Adaptive Neuro-Controller for position control of system of 2-way proportional valve and linear hydraulic motor

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Abstract

This paper deals with position control of system of 2-way proportional valve and linear hydraulic motor. Servo-valves are usually used for accurate position control. However, they are much more expensive than proportional valves. The disadvantages of proportional valves are higher nonlinearity, hysteresis and large extend of the hydraulic fluid. The aim of the work is to design such a controller that would be able to take into account the mentioned properties of the system with proportional valves. It was designed a modified adaptive neural state controller. It is able to accept non-linearity and is able to continuously adapt to the changing system. The controller is tuned for the given system and its ability to control is tested on a model in Matlab / Simulink.

Keywords

gradient descent, dynamic linear neural unit, dynamic quadratic neural unit, adaptive feedback controller, Neuro-Controller, SISO, hydraulic, proportional valve

1. Introduction

In practice they are used two kinds of valve for controlling the position of linear hydraulic motors. The first type are servo valves, the second type are proportional valves. Servo valves are used in applications where are requirements for a small time constant of the valves and the high accuracy position control. In other applications are used proportional valves. The main advantage of proportional valves is their price. It costs about 600 CZK, contrary to the servo valve is around 10,000 CZK. For this reason requirement to design regulator for controlling systems with proportional valves, which would improve the control of hydraulic motors, increased the area of application of proportional valves and reduce price of hydraulic systems. The first part summarizes the properties of hydraulic systems with proportional valves and the requirements for the controller. The second part shows the neuronal state controller, and design method of real time learning. In the last part of the controller is tested on a model formulated in Matlab / Simulink.

2. Properties of hydraulics systems

Basic hydraulics system is shown in Fig.1. System consists of a tank, pump, pressure relief valve, the proportional control valve and a linear motor. The manipulated variable of the system is the voltage solenoid valve. The solenoids control the position of the slide. The flow channels A, B of the proportional valve is dependent on the position of the slide and the pressure difference before and behind the throttle edge. The flow then control the position, velocity and acceleration of the hydraulic motor.

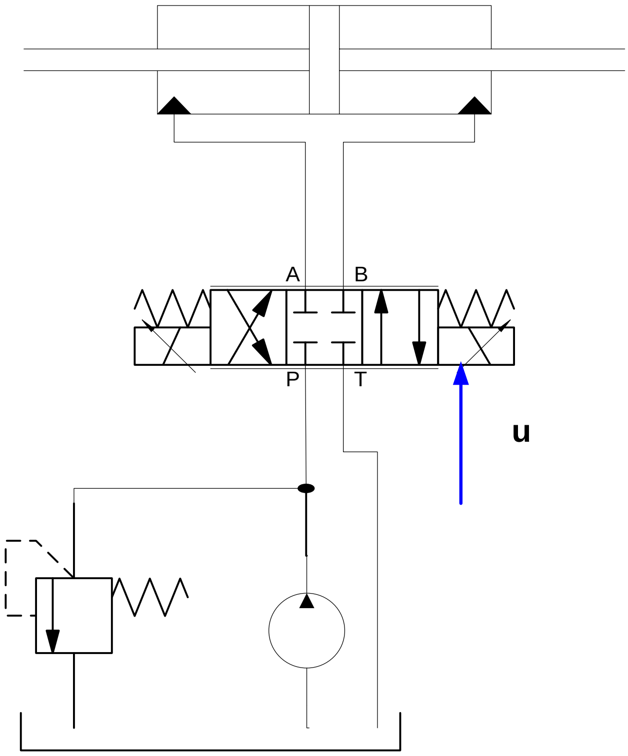


Fig. 1. *Diagram of a simple hydraulic system.*

2.1 The stiffness of the system.

Linear motors have low stiffness. Pliable columns oil before and behind the piston represent springs, by which is the mass of the piston and consequential mechanisms attached to the frame (cylinder body). The relative change in volume of oil $\Delta V/V$ is directly proportional to the pressure increase Δp according to the relationship (1),

$$\frac{\Delta V}{V} = \frac{1}{E_K}\Delta p \qquad (1)$$

where E_K is the coefficient of volume compressibility, whose value in oil gives the limits $1 \div 1{,}6 \cdot 10^9\ N/m^2$, on the water $2{,}1.10^9 N/m^2$. Against the modulus of elasticity of steel ($E=2{,}1.10^{11}$) is the number two orders of magnitude smaller. The stiffness of hydraulic motor is dependent on the position of the piston as shown in Figure 2.

