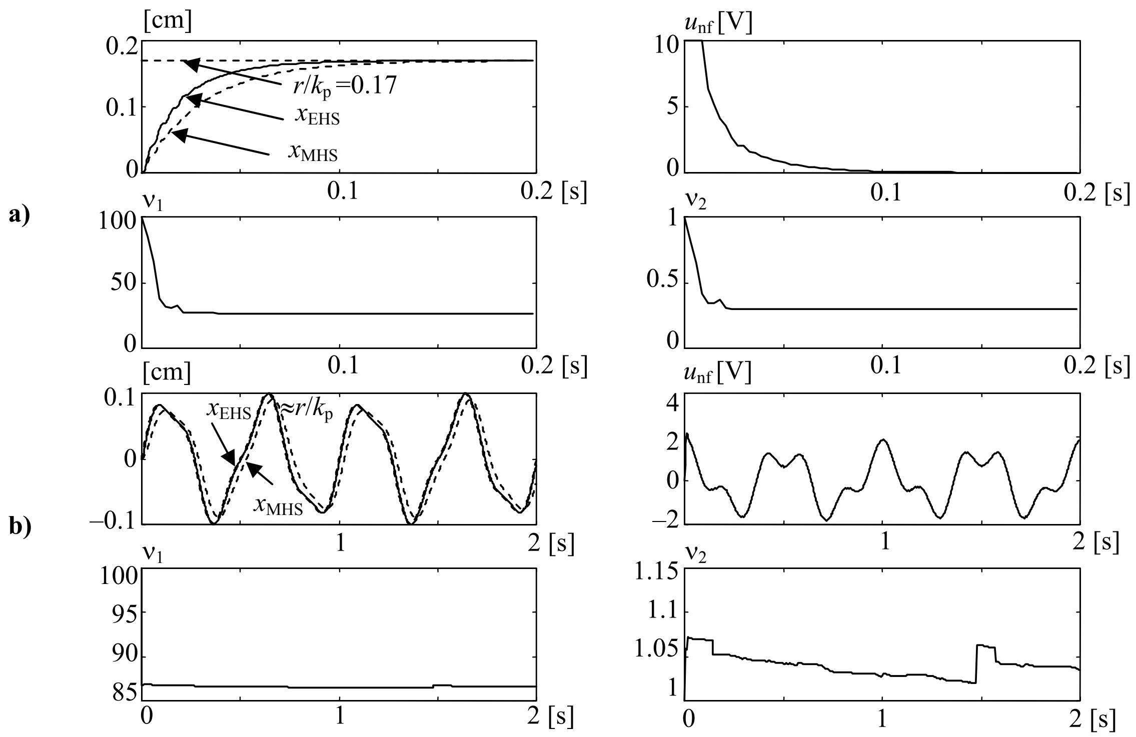

Fig. 5. Neuro-fuzzy controlled EHS, $F_f \neq 0$, comparison with MHS. Desired (r/k_p) and actual (x) piston displacements. a) step reference; b) sinusoidal combination reference.

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 [3] of internal friction F_{f} is defined by $f_{\mathrm{v}} = 60$ Ns/m, $\sigma_0 = 12 \times 10^5$ N/m, $F_{\mathrm{s}} =$ 120N, $\sigma_1 = 300$ Ns/m, $\mathrm{v_s} = 0.1$ m/s, $F_{\mathrm{c}} = 100$ N. In processing numerical experiments, the system operation is restricted to the noncavitation regime, i.e., $p_{\mathrm{s}} \geq p_{\mathrm{i}} > 0$, $\mathrm{i} = 1, 2$. The following set was tuned in a trial and error type process: initial weighting vector $\nu = [100 \;\; 1]$, learning rates $[\delta_1 \; \delta_2] = [5 \times 10^{-2} \;\; 10^{-4}]$ and weights $[q_1 \; q_2] = [300 \;\; 0.1]$ (by using physical units daN and cm in simulation). Better tracking performance of electrohydraulic servo (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.

