COBEM UBERLÂNDIA 2019

ABCM Associação Brasileira de Engenharia e Ciências Mecânicas

25th ABCM International Congress of Mechanical Engineering
October 20-25, 2019, Uberlândia, MG, Brazil

A HYDRAULIC ACTUACTOR MODEL USING FEEDFORWARD NEURAL NETWORKS

Fábio Augusto Pires Borges
Universidade Federal do Rio Grande – Escola de Engenharia, Av Italia, km 8 , Rio Grande, RS, Brazil
fborges@furg.br

Eduardo André Perondi
Universidade Federal do Rio Grande do Sul, Rua Sarmento Leite 425, 90050-170 Porto Alegre, RS, Brazil
eduardo.perondi@ufrgs.br

Mauro André Barbosa Cunha
Instituto Federal de Educação, Ciência e Tecnologia Sul Rio Grandense, Praça Vinte de Setembro, 455, 96015-360 Pelotas, RS, Brazil
maurocunha@ifsul.edu.br

Mario Roland Sobczyk S
Universidade Federal do Rio Grande do Sul, Rua Sarmento Leite 425, 90050-170 Porto Alegre, RS, Brazil
mario.sobczyk@ufrgs.br-

Abstract. *In this work, a neural network is used as a substitute for the analytic functions that are employed in the traditional nonlinear models applied to hydraulic actuators. The traditional mathematical models of hydraulic actuators are highly nonlinear and depend on parameters whose values have significant uncertainties, requiring large amounts of experimental effort to be identified. On the other hand, neural network methods require very little effort regarding such parameter identification. The effectiveness of the proposed method is verified by means of experimental results.*

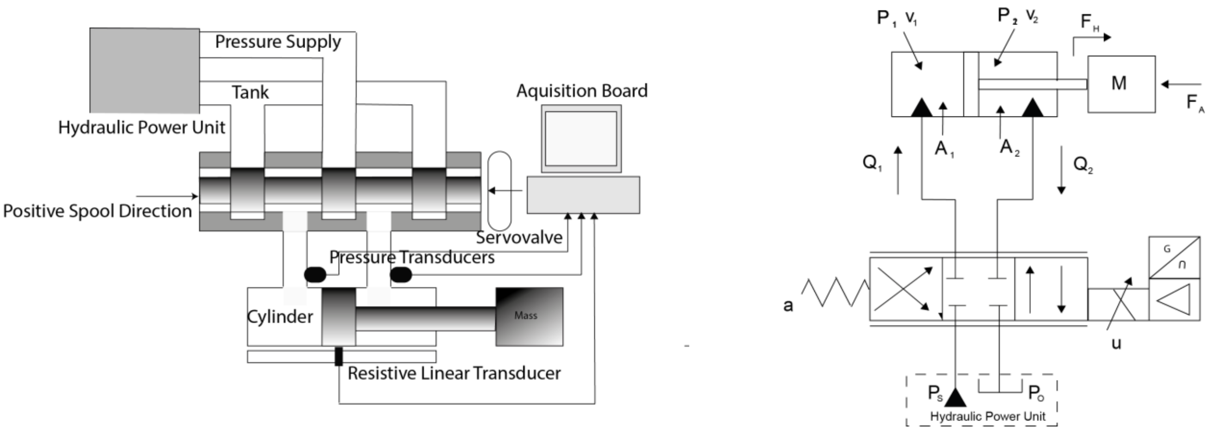
Keywords: *hydraulic actuator, neural networks, mathematical model.*

1. INTRODUCTION

Due to their high force/size ratios, hydraulic actuators are widely used in tasks combining high forces with limited dimensions. However, their dynamic behavior is characterized by several strongly nonlinear phenomena, such as the dependence of pressures on the flow rates going into or out of the actuator chambers, leakages and/or dead zones due to the control valves, and friction forces on the actuating piston (Coelho and Cunha, 2011; Borges, 2017; Noskievič, 2018). Besides resulting in very poor performances when controllers based on linear approximations are employed (Coelho and Cunha, 2011, Pasolli and Ruderman, 2018), these and other nonlinear effects pose significant difficulties even when inherently nonlinear control methods are used, because the corresponding mathematical models depend on many key parameters that are difficult to determine with small uncertainty, such as the oil bulk modulus (Wang et al., 2008), leakages and head losses in piping connections (Li et al., 2019), and dead zone limits in control valves (Gu et al., 2018). Moreover, many parameters are affected by fluid temperature, so that their values appear to be "time-varying" if such dependency is not explicitly accounted for (Borges, 2017). Thus, effective control schemes for these systems can only be attained by means of extensive "fine tuning" procedures, based on several time-consuming experiments.

