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Neural Network MLP with Sliding Mode Controller for Robotic Manipulator

S. H. Hashemipour[1], H. Karimi[2], A. Adeli[3]

[1]Department of Electrical Engineering, Young Researcher Club, Roudsar and Amlash Branch, Islamic Azad University, Roudsar, Iran
[2]Department of Mechanical Engineering, Roudsar and Amlash Branch, Islamic Azad University, Roudsar, Iran
[3]Department of Electrical and Computer Engineering, Tabriz University, Tabriz, Iran

ABSTRACT

In this paper, MLP network with sliding-mode controller and neural control is designed to the joint position control of two-link robot manipulators for periodic motion and predefined trajectory tracking control. Because the nonlinear nature robot, first the nonlinear and robust method sliding mode as a control theory for the system is chosen. Chattering phenomenon is always a problem of sliding mode controller is implemented. To reduce this effect, neural network in combination with a sliding mode controller is used, to estimate part discontinuous of sliding mode controller. In the next step, the robot arm system by two other neural networks was controlled as intelligent control. Simulation results show that this method is very effective in reducing Chattering. Finally, a robustness analysis was also performed and resistance of intelligent control methods is considered**.**

KEY WORD: MLP; Neural network; Nero control; Robotic manipulator; Sliding mode.

I. INTRODUCTION

Robotic trajectory control is a very complicated problem, due to the coupled and nonlinear system dynamics. In addition, when a robotic manipulator operates at high speed, the effects of nonlinearities, time-varying coefficients, and additional uncertainties such as backlash, friction, etc., may cause the system error to become large[1,2]. How to find an effective controller to achieve accurate tracking of desired motion is a concerned problem for the scholars in control field. So lots of control algorithms are applied to robot trajectory control, such as fuzzy control [3], neural network [4], sliding-mode control [5], and robust control [6] etc.

As a robust control strategy, sliding-mode control nowadays has applied in various areas, such as in robotics, industrial process, aerospace, and power converters [7]. The sliding mode control is designed in such a way that all trajectories in the state space are directed toward sliding surface. Once the system state reaches the sliding surface, it slides along it and the system remains insensitive to a class of disturbances and parameter variations. But in applications of practical motion control, a traditional sliding-mode control suffers from the following drawbacks. The first one is that it is difficult to obtain parameters of the system. In [8], two parallel neural networks are used to compute the equivalent control and the corrective control of the sliding-mode control. In [6], a neural network is used to approach the uncertainty of a robust control system. The second drawback is there exists always high frequency oscillation in the control input, which is called "chattering". The high speed switching necessary for the establishment of a sliding mode causes the oscillations. Chattering is undesirable in most real applications because it may excite unmodeled high frequency plant dynamics and this can result in unforeseen instabilities. A simple method for solving the chattering is to introduce a boundary layer [9]. But the method does not ensure the convergence of the state trajectories of system to the sliding surface, and probably results in the existence of the steady state error. In addition, analysis of a system dynamics within the boundary layer is very complicated [10]. In [10], in order to eliminate the chattering, an auto-tuning neuron is used as the direct adaptive neural controller to replace the sliding mode control when the state trajectory of system goes into the boundary layer.

In this paper, unlike other papers [11, 13] MLP neural network for control of a tow link robotic manipulator is used. Simply because this class of neural networks trained using fewer neurons compared with RBF neural networks is the choice of the neural network to control a robot arm. in present work, first a sliding mode controller is designed for system. Due to the discontinuous sign function in sliding mode control term, chattering is a troubling phenomenon. To eliminate this phenomenon, a neural network is used to estimate the discontinuous part. However, at this stage of the saturation function instead of sign function is used. In the next step, the robot arm system by two other neural networks was controlled as intelligent control. Finally, a robustness analysis was performed and shows that controller sliding mode with neural network better resistance to change parameters.

* **Corresponding author**: S. H. Hashemipour is in the Department of Electrical Engineering, Roudsar and Amlash Branch, Islamic Azad University, Roudsar, Iran. Tel. ; +981426212910; Email: C_e_hamid@yahoo.com.