5. Experimental Results

The present work reports that the FSNC was applied to the system described in Section 2. The detailed in Sections 3, 4 algorithm was implemented using a LabView type programming language. Alternate classical algorithms LQR and LQG were also implemented, in order to evaluate and compare the results. Various experimental results were thus collected.

In Figs. 6-9, representative time responses to step and sinusoidal references are shown, and a comparison classical versus FSNC is emphasized. The system controlled with FSNC is proved to be better than the corresponding LQG system (see transitory and stationary regime performances), in accordance with simulation studies. Consequently, the above results are very encouraging from viewpoint of development of the intelligent control strategies.

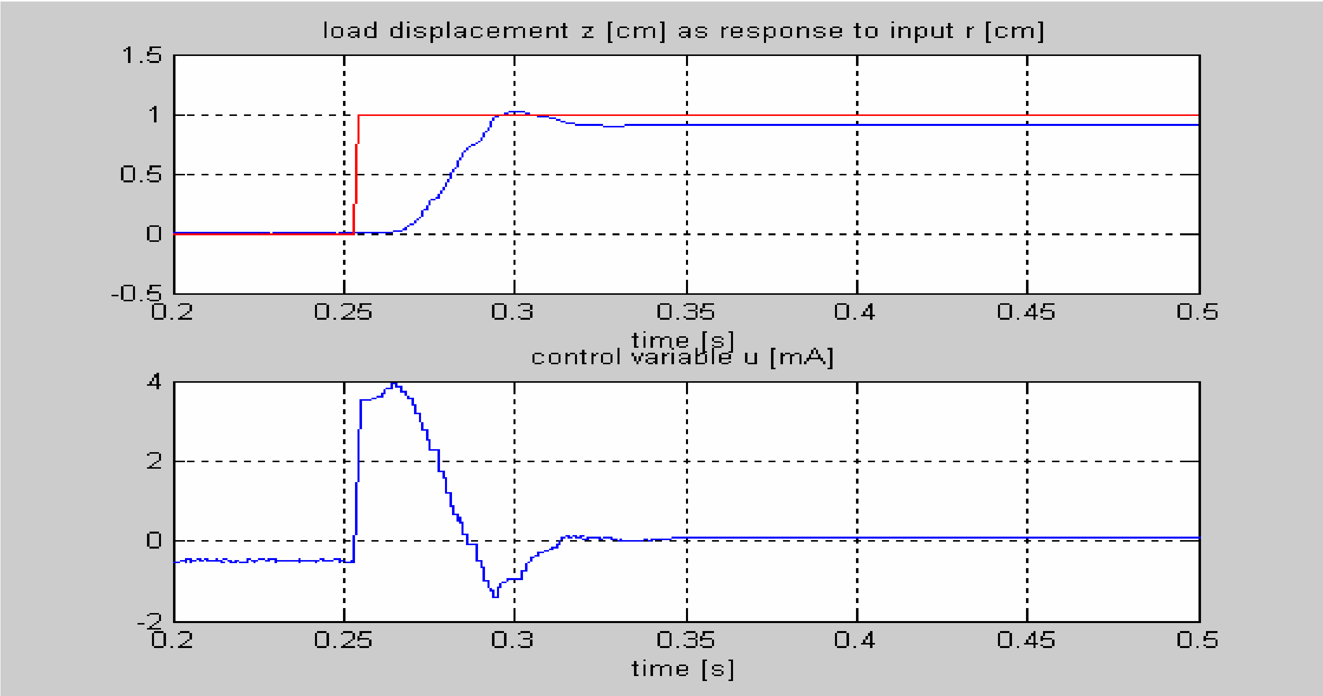

Fig. 6. Experimental tests, LQR algorithm. Overshoot 1.5 %, time constant 0.032 s, stationary error 10 %.

