Neuro-fuzzy control synthesis for hydrostatic type servoactuators. Experimental results

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Abstract
Continuing recent works of the authors, the paper shows the developing and the application of a neuro-fuzzy control law to the positioning outer loop of a hydrostatic type servoactuator. Experimental results are presented concerning dynamical behavior of the system by using this "intelligent" controller. Finally, arguments about the advantages of the new designed controller are summarized.

1. Introduction

Basically, there are two types of electrohydraulic actuators (EHAs), widely used in various actuationl systems: valve controlled actuators [1] and pump controlled actuators (so called hydrostatic actuators) [2]-[5]). Each type of such actuators has its own specificity, advantages and drawbacks. The advantage of traditional, valve controlled, electrohydraulic actuation, versus the pump controlled one, concerns mainly a faster dynamic response. Inversely, the pump controlled system keeps the advantages of a better linearity, stability and efficiency due to the eliminating of throttle losses at the valve. And, first of all, the pump controlled system avoids the requirement of a large central system with a reservoir. Thus, the pump controlled actuation is in fact a cost and weight effective actuation.

The paper shortly describes the developing and the application of a neuro-fuzzy control law to the positioning control of the hydrostatic servoactuator. The organization of the work is as follow. In Section 2, the EHA physical and mathematical models and the control synthesis are described. Section 3 retains some numerical simulations. The Section 4 presents experimental results on the system, underlining its dynamical performance essentially represented by the time constant. Section 5 is devoted to summarize some conclusions concerning the advantages of the intelligent controllers versus classical ones.

2. Mathematical modeling and neuro-fuzzy control synthesis

Consider the architecture of a pump controlled EHA physical model given in Fig. 1. The primary component of the EHA is a double cylinder with simple action supplied with hydraulic oil by a fixed displacement, bidirectional gear pump. The transmission of the fluid power is obtained by very stiffly coupling the pump to the hydraulic cylinder, thus the electrohydraulic servovalve is not required. The pump is driven by an AC electric motor. The system is of closed type, so there is no direct contact between the oil and air. The electric motor has as analog input a speed reference signal from the range of ± 5 Volts. The rod position is controlled by varying the speed of the electric motor. The mathematical model of the EHA system is the following [3]-[6] (see the Notations)

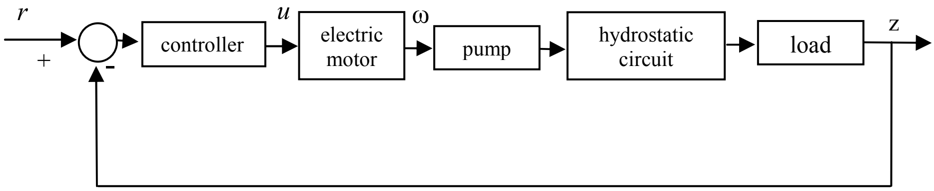

Fig. 1. Architecture of the pump controlled EHA physical model

$$\begin{aligned}
&\dot{x}_1 = x_2\\
&\dot{x}_2 = \frac{1}{m}\left[-kx_1 - fx_2 - F_f + S\left(x_4 - x_5\right)\right]\\
&\dot{x}_3 = x_2 - \frac{\sigma_0 \left|x_2\right| x_3}{F_c + \left(F_s - F_c\right)e^{-\left(x_2/v_s\right)^2}}\\
&F_f = \sigma_1 \dot{x}_3 + f_v x_2 + \sigma_0 x_3\\
&\dot{x}_4 = \frac{B}{V_{01} + Sx_1}\left[D_p x_6 - C_{ip}\left(x_4 - x_5\right) - C_{ep}\left(x_4 - p_r\right) - C_{ec}x_4 - Sx_2\right]\\
&\dot{x}_5 = \frac{B}{V_{02} - Sx_1}\left[-D_p x_6 + C_{ip}\left(x_4 - x_5\right) - C_{ep}\left(x_5 - p_r\right) - C_{ec}x_5 + Sx_2\right]\\
&V_{01} = V_{D_1} + Sl; V_{02} = V_{D_2} + Sl\\
&\tau\dot{x}_6 + x_6 = k_m u
\end{aligned} \tag{1}$$

The system includes a LuGre model of dry friction F_f [6].

