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Full Length Research Paper

A new approach for interval type-2 by using adaptive network based fuzzy inference system

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In this paper, adaptive network based fuzzy inference system (ANFIS) was used in control applications of different type nonlinear systems as interval type-2 fuzzy logic controller (IT-2FL). Two adaptive network based fuzzy inference systems were chosen to design type-2 fuzzy logic controllers for each control applications. Membership functions in interval type-2 fuzzy logic controllers were set as an area called footprint of uncertainty (FOU), which is limited by two membership functions of adaptive network based fuzzy inference systems; they were upper membership function (UMF) and lower membership function (LMF). The double inverted pendulum, a single flexible link and a flexible link carrying pendulum systems were used to test the performances of designed interval type-2 fuzzy logic controllers. System behaviours were defined by Lagrange formulation and MATLAB/SimMechanics computer simulations. The performances of the proposed controllers were evaluated and discussed on the basis of the simulation results. An experiment set up of flexible link carrying pendulum system was built and used to verify the performance of IT-2FL controller.

Key words: Adaptive network based fuzzy inference system, interval type-2, inverted pendulum, a single flexible link, control, simulation.

INTRODUCTION

Fuzzy logic controller (FLC) is credited with being an adequate methodology for designing robust controllers that are able to deliver a satisfactory performance in applications where the inherent uncertainty makes it difficult to achieve good results using traditional methods (Mamdani, 1994). As a result, the FLC has become a popular approach to nonlinear systems such as robot control in recent years (Tınkır et al., 2010; Banga et al., 2011). Some of these investigations on the control of robot manipulators consider adaptive network based fuzzy logic control and hierarchical fuzzy logic control (Tınkır et al., 2010; Akbarzadeh et., 1994; Lin, 2002, 2003; Caswara et al., 2002; Kuo et al., 2002; Jassbi et al., 2011) due to their several advantages over other control techniques.

Fuzzy sets (of type-1) and fuzzy logic are the basis for fuzzy systems, where their objective has been to model how the brain manipulates inexact information. Type-2 fuzzy sets are used to control uncertainty and imprecision in a better way. These type-2 fuzzy sets were originally presented by Zadeh (1975) and are essentially “fuzzy fuzzy” sets, where the fuzzy degree of membership is a type-1 fuzzy set (Zadeh, 1988; Castillo et al., 2008). The new concepts were introduced (Liang et al., 2000; Mendel, 2001; Adak et al., 2011) allowing the characterization of a type-2 fuzzy set with a superior membership function and an inferior membership function; these two functions can be represented, each one by a type-1 fuzzy set membership function. The interval between these two functions represents the footprint of uncertainty (FOU), which is used to characterize a type-2 fuzzy set. While traditionally, type 1 FLCs have been employed widely in nonlinear systems’ control, it has become apparent in recent years that the type-1 FLC cannot fully handle high levels of uncertainties as its MFs (membership functions) are in fact completely crisp (Hagras, 2004; Mendel, 2001; Adak et al., 2011). The linguistic and numerical uncertainties associated with dynamic unstructured environments cause problems in determining the exact and precise MFs during the sysem FLC design. Moreover, the designed type-1 fuzzy sets can be sub-optimal under specific environmental and operational

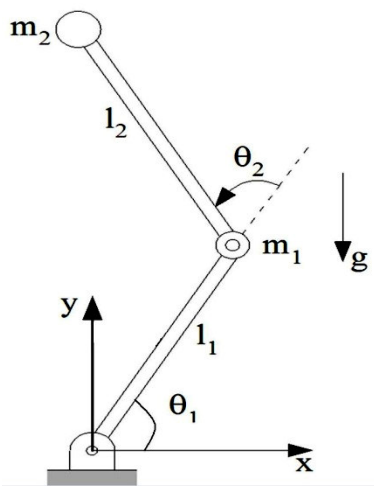

Figure 1. The double inverted pendulum system.

conditions. The environmental changes and the associated uncertainties might require the continuous tuning of the type-1 MFs as other wise, the type-1 FLC performance might deteriorate (Mendel, 2001). As a consequence, research has started to focus on the possibilities of higher order FLCs, such as type-2 FLCs that use type-2 fuzzy sets. A type-2 fuzzy set is characterised by a fuzzy MF, that is, the membership value (or membership grade) for each element of this set is a fuzzy set in [0,1], unlike a type-1 fuzzy set where the membership grade is a crisp number in [0,1] (Hagras, 2004). The MF of a type-2 fuzzy set is three dimensional and includes a footprint of uncertainty. It is the third-dimension of the type-2 fuzzy sets and the footprint of uncertainty that provide additional degrees of freedom making it possible to better model and handle uncertainties as compared to type-1 fuzzy sets. It has been shown that interval type-2 FLCs (that use interval type-2 fuzzy sets) can handle the uncertainties and outperform their type-1 counterparts in applications with high uncertainty levels such as mobile robot control (Hagras, 2004; Figueroa et al., 2005; Adak et al., 2011). However, manually designing and tuning a type-2 FLC to give a good response is a difficult task, particularly as the number of MF parameters increases.

