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Fuzzy Control and Fuzzy Control Adaptive of a Robot Manipulator

[1]Mellah Rabah and [2]Toumi Redouane
[1]Laboratory of Mechanics Precision to Apply (L.M.P.A) Faculty of the Engineering,
University Ferhat Abbas 19000 Setif
[2]Laboratory Robotic, Electro Technical and Parallelism (L.R.E.P),
Faculty of Electric and Data-processing Genius,
University Houari Boumediene (U.S.T.H.B)

Abstract: This study presents an investigation on trajectory control of a robot using fuzzy control and adaptive fuzzy control. We considered initially fuzzy controller of Mamdani type then to equip the proposed control scheme with adaptive controller, we have replaced the fuzzy regulators of Mamdani type by those of Seguno type in order to project the latter in neural networks, thus determining suitable fuzzy control rules and membership functions. We have synthesized two adaptive fuzzy controllers; Neural-fuzzy controller and Neural-fuzzy controller by model of reference.

Key words: Modelling, decentralized control, control by model of reference, fuzzy logic, neural-fuzzy

INTRODUCTION

Robot manipulators are nonlinear dynamic systems normally used to perform generic tasks such as pick and place, seam tracking, assembly, etc (Melek and Goldenberg, 2003). The control of a robot involves two fundamental problems; trajectory planning and motion control (Yildirim, 2004). The strategies of control suggested for the control of the robot manipulators require some a priori knowledge of robot dynamics (Labiod *et al*., 1998). Indeed the influence of the disturbances and the dynamic interaction between the actuators and the articulations of the robot, are not easy to estimate and vary sometimes with time. Thus, it proves to be necessary to choose adaptive control methods, in order to maintain the good tracing performances in the presence of structural uncertainties. Nevertheless, this approach does not compensate for unstructured uncertainties caused by unmodeled dynamics, nonlinear friction, disturbances and high-frequency models of the dynamics, thus making it difficult control using conventional techniques. The improved control of a robot without a priori knowledge of its dynamics, such as fuzzy logic or neural network control, has much attentions in recent years (Tian and Collins, 2005).

Since the first application of the formalism of fuzzy logic to the control of the systems proposed by Mamdani, many work showed that control with fuzzy logic is an adequate method for the control badly definite or completely unknown processes which cannot be modelled easily in a mathematical way (Titel and Belarbi, 1999).

In the last few decades, much research effort has been put into the design of intelligent controllers using fuzzy logic (Tian and Collins, 2005). Fuzzy logic control provides human reasoning capabilities to capture uncertainties, which cannot be described by precise mathematical models (Joo and Gao, 2003). However, most adaptive fuzzy controllers have difficulties in determining suitable fuzzy control rules and membership functions (Titel and Belarbi, 1999).

The traditional approach for the fuzzy design is based primarily on the knowledge obtained by expert operators formulated in the form of rules. It may be that the operators cannot transcribe their knowledge and experiment in the form of controller with fuzzy logic (Titel and Belarbi, 1999).

Recently, hybrid control laws containing Neural Networks (NNs) have attracted more and more attention. The connectionist structure of an NN provides powerful abilities, such as adaptive learning, parallelism, fault tolerance and generalization, to the fuzzy controller. NNs were used to adjust and optimize parameters of fuzzy controller trough offline or online learning (Joo and Gao, 2003). The reason why neural networks are gaining importance is the ability of representing complex nonlinear mappings and they are not as costly as the detailed mathematical models (Akbas and Esin, 2004). Moreover, the goals of neural-fuzzy are to realize the process of fuzzy reasoning using the structure of an neurons networks and express the parameters of fuzzy reasoning through the weights of an neurones networks (Peng and Woo, 2002).