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Artificial intelligence based approach in the treatment of control problems concerns in principle an input-output behavioral philosophy of solution. In fact, herein *the mathematical model (1) will serve only as illustration of applying this strategy. In the on line process variant, the mathematical model is naturally substituted by the physical system.*

The neuro-fuzzy control strategy adopted for the outer loop position control of the system is composed of two components: a neuro-control and a fuzzy logic control supervising the neuro-control to counteract the saturation.

As neuro-control, a unilayered perceptron is used (Fig. 2)

$$u := u_n = \nu_1 y_1 + \nu_2 y_2 =: \nu_1 (r - z) + \nu_2 \dot{z} \tag{2}$$

where $r(t)$ – reference input (command). From the system behavior view point, the input is u_n and the output is $\mathbf{y} = (y_1, y_2)$. From neuro-control 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

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

The weighting vector $\nu = [\nu_1 \ \nu_2]^{\mathrm{T}}$ is updated online by the gradient descent learning method to reduce the cost *J*. Consequently, the update is given by the expression

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

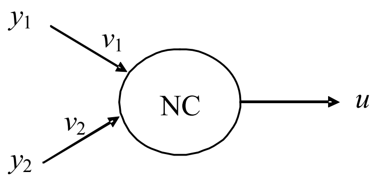


Fig. 2. Percepton type neurocompensator

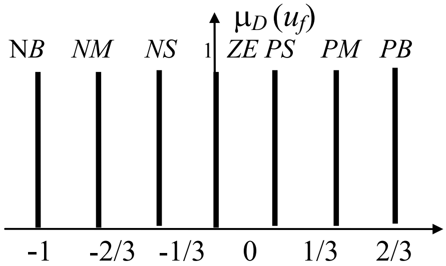


Fig. 3. Singleton membership function for scaled fuzzy control u_f

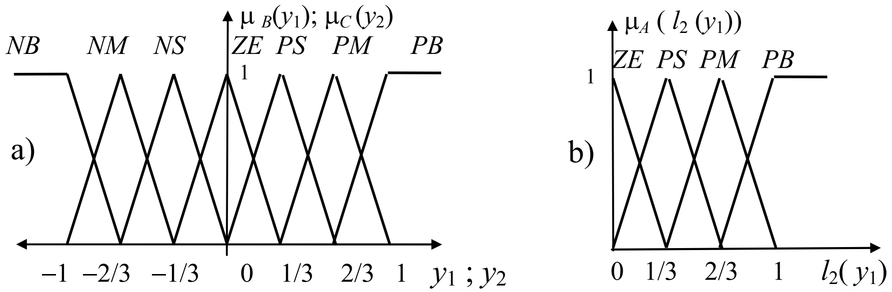


Fig. 4. Membership functions for: a) scaled input variables y_1, y_2 and b) $l_2(y_1)$

\where the matrix $\boldsymbol{diag}(\delta_1, \delta_2)$ introduces the learning scale vector, $\Delta\nu(n)$ 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. $\partial \mathbf{y}(i)/\partial u(i)$ is online approximated by the relationship

$$(\boldsymbol{y}(i)-\boldsymbol{y}(i-1))/(u(i)-u(i-1)) \tag{5}$$

To counteract the risk of neuro-control saturation and achieve the goal of reinforcement learning system, a Fuzzy Supervised Neuro-control (FSNC) was proposed in [7]. FSNC switches to a Mamdani type fuzzy logic control when the just described neuro-control saturated.

Further on, the three standard components of the fuzzy control: fuzzyfier, fuzzy reasoning, and defuzzyfier, will be succinctly exemplified. The used *fuzzyfier* component converts the crisp input signals

$$l_2(y_{1k}) := \sqrt{\sum_{j=k-2}^{k} y_{1j}^2}, \quad y_{1k}, y_{2k}, k = 1, 2, \dots \tag{6}$$

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 Figs. 3, 4). 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.

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
$\vdots$
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
$\vdots$
196) IF l_2 (y_1) is PB and y_2 is NB and y_1 is NB, THEN u_f is NB

Let T 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 $t_k = kT$ (k = 1, 2,...). Taking into account the two ordinates corresponding in Figs. 3, 4 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

$$\text{IF } y_{1k} \text{ is } B_i \text{ and } y_{2k} \text{ is } C_i \text{ and } l_2(y_{1k}) \text{ is } A_i, \text{THEN } u_{fk} \text{ is } D_i,\ i = 1,2,...,M \tag{7}$$