Control of the mechanical systems such as pendulum and flexible link always, is interested by researchers who struggle with design of the controller (Theivasanthi, 2009; Suzuki et al., 2010). Pendulum and flexible link systems are commonly used as test problems to examine the ability of using improved controllers (Erfanian et al., 2009; Nakhaeinia et al., 2011). In this paper, adaptive network based fuzzy inference system (ANFIS) was used as interval type-2 fuzzy logic controller (IT-2FL) in control strategies of the double inverted pendulum, a single flexible link and a flexible link carrying pendulum systems. Interval type2 fuzzy logic control was not taken into consideration by this approach in most of the cited investigations, despite some of its advantages indicated in this study. Proposed type-2 fuzzy logic controller combines two different control techniques which are adaptive network based fuzzy logic inference system control and interval type-2 fuzzy logic control, and uses their control performances together. Adaptive network based fuzzy inference system (ANFIS) uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. A combination of the least-squares method and the backpropagation gradient descent method is used in training fuzzy inference system (FIS) membership function parameters to emulate a given training data set.

Initially, equations of motion of proposed sytems were obtanied by using Lagrange formulation for numerical simulations. Moreover MATLAB/SimMechanics toolbox and computer aided design program (SolidWorks) was used together for visual simulations. Two adaptive network based fuzzy logic inference systems were designed for each system with different type membership functions (such as gauss, triangular and gbell...etc) to determine upper membership functions (UMF) and lower membership functions (LMF) of IT-2FL controllers. The proposed IT-2FL controllers were used for position, oscillation and vibration control of chosen test systems and the performances of the IT-2FL controllers were evaluated by MATLAB/Simulink software. Also MATLAB/ANFIS toolbox was used to create adaptive network based fuzzy logic inference system controllers. In addition, an experiment set up was built for flexible link carrying pendulum system to verify the performance of proposed IT-2FL controller and the results of Lagrange formulation, SolidWorks modeling and, experimentally they were compared in same control figures.

DYNAMIC MODELING OF THE PROPOSED SYSTEMS

The aim of this paper is to model a new approach for interval type-2 fuzzy logic controller by using adaptive network based fuzzy inference system. Three interval type-2 fuzzy logic controllers were designed and used to control different type nonlinear systems. The double inverted pendulum, a single flexible link and flexible link carrying pendulum systems were chosen such as nonlinear systems and they were controlled by proposed IT-2FL controllers to show efficiency of IT-2FL control and verify validity of this new approach.

Equations of motion of the double inverted pendulum system

The most important characteristic of double inverted pendulum system shown in Figure 1 is that the number of actuator of system is less than the system's number of degree of freedom. Double inverted pendulum system with this characteristic differs from two degrees of freedom of rigid link of robotic systems. The system parameters were given in Table 1. The goals of applied controllers to robotic systems and double inverted pendulum system are different. While the control in robotic systems, that is, taking robot arm to desired position, the purpose of the control of the double

Table 1. The parameters of double inverted pendulum system.

Parameter	Value	Unit
Mass of first pendulum, m_1	0. 2	kg
Mass of second pendulum, m_2	0. 5	kg
Length of first pendulum, l_1	0. 1	m
Length of second pendulum , l_2	0. 3	m

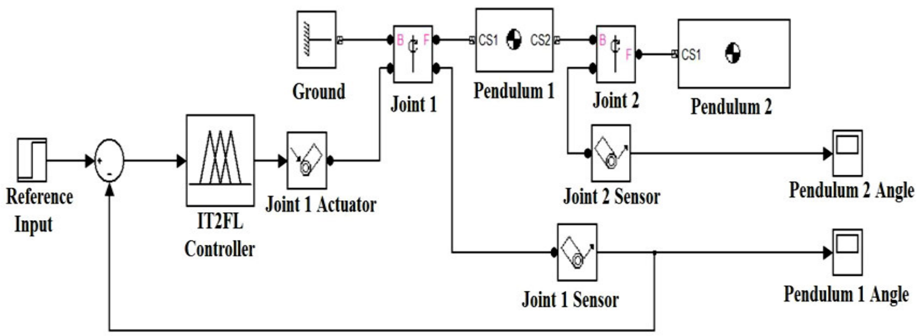

Figure 2. IT2FL control of SimMechanics model.

inverted pendulum system is to balance the pendulums on vertical position. The dynamic equation motion of the double inverted pendulum system was derived in terms of the Lagrange formulation:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}_i}\right)-\frac{\partial L}{\partial q_i}=\tau_i \tag{1}$$

where q_i is the generalized coordinates, $\dot{q}_i$ is the first derivative of the generalized coordinates as to time and τ_i is the applied control torque to ith link.

The generalized coordinate vector was defined as:

$$q=[\theta_1 \;\; \theta_2] \tag{2}$$

The control torque was expressed by input vector as:

$$\tau=[\tau_1 \;\; 0] \tag{3}$$

The goal of the control that was applied to the double inverted pendulum system was to supply output values of the system equal to reference value. The control action was that it produces appropriate input torque to feed the system for the system to realized desired motion. By another expression, it was that desired output value was obtained from the system, as a result of the applied convenient input value to system. The applied input to the double inverted pendulum system was motor torque and output of the system was angles of pendulums with vertical direction. The purpose of the designed controller for the system was to get the pendulums to unstable equilibrium point in minimum time and tosupply motor torque that provides position of the pendulums in tolerance range.