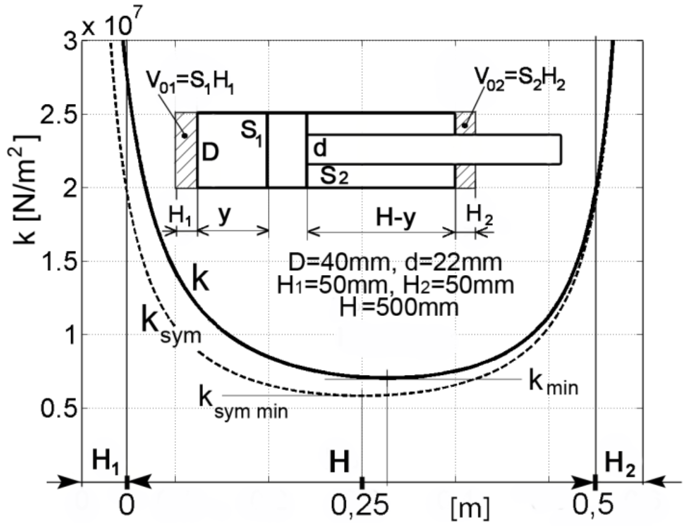


Fig. 2. *The dependence of stiffness on linear hydraulic motor*

2.2 Flow of fluids of proportional valve

Flow of fluids of valve can be deduced Stokes equations (2) and the continuity equation for an ideal fluid (3).

$$\frac{p_0}{\rho} = \frac{p}{\rho} + \frac{v^2}{2} + \alpha \cdot \frac{v^2}{2} \tag{2}$$

$$Q = S \cdot v \tag{3}$$

The area S is in this case a gap opening of the channel and is a function of the channel opening and a groove in the slide. Substituting (2) to (3) we get an equation for the flow channel as a function of the relative opening of the canal and the pressure difference (4).

$$Q = S \cdot \sqrt{\frac{p_0 - p}{\rho} \cdot \frac{2}{(1+\alpha)}} \tag{4}$$

The real dependence of the flow proportional valve to control signal is shown in Figure 3.