Corresponding Author: Mellah Rabah, Laboratory of Mechanics Precision to Apply (L.M.P.A) Faculty of the Engineering, University Ferhat Abbas 19000 Setif

The objective of this research falls under the setting of a strategy of control applied to a robot manipulator with two articulations rotoïdes by using controllers of the Mamdani type initially. Thereafter we replaced the latter by those of Seguno to be able to readjust the parameters of the functions of membership and the whole of the rules of inference by projecting the latter in networks multilayer. We present in this study the dynamic model of the robot manipulator. In present study we clarify the strategy of fuzzy control used. This study gives some details about the two proposed neural-fuzzy control schemes. The model of the law of order applied to each articulation of the robot is the subject of paragraph. In this study, we are interested in the technique of adjustment of the parameters by projecting the fuzzy controllers developed in networks connectionist in order to readjust the parameters of the functions of membership and the whole of the rules of inference. The results of simulation are presented in this study, to illustrate the performances of the developed diagram of control. Lastly, the conclusions of the investigation are summarized.

Dynamic model of the robot manipulator: Figure 1 shows a schematic drawing of the links 1 and 2 of the adept one. Both actuators are located at the base of the robot. Joint 1's actuator applies torque T_1 to the link 1 structure and Joint 2's applies torque T_2 to the link 2 structure (Gousmia and Himrane, 2000).

The compact form of the dynamic model of robot is given by Gousmia and Himrane (2000):

$$t = H(q)\ddot{q} + C(q,\dot{q})\dot{q} + E(q,\dot{q}) \tag{1}$$

Where q,q,q denotes the link position, velocity and acceleration vectors, respectively, H(q) the inertia matrix, C(q,q) the coriolis/centripetal matrix and E(q,q): vector gathering the forces of gravity and the forces of friction.

Control by fuzzy logique: Since fuzzy control is a model-free approach, it may provide a possible solution to robotic control, which deals with high nonlinearity, high coupling and unmodeled uncertainties (Peng and Woo, 2002).

The bloc diagram in Fig. 2 shows the main parts of a fuzzy control system, of which the fuzzy rule-based inference engine is the kernel and fuzzification and defuzzification are the interfaces with crisp data in the out side physical world (Peng and Woo, 2002).

In general, a Fuzzy Logic Controller (FLC) consists of a set of linguistic conditional statements that are derived from human operators and which represent experts

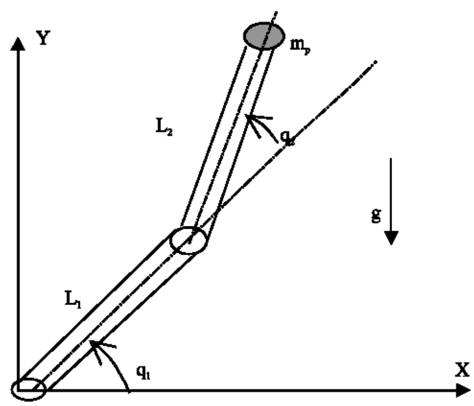

Fig. 1: Geometrical representation of a two-link planar manipulator

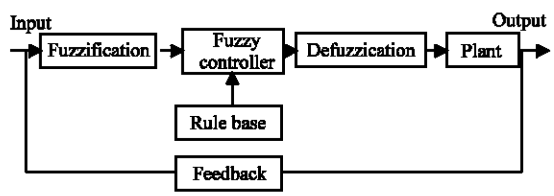

Fig. 2: Fuzzy logic system

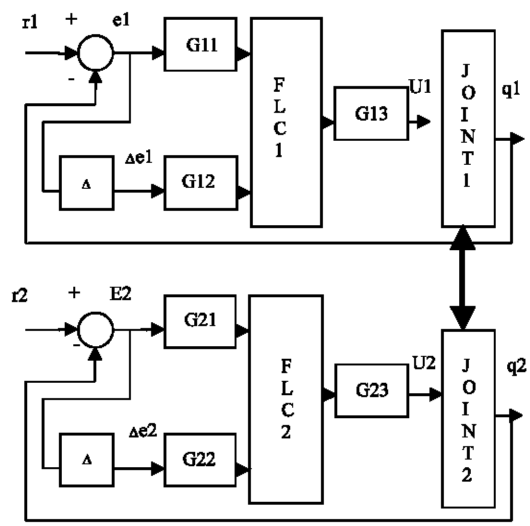

Fig. 3: Fuzzy logic control scheme with decentralized structure

knowledge about the system bein controlled. These statements define a set of control actions using if-then rules (Tian and Collins, 2005). The structure of control adopted for the Robot is schematized by the Fig. 3: (Gousmia and Himrane, 2000)

For each articulation of the robot the instantaneous error and its derivative are given respectively by these equations:

$$e(k) = r(k) - q(k) \tag{2}$$

$$\Delta e(k) = \frac{e(k) - e(k-1)}{\Delta T} \tag{3}$$

With ΔT period of sampling and e(k-1) the error at the moment k-1.