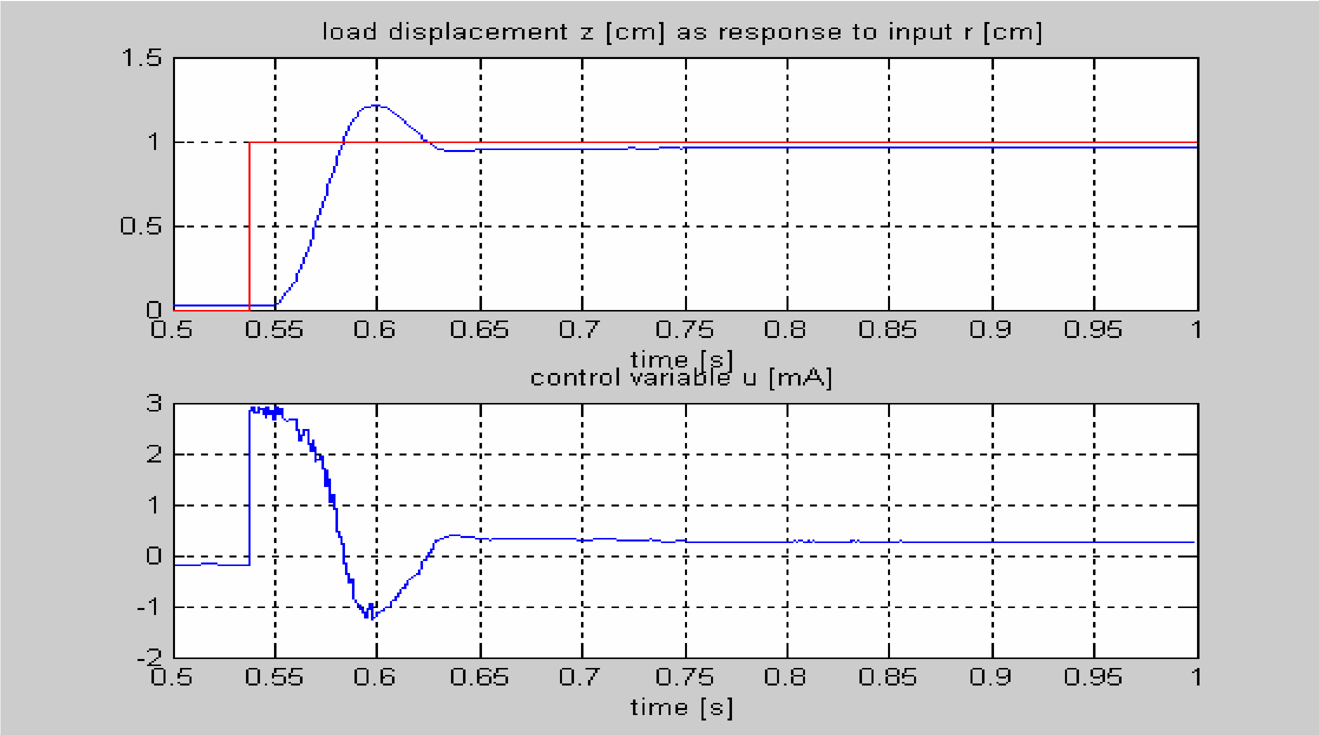

Fig. 7. Experimental tests, FSNC algorithm. Overshoot 21%, time constant 0.03 s, stationary error 4%.