(A_i,B_i, C_i, D_i are linguistic terms belonging to the sets A, B, C, D and $D = B = C$, see Figs. 3, 4). 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 (10) 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

$$\mu_{u_i} = \min[\mu_{B_i}(y_{1k}), \mu_{C_i}(y_{2k}), \mu_{A_i}(l_2(y_{1k})), \mu_{D_i}(u)],\ i = 1,\ \dots\ , M, (k = 1,\ 2,\ \dots) \tag{8}$$

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 [8]

$$u_f = \sum_{i=1}^{M} \mu_{u_i} u_i^0 \Big/ \sum_{i=1}^{M} \mu_{u_i} \tag{9}$$

The FSNC operates as fuzzy logic control u_{f} in the case when neuro-control u_{n} saturated, or so called l_2 - norm of tracking error y_1 increased. In the case of fuzzy control operating, the fuzzy neuro-control 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 neuro-control whenever readjusted neuro-control 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 neuro-control occurs, the readjusted weighting vector ν_r will be derived by considering a scale factor $u_{\text{f}}/u_{\text{n}}$ [6]

$$\nu_{1\text{r}} = (u_{\text{f}} - \nu_2 y_2) u_{\text{f}} / (u_{\text{n}} y_1),\ \nu_{2\text{r}} = \nu_2 u_{\text{f}} / u_{\text{n}} \tag{10}$$

3. Numerical simulations

The aforementioned control was firstly brought to the proof in numerical simulations, having partially as reference the data given in [3] and also the data concerning the CESAR FP6 Project [9] and CNMP SAHA Project [10].

In the Figs. 5-6, representative time responses to step and sinusoidal references are shown. In accordance with simulation studies, in [5] it is proved that: a) the nonconventional neurofuzzy control, as compared with a proportional – P – control, improves the transients of EHA dynamics, mainly in the case of sinusoidal references: thus, a better tracking, meaning smaller attenuation and dephasage, are achieved; b) worthy noting, the neurofuzzy control is proved to ensure a more robust controlled EHA than classical P controlled system.

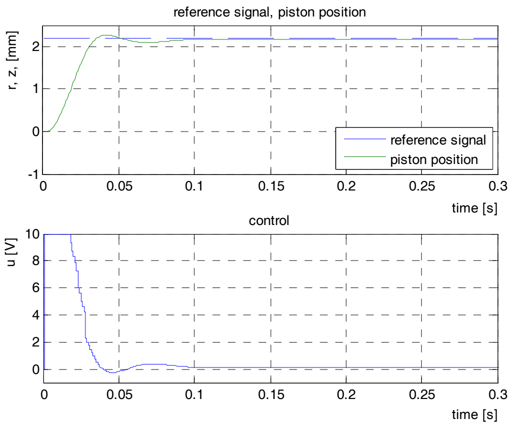


Fig. 5. Numerical simulation, neuro-fuzzy control, 2.2 mm step reference.
The result: actual servoactuator time constant $\tau_s \cong 0.023$ s [5]

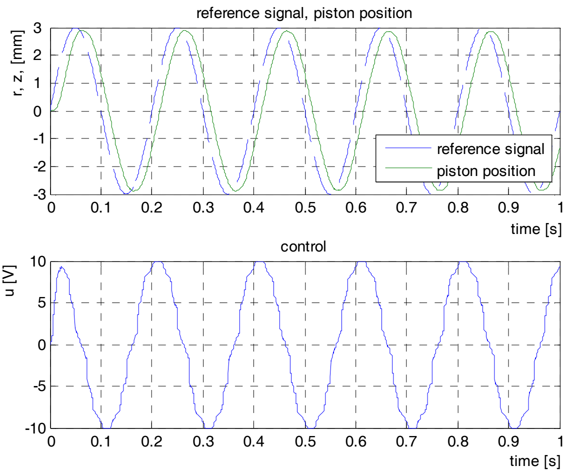


Fig. 6. Numerical simulation, neuro-fuzzy control: sinusoidal reference.
The result: 0.4dB attenuation, 0.015 s delay [5]

4. Experimental results

To test the proposed neuro-fuzzy control strategy and study fundamental problems associated with the control of hydrostatic EHA systems, the cylinder doublet – each part having simple action – is supplied with hydraulic oil by a fixed displacement, bidirectional *Haldex Hydraulics HX G2204C1A300N00 gear pump*. The transmission of the fluid power is obtained by very stiffly coupling the pump to the hydraulic cylinder. The pump is driven by an *AC Anaheim BLW235S-36V-4000 electric motor*. A *planetary gearbox* with 3:1 gear ratio is a part of electric motor. The main data of the pump: pump displacement – 1.07 cm^3/rot; nominal pressure – 207 bar; pump (and motor shaft) maximal speed (rad/s) – 3600 RPM; maximal flow – 3.86 l/min. The main data of the electric motor: peak torque – 1.3 Nm; rated power – 180 W; rated speed 4000 RPM; mass – 1.4 Kg; peak current – 22.5 A; rated voltage – 36 V; control maximal voltage – ± 5 V. A view of the motor-pump-hydraulic cylinder components of the system on the test rig is shown in Fig. 7.