Moreover, in order to have energy necessary to ensure the good continuation of the performances, we chose the following gains of standardization:
Gains of the error: Ge1 = Ge2 = 0.005
Gains of variation of the error: $G\Delta e1 = G\Delta e2 = 0.0005$.
Gains of control: Gu1 = 180; Gu2 = 40.

Adaptive fuzzy control: This approach consists in combining the network analysis of artificial neurons and the fuzzy systems, in order to benefit from the capacities of the training of the networks of artificial neurons (RNA) and of those of the approximate reasoning of fuzzy logic, thus to minimize the disadvantages of each method alone. To be done we replaced the fuzzy regulators synthesized previously by those of seguno. Two strategies of adaptive fuzzy control are synthesized namely Neural-fuzzy control and Neural-fuzzy control by model of reference. Thus the training of the network Neural-fuzzy synthesized in each strategy of control allows to adjust the parameters of design and to extract the inferences after convergence (JYH-Shing and Chune-Tsai, 1995).

Principle of the method: In this strategy of control, we propose to impose for each articulation of the robot a law of control in order to reach the imposed performances of continuation, by using a multi-regulating composed of four elementary regulators, of which each one equipped with a nonlinear interpolator who replaces the technique of conventional regulation. The parameters of the law of control are estimated recursively in order to minimize the quadratic error between the robot joint's desired position q_d and its actual one, q, whose principle is illustrated by Fig. 4 (Gousmia and Himrane, 2000) or between the output of reference model q_m and robot joints actual position q, as Fig. 5 shows it (JYH-Shing and Chun-Tsai, 1995).

Model of the law control applied to each joint of robot: It is primarily made up by a whole of local rules dependent on the error and its variation at the current moment. The consequence of each rule can be an elementary regulator or a local regulator, due to the fact that its behaviour is confined in a particular field in relation to the premises of each rule. The output of these regulators is then a linear function of the error and its variation (JYH-Shing and Chun-Tsai, 1995).

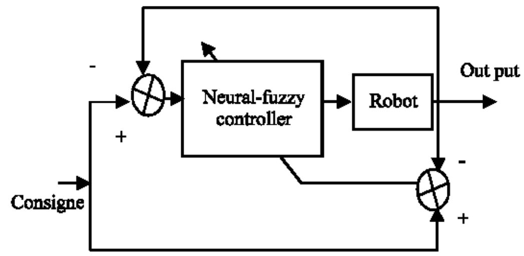

Fig. 4: Neural-Fuzzy control scheme

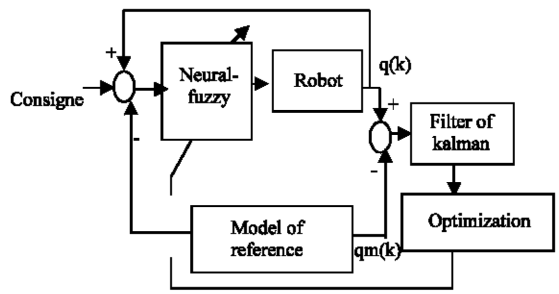

Fig. 5: Strategy of neural-fuzzy control by model of reference

To limit the complexity of the structure of the regulator, we consider only two unit sets M- and M + representing the fields in which the error and its variation are negative or positive. As well as the functions of membership of the error and its variation with the sets M- and M + are selected of triangular form because of their simplicity.