The contribution in this paper is:
a) A method neural control for nonlinear system is was presented.
b) Using neural network chattering significantly reduced.
c) Of Multi layer perceptron (MLP) for chattering reduction and tracking increase is used.
This paper is organized as follows. In section 2, the robot dynamics along with some of its fundamental properties and the problem statement is presented. In section 3, the design and analysis of the controller is presented. The simulation results of the two link manipulator are given in section 4 and finally the conclusion is in section 5.

II. DYNAMIC OF ROBOTIC MANIPULATOR

The dynamic equation of an n -link robotic manipulator is

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau \tag{1}$$

Where **q** joint position vector, $\dot{q}$ joint velocity vector, $\ddot{q}$ joint acceleration vector, M (q) inertia matrix, $C(q,\dot{q})$ matrix of centripetal and Coriolis forces, G (q) the gravity vector, τ the motor torque vector. This matrix is as follow [11].

$$M(q) = \begin{bmatrix} (\frac{1}{4}m_1 + m_2)l_1^2 + \frac{1}{4}m_2 l_2^2 + m_2 l_1 l_2 \cos q_2 & \frac{1}{4}m_2 l_2^2 + m_2 l_1 l_2 \cos q_2 \\ \frac{1}{4}m_2 l_2^2 + m_2 l_1 l_2 \cos q_2 & \frac{1}{4}m_2 l_2^2 \end{bmatrix}$$

$$C(q) = \begin{bmatrix} -m_2 l_1 l_2 \dot{q}_2 \sin q_2 & -\frac{1}{2}m_2 l_1 l_2 \dot{q}_2 \sin q_2 \\ \frac{1}{2}m_2 l_1 l_2 \dot{q}_1 \sin q_2 & 0 \end{bmatrix} \tag{2}$$

$$G(q) = \begin{bmatrix} (\frac{1}{2}m_1 + m_2) g l_1 \cos q_1 + \frac{1}{2}m_2 l_2 g \cos(q_1 + q_2) \\ \frac{1}{2}m_2 l_2 g \cos(q_1 + q_2) \end{bmatrix}$$

Where l_1 and l_2 are the lengths; m_1 and m_2 are the mass of the links, respectively. The geometric structure of a two-link manipulator is shown in Figure 1.

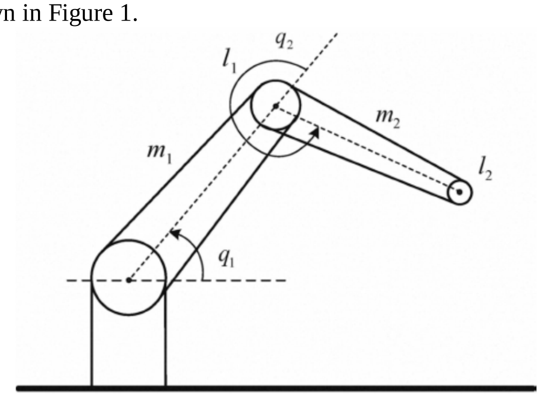

Fig. 1. Two-link robotic manipulator

There are five properties for the dynamics of a robotic manipulator in the following [11]

a) Symmetric and positive definite $M^T=M$.
b) The parameter M (q) is bounded, i.e., $\mu_1(q)I \le M(q) \le \mu_2(q)I$, where $\mu_1(q)$ and $\mu_2(q)$ are scalars. For revolute links, they are constants. I is an identical matrix.
c) Matrix $\dot{M} - 2C$ is skew symmetric, i.e., for any vector X
$X^T(\dot{M} - 2C)X = 0.$

d) $C(q,\dot{q})\dot{q}$ is quadratic $\dot{q}$ to and bounded as $\left\|C(q,\dot{q})\dot{q}\right\| \le \mu_3(q)\left\|\dot{q}\right\|^2$,where , $\mu_3(q)$ is a scalar constant for revolute links.

e) The gravity vector G is bounded as $\left\|G(q)\right\| \le \mu_4(q)$, where $\mu_4(q)$ is a scalar constant for revolute links. It is independent of q.