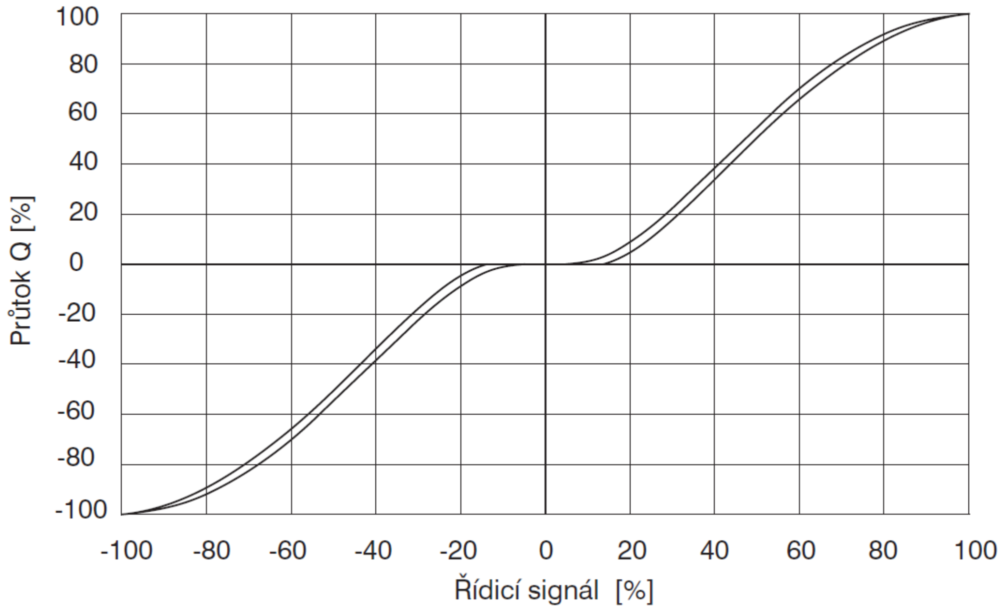


Fig.3. *Flow static characteristic of a proportional valve PRM7-04 Argo-Hytos*

$$\Delta p = 10bar \quad \nu = 32 \, {}^{mm^2}\!/_{s}$$

2.3 Change oil temperature

In real applications, the temperature of the oil in the system can change by 80° during the work. If the temperature changes from 20° to 100° then the oil viscosity will change from $\nu = 80 mm^2 s^{-1}$ to $\nu = 4 mm^2 s^{-1}$. This has resulted in a change of pressure losses in the valve and a change in leakage of the valve and the hydraulic motor.

2.4 Requirements for Controller

The regulator which controls the system with proportional valves must accept the nonlinear behaviour of the system caused by changing the stiffness of the piston position, nonlinear static flow characteristic and hysteresis given change friction model in proportional valve. The controller must be able to adapt in real time according changes in system parameters which are caused by temperature oil. Furthermore, is required computational low demands controller given high sample rate.

3. Neural State-Feedback Controller

The controller which is able to satisfy largely the above requirements is a Neural State-Feedback Controller [1],[2],[3]. Control principle is based on the classical Linear State-Feedback Controller. We try to impose behaviour of the reference model to the control system with the gain in feedback. Instead of feedback gain is used linear, quadratic or cubic neuron unit in the feedback as is shown in Figure 4.

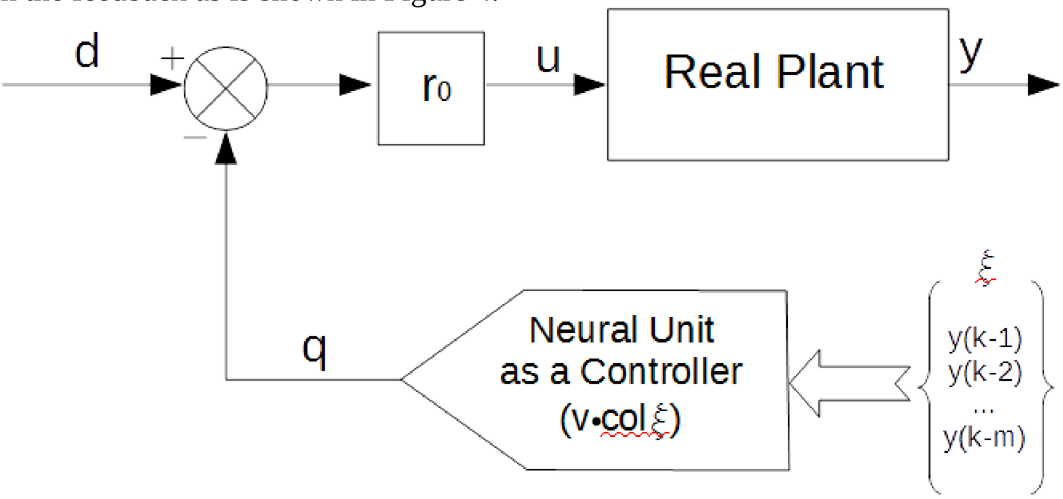


Fig.4. *Control Scheme of the Neuro-Controller*

His ability to control nonlinear systems was demonstrated in laboratory models [4],[5].

3.1 New real-time learning method

To fulfil requirements for adaptation controller during the activity I developed a new method of learning. The basic issue for real-time learning is how to compare the behaviours of the controlled system with reference model at each time step. The solution to this problem is to initialize the reference model in each time steps. It is then possible to calculate the error between the controlled system and the reference model (5). The basic scheme of the controller is shown in Figure 5.