The list of the rules is as follows:

$$\begin{aligned}
&R^1 : \text{if } e(k) \in M^- \text{ and } \Delta e(k) \in M^- \text{ then} \\
&\quad u_1(k) = a_1 e(k) + b_1 \Delta e(k) + r_1 \\
&R^2 : \text{if } e(k) \in M^- \text{ and } \Delta e(k) \in M^+ \text{ then} \\
&\quad u_2(k) = a_2 e(k) + b_2 \Delta e(k) + r_2 \\
&R^3 : \text{if } e(k) \in M^+ \text{ and } \Delta e(k) \in M^- \text{ then} \\
&\quad u_3(k) = a_3 e(k) + b_3 \Delta e(k) + r_3 \\
&R^4 : \text{if } e(k) \in M^+ \text{ and } \Delta e(k) \in M^+ \text{ then} \\
&\quad u_4(k) = a_4 e(k) + b_4 \Delta e(k) + r_4
\end{aligned} \tag{4}$$

Finally, the order applied to each articulation of the robot is a barycentric combination of the partial orders worked out by each rule.

Principle of readjustment of the parameters of law control: Each elementary regulator is thus characterized by three adjustable parameters with knowing; a_i, b_i et r_i. However complete determination of the law control applied to each joint consists in adjusting these parameters according to the selected objective of regulation.

Moreover, in order to carry out the tracking of the trajectory of reference and to estimate the parameters of the law control, we have considered the instantaneous errors at the output expressed between the robot joint's desired position and its actual one, for each articulation of the robot $e_i(k) = q_{di}(k)-q_i(k)$ in the case of the Neural-fuzzy control and between the output of reference model and actual position of robot, for each articulation of the robot $e_i(k) = q_m(k)-q_i(k)$ in the other case.

Where $q_m(k)$ is the output at the moment K of the first order of reference model:

$$q_m(k+1) = 0.1 q_m(k) + 0.9 u(k) \tag{5}$$

In order to minimizing these errors, we used the approach of the filter of extended Calman, who consists in linearizing the output q_i at any moment around the estimated vector $\hat{\theta}$.

The law of adaptation used is given by the following relation (Labiod *et al*., 1998):

$$\theta_i(k+1) = \theta_i(k) + p(k) J_{\theta i}\, e_i(k+1) \tag{6}$$

Where

$J_{\theta i} = \delta q_i/\delta q_i$ is given by the method of retropropagation used in the networks of neurons and p(k) is the profit of adaptation expressed by the following relation (Labiod *et al*., 1998):

$$p(k) = \frac{a_1}{a_2 + J_{\theta i}^T J_{\theta i}} \tag{7}$$

RESULTS AND DISCUSSION

The feasibility and the efficiency of the approaches described in the previous sections have been studied by a series of simulations. During the simulations, the main objective is to keep track of the reference signal which is a cycloid trajectory for each joint on a horizon of 2s. The robot moves from the initial position P_i = [-135 135] to the final position P_f = [-85 30].

The graphs given by Fig. 6 to 8 represent the control and the tracking error of each joint, relating to the proposed control schemes: Fuzzy control, Neural-fuzzy control and Neural-fuzzy by model of reference.

These results show satisfactory qualities of tracking performances. Indeed, we notice on the one hand that the