III. DESIGN CONTROLLER

a) Sliding mode

Sliding mode control is a tracking method. The purpose of this paper is track the reference signal by robotic manipulator. Therefore, error is defined as follows [11]:

$$\tilde{q} = q - q_d \tag{3}$$

Where $\tilde{q}$ is tracking error and q_d is reference signal. The dynamic equations of the robot arm are of two orders; hence sliding surfaces are defined as follows.

$$S(x,t) = \left(\frac{d}{dt} + \lambda\right)^{n-1} \tilde{x} \tag{4}$$

Where n=2 and

$$S = \dot{\tilde{q}} + \lambda \tilde{q} \tag{5}$$

According to the sliding mode method $\dot{S} = 0$ and control law is derived as follows.

$$\dot{S} = \ddot{\tilde{q}} + \lambda \dot{\tilde{q}} = \ddot{q} - \ddot{q}_d + \lambda \dot{q} - \lambda \dot{q}_d \tag{6}$$

To derive the control law expression of the matrix M is multiplied on both sides.

$$M\dot{S} = M\,\ddot{q} - M\,\ddot{q}_d + M\lambda(\dot{q} - \dot{q}_d) \tag{7}$$

If the system parameters are constant values, then $M\dot{S} = 0.$ therefore, using equation (1) control law is:

$$\tau_{eq} = C(q,\dot{q})\dot{q} + G(q) + M\ddot{q}_d - M\lambda(\dot{q} - \dot{q}_d) \tag{8}$$

Since the operating system parameters are not constant and change, Sliding mode method was chosen for this system. for change the parameters of the sliding mode controllers have good resistance, sign function is added to the control law. Hence

$$\dot{S} = -Ksign(s) \Rightarrow \tau = \tau_{eq} - Ksign(s) \tag{9}$$

For investigate the stability of the system is chosen Lyapunov function as below:

$$V = \frac{1}{2}s^2 \tag{10}$$

The derivative of V is

$$\dot{V} = \frac{1}{2}(s\dot{s}) = \frac{1}{2}s(-ksign(s)) = -\frac{1}{2}\left|s\right|k < 0, \; if \quad k > 0 \tag{11}$$

Therefore, system stability is guaranteed.

b) Sliding mode in combination with neural network

MLP neural network is an approximation of the global offensive and the approximate any piecewise continuous function calls [12]. Because of the sign function on the sliding mode control and resulting in high frequency oscillation and also, due to the uncertain robot arm dynamic model of neural network is used in this work. In this paper to eliminate this undesirable oscillation rather than sign function of the saturation function is used. The inputs to the neural network were selected sliding surfaces. A two-layer neural network with seven hidden layer and the input and output layer to approximate the nonlinear function is considered, as shown in figure 2.

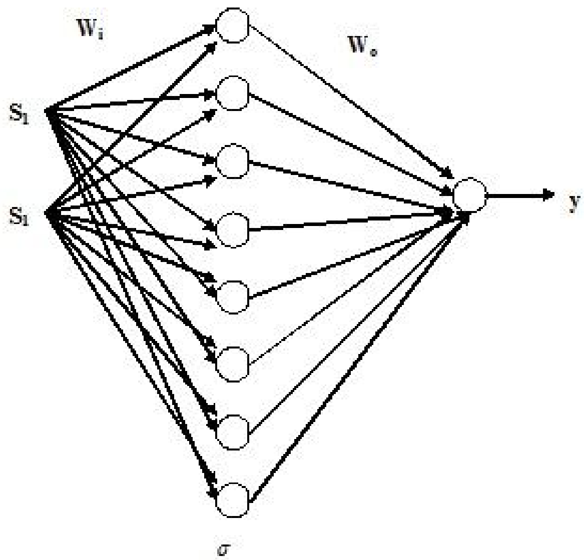

Fig. 2. Structure of two-layer neural network

Levenberg-Marquardt method is used for neural network training. The output of the network is equal

$$y = W_o \sigma,\ \ \sigma = \tan sig(x),\ x = W_i S \tag{12}$$

That W_i and W_o weights of the input and output vectors, respectively. S vector is input and y is network output. Control law in this way is as follows.

$$\tau = \tau_{eq} - y \tag{13}$$

That τ_{eq} of equation (8) is obtained. Figure 3 shows a block diagram of a control system in below.

