

Comparison of Neural Network and Fuzzy Logic Control for Nonlinear Model of Two Link Rigid Manipulator

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Abstract

A model with multiple inputs and multiple outputs is considered to simulate two links rigid manipulator. Its mathematical model is obtained by using Euler's Lagrange method. A new intelligent scheme based on fixed stabilization technique is proposed in this paper for controlling the system. Comparison of Neural Network and Fuzzy Logic controller designed by utilizing this technique is also presented. The control law is determined such that the system output follows the reference trajectory. Controller design and simulation is done in MATLAB & Simulink. Simulation results validate the proposed controllers design and their comparison shows that Fuzzy Logic controller outperforms Neural Network controller.

Keywords: *Fuzzy Logic, NARMA-L2, Neural Networks, PID, Rigid Manipulator*

1. Introduction

Robotic manipulator or a robotic arm is a machine that has functions similar to human upper arm and is used for moving the objects spatially without direct contact. Its dynamics is characterized by complex nonlinearities and parametric uncertainties. Conventional industrial controllers are not capable of dealing with such highly nonlinear dynamic behavior. Also, conventional controller design requires the exact mathematical model of system dynamics which is often unavailable due to parameter variation. To overcome such problems, in recent years wide range of research is done in area of intelligent control such as neural networks and fuzzy logic, because these controllers are capable of controlling nonlinear systems without needing the mathematical model of the system.

Learning, approximation and generalization capabilities of neural network make it suitable for control of nonlinear robotic manipulator. Without defining a precise and specific plant model, neural network is utilized to learn the system's dynamic characteristics via a nonlinear mapping procedure in [1], to be used as function approximator. Various architectures including fixed stabilization are proposed in [1], which implement neural network for control of robot arm trajectory.

Neural network controller based on PID controller is implemented for control of manipulator with different load in [2] and its comparison with conventional PID controller is shown. NARMA L2 neurocontroller is designed and implemented for control of trajectory of a nonlinear telemanipulator system, with the reference trajectory being generated in real time [3]. NARMA-L2 neurocontroller not only eliminates the nonlinearities but also the dynamic behavior of the system and thus efficiently controls the trajectory [3,4]. But this controller is implemented for a manipulator with single degree of freedom. Also for a single link in [4],

smoothed NARMA-L2 control is implemented by adding a linear feedback to standard NARMA-L2 to avoid the chattering, for point to point and continuous path motion control.

Fuzzy logic is a non-mathematical approach to control problem based upon human knowledge and experience. Its robustness is very efficiently utilized for control of nonlinear systems with parametric uncertainties without even needing the system model [5]. Position control of a two-link manipulator is achieved by using a Fuzzy Logic controller, modeled and designed in FIDE (Fuzzy Inference Development Environment) in [6]. Design of a robust FLC is proposed in [7], for dynamic control of robotic manipulators with uncertainties based upon the stability analysis of the FLC. A hybrid controller is presented in [8], by combining fuzzy controller with a conventional PID to enhance the performance and robustness of the controller.

A stable Fuzzy Model Reference Learning Controller (FMRLC) is implemented and phase plane method is utilized for its stability analysis in [9]. The design of FMRLC required development of two fuzzy controllers, which made the tuning procedure more complex. Though it offers better tracking than standard FLC, as load increases this accuracy decreases due to oscillations about model reference trajectory.

In the present work, a new control strategy based on fixed stabilization technique for the control of two links rigid manipulator is proposed. This method combines conventional control technique with intelligent control to enhance the controller performance. This method is implemented for both neural network and fuzzy logic for varying load. The comparison of simulation results show that fuzzy logic controller performs better.

2. Mathematical Model

The mechanical structure of a manipulator consisting of two rigid link connected by means of revolute joints to ensure human arm like mobility is demonstrated in Figure.1. The dynamic model of the manipulator represents the relationship between the movements of the links and torque applied to the joints. In this paper, system dynamics is formulated by using Euler Lagrange method. The mass of each link is assumed to be a point mass located at the centre of mass of each link.