Intelligent strategies, such as Fuzzy Logic or Neural Networks, have been widely used in many different applications, largely because of their ability of "learning by themselves" how to adapt to their working environment. In the area of control systems, for instance, neural networks are extensively used as the core of many control algorithms with the aim of depicting the mathematical model of the system (Narendra and Parthasarathy, 1990; Lewis et al., 1999; Blokdyk, 2019). Specifically in the control of hydraulic actuators, neural network approaches have also been successfully used in many high-precision applications (Daachi and Sirdi, 2001; Li, et al., 2013; Pedro and Ekorn, 2013; Liu et al.,2019).

In this work, a feedforward multilayer neural network is employed as a substitute for the analytical nonlinear functions commonly used for the representation of the mathematical model in a hydraulic actuator. With this approach, one avoids time-consuming experimental identification procedures for all necessary parameters. The effectiveness of the proposed method is shown by means of experimental results.



(a) (b)

Figure 1. Hydraulic actuator: (a) general view, (b) schematic circuit (Borges et al., 2016)

The work is organized as follows. In Section 2, a nonlinear analytical model for the actuator is presented, whereas its neural network-based counterpart is discussed in Section 3. Experimental results are presented in Section 4. Finally, the main conclusions are outlined in Section 5.

2. DYNAMIC MODEL OF A HYDRAULIC ACTUACTOR

Figure 1 depicts a hydraulic actuator, which comprises a differential cylinder attached to an external load and controlled by a symmetrical four-way servovalve. Its operation can be better understood by means of a schematic circuit (Fig.1b): by regulating the volumetric flow rates Q_1 and Q_2 into and out of chambers 1 and 2, respectively, the servovalve applies a hydraulic force F_H on the piston, thus causing its motion. The most important variables and parameters involved in this process are also highlighted in the Fig.1b: the chamber pressures are p_1 and p_2, whereas p_s is the supply pressure and p_0 is the reference pressure. M is the total mass, and B is the piston seal viscous friction coefficient. A_1 is the piston cross section area, A_2 is the difference between the areas of the piston and the rod, v_1 and v_2 are the total volumes in lines 1 and 2, and u is the electrical control signal applied to the valve. The traditional dynamic modeling of the system is based on Newton's Second Law combined with flow-continuity considerations, as described in detail in Watton (2012). The main equations representing the system dynamics are:

$$F_H = p_1A_1 - p_2A_2 = M\ddot{y} + B\dot{y}\,. \tag{1}$$

$$\dot{p}_1 = \frac{\beta}{v_1 + A_1 y}\left(Q_1 - A_1\dot{y}\right) \tag{2}$$

$$\dot{p}_2 = -\frac{\beta}{v_2 - A_2 y}\left(Q_2 - A_2\dot{y}\right) \tag{3}$$

where y, $\dot{y}$ and $\ddot{y}$ are the position, velocity and acceleration of the piston-load assembly, respectively; and β is the effective bulk modulus of the hydraulic fluid. The volumetric flow rates through the valve orifices are functions of the pressures in the chambers and the input signal applied to the valve, and can be expressed by means of:

$$\begin{aligned} Q_1 &= K_{v1}ug_1, \quad g_1 = \begin{cases} \sqrt{p_s - (p_1 + l_1)}, & u \ge 0 \\ \sqrt{p_1 - l_3}, & u < 0 \end{cases} \\ Q_2 &= K_{v2}ug_2, \quad g_2 = \begin{cases} \sqrt{p_2 - l_4}, & u \ge 0 \\ \sqrt{p_s - (p_2 + l_2)}, & u < 0 \end{cases} \end{aligned} \tag{4}$$

where K_{v1} and K_{v2} are the gains that characterize each orifice of the valve, and l_1 to l_4 are the pressure losses caused by the hydraulic line couplers, which are significant and must be taken into account when high-precision tasks are considered. Defining auxiliary terms f_1 and f_2 as:

$$\cdot\ f_1 = \frac{\beta}{v_1 + A_1 y}, \quad f_2 = \frac{\beta}{v_2 - A_2 y}. \tag{5}$$