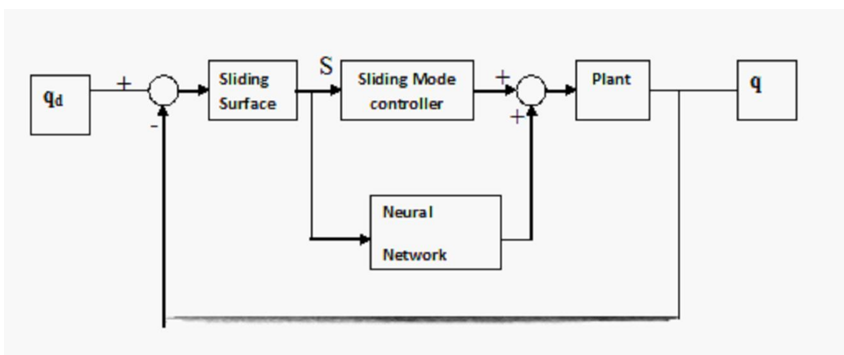

Fig. 3. Control system sliding mode in combination with neural network

c) Neural control

In this method, the neural network of the above mentioned two other neural networks are used to estimate the control. Feed forward neural network is used to estimate the follow term.

$$\tau_{eq1} = C(q,\dot{q})\dot{q} + G(q) + M\lambda\dot{q} \tag{14}$$

Inputs to the neural network are $q_1, q_2, \dot{q}_1, \dot{q}_2$. Hidden neuron number seven and number four input neurons and output neurons is two. To approximate this term, MLP neural network with Levenberg-Marquardt training method was chosen. Also, another neural network to approximate term control is selected.

$$\tau_{eq2} = M\ \ddot{q}_d + M\lambda\dot{q}_d \tag{15}$$

Inputs to the neural network are $q_2, \dot{q}_{d1}, \dot{q}_{d2}, \ddot{q}_{d1}, \ddot{q}_{d2}$ .the difference in this neural network with previous neural network is in the number of input neurons. In this state, system by three neural networks with different inputs is controlled to neural network method. Control law in this case is:

$$\hat{\tau}_{eq1} = \sum W_{o1}{}^T \tan sig(x_1),\ \ x_1 = \sum W_{i1}{}^T u_1,\ u_1 = [q_1\ \ q_2\ \ \dot{q}_1\ \ \dot{q}_2] \tag{16}$$

$$\hat{\tau}_{eq2} = \sum W_{o2}{}^{T} \tan sig(x_2),\ \ x_2 = \sum W_{i2}{}^{T} u_2,\ u_2 = [q_2 \quad \dot{q}_{d1} \ \ \dot{q}_{d2} \ \ \ddot{q}_{d1} \ \ \ddot{q}_{d2}] \tag{17}$$

$$\tau = \hat{\tau}_{eq1} + \hat{\tau}_{eq2} - y \tag{18}$$

In relation above, y of equation (12) is obtained. Figure 4 shows a block diagram of a control system in state.

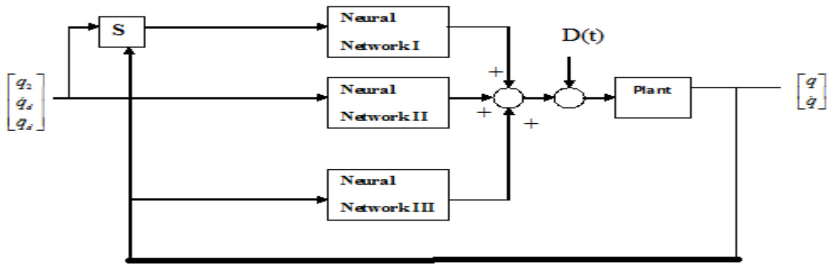

Fig. 4. Control system neural control

IV. RESULTS AND DISCUSSION

Dynamic model of the robotic manipulator is shown in Figure 1. Values of model parameters and initial conditions are as follows [11].

$$m_1 = 4kg,\ m_2 = 2kg,\ l_1 = 2m,\ l_2 = 1m,\ g = 9.8\, m/s^2,$$

$$q_1(0) = 0.5,\ q_2(0) = 0.5,\ \dot{q}_1(0) = 0,\ \dot{q}_2(0) = 0.$$

The purpose of this paper is track the reference signal by controlling the robot arm. Reference signal is

$$q_d = [1.5\sin(2\pi/3)t \qquad 2\sin(2\pi/3)t]^T \tag{19}$$

For simulation, a friction vector is considered, too. Hence, system model was considered as follows.