Earlier studies about pendulum systems were realized to find dynamic model by using Euler and Lagrange equations. In this study, dynamic model of the system was obtained by using both Lagrange formulation and MATLAB/SimMechanics toolbox. System parameters were used for modeling of system. By means of this approach dynamic modeling becomes easy and clear. SimMechanics modeling and control block diagram of double inverted pendulum system were given in Figure 2.

Equations of motion of a single flexible link system

The schematic diagram of the flexible robot manipulator was given in Figure 3. This considered robot arm consisted of a flexible beam with a distributed mass. The mass and flexible properties were assumed to be distributed uniformly along the flexible arm. The flexible arm was assumed as an Euler-Bernoulli beam. θ represented the angular position of the equivalent rigid link with respect to the fixed frame *XY*. *D* represented the position of the end point on the flexible arm with respect to the equivalent rigid link. Assuming small deflection of the link, an approximate linear time invariant dynamic model was derived using Lagrange formulation and the dynamic equation was represented in matrix form as:

$$\mathbf{M}\ddot{q}+\mathbf{C}\dot{q}+\mathbf{K}q=\mathbf{F} \tag{4}$$

where the vector q is generalized coordinates. $q=[\theta \;\; \alpha]^T$, M is the mass matrix, C is the damping matrix, K is the stiffness matrix and $F=[T\,0]^T$ and T is the input torque applied at the joint. The variable α (α=*D/L*) represented the slope at the free end of the flexible link.

The dynamic model was represented in state-space form as:

$$x=\mathbf{A}\,\dot{x}+\mathbf{B}u$$
$$y=\mathbf{C}\,x \tag{5}$$

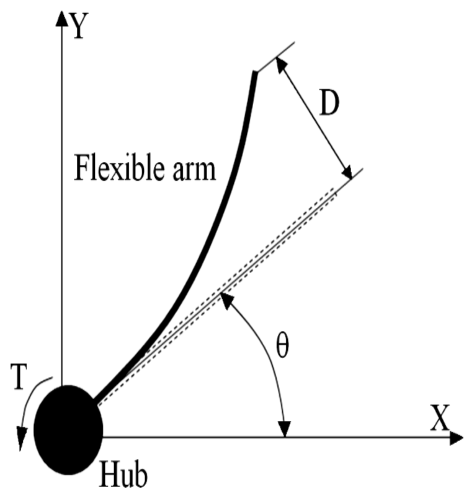

Figure 3. Schematic diagram of the flexible link.

Where the vector $x=\begin{bmatrix}\theta & \alpha & \dot{\theta} & \dot{\alpha}\end{bmatrix}^T$, the matrices A, B and C were given by:

$$\mathbf{A}=\begin{bmatrix}0_{2x2} & I_{2x2}\\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{C}\end{bmatrix},\ \mathbf{B}=\begin{bmatrix}0_{2x1}\\ -\mathbf{M}^{-1}\end{bmatrix},\ \mathbf{C}=I_{2x4} \tag{6}$$

Equations of motion of flexible link carrying pendulum system

The dynamic model of the flexible link carrying pendulum system was obtained by Lagrange formulation, 3D solid modeling technique and MATLAB/SimMechanics toolbox (Tınkır et al., 2010). Figure 4 depicts the simplified system with flexible link and pendulum by (a) top view and (b) front view of system. According to Lagrange formulation both kinetic and potential energy terms of flexible link and pendulum were obtained. The flexible link was modeled as a beam rotating around z-axis. Lagrange formulation was described $L=T-V$ and where *T* is total kinetic energy and *V* is total potential energy of system:

$$T=\frac{1}{2}J_{Hub}\dot{\theta}^2+\frac{1}{2}J_{Link}(\dot{\theta}+\dot{\eta})^2+\frac{1}{2}M_{pendulum}V_s^{\,2} \tag{7}$$

$$V=\frac{1}{2}K\eta^2+M_s gl(1-\cos\varphi) \tag{8}$$

According to aforementioned equations, five equations of motion were written to define dynamic behavior of system as follows:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial\dot{\theta}}\right)-\frac{\partial L}{\partial\theta}=T_L-B.\dot{\theta} \tag{9}$$

$$\frac{d}{dt}\left(\frac{\partial L}{\partial\dot{\eta}}\right)-\frac{\partial L}{\partial\eta}=0 \tag{10}$$

$$\frac{d}{dt}\left(\frac{\partial L}{\partial\dot{\varphi}}\right)-\frac{\partial L}{\partial\varphi}=0 \tag{11}$$

$$\frac{d}{dt}\left(\frac{\partial L}{\partial\dot{\phi}}\right)-\frac{\partial L}{\partial\phi}=0 \tag{12}$$

$$\frac{d}{dt}\left(\frac{\partial L}{\partial\dot{\alpha}_L}\right)-\frac{\partial L}{\partial\alpha_L}=0 \tag{13}$$

where $[\theta,\eta,\varphi,\phi,\alpha_L]$ was defined as generalized coordinate vector, T_L is actuated torque and *B* is damping coefficient.

