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# Position Control of a Single Link Flexible Joint Robot Manipulator using Adaptive Neuro-Fuzzy Control System

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**ABSTRACT**

The advance methodologies to optimize fuzzy logic controller parameters via neural network and use the neuro- fuzzy scheme to control the single link flexible joined robot manipulators. The dynamics of robot single link manipulators are highly nonlinear with strong couplings existing between joints and are frequently subjected to structured and unstructured uncertainties. The increased complication of robots manipulator considering joint elasticity makes conventional model-based control strategies complex and difficult to manufacture. This paper presents investigations into the development of neuro fuzzy control for position control of a single link flexible joint manipulator. To study the effectiveness of the controllers, an adaptive Neuro Fuzzy Controller is developed for tip angular position control of a flexible joint manipulator. This is then extended to incorporate a neuro fuzzy Controller for position error decrease of the flexible joint system. Simulation results of the response of the flexible joint manipulator with the controllers are obtained in time domains. The performances of the adaptive neuro fuzzy control schemes are examined in terms of input tracking of position in robotics, and also graphically plotted in time response specifications.

***Keywords:*** *Flexible structure, Manipulator, Adaptive neuro-fuzzy control, Uncertain system.*

## I. INTRODUCTION

In most existing robotic manipulators, maximizing stiffness to minimize vibration and achieve good position accuracy of robotic manipulators is a key element in their design. This high stiffness is achieved by using weighty material and a huge design. Hence, the existing heavy rigid manipulators are shown to be inefficient in terms of power consumption and operational speed. In order to develop industrial productivity, dropping the weight of the arms and increasing their speed of operation are required. Therefore, flexible-joint manipulators have received a thorough attention lately, thanks to their lightweight, lower cost, larger work volume, better maneuverability, higher operational speed, power efficiency, and larger number of applications.

However, controlling such systems still faces several challenges that have to be addressed before they can be used in abundance in everyday real-life applications. The control issue of the single link flexible joint is to design the controller so that link of robot can attain a desired position for track a prescribed trajectory accurately with minimum vibration to the link. In order to achieve these goals, several methods using different technique have been proposed. However, controlling such systems are faces several challenges that need to be addressed before they can be used in abundance in everyday real-life applications. The severe nonlinearities, coupling stemming from the manipulator's flexibility, varying operating conditions, structured and unstructured dynamical uncertainties, and external disturbances, are among the emblematic challenges to be faced with when trade with such often ill-defined systems. These kind of Industrial single link flexible robot manipulators are mainly positioning and handling devices. The essential problem in controlling robots is to make the robot manipulator follow a desired input trajectory. In general degree of freedom rigid robot manipulator is characterized by nonlinear, dynamic, coupled differential equations. The problem of controlling robot manipulators still offers much kind of practical and theoretical challenges due to the complexities of the robot dynamics and the requirement to attain high precision trajectory tracking in the cases of high velocity movement and highly varying loads.

This paper presents investigation into the development of adaptive neuro fuzzy control for trajectory tracking of tip angular position and vibration control of flexible joint manipulator. Initially a adaptive neuro fuzzy Control is developed for trajectory tracking of tip angular position. The performances of the composite control schemes are examined in terms of input tracking capability, level of vibration reduction and time response specifications. The rest of the paper is structured as follows: Section II provides a brief description of the flexible joint manipulator system considered in this study. In Section III, we introduce a number of soft computing-based controllers. The design of the proposed controller is detailed in Section IV. In Section V, simulation results are reported and discussed. We conclude with a few remarks and suggestions for further studies pertaining to this important, yet complex, control problem.

## II. FLEXIBLE-JOINT MANIPULATOR DYNAMICS

### *A. Flexible-Joint Manipulator Modeling*

Typically, a flexible joint can be modeled as shown in Fig.1.The actuator is coupled to a flexible transmission through an r : 1 reduction gear. The transmission is directly linked to the load (e.g., manipulator link).Consider a robot manipulator with n revolute flexible joints.