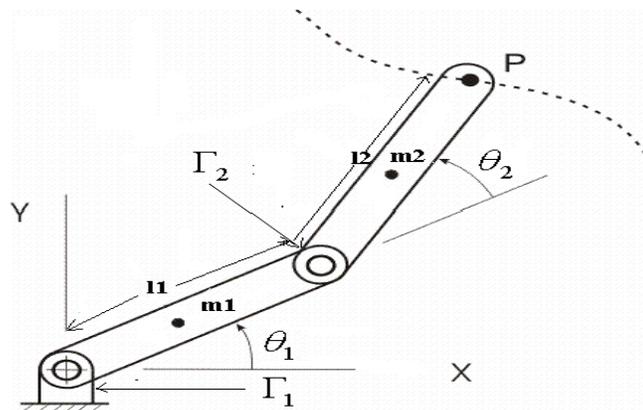


Figure 1. Model of two link rigid manipulator

Table 1. Parameter Values

m_1, m_2	Mass of links (1 kg, 1 kg)
θ_1, θ_2	Angular displacement of link1 from horizontal, Angular displacement of link2 with respect to link1
L_1, L_2	Length of links (0.3m, 0.3m)
g	Acceleration due to gravity (9.8m/s^2)
τ_1, τ_2	Torques applied to joints

The Lagrange function (Lagrangian) L is defined to develop the manipulator Equations of Motion (EOM). It requires the total kinetic and potential energies of the manipulator. The kinetic energy, K_1 and potential energy, P_1 for link1 can be expressed as:

$$K_1 = \frac{1}{6} m_1 L_1^2 \dot{\theta}_1^2 \quad \& \quad P_1 = \frac{1}{2} m_1 g L_1 \sin \theta_1 \quad (1)$$

Where L_1 is the length of link1 and θ_1 is the angular movement. The kinetic energy, K_2 and potential energy, P_2 for link2 can be expressed as

$$K_2 = \frac{1}{2} m_2 L_1^2 \dot{\theta}_1^2 + \frac{1}{6} m_2 L_2^2 (\dot{\theta}_1 + \dot{\theta}_2 + 2\dot{\theta}_1 \dot{\theta}_2) + \frac{1}{2} m_2 L_1 L_2 C_2 (\dot{\theta}_1^2 + \dot{\theta}_1 \dot{\theta}_2) \quad (2)$$

$$P_2 = m_2 g L_1 S_1 + \frac{1}{2} m_2 g L_2 S_{12} \quad (3)$$

Hence Lagrangian, $L = K_1 + K_2 - P_1 - P_2$ is calculated for the two links as

$$L = \frac{1}{2} \left(\frac{1}{3} m_1 + m_2 \right) L_1^2 \dot{\theta}_1^2 + \frac{1}{6} m_2 L_2^2 (\dot{\theta}_2^2 + \dot{\theta}_1^2 + 2\dot{\theta}_1 \dot{\theta}_2) + \frac{1}{2} m_2 L_1 L_2 C_2 (\dot{\theta}_1^2 + \dot{\theta}_1 \dot{\theta}_2) - \left(\frac{1}{2} m_1 + m_2 \right) g L_1 S_1 - \frac{1}{2} m_2 g L_2 S_{12} \quad (4)$$

The Lagrange Euler formulation gives the actual joint torques for the both the revolute joints

$$\tau_1 = \frac{d}{dt} \left(\frac{\partial L}{\partial \dot{\theta}_1} \right) - \frac{\partial L}{\partial \theta_1} \quad (5)$$

$$\tau_2 = \frac{d}{dt} \left(\frac{\partial L}{\partial \dot{\theta}_2} \right) - \frac{\partial L}{\partial \theta_2} \quad (6)$$

The EOM of two link rigid manipulator obtained after simplification from (4) and (5) is given as

$$\begin{aligned}\tau_1 &= M_{11}\ddot{\theta}_1 + M_{12}\ddot{\theta}_2 + H_1 + G_1 \\ \tau_2 &= M_{21}\ddot{\theta}_1 + M_{22}\ddot{\theta}_2 + H_2 + G_2\end{aligned}\quad (7)$$

Where M is the Inertia Matrix, H is centrifugal and coriolis acceleration force vector and G is the gravity loading force vector. This nonlinear model of the two link rigid manipulator system is simulated in MATLAB Simulink environment by using s-function.