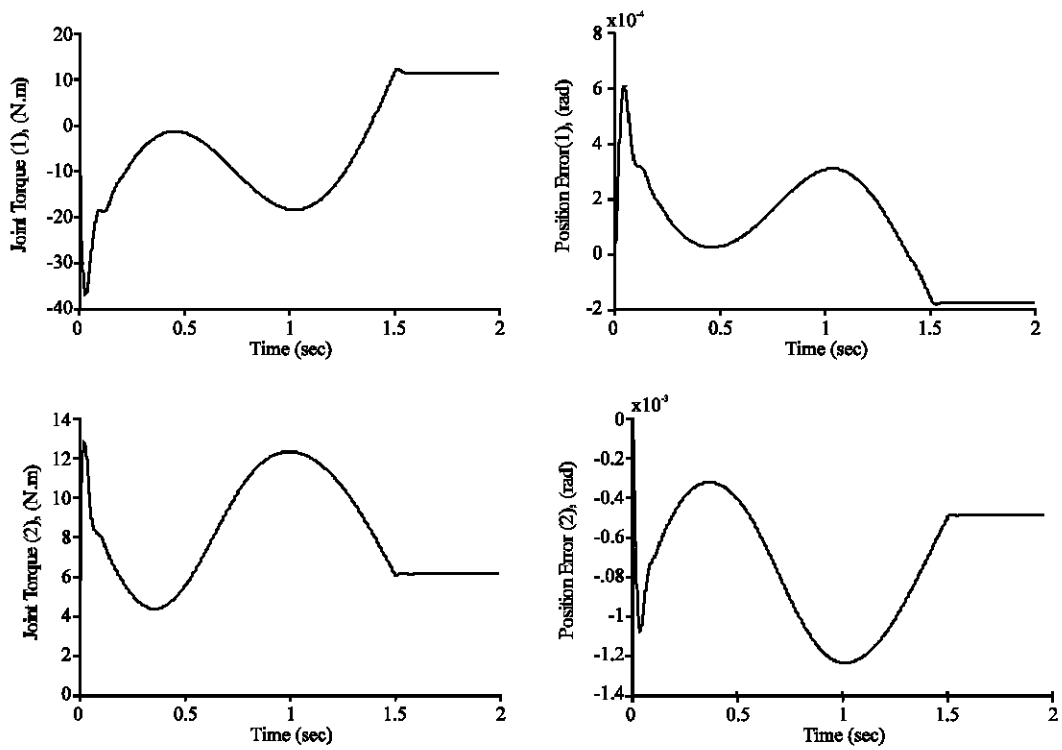

Fig. 6: Simulation results of fuzzy logic control scheme without payload

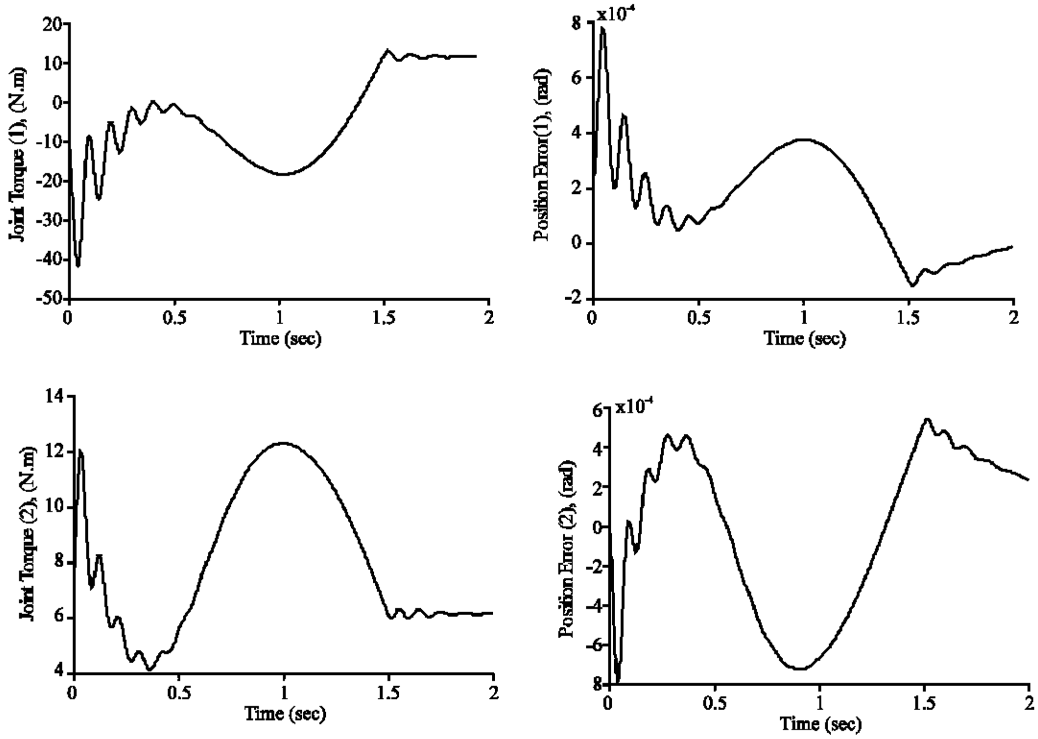