Fig. 7. View of the test rig for the hydrostatic actuator

The experimental set up is presented in Fig. 8. The switches labeled L1 and L2 are used to stop the electrical motor at a stroke about than half of maximum stroke of the piston, as a measure of safety. The switch with positions labeled LIM (limited) and FREE is used to enable this protection on the LIM position. The other switch is used to select the motor command, MAN (manually) or AUT (automatically).

Some conclusive experimental recordings are shown in Figs. 9-12, which collect time responses to step and sinusoidal references. Implementation of neuro-fuzzy algorithm was performed using LabView programming language. The initial values of weighting vector ν (noted on figures w) has a certain importance, but not decisive for the algorithm working; compare Figs. 9-11 with Fig. 12. As it can be seen from Fig. 10, a value of the actual servoactuator time constant $\tau_s = 0.0824\,\mathrm{s}$ is obtained. This value is confirmed by a theoretical evaluation. Indeed, let us consider the paradigmatic structure of control (compare with (2))

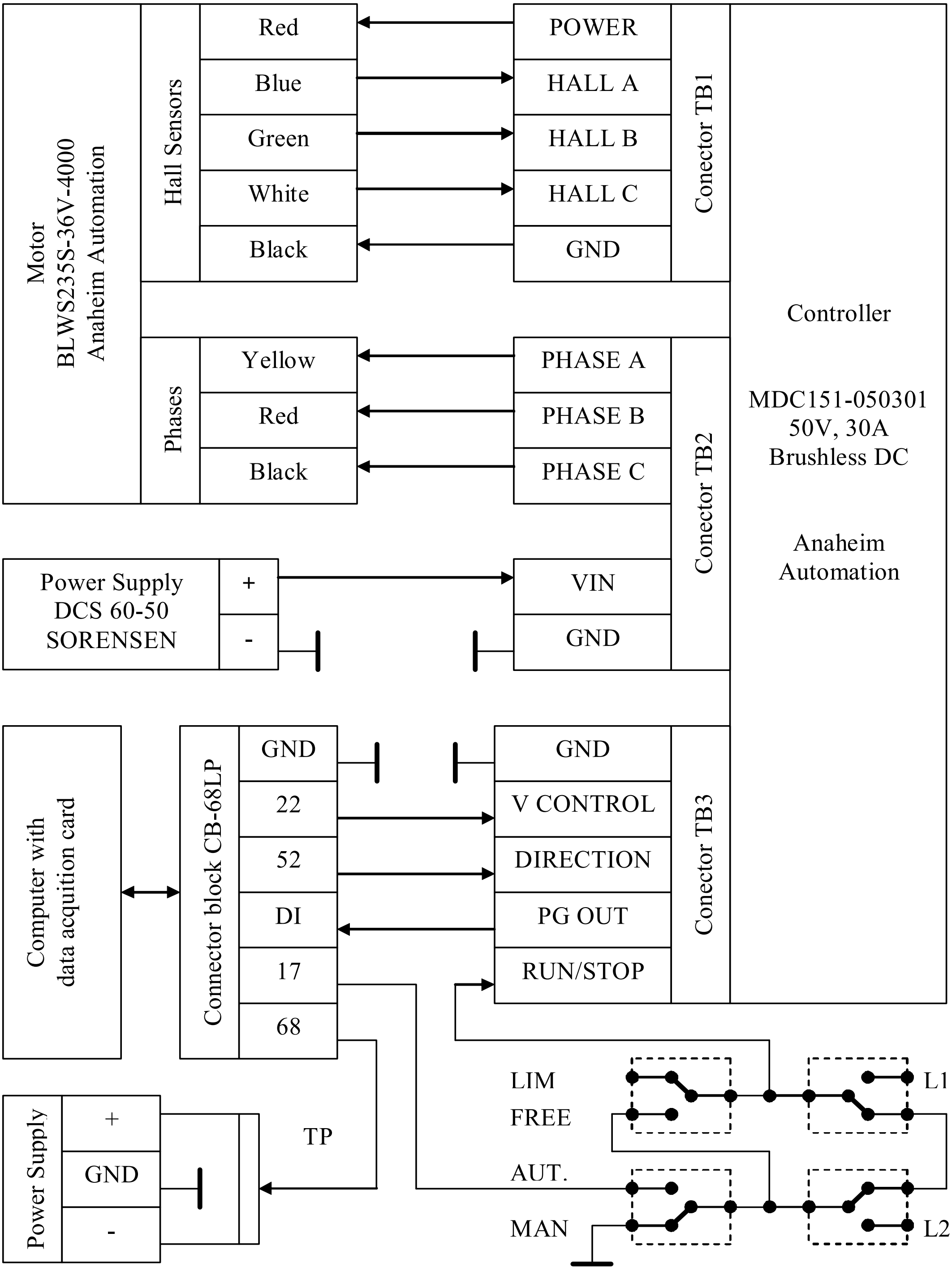
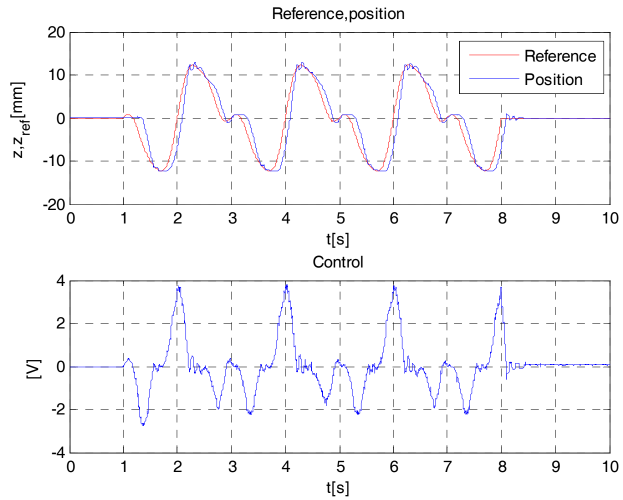