3. Controller Design

To attain a desired position, a manipulator is required to accelerate from rest, travel in a specified path and finally decelerate to stop at the specified position. To accomplish this task, controlling torque is applied by the actuator at the manipulator joint. An independent controller for each link is designed to compute the torque delivered by the actuator for the link to follow the desired trajectory. In this way the controllers are allowed to operate independently and simultaneous control of the two links of the manipulator is realized.

In this paper, fixed stabilization control technique is used to design neural network and fuzzy logic controller to obtain optimal performance. Figure 2 shows the fixed stabilization control scheme. A conventional PID controller is used as stabilizing feedback controller in this work. The total input that enters the plant is the sum of the feedback control signal and the feedforward control signal, which is calculated by the intelligent controller which can be NN or FLC. Intelligent controller uses the feedback control signal as an error signal so as to learn and adapt from.

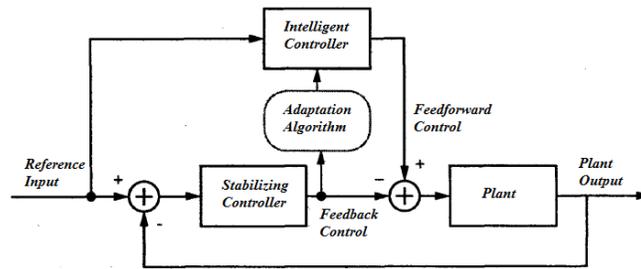


Figure 2. Fixed stabilizing control structure

3.1 Design of PID Controller [10]

Basically PID is a feedback type controller, where the error between set-point and plant output is used to generate the control action. Here Proportional-Integral-Derivative controller in parallel form is used for control of two links rigid manipulator. The transfer function of parallel PID employed is given by (8).

$$G(s) = K_p + K_i \frac{1}{s} + K_d s \quad (8)$$

For determination of PID gains, RH criterion is used in this work. The characteristic equation of closed loop transfer function of the control structure with single link manipulator and PID controller is used to find gains for PID which stabilizes the system. The open loop

transfer function of the single link is considered as specified by (9) and the closed loop transfer function with PID controller is specified by (10).

$$\frac{\theta}{\tau} = \frac{1}{Js^2 + Bs} \quad (9)$$

$$H(s) = \frac{s^2 K_d + sK_p + K_i}{Js^3 + (B + K_d)s^2 + K_i} \quad (10)$$

Where $J = \frac{mL^2}{3}$ and B is the mean friction coefficient.

Now for the system to be stable, Routh's stability criterion is implemented. It is obvious that for stability here, $\frac{k_p(B+k_d) - Jk_i}{B+k_d} > 0$ and $k_i > 0$.

3.2 Neural Network Controller

Neural networks possess capability to approximate and predict, once trained adequately. Hence this controller does not require exact mathematical model of the system to be controlled. NARMA-L2 architecture is used for control and prediction for this work. This controller is just the rearrangement of plant model such that it can cancel the nonlinearities and dynamic behavior of the system.

Any nonlinear discrete time system can be represented by standard Nonlinear Auto-Regressive Moving Average (NARMA) model as given by (11).

$$y(k + d) = N [y(k), y(k - 1), \dots, y(k - n + 1), u(k), u(k - 1), \dots, u(k - n + 1)] \quad (11)$$

Where $u(k)$ and $y(k)$ are the system input and output respectively, d represents delay of system from control effort ' $u(k)$ ' and N is the nonlinear function.