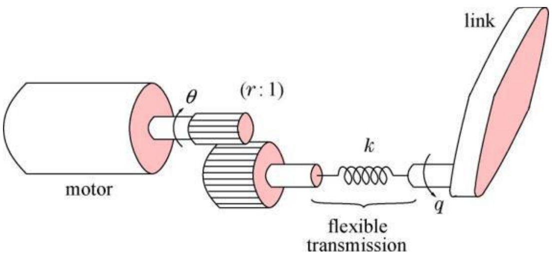


**Fig.1.** Flexible-joint model

Using Euler– Lagrange formulation and neglecting gyroscopic effects, the dynamic equations of the manipulator can be written as:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau_t - \tau_{fl} - \tau_{dl} \quad (1)$$

$$j_m\ddot{\theta} = \tau_m - \frac{1}{r}\tau_t - \tau_{fm} - \tau_{dm} \quad (2)$$

$$\tau_t = K\left(\frac{\theta}{r} - q\right) \quad (3)$$

Where,

$q$ = $R^n$ vector of links' positions;

$\theta$ =$R^n$ vector of motors' positions;

$M(q)$ =$R^{n\times n}$ manipulator's positive definite inertial matrix;

$C(q, \dot{q})$ =$R^{n\times n}$ matrix of Coriolis and centrifugal terms;

$G(q) = \mathrm{R}^n$ vector of gravitational torques;

$J_m = \mathrm{R}^{n\times n}$ motors' diagonal inertial matrix;

$\tau_t = \mathrm{R}^n$ vector of transmission torques;

$\tau_m = \mathrm{R}^n$ motors' generalized torque vector (control input);

$\tau_{fl} = \mathrm{R}^n$ load friction vector;

$\tau_{fm} = \mathrm{R}^n$ motors' friction vector;

$\tau_{dl} = \mathrm{R}^n$ load's unmodeled dynamics and external disturbance vector;

$\tau_{dm} = \mathrm{R}^n$ Motors' unmodeled dynamics and external disturbance vector;

$K = \mathrm{R}^{n\times n}$ Diagonal matrix of joints' stiffness coefficients;

$r = \mathrm{R}$ Gear ratio.

Given the desired trajectories $q_d$ and $\dot{q}_d$, we aim to design a control law $\tau_m$ which ensures that the manipulator's position $q$ and velocity $\dot{q}$ track their desired trajectories under unknown dynamics and in the presence of external disturbances. The proposed controller uses $q$, $\dot{q}$, and $\dot{\theta}$ as system's measurable states, and the manipulator's parameters $M(q)$, $C(q, \dot{q})$, $G(q)$, $J_m$, $\tau_{fl}$, $\tau_{fm}$, $\tau_{dl}$, and $\tau_{dm}$ are assumed to be unknown.

### B. Problem Statement

The control objective is to design a control law $\tau_m$ to force the manipulator's position $q$ and velocity $\dot{q}_d$ to track their predefined time-dependent desired values $q_d$ and $\dot{q}_d$, respectively. This objective is to be reached under unknown or uncertain system's dynamics.

## III. SOFT COMPUTING BASED CONTROL

In spite of the recent advances in the area of nonlinear control systems, the common point still shared by the vast majority of conventional control techniques is their dependence on precise mathematical models of the systems to be controlled for them to provide satisfactory performance. In real life, and due to the typical high nonlinearities within the dynamics of flexible-joint manipulators, deriving a precise model for such systems could be a difficult undertaking. Although conventional adaptive control strategies, such as in sliding mode controllers, compensate for the system's parametric uncertainties, they are still vulnerable in the face of unstructured modeling uncertainties. Expert controllers based on tools of soft computing, on the other hand, may not have such a limitation. In fact, computational intelligence tools, in general, have been credited in a number of applications to provide satisfactory results in the face of relatively large magnitudes of noise in the input signals, of dynamically variable parameters, and in the lack of a precise mathematical model of the system in hand. The two types of computational intelligence tools that we are concerned with in this work are fuzzy logic controllers (FLCs) and artificial neural networks (ANNs).

Among the main features of FLCs is their ability to generate adequate control decisions inference through human- like linguistic descriptions. These are represented by fuzzy rules based on heuristics, knowledge, and experience, and are often used to control a given system. A special inference mechanism processes the information stored in the knowledge base to determine the adequate control action to be taken at any given operating condition.