Fig. 7: Simulation results of neural-fuzzy control scheme without payload

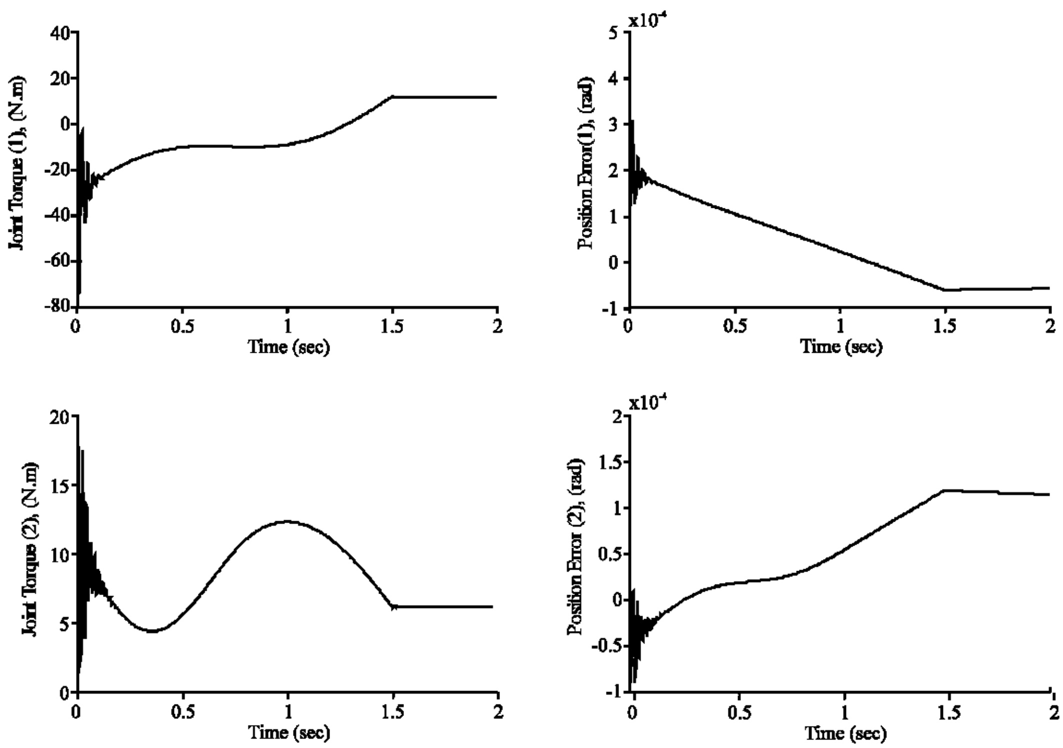

Fig. 8: Simulation results of neural-fuzzy control scheme by reference model without payload