For NARMA-L2 controller design, an approximated NARMA model of the plant as given by (12) is used.

$$y(k + d) = f[y(k), y(k - 1), \dots, y(k - n + 1), u(k), u(k - 1), \dots, u(k - n + 1)] + g[y(k), y(k - 1), \dots, y(k - n + 1), u(k), u(k - 1), \dots, u(k - n + 1)]. u(k + 1) \quad (12)$$

Here f and g are functions which cancel the nonlinearities and dynamic behavior and causes system to track reference trajectory.

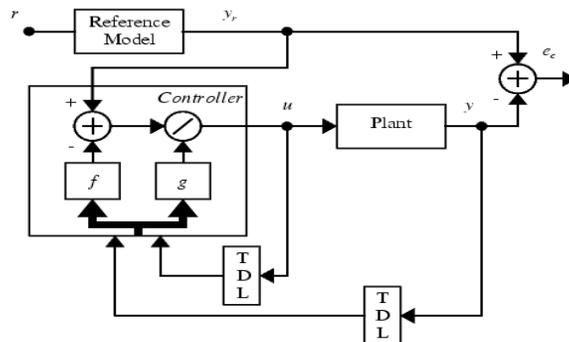


Figure 3. NARMA-L2 control structure

From (12) the control effort which gives output equal to reference trajectory is determined and the controller structure given by (13) is obtained. Figure 3 shows the NARMA-L2 control schematic.

$$u(k + 1) = \frac{y_r(k+d) - f[y(k), \dots, y(k-n+1), u(k), \dots, u(k-n+1)]}{g[y(k), \dots, y(k-n+1), u(k), \dots, u(k-n+1)]} \quad (13)$$

There are two steps involved in designing neural network based NARMA-L2 controller: system identification and control design. In system identification stage, a neural network model of the plant is trained with a set of input output data obtained from the plant. During training the weights and biases of the network are adjusted such as to approximate functions f and g .

Input output data set with 4000 samples is obtained from simulation of nonlinear plant model developed in Simulink with sample time of 0.005sec. This data is divided in two parts, training data and testing data. The parameters of the controller are chosen as

- The number of delayed plant inputs: 2
- The number of delayed plant outputs: 3
- The size of hidden layer: 5
- The sampling interval: 0.005

Now the neural network is trained offline in batch mode with Levenberg-Marquardt back propagation algorithm [11] with 100 epochs and is shown in Figure.4. Performance function used for training the network is mean square error. The training error decreases with advance of the training process as the network learns.