Now, replacing Q_1, Q_2, f_1, and f_2 in (2) and (3) by their corresponding terms given in (4) and (5), one obtains:

$$\dot{p}_1 A_1 - \dot{p}_2 A_2 = A_1 f_1 Q_1 + A_2 f_2 Q_2 - (A_1^2 f_1 + A_2^2 f_2)\dot{y}\,. \tag{6}$$

These equations show that practical application of the model implies the knowledge of several parameters. Whereas A_1, A_2, v_1 and v_2 are usually obtained accurately from catalog data or straightforward measurements, determination of the remaining parameters is seriously hindered by the following issues:

- the bulk modulus β is a known constant for each hydraulic fluid. However, in practice, Its value is affected by the overall equivalent stiffness of the system, which can be significantly reduced by the combined effects of hose flexibility, oil temperature and the presence of dissolved gases (Wang et al., 2008);
- valve gains K_{v1} and K_{v2} vary significantly with spool position. and, in particular, due to dead zone effects, these gains may fall to zero in the vicinity of the valve's neutral position (Pasolli and Ruderman, 2018; Gu et al., 2018);
- dry-friction forces on the actuator piston depend simultaneously both on its velocity and on the other forces acting on it, with sharp variations that are very difficult to measure at near-zero velocities (Pasolli and Ruderman, 2018);
- pressure drops and internal leakages due to connections and moving parts often occur on difficult-access spots (Borges, 2017).

As these combined factors lead to the need of considerable efforts to obtain a reliable set of model parameters, an alternative modeling approach is desirable for these systems. This is the main purpose of the proposed work.

3. NEURAL MODEL OF A HYDRAULIC ACTUATOR

The feedforward multilayer perceptron (MLP) neural network is usually applied to static mappings and defined as

$$y = \Gamma\left[\mathbf{W_n}\Gamma\left[\mathbf{W_{n-1}}...\Gamma\left[\mathbf{W}_1\mathbf{u} + \mathbf{b}_1\right] + ... + \mathbf{b_{n-1}}\right] + \mathbf{b_n}\right] \tag{7}$$

where $\mathbf{W_i}$ is the weighting matrix of the i-th layer, $\mathbf{b_i}$ is the bias vector associated with each layer node, and $\mathbf{\Gamma}(x)=[\gamma_1(x), \gamma_2(x), \dots, \gamma_n(x)]$ is a nonlinear operator where each $\gamma_i(.)$ is a monotonic and continuously differentiable activation function. The work of Haykin (2001) yields a complete description and the range of applications of a MLP neural network. Figure 2 shows the representation of a MLP neural network.

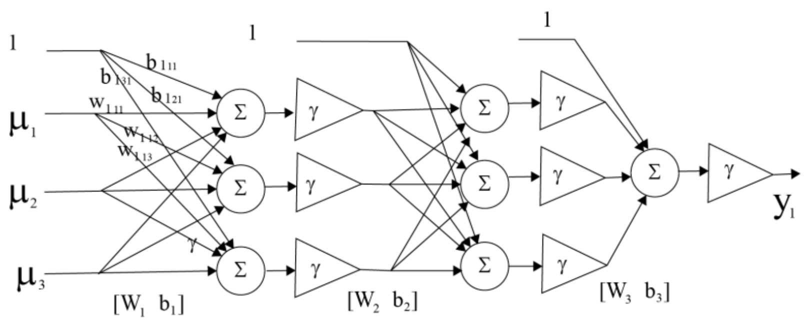


Figure 2. Feedforward multi-layer perceptron neural network

In the present work, a MLP neural network is applied to replace the nonlinear terms present in Equation (4). Another MLP is also applied as a friction model, replacing the viscous friction model expressed in the Equation (1). The new representations for these equations are defined by

$$F_H = p_1 A_1 - p_2 A_2 = M\ddot{y} + N_\Delta(\dot{y}) \tag{8}$$

$$\begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} = \mathbf{N}_\gamma(\dot{y}, p_1, p_2)u \tag{9}$$

where N_Δ and $N\gamma$ are MLP neural networks. The Neural Networks training process is performed off-line.