Fig. 8. Electrical connection diagram

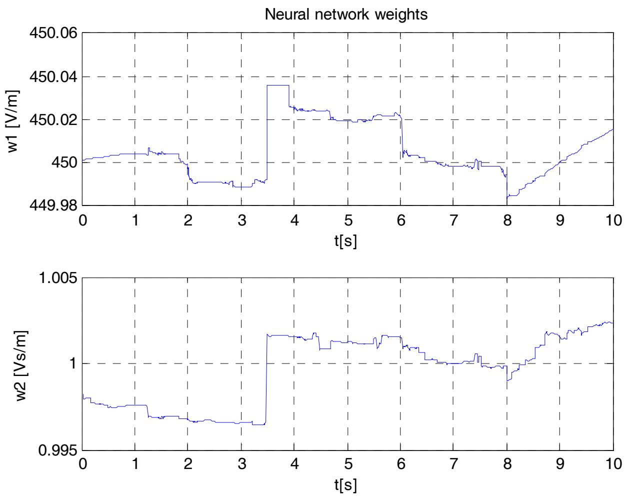
$$u = K\left(r - z\right) \tag{11}$$

A reduced mathematical model derived from (1) is

$$\begin{gathered} m\ddot{z} + f\dot{z} + kz = Sp,\ p := x_4 - x_5 \\ \frac{V}{B}\dot{x}_4 = D_p x_6 - S\dot{z},\ \frac{V}{B}\dot{x}_4 = -D_p x_5 + S\dot{z} \\ \tau\dot{x}_6 + x_6 = k_m u \end{gathered} \tag{12}$$