$$eref(k) = yref(k) - y(k) \tag{5}$$

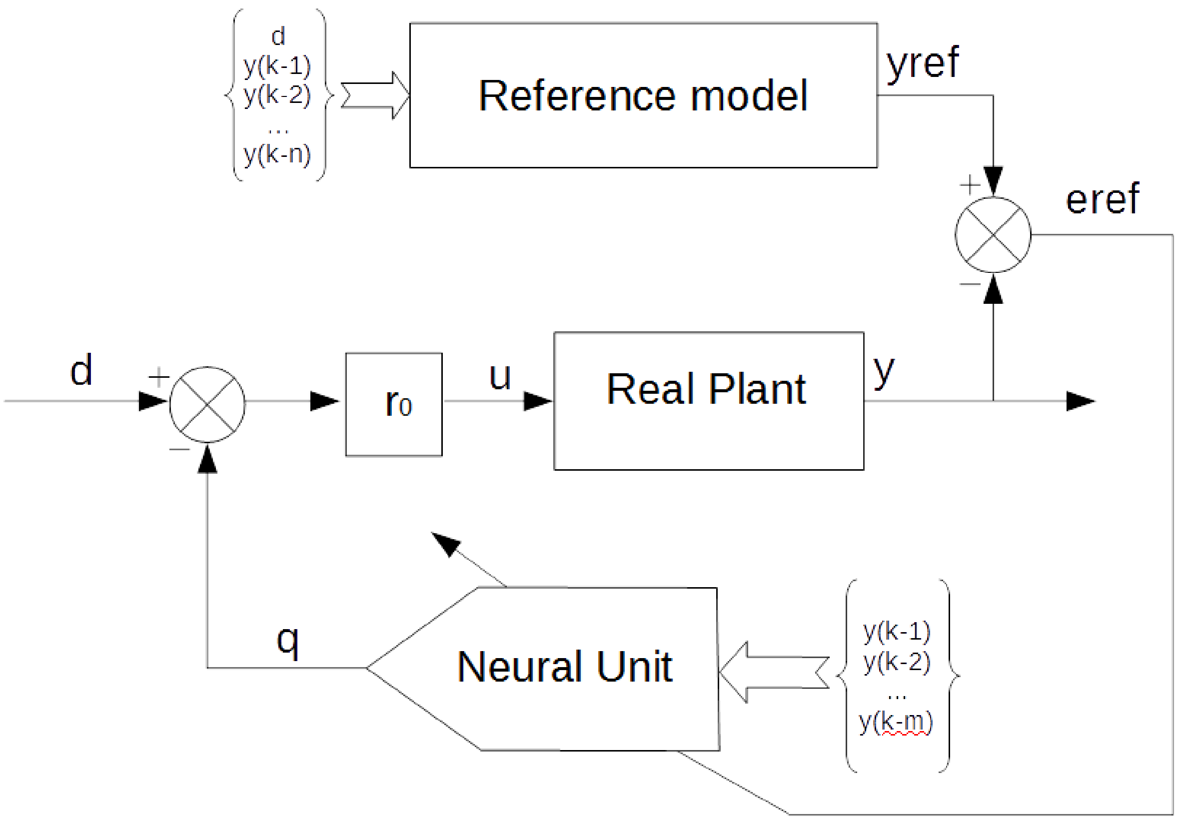


Fig.5. *Conrole Scheme of Neuro-Controller with real-time learning*

The reference model is usually linear differential equation (5). This equation is discretized (6) and the reference output is computed from the desired value and outputs of the real plant from the previous time steps (7).

$$a_5 \cdot y^{V}(t) + a_4 \cdot y^{IV}(t) + a_3 \cdot y^{III}(t) + a_2 \cdot y^{II}(t) + a_1 \cdot y^{I}(t) + a_0 \cdot y(k) = u(t) \quad (6)$$

$$A_5 \cdot y(k-5) + A_4 \cdot y(k-4) + A_3 \cdot y(k-3) + A_2 \cdot y(k-2) + A_1 \cdot y(k-1) + A_0 \cdot y(k) = u(k) \quad (7)$$

$$yref(k) = \frac{u(k) - \left(A_5 \cdot y(k-5) + A_4 \cdot y(k-4) + A_3 \cdot y(k-3) + A_2 \cdot y(k-2) + A_1 \cdot y(k-1)\right)}{A_0} \quad (8)$$

If we calculate *yref* by (8) and *ereref* by (5) then we can ingested to adapt the weights of the neural unit by Gradient Descent method (9).

$$v_i(k) = v_i(k-1) - \mu_v \cdot eref(k-1) \cdot \frac{\partial y(k-1)}{\partial v_i} \quad (9)$$

The ability to adapt the controller to change the parameters of the system is shown in Figure 6.