An n-input m-output fuzzy logic controller (FLC) can be regarded as a mapping from U = U1×U2×………Un into V = V1×V2×……Vm, where Ui ϵ R, Vj ϵ R, for i = 1, 2………. n and j = 1, 2………m. The output y = (y1………… ym) T of an n-input m-output FLC with a center-average defuzzifier,

Sum product inference, and singleton output fuzzifier, is given by:

$$y_j = \frac{\sum_{l=1}^{L} y_j^{(l)} \left( \Pi_{i-1}^{n} \mu_{A_i^{(l)}}(x_i) \right)}{\sum_{l=1}^{L} ( \Pi_{i=1}^{n} \mu_{A_i^{(l)}}(x_i) )}$$

Where, $x = (x_1 \ldots\ldots\ldots\ldots x_n)^T \in U$ is the FLC's input vector, $\mu A(t)\ I$ are the membership functions of the fuzzy sets $A^{(l)}$t, Σ denote the fuzzy t-norm and t-conorm operations used, respectively, *l* is the rule index from a total of *L* rules, and *y*(*l*) *j* is the point in $V_j$ at which *B* (*l*) *j* achieves its maximum value which is assumed to be 1. In this paper, we use the "min" and "max" operators as the t-norm and t-conorm, respectively. The FLC is capable of uniformly approximating any well-defined nonlinear function over a compact set *U* to any degree of accuracy.

ANNs represent another type of soft computing technique and an important class of numerical learning tools known as connectionist modeling. An ANN is a set of interconnected computational nodes in which information is processed and transferred from one node to another through the means of weighted links with the purpose of mimicking the functionality of the neurons in the human brain. ANNs are characterized by their nonlinear behavior, parallel processing, and their automatic optimization and learning capabilities. These advantages have been behind the increasing popularity of ANNs for numerical modeling and control, especially for systems on which little is known about their dynamics and operating environments. Just like FLCs, the neural network universal approximation theorem guarantees that any sufficiently smooth function can be approximated to any degree of accuracy using a single-hidden-layer ANN. Although several neural network-based controllers have been proposed in the literature, the supervised multi-layer perceptron scheme is among the simplest and most popular schemes, particularly in control systems' applications. The network's learning mechanism is often carried out as to minimize the network's output error based on a user-defined feedback signal

## IV. ADAPTIVE NEURO FUZZY CONTROL

In recent years, intelligent control in general, and neuro-fuzzy control in particular, have been quite inspiring paradigms for real-time control applications. Neuro-control based artificial neural networks, having the ability to learn from input-output non-linear functions, are good candidates for solving complex nonlinear control problems. Neurons are basically non-linear elements; hence, neural networks are basically non-linear systems which can be used to learn and solve non-linear control problems that are usually too difficult for traditional and conventional control methods to handle. Using the inverse model as the main block in the neuro-control approach is one of the most widely applied schemes.

In order to achieve accurate trajectory tracking and good control performance, a number of control schemes have been developed. Amongst these, Adaptive Neuro-Fuzzy System has provided best results for control of robotic manipulators as compared to the conventional control strategies. ANFIS is a fuzzy inference system implemented in the framework of adaptive networks. By using a hybrid learning procedure, the ANFIS can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs. The hybrid learning algorithm identifies the membership function parameters of single-output, Sugeno type fuzzy inference systems (FIS). A combination of least mean squares (LMS) and back propogation gradient descent methods are used for training FIS membership function parameters to model a given set of input/output data. The parameters associated with the membership functions change through the learning process. The training process stops whenever the designated epoch number is reached or the training error goal is achieved.

The nonlinearity prevailing in the arm dynamics induces high uncertainty in the performance of the robotic manipulators under conventional control strategies. The use of the intelligent systems such as neural networks and fuzzy control has provided better results. But a combination of such intelligent systems, like, neuro-fuzzy or ANFIS provides even better results than just neural networks.

### *A. ANFIS architecture*

For simplicity, we assume the fuzzy inference system under consideration has two inputs x and y and one output z. Fig.2 Depicts the structure of Adaptive neuro fuzzy controller below:

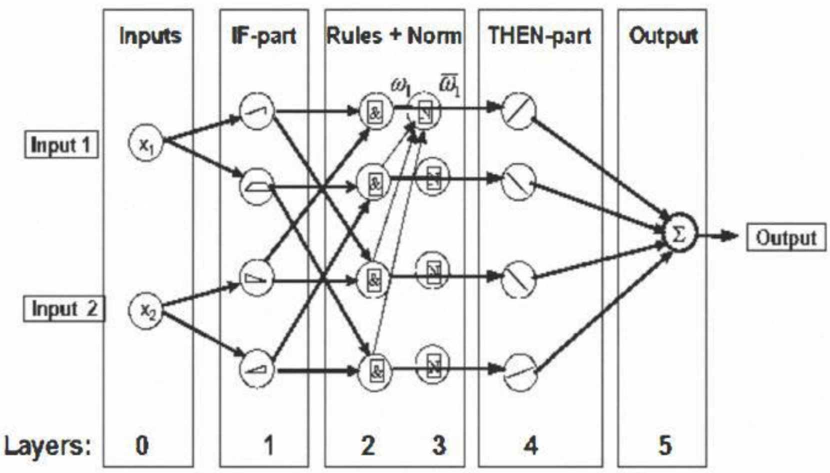


**Fig.2.** Structure of neuro fuzzy controller

### *B. ANFIS Modeling*

Modeling was performed using MATLAB 7.8. ANFIS and Sugeno-type fuzzy inference systems were used in the modeling of robot manipulator. Single Input Single Output models consisting of inputs including position and velocity were developed to predict outputs. Sugeno-type fuzzy inference systems were generated by using Genfis which utilized subtractive clustering to compute the models for the product properties. The purpose of clustering was to identify natural groupings of data to produce a concise representation of the behavior of the system. The fuzzy models generated from the membership functions and rules were data-driven by the process data for each mechanical property. Each set of process data collected from the extrusions consisted of 40 data points from which 70% and 30% were selected randomly for training and testing, respectively. The models were developed and implemented using 3000 epochs and a radius of 0.5. The input data were the process data acquired by the computer consisting position and velocity readings from extrusion. The input and output data sets contained inputs (position, velocity) and one output torque.

## V. SIMULATION RESULTS AND DISCUSSION

### *Experimental Setup*

Let $\Delta q = q - q_d$ and $\Delta\mu = \mu - \mu_d$ denote the links' and motors' position errors, respectively, with $\mu_d$ being the unknown desired time-dependent motor position vector. The control strategy is based on the design of an adaptive controller that not only leads to a precise tracking of the system's nominal desired signals, but also improves the motors' internal stability. Should the motors' desired position $\mu_d$ have been available, the control strategy would be based on tracking $\Delta q$ and $\Delta\mu$ to zero. Since that is not the case, we define the following compounded velocity error signal

$$\Delta \dot{\epsilon}_r = \dot{q}_d - \left(\lambda_{\dot{q}} + (1-\lambda)\frac{1}{r}\dot{\theta}\right)$$

For a diagonal matrix $\lambda = \text{diag}(\lambda_1, \lambda_2 \ldots\ldots \lambda_n)$ with , $\lambda_i \in [0,1]$, $i = 1 \ldots\ldots n$. The feedback gain $\lambda$ is introduced to provide a trade off between the link tracking performance and internal stability, due to the high nonlinear coupling between the two.

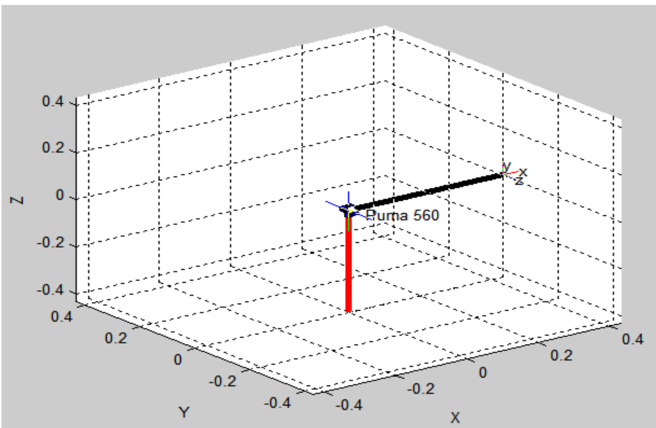


**Fig.3** simulation diagram of single link flexible robot manipulator

To demonstrate the performance of the proposed controller, a set of numerical experiments is carried out on a single link flexible-joint manipulator. The manipulator's dynamics in terms of its physical parameters is defined by $M(q) = I$, $C(q, \dot{q}) = 0$, and $G(q) = mgl\sin(q)$, where $m$ is the link's mass, $g$ is the gravity constant, and $l$ is the link's length. Table I summarizes the manipulator's physical parameters along with their respective values. The stiffness coefficient and gear ratio are assumed to be $K = 5$ N · m/rad and $r = 1$.