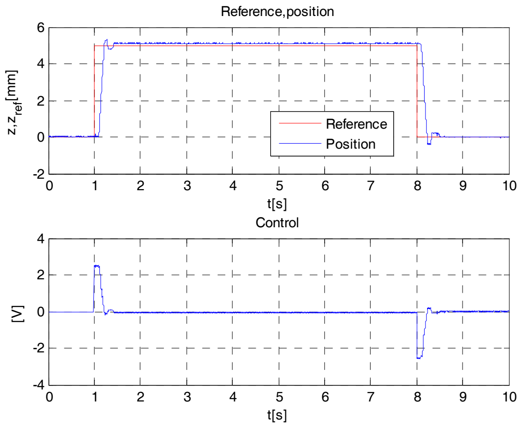


a) Time histories for reference r, position z and control u variables

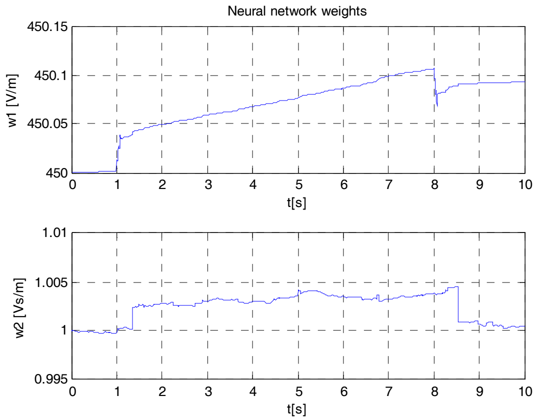


b) Time histories for weighting vector, noted v in the relation (2)

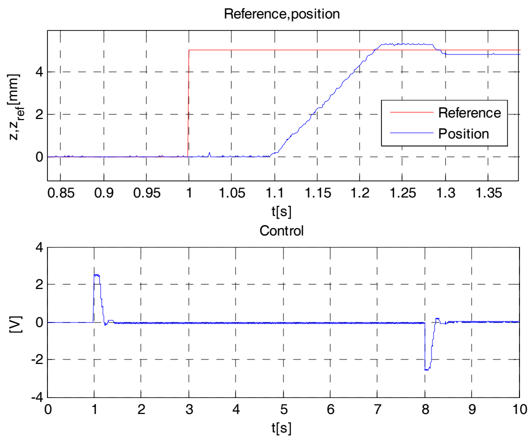
Fig. 9. Experimental recording, neuro-fuzzy control, sinusoidal signals combination reference



a) Time histories for reference r, position z and control u variables



b) Time histories for weighting vector noted v in the relation (2)



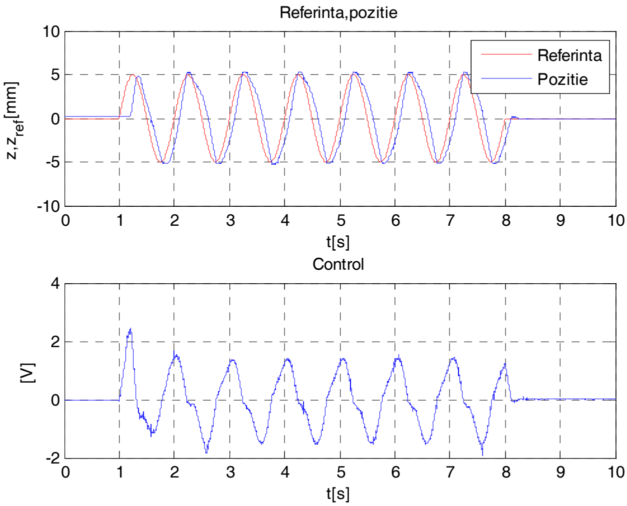
c) zoom on a)

Fig. 10. Experimental recording: neuro-fuzzy control, step reference signal.

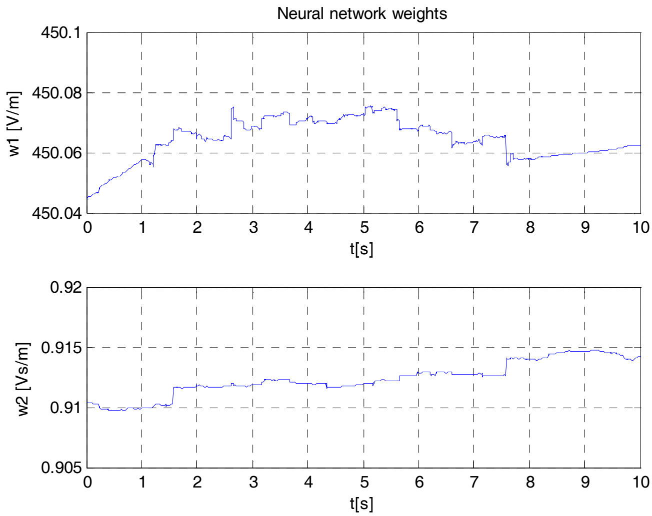
The result: actual servoactuator time constant $\tau_s = .0824$ s (delay ignored!)