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F(\dot{q}) = \tau \tag{20}$$

Where

$$F(\dot{q}) = \left[20\dot{q}_1 + 0.8\,\mathrm{sgn}(\dot{q}_1) \quad 4\dot{q}_2 + 0.16\,\mathrm{sgn}(\dot{q}_2)\right]^T \tag{21}$$

To show the capability Controller is designed, an external disturbance D (t) is also considered. Despite disturbance, simulations have been performed. Disturbance equation is

$$D(t) = [560\sin t \qquad 85\sin t]^T \tag{22}$$

In figure 5 position robot with reference signal and torque applied to robotic manipulator is demonstrated by applying the sliding mode controller. Chattering phenomenon in torque applied to the robotic manipulator clearly exists in this case. In figures 6 and 7 position robot with reference signal and torque applied to robotic manipulator is demonstrated by applying the sliding mode in combination with neural network and neural controller, respectively. It is observed that chattering significantly reduced in both types of controllers. In figure 8 robustness analyze is performed. In this state is assumed that m_1 and m_2 changed as Δm=10. Simulation results shows that sliding mode in combination with neural network have better resistance against changing its parameters.

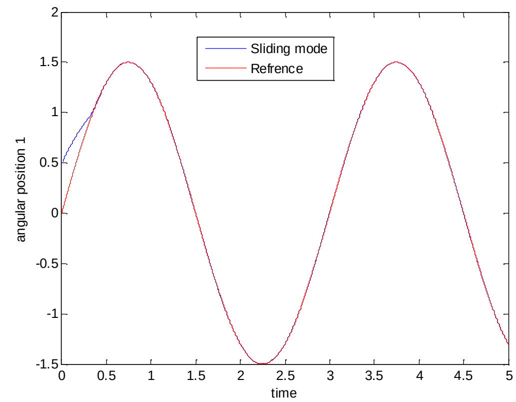

Fig. 5a. position first joint robot by sliding mode control

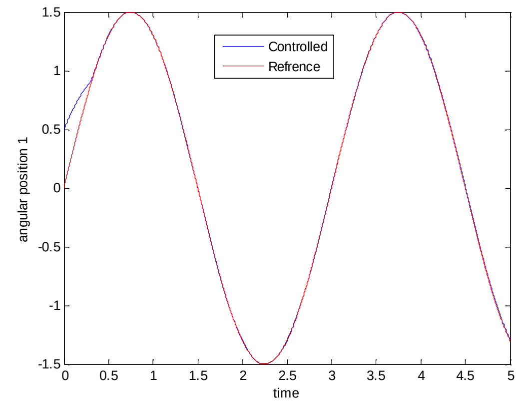

Fig. 6a. position first joint robot by sliding mode hybrid

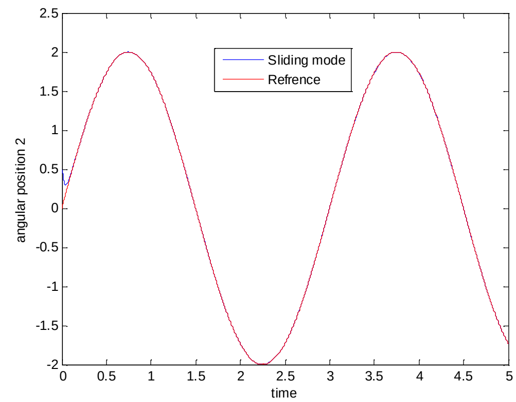

Fig. 5b. position second joint robot by sliding mode control

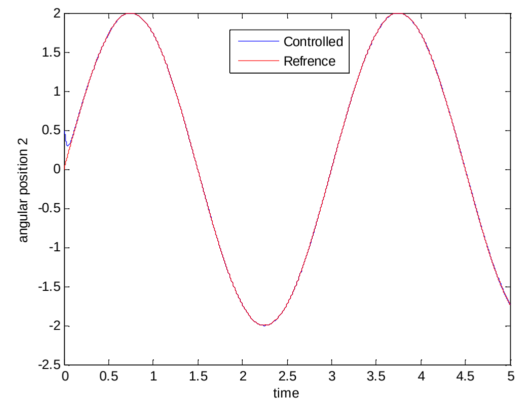

Fig. 6b. position second joint robot by sliding mode hybrid

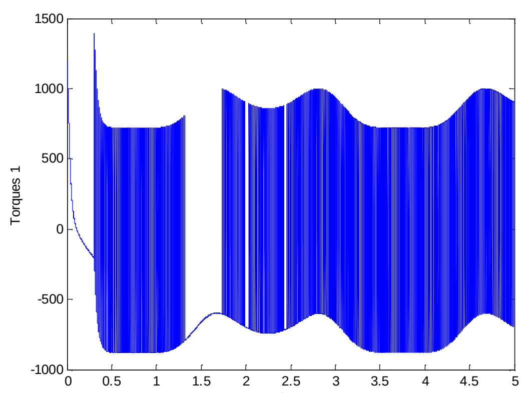

Fig. 5c. Torque first joint robot by sliding mode control