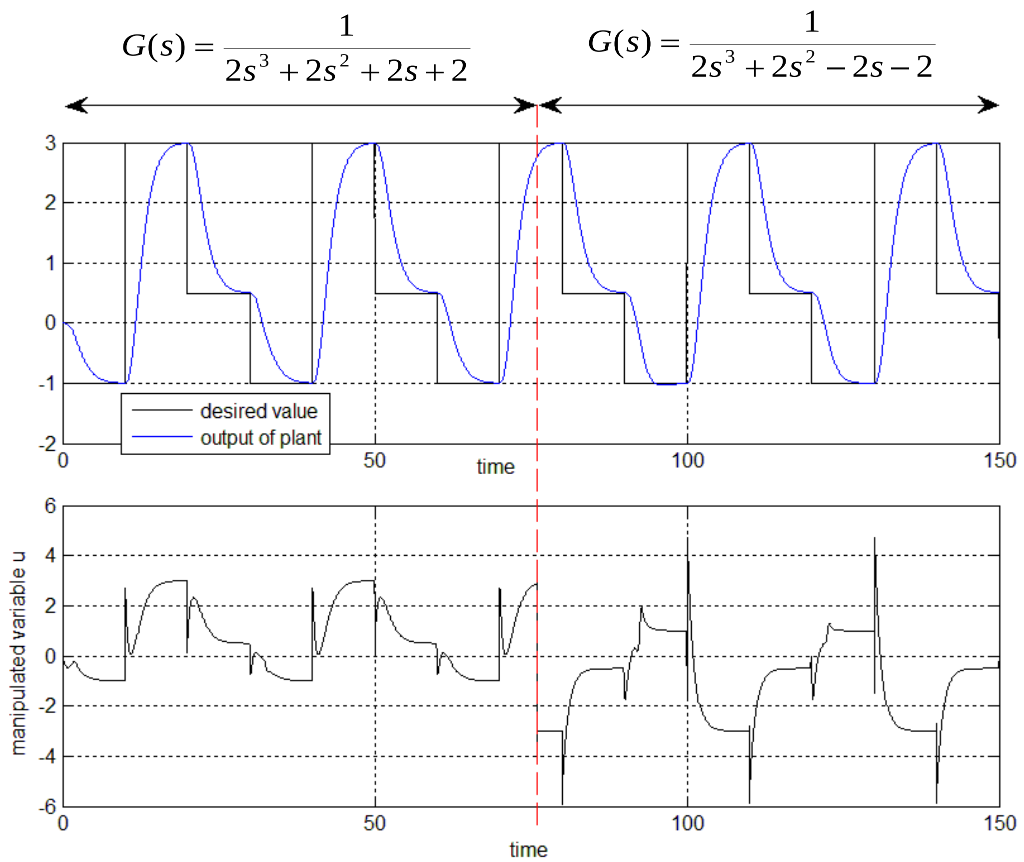


Fig.6. Control by adaptive controllers with a step change in the plant from stable to unstable.

The controller was able to adapt itself to a step change from stable to unstable plant. In Figure 6 we can see that the output of the system is almost unchanged but changed the manipulated variable.

3. Testing on a model of the hydraulic system with a proportional valve

Model of hydraulic system with proportional valve according to Figure 1 was built in Matlab Simulink Hydraulic Toolbox (Figure 7).