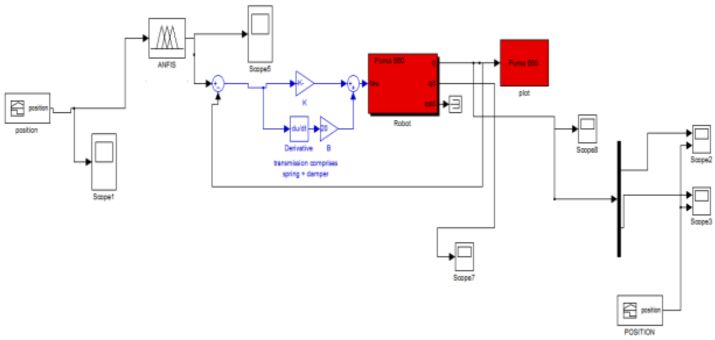

**Fig.4** Model of single link robot manipulator position control Simulink

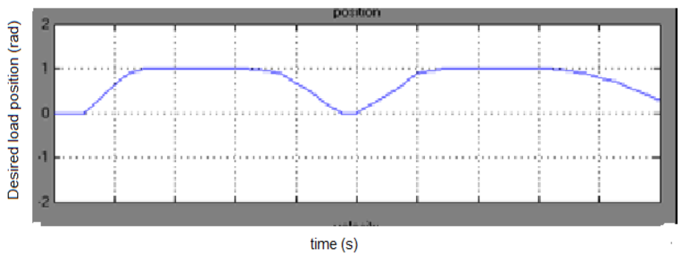


**Fig.5** Manipulator's position reference signals.

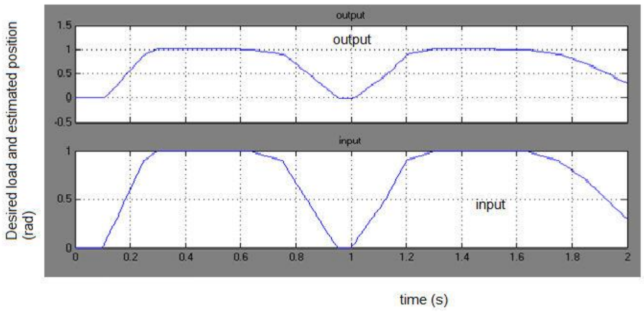


**Fig.6** output of single link flexible robot manipulator position

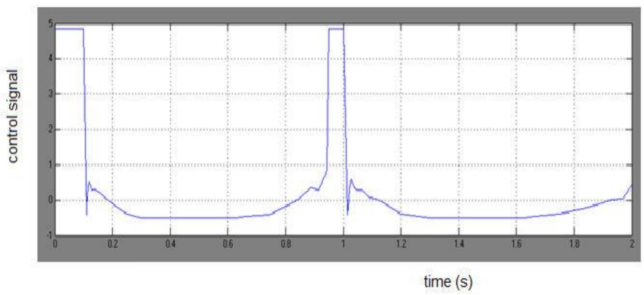


**Fig.7** Anfis controller response of manipulator position

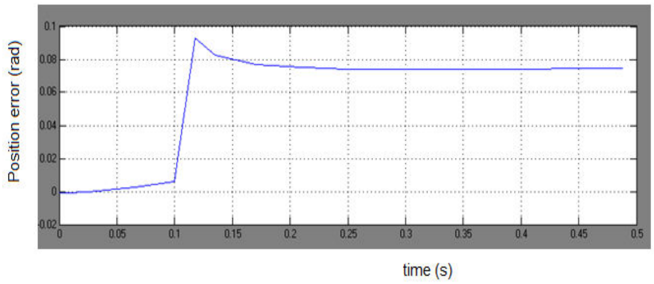


**Fig.8** Single link manipulator's Position error

## VI. CONCLUSION

The development of adaptive neuro fuzzy control techniques for position error reduction of a single link flexible joint robot manipulator has been presented. The proposed control schemes have been implemented and tested. The control strategy is based on a neuro fuzzy control approach while taking into account the actuators relative stability criterion by introducing a trade-off between the actuators' internal stability and the link's position. The performances of the control schemes have been evaluated in terms of input position and velocity error reduction at the resonance modes of the manipulator. Acceptable performance in input position and velocity control has been achieved with proposed control strategies. The work has developed and reported in this forms the basis of design and development of hybrid control schemes for input position and velocity error reduction of multi-link flexible manipulator systems and can be extended to and adopted in practical applications.

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