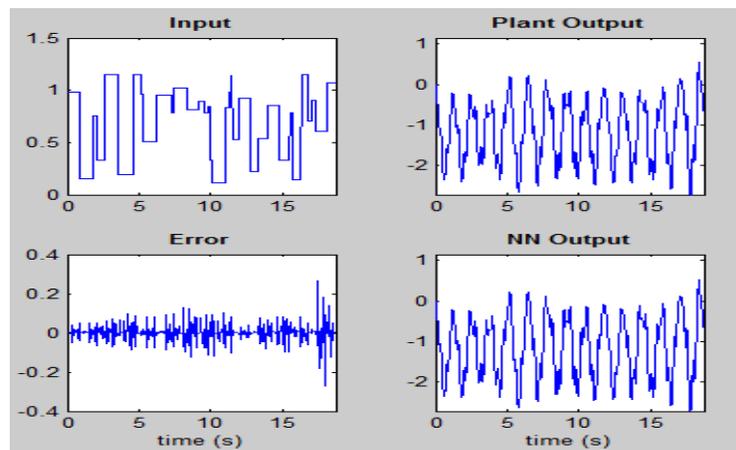


Figure 4(a). Neural network training for theta1

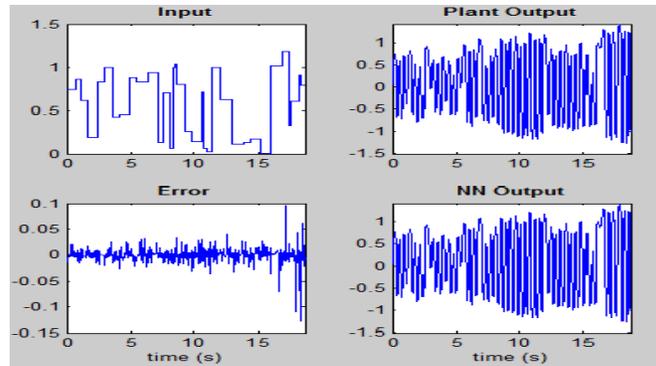


Figure 4(b). Neural network training for theta2

The final control schematic of neural network controller developed by employing fixed stabilization technique is shown in Figure 5. NARMA-L2 controller takes over the control after stabilization and provides optimum performance as it keeps learning from error input and provides control based on prediction to cancel the effect of disturbances and nonlinearities.

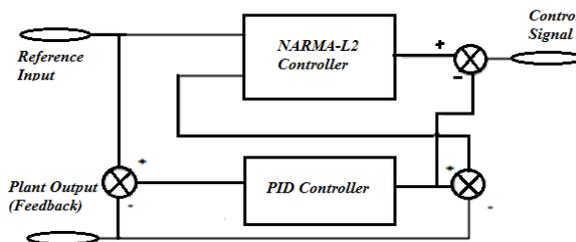


Figure 5. Neural network control schematic

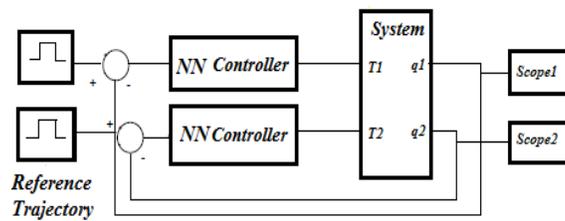


Figure 6. Block diagram of a NN controlled system

3.3 Fuzzy Logic Controller

Fuzzy systems possess efficient learning capability which could be utilized to form inferential systems for effective and real-time Motion Planning. Fuzzy controller basically consists of four components: fuzzifier, fuzzy inference engine, fuzzy rule base and defuzzifier.

To design a fuzzy controller first step is to specify number of inputs, outputs and their range. For this work, the two inputs taken are error in the position of link and the rate of change of error. The span of error is $[-2.5 \ 2.5]$, rate of change of error is $[-30 \ 30]$ and that of control is $[-2 \ 2]$. These inputs are fuzzified to represent their linguistic variables, for which 7 Gaussian membership functions are used.

To comprise fuzzy logic, 49 IF THEN rules with minimum operator are specified as shown in Table 2, which maps the fuzzy inputs to fuzzy output. This fuzzy output is then defuzzified to obtain crisp value of output control. The centroid method is employed for defuzzification.

Table 2. Fuzzy Control Rules

error rate	NL	NM	NS	Z	PS	PM	PL
error							
NL	PL	PL	PM	PM	PM	PS	PS
NM	PL	PM	PS	PS	PS	PS	PS
NS	PM	PM	PS	PS	Z	Z	PS
Z	PS	PS	Z	Z	Z	NS	NS
PS	NS	Z	Z	NS	NS	NM	NM
PM	NS	NS	NS	NS	NM	NM	NL
PL	NM	NM	NM	NM	NL	NL	NL

Two controllers with the same rules and membership functions are designed and implemented with fixed stabilization technique to control the two links for optimum performance. The advantage of using this technique is that fuzzy control can start with stabilized system, thereby providing faster response. The control schematic is shown in Figure 7 and Figure 8.