From (11)-(12), the transfer function $r \rightarrow z$ can be written as

$$\left\{(\tau s+1)\left[ms^3 + fs^2 + \left(k + \frac{2S^2B}{V}\right)s\right] + \frac{2SBD_pk_mK}{V}\right\}z = \frac{2SBD_pk_mK}{V}r \qquad (13)$$



a) Time histories for reference r, position z and control u variables

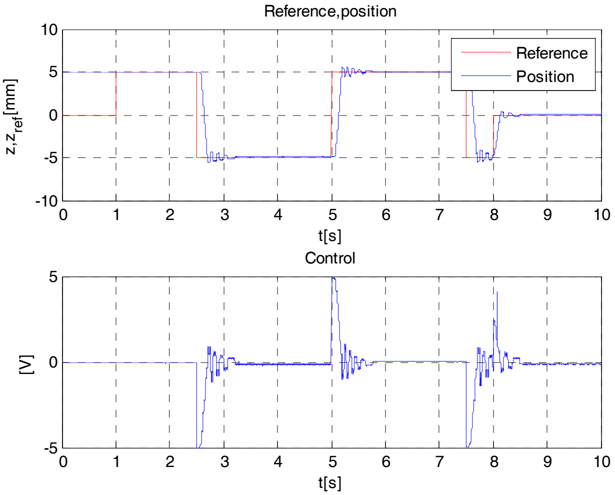


b) Time histories for weighting vector noted ν in the relation (2)

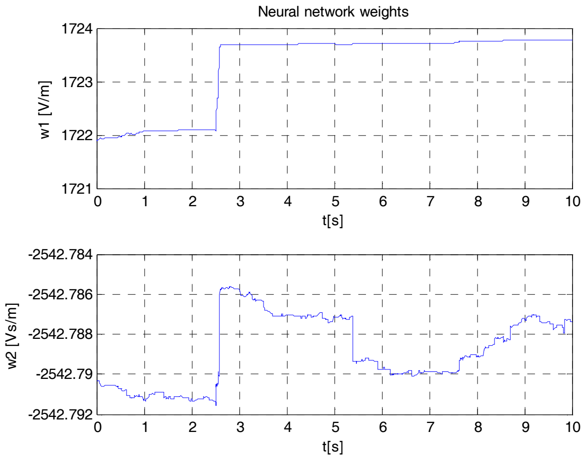
Fig. 11. Experimental recording: neuro-fuzzy control, sinusoidal reference

The system can be expressed as an order one system in the manner

$$(a_0 s + a_1) z = b_0 r \tag{14}$$



a) Time histories for reference r, position z and control u variables



b) Time histories for weighting vector noted v in the relation (2)

Fig. 12. Experimental recording: neuro-fuzzy control, step reference

so we have the time constant

$$\tau_s = \frac{a_0}{a_1} = \frac{\dfrac{k + 2S^2 B}{V}}{\dfrac{2SBD_p k_m K}{V}} = \frac{kV + 2S^2 B}{2SBD_p k_m K} \tag{15}$$

or, taking into account the value $k \cong 0$ in experiment,

$$\tau_s \cong \frac{S}{D_p k_m K} \tag{15'}$$

To determine motor speed-control voltage gain k_m, the measurement shown in Fig. 13 was performed, with 1V control voltage in loaded regime; the found time constant is $\tau = 0.265\,\mathrm{s}$. Based on equation $\tau\dot{x}_6 + x_6 = k_m u$, we have

$$0.265\frac{\theta_1 - \theta_0}{\Delta t} + \theta_0 = k_m,\ 0.265\frac{300-0}{0.0978} + 0 = k_m,\ k_m = 85.12\,\mathrm{rad/(sV)}$$

but a speed reduction factor $1/3$ from motor to pump is involved, thus

$$k_m = 85.12/3\,\mathrm{rad/(sV)} = 28.37\,\mathrm{rad/(sV)}$$

Substituting in (15′) the cylinder-pump-motor main data and the optimized by an *trial and error* procedure controller gain K

$$S = 2\times 10^{-4}\,\mathrm{m}^2,\ D_p = 1.7\times 10^{-7}\,\mathrm{m}^3/\mathrm{rad},\ k_m = 28.37\,\mathrm{rad/(sV)}, K = 450\frac{\mathrm{V}}{\mathrm{m}}$$

(little piston’s surfaces are suplied) gives

$$\tau_s \cong 0.09\,\mathrm{s}$$

that is a value close to the experimental value $\tau_s \cong 0.0824\,\mathrm{s}$. The size of controller gain K is in fact provided as the value of ν_1 weight in Figs. 9-11, where ν_2 is relatively negligible.