4. EXPERIMENTAL RESULTS

The experimental setup comprises a Bosch Rexroth CDT3ME5 double action hydraulic cylinder, with 200 mm utile stroke, controlled by means of a 4-way Bosch Rexroth 4WRPEH6 directional servo valve. All hydraulic connections use 1/4-inch (6.285 mm) diameter hoses. The pressure transducers are Rexroth HM-18-210 bar for the pressure chamber 1 and Huba Tp-491-400 bar for the pressure chamber 2. The piston position is measured using a Novotechnic TLH300 resistive sensor. The corresponding velocity is estimated by numeric differentiation of the position signal. All measured signals are digitally filtered and the control algorithm is processed in a PC-hosted DSpace 1104 real-time control board. Algorithm programming is performed with a Matlab-Simulink software package. The experimental setup is illustrated by means of the Fig.3. The parameters of the model are outlined in Tab.1.

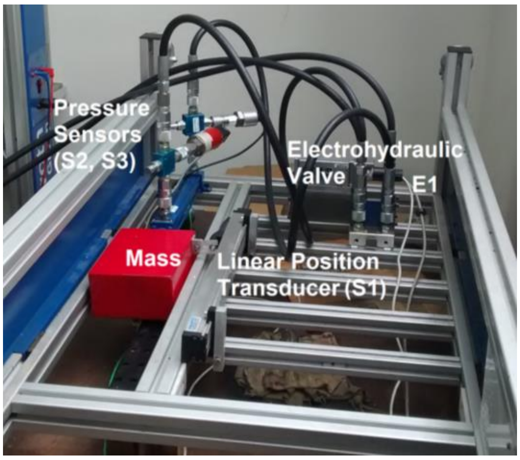


Figure 3. Experimental Setup.

Table1. System parameters (Borges, 2017)

Parameter	Value	Estimation method
V_{10}	1.2446×10^{-4} m^3	Direct measurement
V_{20}	9.9060×10^{-5} m^3	Direct measurement
y_0	0.1 m (center)	Direct measurement
K_{v1} ; $K_{v2,}$	$\sqrt{2}.15.11\times10^{-9}$ m^3/(s$\times\sqrt{\text{Pa}}$)	Manufacturer catalog
l_1	$5.68\times10^{10}\text{Q}_1$ Pa	Interactive simulation
l_2	$4.35\times10^{10}\text{Q}_2$ Pa	Interactive simulation
l_3	$3.59\times10^{10}\text{Q}_1$ Pa	Interactive simulation
l_4	$3.59\times10^{10}\text{Q}_2$ Pa	Interactive simulation
M	14.54 kg	Direct measurement
A_1	4.91×10^{-4} m^2	Direct measurement
A_2	2.37×10^{-4}m^2	Direct measurement
β	1.0×10^9N/m^2	Typical value
P_s	50×10^5Pa	Input choice
B	3600 Ns/m	Indirect measurement

The training process of the neural networks were performed using three training sets according the methodology proposed in Haykin (2001). These training sets were acquired experimentally. A single proportional controller was used to perform a tracking position control, where a suitable polynomial position trajectory was tracked. Then, the signals applied to the valve input were saved and applied to the open loop system. Finally, these inputs and the corresponding measurements of the system's variables formed the neural network training sets. This procedure is illustrated schematically in figures 4 and 5.