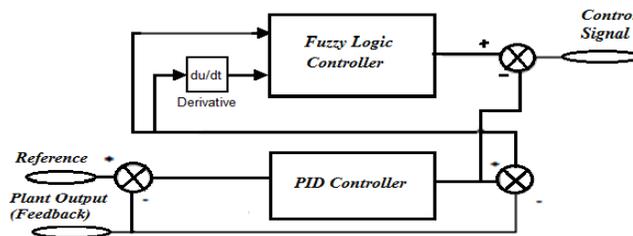


Figure 7. Fuzzy logic control schematic

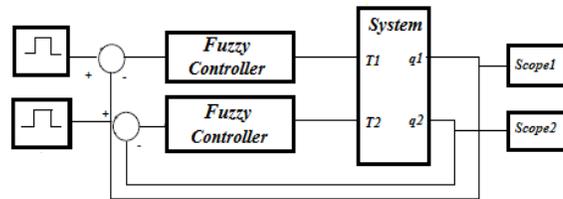


Figure 8. Block diagram of fuzzy controlled system

4. Simulation & Results

The nonlinear model of two links rigid manipulator system is simulated in MATLAB GUI Simulink environment using s-function. For this model effectiveness of the designed neural network and fuzzy controller based on fixed stabilization technique for reference tracking is evaluated and compared for step input and is shown in Figure 9.

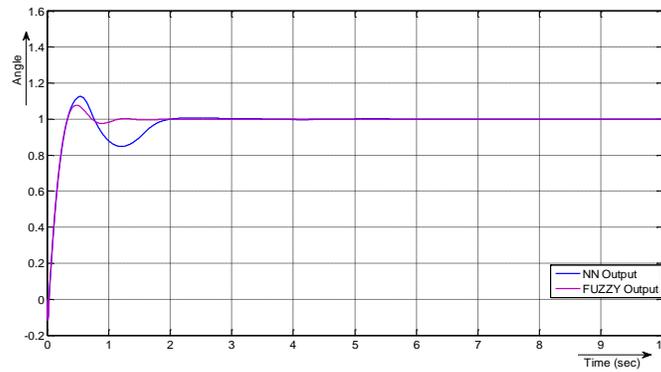


Figure 9(a). Reference tracking performance of link1

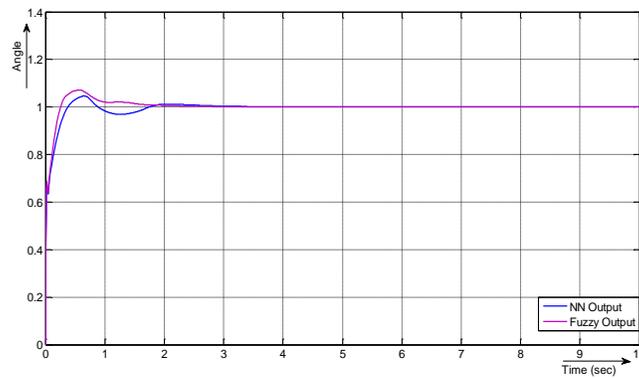


Figure 9(b). Reference tracking performance of link2

Figure 10 and Figure 11 show the performance of the proposed controllers for perturbed model with varying load added to link2. Neural network and fuzzy logic controller are capable of controlling the system but it is observed that settling time and peak overshoot increases with increase in the load.