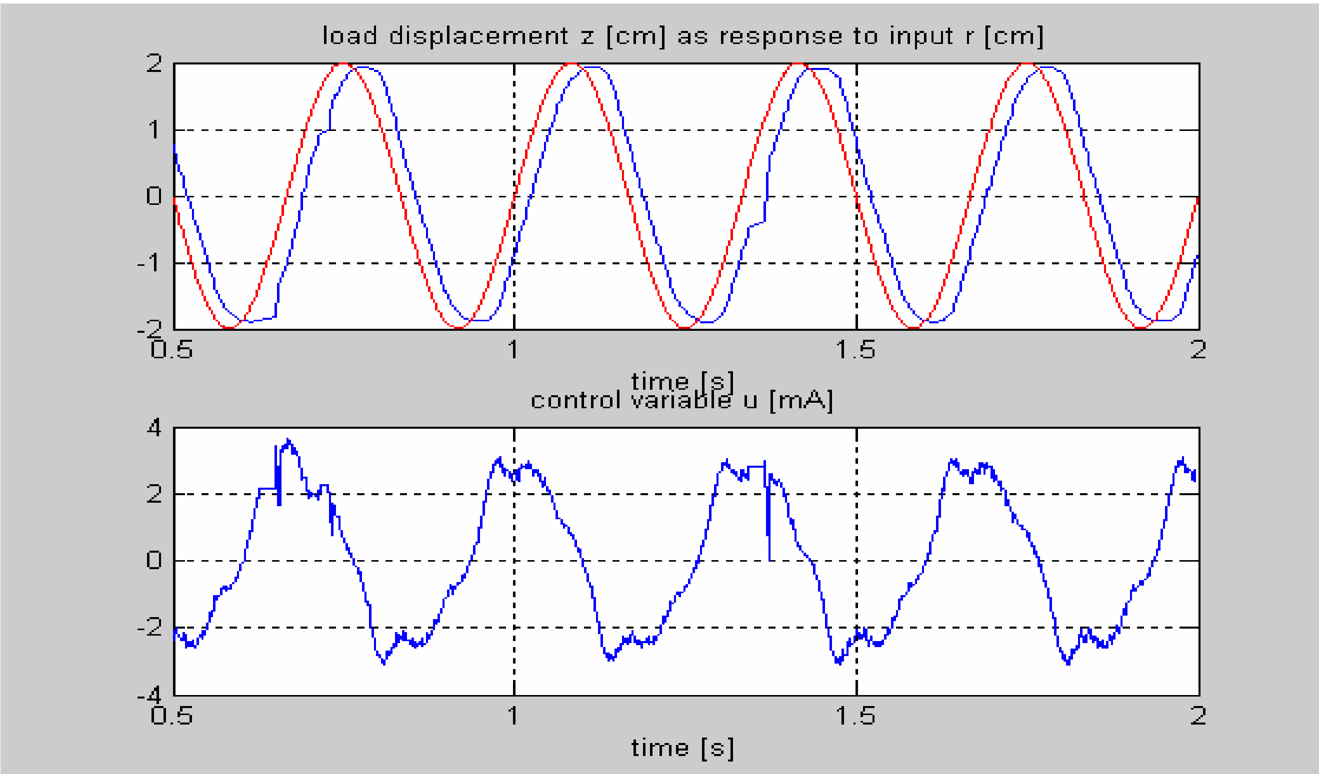

Fig. 8. Experimental tests, LQG algorithm: sinusoidal reference (amplitude 2 cm, frequency 3 Hz). Time delay 0.025 s, 10 % attenuation.