By using Lagrange formulation, equations of motion were obtained and the proposed modeling technique called as 3D solid modeling method was realized (Tınkır et al., 2010). For this purpose, firstly flexible link and pendulum system was drawn in respect of the actual experiment set up in SolidWorks CAD program. The psychical properties of flexible link and pendulum were considered such as material, dimensions and thickness of link. Ceramic billiards ball was used for modeling tip mass of pendulum. In servo, plant gears and a DC servo motor were assumed as a revolute joint. This approach was verified at the end of the paper when Lagrange formulation and 3D solid modeling method results were compared. Figure 5a shows that computer aided model design of flexible link carrying pendulum system. Computer aided CAD model was converted into the MATLAB/SimMechanics program via 'Solid to MATLAB' converter program. SimMechanics model was given in Figure 5b. This model was simulated and controlled to figure out the dynamic behaviour of flexible link carrying pendulum system without using complex differential equations. In this manner, differential equations which are mostly used in dynamic modeling of systems are not needed any more. Moreover, we can implicate real system properties to our model as material (stainless steel flexible link) by such way.

THE DESIGN OF INTERVAL TYPE-2 FUZZY LOGIC CONTROLLERS

In this study, six adaptive network based fuzzy inference system (ANFIS) controllers were designed and applied to nonlinear systems to control positions, vibrations and oscillations. These systems were defined before as double inverted pendulum, a single flexible link and flexible link carrying pendulum systems. Two of the six ANFIS controllers were used for control of each system with different type membership functions and different number of rule bases. Moreover these two ANFIS controllers were combined to create an interval type-2 fuzzy logic controller. Eventually an interval type-2 fuzzy logic controller was obtained for each proposed systems by using six different type adaptive network based fuzzy inference systems.

The adaptive network based fuzzy inference system (ANFIS) uses a hybrid learning algorithm to identify the parameters of the Sugenotype fuzzy inference systems. It applies a combination of the least-squares method and the back propagation gradient descent method for training the fuzzy inference system (FIS) membership function parameters to emulate a given training data set.

In this paper, the forward hybrid learning algorithm is used for the neural network part of the ANFIS controllers shown in Figure 6a. The hybrid learning algorithm was described in the literatures

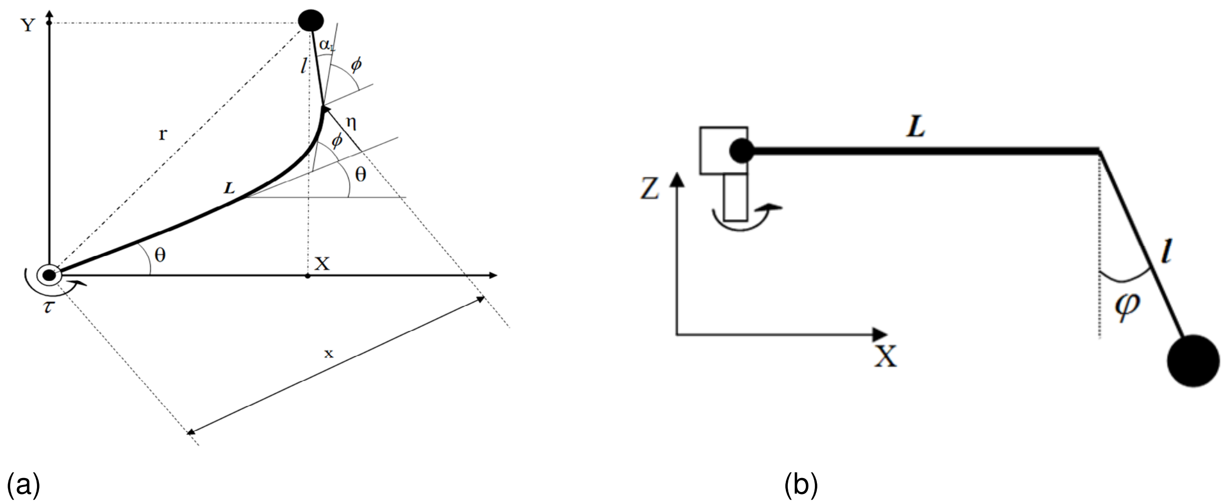

Figure 4. (a)The flexible link carrying pendulum system. (b) The front view of system.

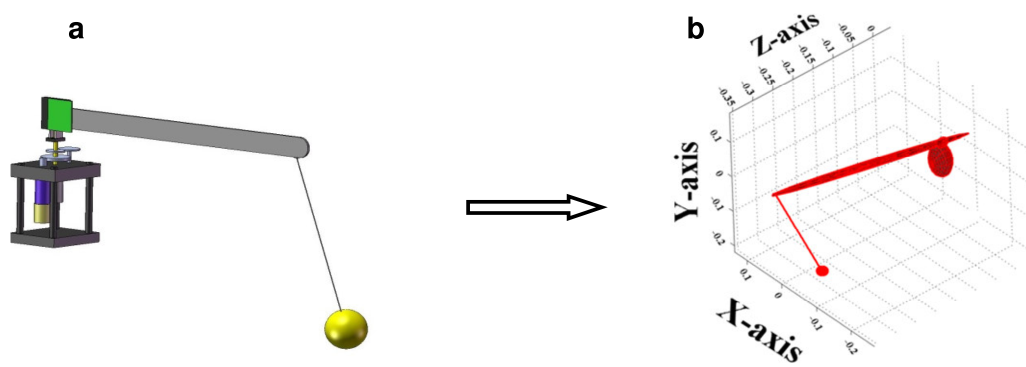

Figure 5. (a) Computer aided model. (b) SimMechanics model.