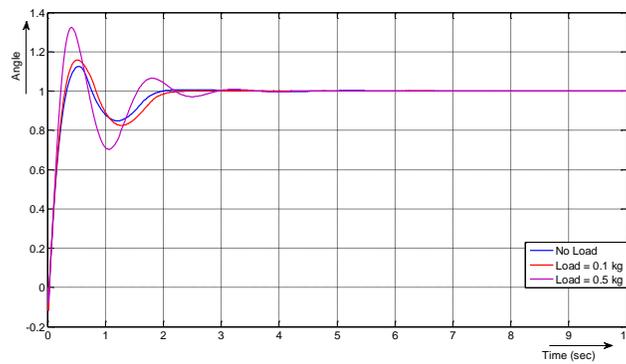


Figure 10(a). NN controlled response with varying load for link1

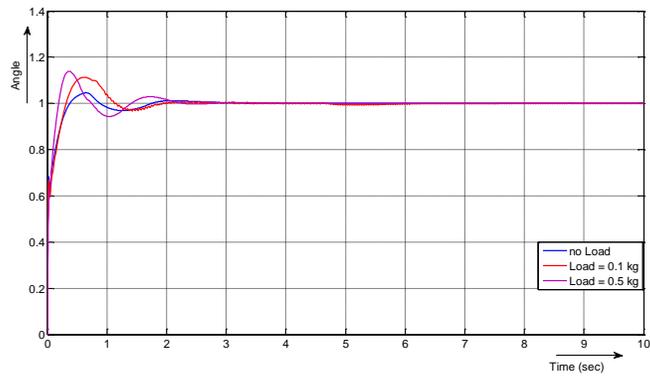


Figure 10(b). NN controlled response with varying load for link2

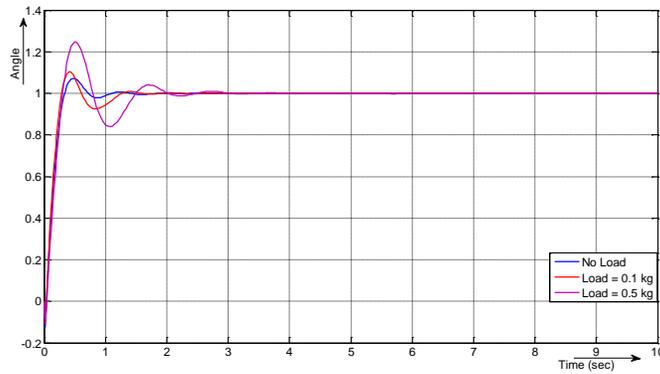


Figure 11(a). Fuzzy controlled response with varying load for link1

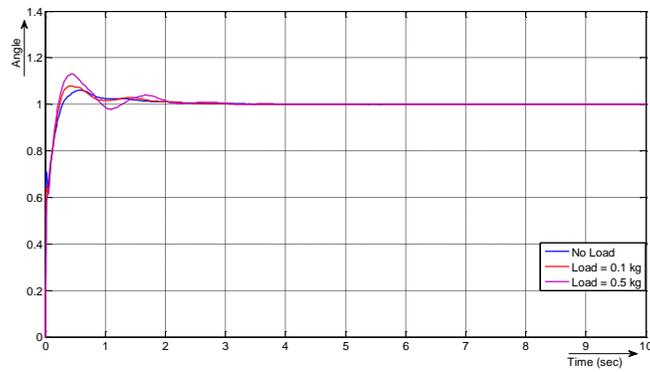


Figure 11(b). Fuzzy controlled response with varying load for link2

The time domain specifications in reference tracking for the system under consideration equipped with the proposed controllers are given in TABLE 3 and TABLE 4 respectively.

Table 3. Tracking Performance Comparison For Link1

Time Domain Specification	Neural Network Control	Fuzzy Logic Control
Settling Time (sec)	1.7	1.2
Overshoot (%)	12.5	7.5
Steady State Error	0	0

Table 4. Tracking Performance Comparison For Link2

Time Domain Specification	Neural Network Control	Fuzzy Logic Control
Settling Time (sec)	1.8	1.1
Overshoot (%)	4.5	6.5
Steady State Error	0	0

5. Conclusion

Neural network and fuzzy logic controllers are successfully designed and implemented for control of two link rigid manipulator with varying load by utilizing fixed stabilization technique. Based on the simulation results, it is found that, settling time is reduced by 70% and peak overshoot is reduced by 60% with fuzzy control for link1. For link2, settling time is reduced by 61% but peak overshoot is increased by 44% with fuzzy control as compared with neural control. It is concluded that Fuzzy controller provides better response as compared to neural network controller.

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