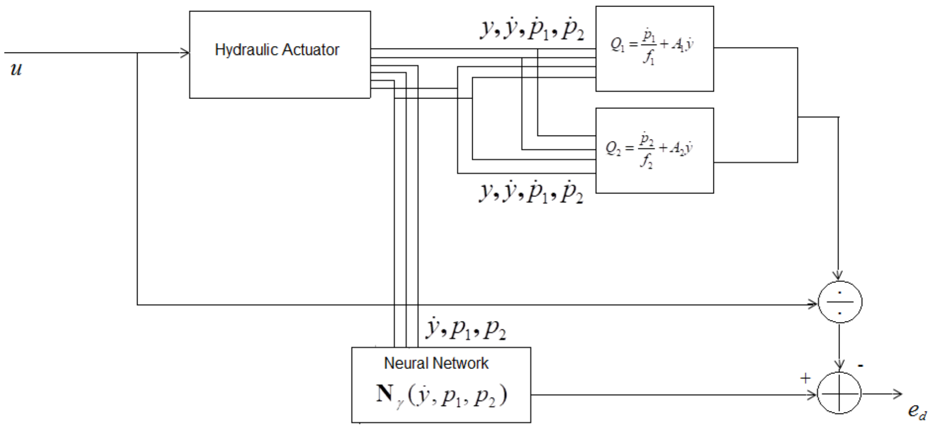


Figure 4. Neural Network Training: Volumetric Flows per Volt.

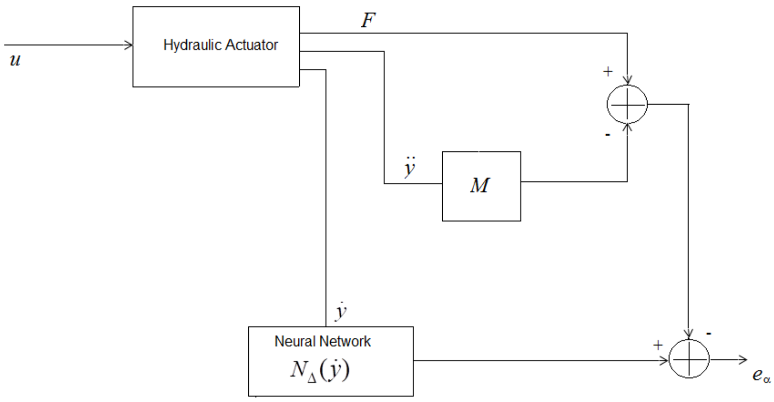
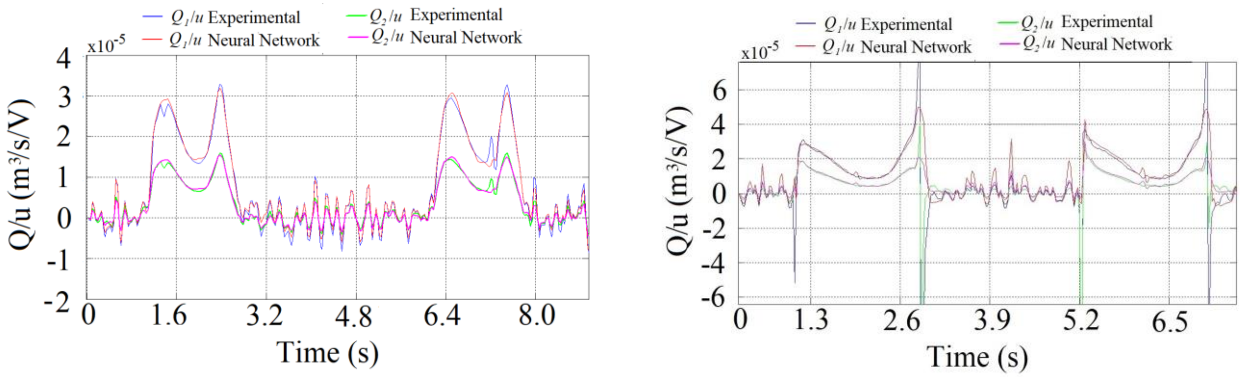


Figure 5. Neural Network Training: Friction Force.