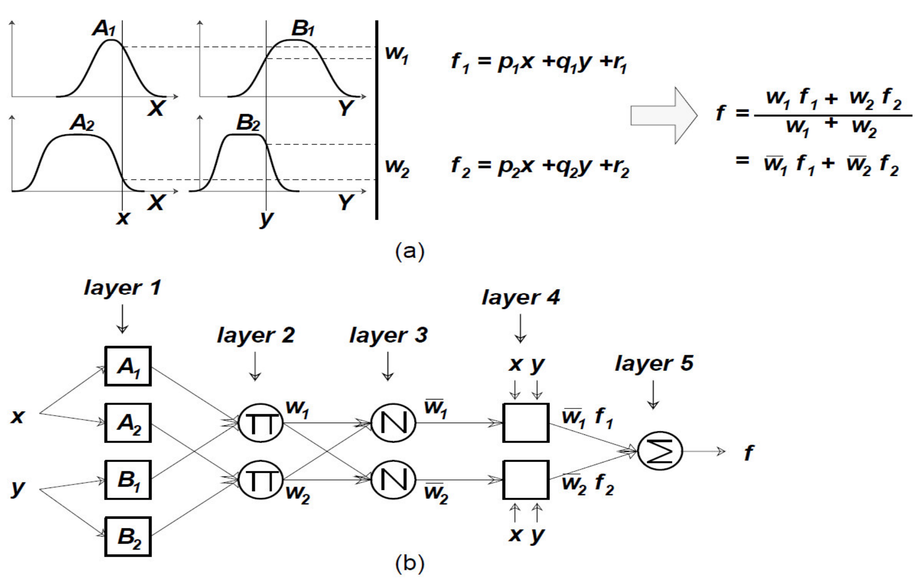

Figure 6. (a) TSK fuzzy inference system with two inputs and two rules. (b) Architecture of ANFIS of first order TSK model with two inputs.

(Jang, 1993; Zhang et al., 2004, Sha et al., 2002; Denai et al., 2004, Siddique et al., 2006; Güler et al., 2005). In the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent are identified by the least-squares method. When the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters.

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang, 1993; Zhang et al., 2004). Such framework makes the ANFIS control more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy IF-THEN rules based on a first-order Sugeno model are considered:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1y + r_1$).
Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2y + r_2$).

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i is the outputs within the fuzzy region specified by the fuzzy rule, p_i and q_i and r_i are the design parameters that are determined during the training process (Widrow et al., 1985). The ANFIS architecture to implement these two rules is shown in Figure 6b, in which a circle indicates a fixed node, whereas a square indicates an adaptive node:

$$\begin{aligned} f &= \frac{w_1}{w_1+w_2} f_1 + \frac{w_2}{w_1+w_2} f_2 \\ &= \overline{w}_1 f_1 + \overline{w}_2 f_2 \\ &= (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_1 y) q_2 + (\overline{w}_1) r_2 \end{aligned} \quad (14)$$

which is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2.

Here, we present a hybrid learning rule (Jang, 1993) which combines the gradient method and the least squares estimate (LSE) to identify the parameters. For simplicity, assume that the adaptive network under consideration has only one output as follows:

$$output = F(\overline{I}, S) \quad (15)$$

where $\overline{I}$ is the set of the input variables and S is the set of parameters. If there exists a function H such that the composite function $H \circ F$ is linear in some of the elements of S, then these elements can be identified by the least squares method. More formally, if the parameter set S can be decomposed into two sets as:

$$S = S_1 \oplus S_2 \quad (16)$$

(where $\oplus$ represents direct sum) such that $H \circ F$ is linear in the elements of S_2, then upon applying H to Equation 15, we have:

$$H(output) = H \circ F(\overline{I}, S) \quad (17)$$

Which is linear in the elements of S_2. Now given values of elements of S_1, we can plug P training data into Equation 17 and obtain a matrix equation:

$$f = \begin{bmatrix} \overline{w}_1 x & \overline{w}_1 y & \overline{w}_1 & \overline{w}_2 x & \overline{w}_2 y & \overline{w}_1 \end{bmatrix} \begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix} = XW \quad (18)$$

where X is input matrix and W is a weight vector (firing strength of each rule) whose elements are parameters in S_2. Let $|S_2| = M$, then the dimensions of X, W and f are $P \times M, M \times 1$ and $P \times 1$, respectively. Since P (number of training data pairs) is usually greater than M (number of linear parameters), this is an over determined problem and generally, there is no exact solution to Equation 18. Instead, a least squares estimate (LSE) of W, W^*, is sought to minimize the squared error $\|XW - f\|^2$ (Aström et al.., 1984). This is a standard problem that forms the grounds for linear regression, adaptive filtering and signal processing.

Lemma 1

The inverse X^{-1} of a matrix X exists only if X is square and has full rank. In this case, $f = XW$ has the solution $W = X^{-1} f$.