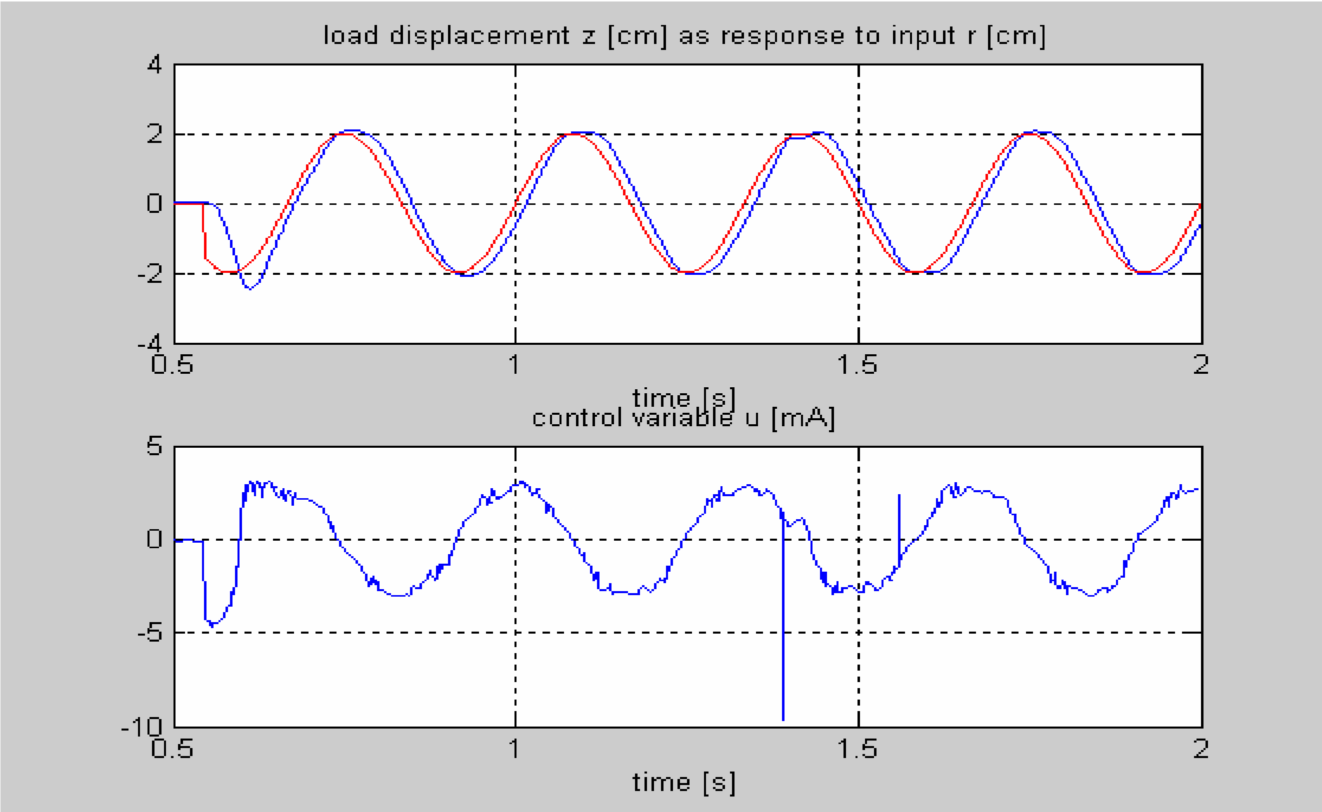

Fig. 9. Experimental tests, FSNC algorithm: sinusoidal reference response (amplitude 2 cm, frequency 3 Hz). Time delay 0.016 s, 0% attenuation.

5. Conclusions

The aforementioned FSNC is applied both in simulation studies and laboratory tests of the electrohydraulic servo system. The simulation studies The results attest good tracking performance in the presence of sinusoidal combination type signals, particularly in the presence of step signals. The assertion that "neural networks seem to be the most promising technique to design a robust, adaptive and intelligent control systems" [7] is worthy of noticing. With regard to fuzzy logic, this offers on excellent way "to combine mathematical models and heuristics into controllers" [6]. The artificial intelligence based synthesis of control law (in other words, using neurocontrol and fuzzy logic control) provides also the means to evade the mathematical model of the system. In fact, the salient feature of neurocontrol and fuzzy logic control, which distinguish them from the traditional control and adaptive approaches, is that they provide a model-free description of the control system.

Thus, our conclusion is that, in various approaches [1]–[3], [8]-[10], regarding as applications active and semiactive suspensions, electrohydraulic servo actuating primary flight controls and antilock-braking systems (ABS), the neuro-fuzzy control worked very well, frequently much better than the classical methodologies.

5. Nomenclature

Variables:

$x(t)$ – load displacement (defined from the center of the actuator cylinder [m])

$p_i(t)$ – actuator cylinder pressures (i = 1, 2) [N/m^2]

$r(t)$ – reference input (command) ([V], for EHS; [m], for MHS)

$u(t)$ – control, that is, valve input voltage [V]

$x_v(t)$ – valve spool displacement relatively to its sleeve, defined from the valve's neutral position [m]
$x_f(t)$ – internal friction state variable [m]
$F_f(t)$ – 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 [m^3], $C = S \times x_M$
B – bulk modulus of oil [N/m^2]
k_p – position transducer coefficient [V/m]
k_v – velocity scale factor [V×s/m]
$k_{x_v u}$ – 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]
c – valve discharge coefficient
λ – kinematic feedback coefficient of MHS
ρ – oil density [kg/m^3]

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
$\dot{f}$ – derivative of a function f with respect to time t

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