Figure 6 shows the experimental test set from the plant and the time response of the MLP that represents the volumetric flows per volt (Equation (9)). In Fig.6.a it is showed the positive displacement of the piston, whereas Fig.6.b presents the negative one. Figure 7 presents the experimental test set from the plant and the time response for the MLP that represents the friction force (Equation (8)). When a new set of input values (i.e., different from the one used to train the networks) is applied to the open loop system, one can infer from Fig.8 that the experimental time response for the piston position is similar to the neural model one for the same signals.



(a) (b)

Figure 6. Neural Network: volumetric flows: (a) positive displacement, (b) negative displacement

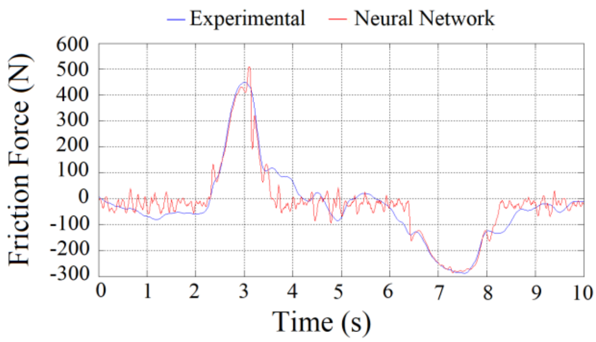


Figure 7. Neural Network: The Friction Force

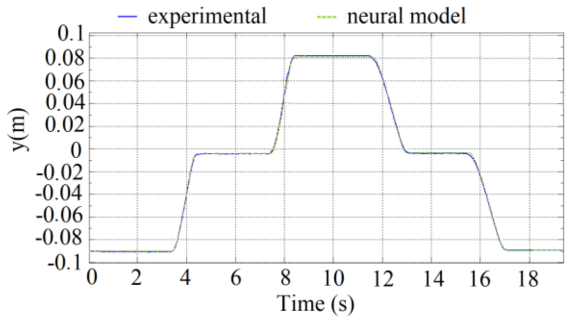


Figure 8. Neural model and experimental responses

Figure 9 shows the results of the pressure in the chambers 1 and 2 for the input signal applied in the valve. The response of the simulation using the neural model is closer than the response obtained applying the analytical model obtained in Borges (2017), using the analytical traditional methods, when both responses are compared with the experimental one. This result is more evident when the input signal is close to zero volts. According to Merrit (1967) the valve spool is close to the overlap region between the spool and the valve land when the input signal is close to zero. The traditional analytical model applied in Borges (2017) is not able to reproduce an accurate response in this region of operation, while the neural model, trained using examples of the plant response, is able to reach better results due the learning proprieties of the MLP neural network.

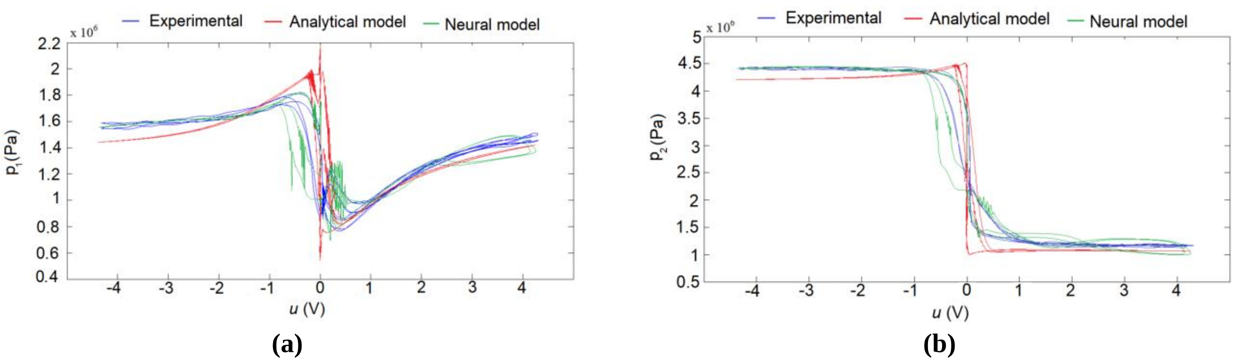


Figure 9. Pressure responses: (a) pressure in the chamber 1, (b) pressure in the chamber 2.