Lemma 2

The pseudo-inverse X^* (beware, it is often denoted otherwise) is a generalization of the inverse, and exists for any $m \times n$ matrix. We assume $m \rangle n$, If X has full rank (n defined by us):

$X^* = (X^T X)^{-1} X^T$ and the solution of $f = XW$ is $W = X^* f$ otherwise a pseudo-inverse (X^*) of X is used to solve for W:

$$W = (X^T X)^{-1} X^T f \quad (19)$$

where X^T is the transpose of X, and $(X^T X)^{-1} X^T$ is the pseudo-inverse of X if $X^T X$ is non-singular. While Equation 19 is concise in notation, it is expensive in computation when dealing with the matrix inverse and, moreover, it becomes ill-defined if $X^T X$ is singular. As a result, we employ sequential formulas to compute the LSE of X. This sequential method of LSE is more efficient (especially when M is small) and can easily be modified to an on-line version for system with changing characteristics. Specifically, let the i th row vector of matrix X defined in Equation 18 be a_i^T and the i th element of f be b_i^T, then W can be calculated iteratively using the sequential formulas widely adopted in the literature (Goodwin et al., 1984; Lijung, 1987; Strobach, 1990; Lin, 2005):

$$\left.\begin{aligned} W_{i+1} &= W_i + S_{i+1}a_{i+1}(b_{i+1}^T - a_{i+1}^T W_i) \\ S_{i+1} &= S_i - \frac{S_i a_{i+1} a_{i+1}^T S_i}{1 + a_{i+1}^T S_i a_{i+1}}, i = 0,1,...,P-1 \end{aligned}\right\} \quad (20)$$

where S_i is often called the covariance matrix and the least squares estimate W^* is equal to W_P. The initial conditions to bootstrap Equation 20 are $W_0 = 0$ and $S_0 = \gamma I$, where γ is a positive large number and I is the identity matrix of dimension $M \times M$. When dealing with multi-output adaptive networks (*output* in Equation 15 is a column vector), Equation 20 still applies except that b_i^T is the i-th rows of matrix f.

When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least-squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least-squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard backward pass algorithm. It has been proven that the hybrid algorithm is highly efficient in training the ANFIS (Jang, 1993). In this study, checking data was chosen from some part of training data and the convergence of one of the ANFIS controllers for a single flexible link was given in Figure 7.

Fuzzy control is by far the most successful applications of the fuzzy set theory and fuzzy inference systems. Due to the adaptive capability of ANFIS, its applications to adaptive control and learning control are immediate. For this purpose, the adaptive network-based fuzzy inference system has been used to optimize the fuzzy IF-THEN rules and the membership functions to derive a more efficient fuzzy control. The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach (Zadeh, 1989). Intelligent systems based on fuzzy logic are fundamental tools for nonlinear complex system control. Type-2 fuzzy sets are used to control uncertainty and imprecision in a better way. These type-2 fuzzy sets were originally presented by Zadeh (1975) and are essentially “fuzzy fuzzy” sets where the fuzzy degree of membership is a type-1 fuzzy set (Zadeh, 1989). The new concepts were introduced by Liang and Mendel allowing the characterization of a type-2 fuzzy set with a superior membership function and an inferior membership function; these two functions can be represented each one by a type-1 fuzzy set membership function.

The interval between these two functions represents the footprint of uncertainty (FOU), which is used to characterize a type-2 fuzzy set shown in Figure 8. Structure of interval type-2 fuzzy logic inference system was given in Figure 9. After all these instructions about ANFIS and interval type-2 fuzzy inference systems, ANFIS controllers were used in control applications, then IT-2FL controllers were built according to performances of ANFIS controllers over the double inverted pendulum, a single flexible link and flexible link carrying pendulum systems. Realization phases of this study were given in Figure 10. Explanation of first and second type controllers was shown in Table 2.

Membership functions of IT-2FL controllers

The membership functions of IT-2FL controller for double inverted pendulum system were given in Figure 11. Ten rules were used and two rules were described as an example:

1. If position error of first pendulum is NEGATIVE BIG then control action is CV_1.
2. If position error is first pendulum POSITIVE BIG then control action is CV_{10}.

The membership functions of IT-2FL controller of a single flexible link system were given for position error input in Figure 12. There are ten fuzzy membership functions that correspond to zero (Z), positive (P), positive medium (PM), positive big (PB) and positive big big (PBB) values of position error.

Same linguistic variables were used for gbell and triangular type membership functions. Rule base of IT-2FL controller for a single flexible link system was described as:

1. If position error is Z_1 or Z_2 then control action is CV_1.
2. If position error is P_1 or P_2 then control action is CV_2.
3. If position error is PM_1 or PM_2 then control action is CV_3.
4. If position error is PB_1 or PB_2 then control action is CV_4.
5. If position error is PBB_1 or PBB_2 then control action is CV_5.

Here CV_i (i = 1, 2...) is constant value of IT-2FL controller’s output, zero (Z), positive (P), positive medium (PM), positive big (PB) and positive big big (PBB) linguistic variables are divided to two parts such as P= [P_1 P_2].