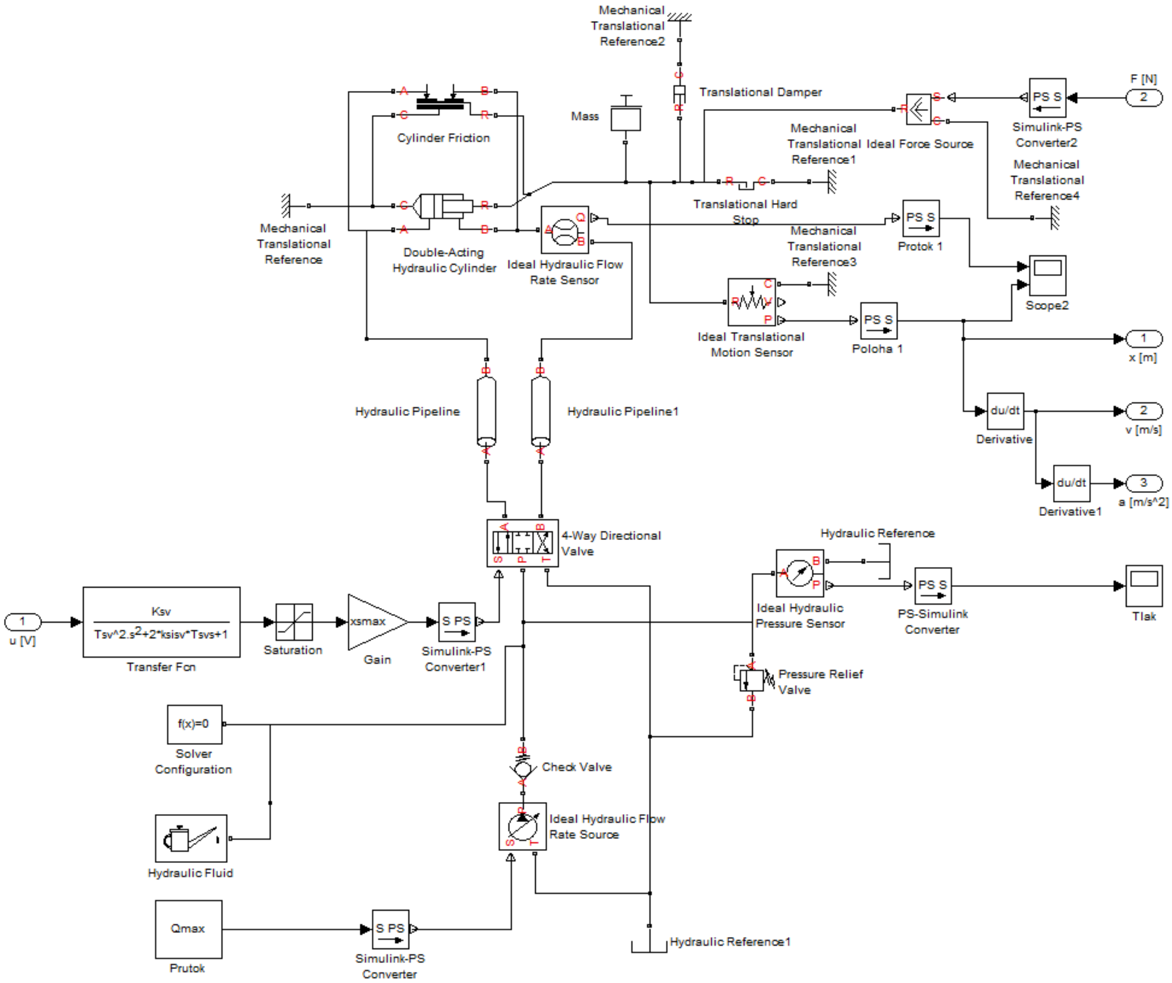
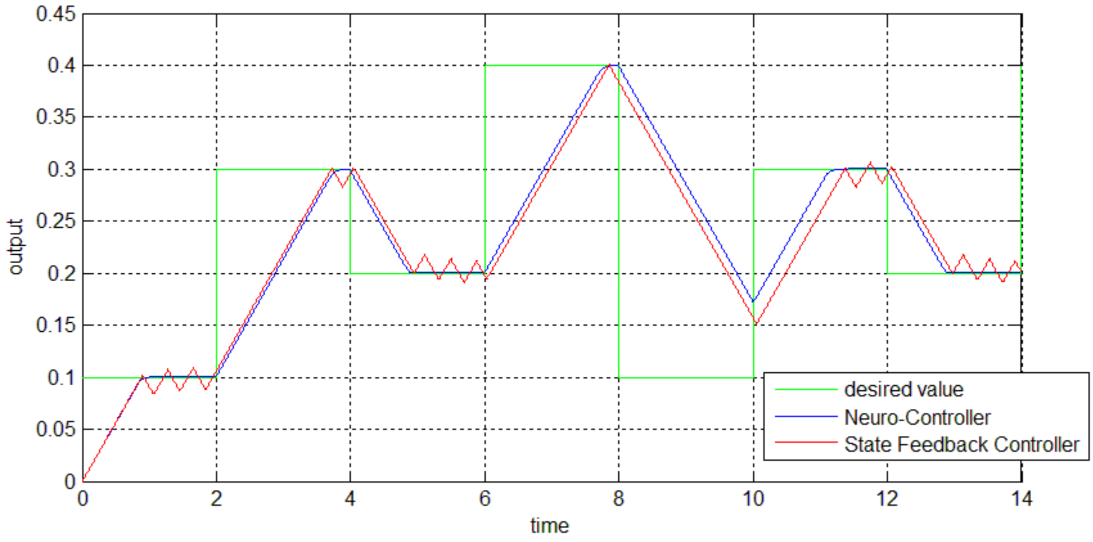