5. CONCLUSIONS

A strategy to employ feedforward multilayer neural network was used to replace nonlinear analytical function in the model of a hydraulic actuator. The results obtained allow to conclude that the response of the experimental system and the response of the proposed neural model are similar. Since the use of the proposed method only requires a set of relatively simple experiments performed with the controlled system in order to train the neural network, a suitable representation of the real system is obtained avoiding the extensive experimental work usually involved when the traditional experimental method are used.

Future work will focus on examining the performance of the proposed method when applied to a closed-loop control task.

6. REFERENCES

Blokdyk, G. Neural network. A Complete Guide - 2019 Edition. 5STARCooks, 2019.

Borges, F. A. P. ; Perondi, E. A. ; Cunha, M. A. B. ; Sobczyk, M. R. “A Hybrid Feedback Linearization and Neural Network Control Algorithm Applied to a Hydraulic Actuator,” in 9th FPNI Ph.D. Symposium on Fluid Power, 2016.

Borges, F. A. P. Controle em Cascata de um Atuador Hidráulico utilizando Redes Neurais. Tese de Doutorado, Universidade Federal do Rio Grande do Sul. 2017.

Coelho, L. S.; Cunha, M. A. B. Adaptive cascade control of a hydraulic actuator with an adaptive dead-zone compensation and optimization based on evolutionary algorithms. Expert Systems with Applications, n. 38, p. 12263-12269, 2011.

Daachi B.; Sirdi, M. K. M. A stable neural adaptive force controller for a hydraulic actuator. Proceeding of the 2001 IEEE international conference on robotics and automation, Seoul, Korea, p. 3465-3470, 2001

Gu, W. ; Yao, J. ; Yao, Z. ; Zheng, J. Robust Adaptive Control of Hydraulic System With Input Saturation and Valve Dead-Zone. IEEE Access,Vol.6, pp.53521-53532, 2018.

Haykin, S. Redes Neurais, Princípios e Prática. Bookman. 2.ed. 2001.

Lewis, F. L.; Jagannathan, S.; Yesildirak, A. Neural Network Control of Robot Manipulators and Nonlinear Systems. Taylor & Francis. 1999.

Li, T. ;Yang, T. ; Cao, T. ; Xie, R. ; Wang, X. Disturbance-Estimation Based Adaptive Backstepping Fault-Tolerant Synchronization Control for a Dual Redundant Hydraulic Actuation System With Internal Leakage Faults. IEEE Access (Volume: 7), p. 73106 – 73119. 03 June, 2019.

Liu, Y. ; Zeng, Q. ; Tong, S. ; Chen, C. ; Liu, L. Adaptive Neural Network Control for Active Suspension Systems with Time-Varying Vertical Displacement and Speed Constraint. IEEE Transactions on Industrial Electronics. 23 January 2019

Li, X.; Xu, F.; Zhang, J.; Wang, S. A multilayer feed forward small-word neural network controller and its application on electrohydraulic actuation system. Journal of Applies Mathematics, p. 1-8, 2013.

Merrit, H. E. Hydraulic control systems. John Wiley & Sons, 1967.

Naredra, K.; Parthasarathy, K. Identification and Control of Dynamical Systems Using Neural Networks. IEEE Transaction on Neural Networks, v.1, n.1, 1990.

Noskievič, P. Smart control of the integrated hydraulic actuator. 2018 19th International Carpathian Control Conference (ICCC). 28-31 May 2018.

Pasolli, P. ; Ruderman, M. Linearized Piecewise Affine in Control and States Hydraulic System: Modeling and Identification. IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society. 21-23 Oct. 2018.

Pedro, J.; Ekorn J. NARMA L-2 control of a nonlinear half-car servo-hydraulic vehicle suspension system. Acta polytechnica hungarica, v. 10, n. 4, pp. 4-6, 2013.

Wang, J. ; Gong, G. ; Yang, H. Control of Bulk Modulus of Oil in Hydraulic Systems. 2008 IEEE/ASME International Conference on Advanced Intelligent Mechatronics. 2-5 July 2008.

Watton, J. Fundamentos de Controle em Sistemas Fluidomecânicos. LTC. 2012.

7. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.