IT-2FL controller’s membership functions for flexible link carrying pendulum system were given in Figure 13. There are seven fuzzy membership functions that correspond to zero (Z), positive (P), positive medium (PM), positive big (PB) and positive big big (PBB) values of rotation error. Same linguistic variables are used for gauss and triangular type membership functions.

Rule base of IT-2FL controller for flexible link carrying pendulum system was described as:

1. If rotation error is Z then control action is CV_1.
2. If rotation error is P_1 or P_2 then control action is CV_2.
3. If rotation error is PM_1 or PM_2 then control action is CV_3.
4. If rotation error is PB_1 or PB_2 then control action is CV_4.

Defuzzification process

Once the fuzzy controller is activated, the rule evaluation is performed and all the rules which are true are fired. Utilizing the true output membership functions, the defuzzification is then applied to determine a crisp control action. The defuzzification is to transform the control signal into an exact control output. For the Sugeno-style inference, we have to choose between wtaver (weighted average) or wtsum (weighted sum) defuzzification method. In the defuzzification process of the adaptive network based fuzzy logic controller, the method of weighted average (wtaver) is used:

$$u = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i} \quad (21)$$

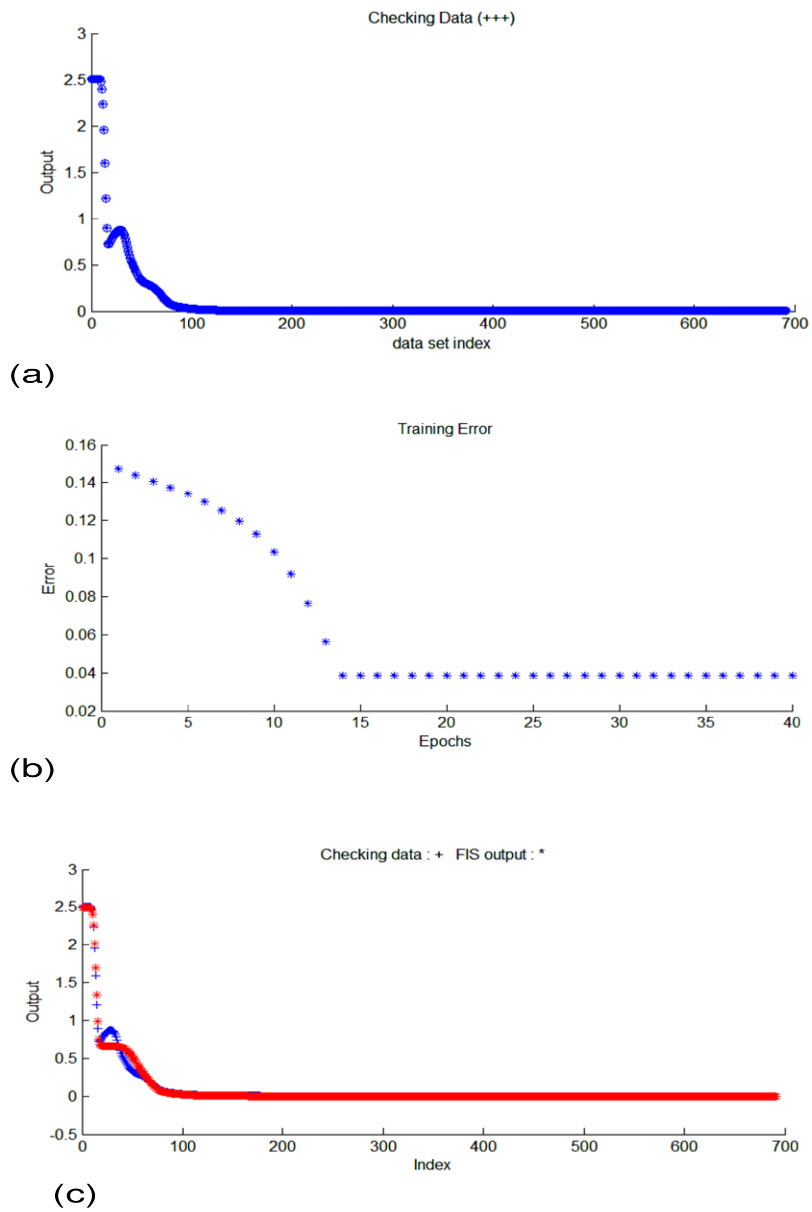

Figure 7. (a) Input data. (b) Convergence of ANFIS after training. (c) Checking of ANFIS.

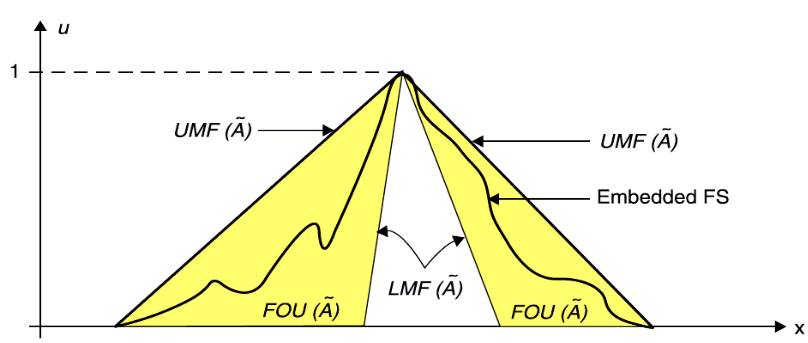

Figure 8. Definition of membership functions of interval type-2 fuzzy logic inference system.