Fig.7 *Model of hydraulic system with proportional valve*

This model accepts the characteristics mentioned in chapter 2. Controlling by Neuro-Controller are compared with a Linear State-Feedback controller, which was tuned to the linearized system of the same system (Figure 8). We can see that the Neuro-Controller was able to regulate this system compared to linear state-feedback controller.



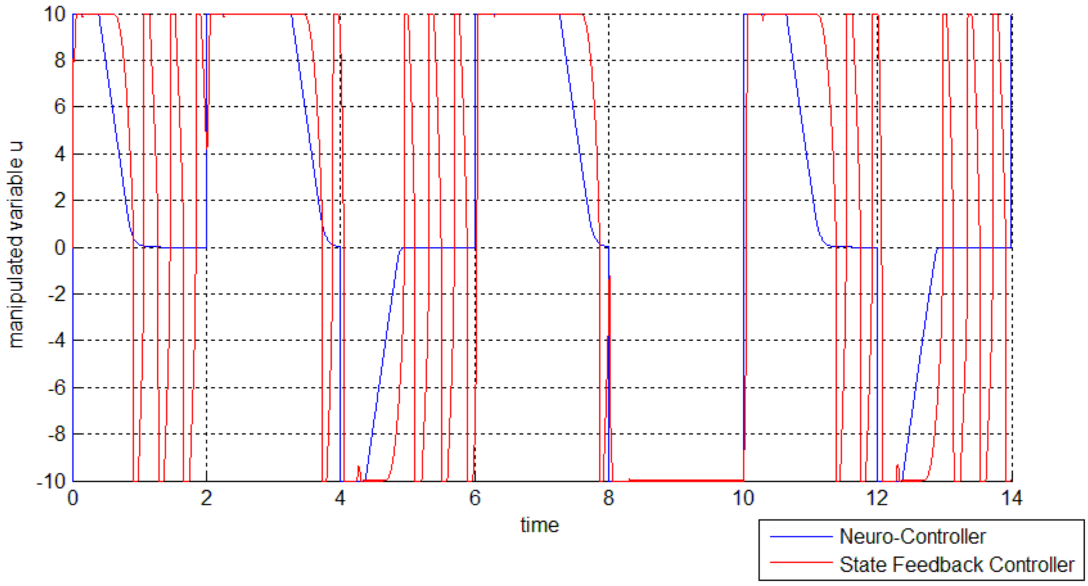


Fig.8 *Controlling hydraulic system by Neuro-Controller and Linear State Feedback Controller*

4. Conclusion

For the purpose to improve control of hydraulic systems with proportional valves, was used nonlinear Neural State-Feedback Controller. For this controller was found a new method of learning in real time using an initialization of the reference model of the real system outputs in each time steps. It was shown that this method allows learning systems with high changing parameters during work. The controller was tuned for the given system and its ability to control was tested on a model in Matlab / Simulink. It was confirmed that the controller is able to control the nonlinear hydraulic system with proportional valve where traditional control methods fail.

Symbols

p	Pressure	$[Pa]$
Q	Flow	$\left[\frac{m^3}{s}\right]$
ν	Kinematic viscosity	$\left[\frac{mm^2}{s}\right]$
$v_i(k)$	Weight coefficient neuron unit	
μ_v	Learning rate	

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