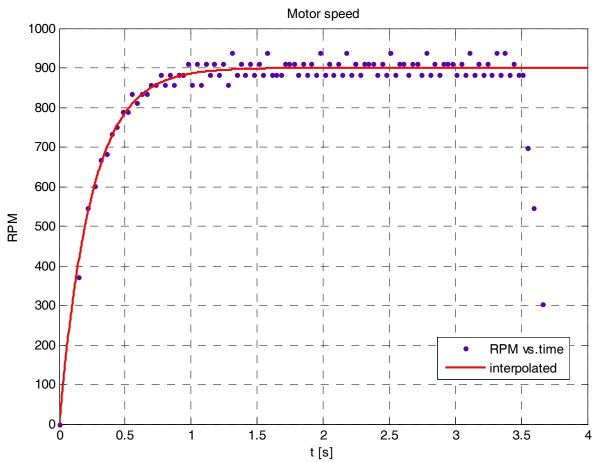


Fig. 13. Measuring motor time constant τ and angular speed-control voltage gain k_m in loaded regime, 1 V control input

Worthy noting, the value $\tau_s \cong 0.023\text{s}$ testified in Fig. 5 is associated with different values of the physical parameter $D_p = 1.6925 \times 10^{-7}\,\text{m}^3/\text{rad}$ and with different K, see [6].

5. Conclusions

The studies and experimental results in the literature show that the neuro-fuzzy control not only extends the system bandwidth, but also provides excellent control performance on contrast with various classical control strategies in hydraulic servo position systems [11], [12].

Considering previous researches of the authors [1], [5]-[7], the main conclusion of the paper concerns the remarkable fact that neuro-fuzzy control algorithm ensured well dynamical behavior of the hydrostatic servoactuator. Let note the most meaningful feature of this proposed controller: because is in fact a free model strategy, this methodology ensures a reduced design complexity and provides antisaturating and antichattering properties of the controlling system [13], thus favourising its robustness.

Notations and values of the parameters

Variables

$x_1 \equiv z$ – load displacement [m]; x_2 – load velocity [m/s]; x_3 – state value concerning internal friction [m]; x_4 – pressure in cylinder chamber one [Pa]; x_5 – pressure in cylinder chamber two [Pa]; $\omega := x_6$ – pump and motor shaft speed [rad/s]; F_f – internal friction force due the tight sealing [N]; r – reference input (command) [m]; u [V] – control variable

Parameters

$m = 20\text{Kg}$ – total mass of the piston and the load referred to piston; $f = 10^4\,\text{Ns/m}$ – load viscous damping coefficient; $k = 1190000\,\text{N/m}$ – load spring gradient; $S = 2 \times 10^{-4}\,\text{m}^2$ – piston area; $l = 0.1\,\text{m}$ – half of piston stroke; $V_{D_1} = V_{D_2} = V = 3.95 \times 10^{-7}\,\text{m}^3$ – dead volumes of the hydraulic lines; $D_p = 1.6925 \times 10^{-7}\,\text{m}^3/\text{rad}$ – pump displacement; $B = 6 \times 10^8\,\text{Pa}$ – bulk modulus of the oil; $p_a = 207 \times 10^5\,\text{Pa}$ – nominal pressure; $p_r = 5 \times 10^5\,\text{Pa}$ – minimal pressure of the hydraulic system; $k_m = 28.37\,\text{rad}/(\text{sV})$ – motor gain; τ – motor time constant [s]; τ_s – servoactuator time constant [s]; K – controller gain [V/m]; $C_{ec} = 1.9 \times 10^{-13}\,\text{m}^3/(\text{Pa}\times\text{s})$ – external leakage coefficient; $C_{ip} = 2 \times 10^{-13}\,\text{m}^3/(\text{Pa}\times\text{s})$ – internal leakage coefficient; $\sigma_0 = 2 \times 10^4\,\text{N/m}$ – stiffness coefficient ; $\sigma_1 = 3 \times 10^2\,\text{Ns/m}$ – damping coefficient; $f_v = 60\,\text{Ns/m}$ – viscous friction coefficient; $v_s = 0.1\,\text{m/s}$ – Stribeck velocity; $F_c = 100\,\text{N}$ – Coulomb friction; $F_s = 120\,\text{N}$ – static friction.

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