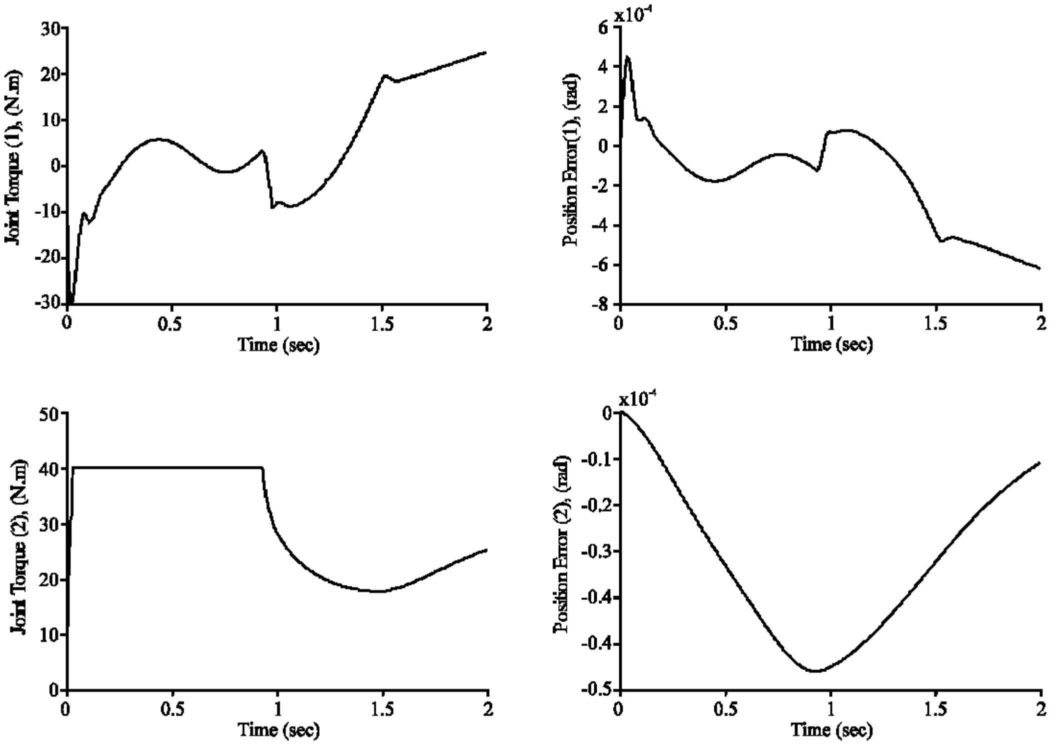

Fig. 9: Simulation results of fuzzy logic control scheme with payload

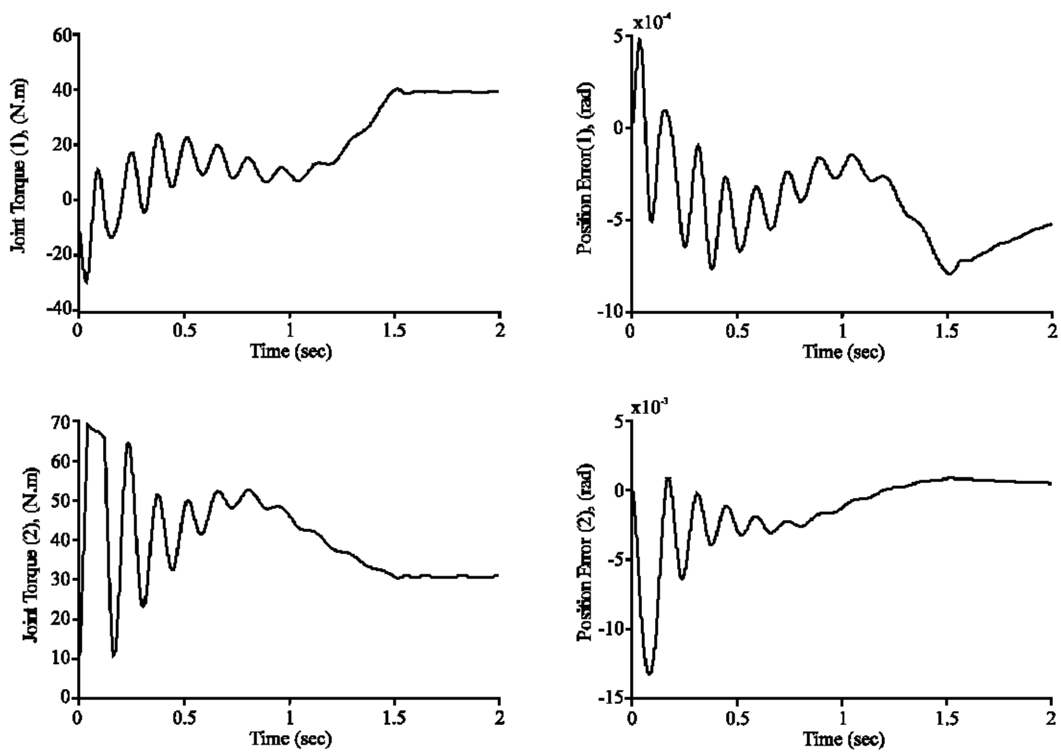

Fig. 10: Simulation results of neural-fuzzy control scheme with payload

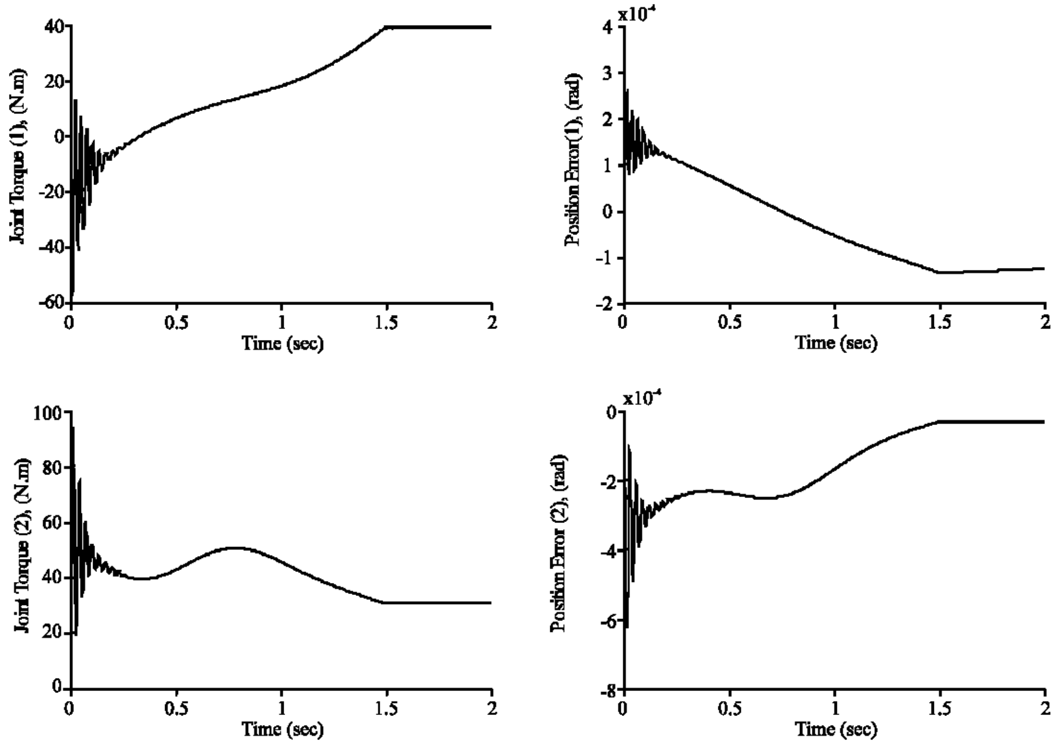

Fig. 11: Simulation results of neural-fuzzy control scheme by reference model with payload

tracking errors are limited by low values and in addition, that the control variables are smooth.

To test the ability of the proposed control schemes to adapt to different robot payloads, the load carried by the robot was increased to 20 kg following training on the 10 kg payload. The effect of a change in the payload mass from 10 kg to 20 kg for the proposed control schemes may be seen in Fig. 9 to 11.

From these results obtained, it can be seen that tracking error of second joint is very large compared to that the first joint. Because, the control adopted is decentralized, then the second joint is subject to the influence of the load through link 2.

In addition, by comparing Fig. 9 to 11, it can be seen that the proposed adaptive fuzzy controllers produced the best performance while the fuzzy controller yielded poor control. A reason for the strong performance of adaptive fuzzy control system was the inclusion of neural networks used to adjust and optimize parameters of fuzzy controller through online learning. Thus, the proposed adaptive fuzzy controllers provide a very large torque in order to compensate le effect of the additional load. What shows very satisfactory qualities of tracking performances even in the presence payloads. This clarifies the capacity of adaptation of the proposed control schemes.

CONCLUSION

In this investigation, the proposed controllers that consist of a fuzzy logic control and two adaptive fuzzy logic control, have been described in this study with decentralized structure. Each control scheme has been modeled and applied to the control of a two link planar manipulator. It has been shown that the integration of fuzzy logic and neural networks can combine the advantages of both techniques. The followed step initially consists in synthesizing the regulator of Mamdani type with two classes. Nevertheless sight the fixed structure of this regulator, the tracking performances are degraded in the presence of the payloads. In order to solving this problem, the design of a neural-fuzzy controller for a robotic manipulator system becomes a possible solution. Because here, the difficulty lies in how to provide an NN mechanism that realizes the fuzzy logic reasoning. Thus, we have considered projection structural of the fuzzy system of inference in a neural networks as well as the regulator of the Sugeno type, in order to adjust the weights of the connections, by an algorithm of training based on the wide Filter of Calman who consists in at any moment linearizing the law control around the estimated vector.

The simulations carried out on a Robot manipulator with two articulations rotoïdes showed very good tracking performances even in the presence payloads. The Simplicity relating to the structure of the correctors as well as the results obtained can allow us to consider an adjustment of the parameters on too complex systems.

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