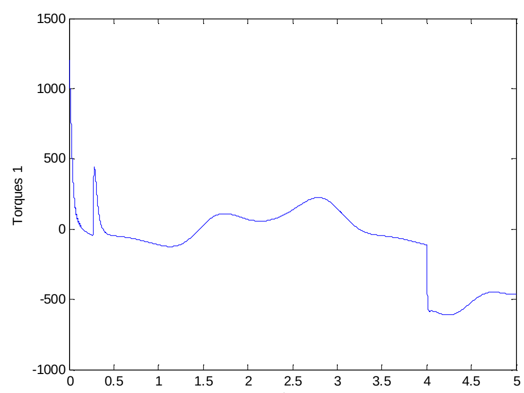

Fig. 6c. Torque joint first robot by sliding mode hybrid

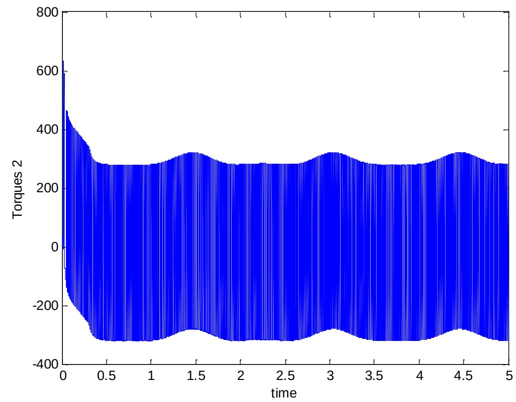

Fig. 5d. Torque second joint robot by sliding mode control

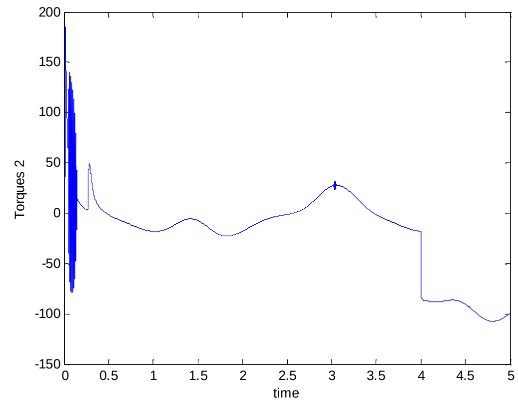

Fig. 6d. Torque joint second robot by sliding mode hybrid

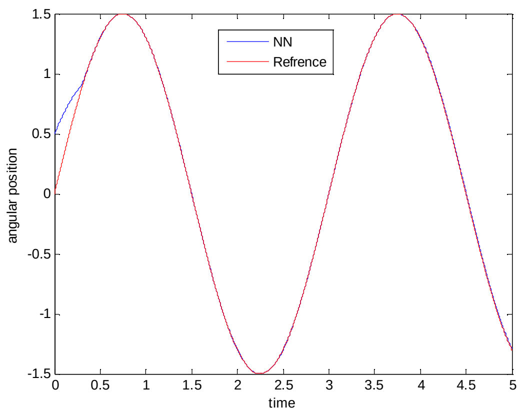

Fig. 7a. position first joint robot by neural control

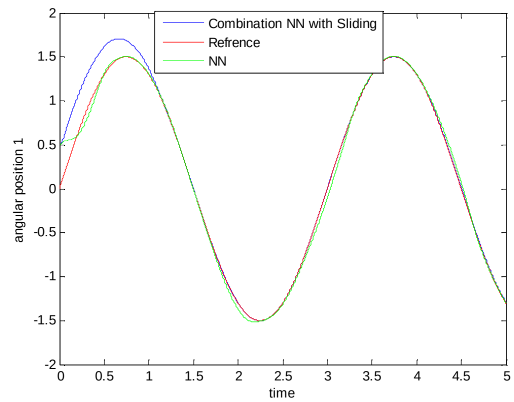

Fig. 8a. position first joint robot (robustness analyze)

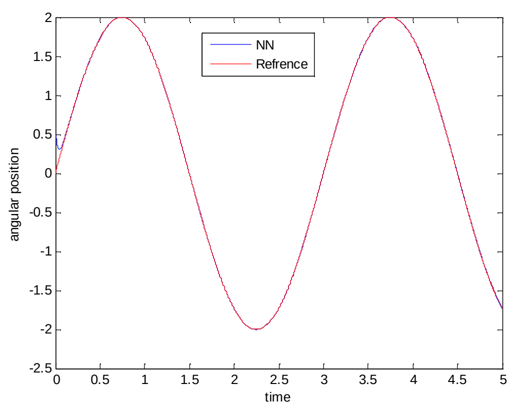

Fig. 7b. position second joint robot by neural control

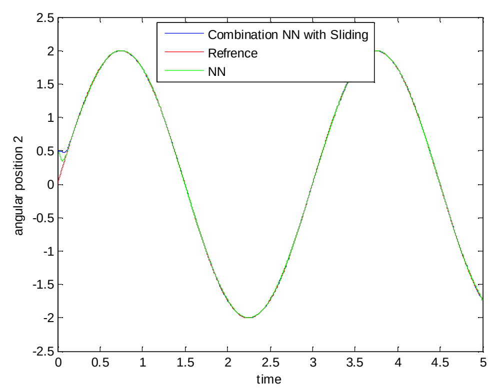

Fig. 8b. position second joint robot (robustness analyze)

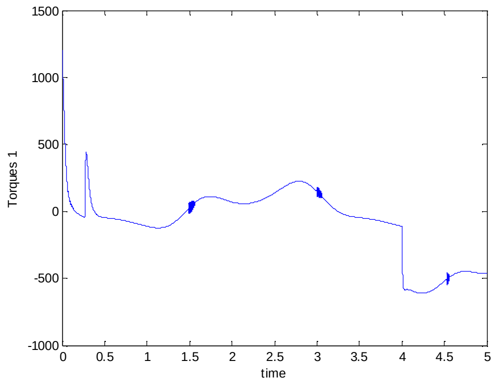

Fig. 7c. Torque first joint robot by neural control

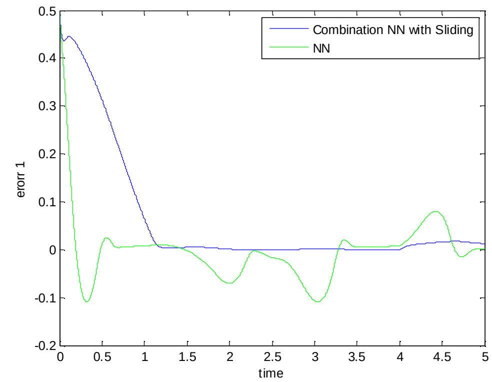

Fig. 8c. Error tracking first joint robot (robustness analyze)

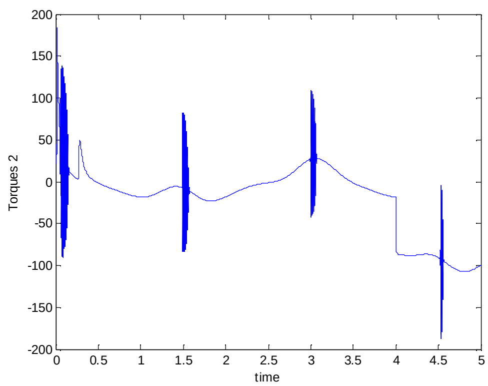

Fig. 7d. Torque second joint robot by neural control

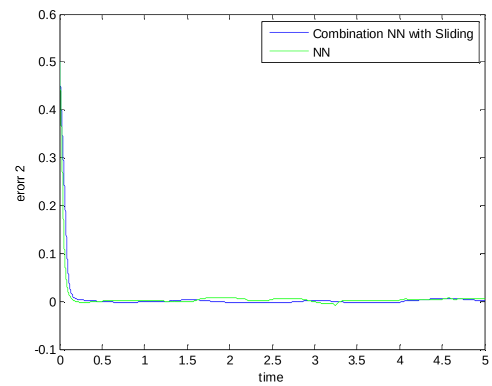

Fig. 8d. Error tracking second joint robot (robustness analyze)

I. CONCLUSION

In this paper for nonlinear model robotic manipulator is designed a sliding mode controller. Chattering phenomenon always in this case of controller is a troublesome factor. To design a sliding mode controller in combination with neural network, chattering significantly is reduced. In next step, a neural controller for control dynamic nonlinear robotic manipulator is used. Neural network considered in this paper is a two layer MLP neural network. Simulation results show that sliding mode with combination neural network have better resistance against changing its parameters and both controllers have been successful in reducing chattering.

REFERENCES

[1]- Liangyong Wang; Tianyou Chai, Chunyu Yang. “Neural-Network-Based Contouring Control for Robotic Manipulators in Operational Space”. IEEE Trans. Control Systems Technology, Volume: 20, 2012, Page(s): 1073 – 1080.

[2]- Ya Chen Hsu, G. Chen and H. X. Li. “A Fuzzy Adaptive Variable Structure Controller with Applications to Robot Manipulators”. IEEE Trans. Syst., Man, Cybernetics. 2001, 31(3):331-340.

[3]- B.A.M. Wakilah and K.F. Gill. “Robot control using self-organizing fuzzy logic”. Computation Industry, 1990, 15(3):175-186.

[4]- Yaonan Wang. “Self-learning Controller Based On Neural Networks for Robotic Manipulator”. Journal of Automation. 1997, 23(5):335-340.

[5]- Q. P. Ha et al. “Fuzzy Sliding-Mode Controllers with Applications”. IEEE Trans. Ind. Electron 2001, 48(1):38-46.

[6]- Wei Sun. “The Researches of Intelligent Neural Network Theories and Their Applications on Robot Control”. Changsha: Hunan University, 2002.

[7]- Yueming Hu. “Theory of Variable Structure Control and its applications”. Beijing: Technology Press, 2003.

[8]- C.H. Tsai, H.Y. Chung, and F.M. Yu. “Neuro-Sliding Mode Control with Its Applications to Seesaw Systems”. IEEE Trans Neural Networks, 2004,15(1):124-134.

[9]- K.S. Yeung and Y.P. Chen. “A New Controller Design for Manipulators Using the Theory of Variable Structure Systems”. IEEE Trans. Automat. Control, 1988, 33(2):200-209.

[10]- W.D. Chang, R.C. Hwang, and J.G. Hsieh. “Application of an Auto-Tuning Neuron to Sliding Mode Control”. IEEE Trans. Syst., Man, Cybern, 2002, 32(4):517-522.

[11]- Hung-Ching Lu, Cheng-Hung Tsai, Ming-Hung Chang, “Radial basis function neural network with sliding mode control for robotic manipulators” International Conference on Systems Man and Cybernetics (SMC), IEEE 2010

[12]- S. S. Haykin, “Neural networks and learning machines” 1999.

[13]- Ayca Gokhan Ak; Cansever, G. “Three link robot control with fuzzy sliding mode controller based on RBF neural network”, International Conference on Control Applications, 2006 IEEE.