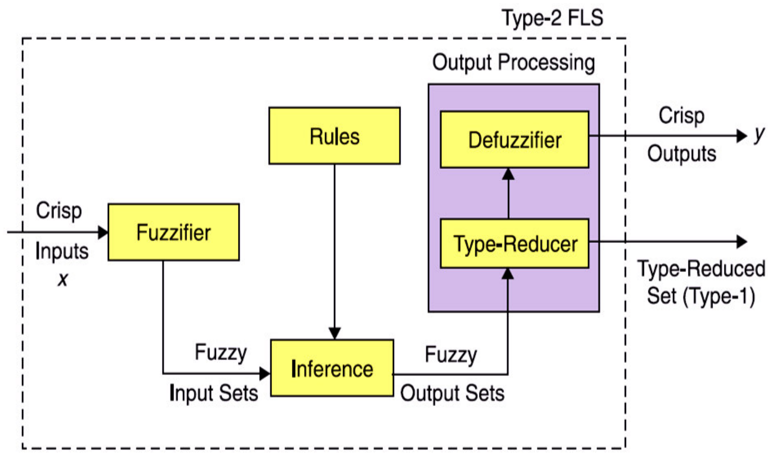

Figure 9. Structure of interval type-2 fuzzy logic inference system.

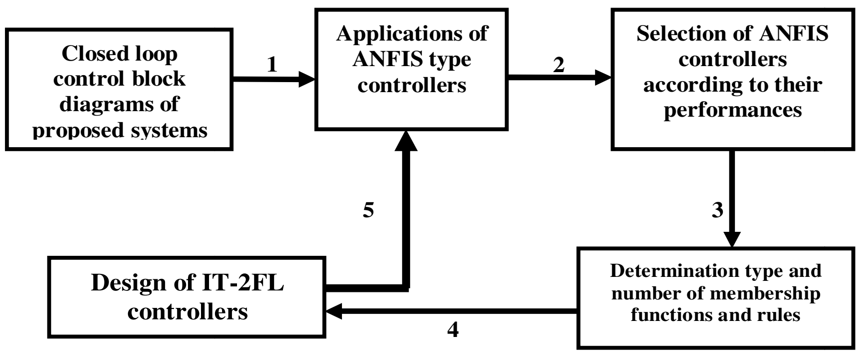

Figure 10. Realization phases of the study.

Table 2. Explanation of first and second type controllers.

The proposed systems	First controllers	Second controllers
Double inverted pendulum	Two ANFIS type controllers	Interval type-2 fuzzy logic controller
A single flexible link	Two ANFIS type controllers	Interval type-2 fuzzy logic controller
Flexible link carrying pendulum	Two ANFIS type controllers	Interval type-2 fuzzy logic controller

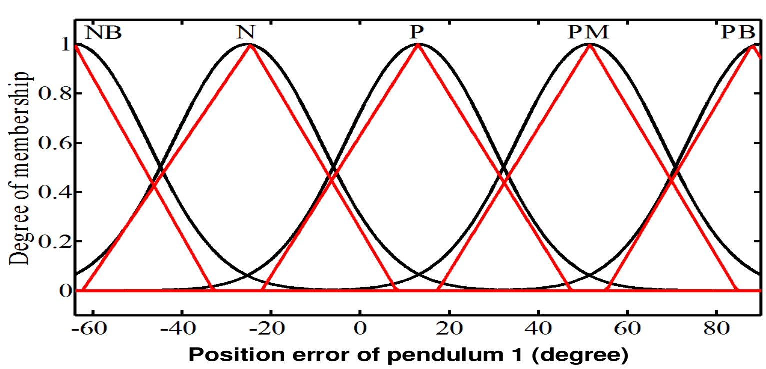

Figure 11. Membership functions of IT-2FL controller for double inverted pendulum system.

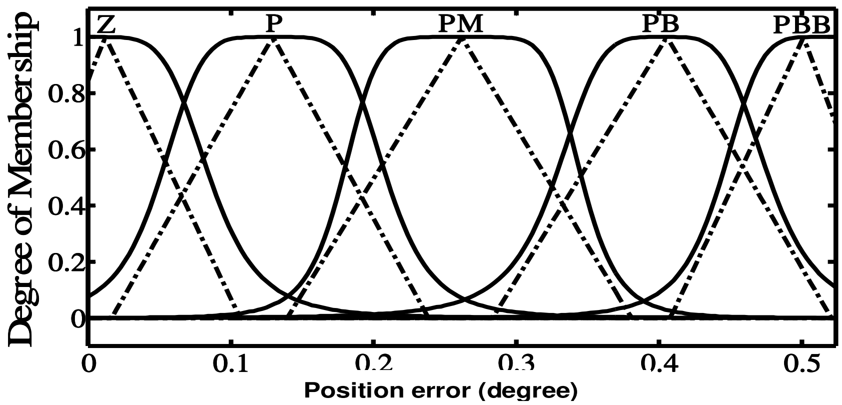

Figure 12. Membership functions of IT-2FL controller for a single flexible link system.

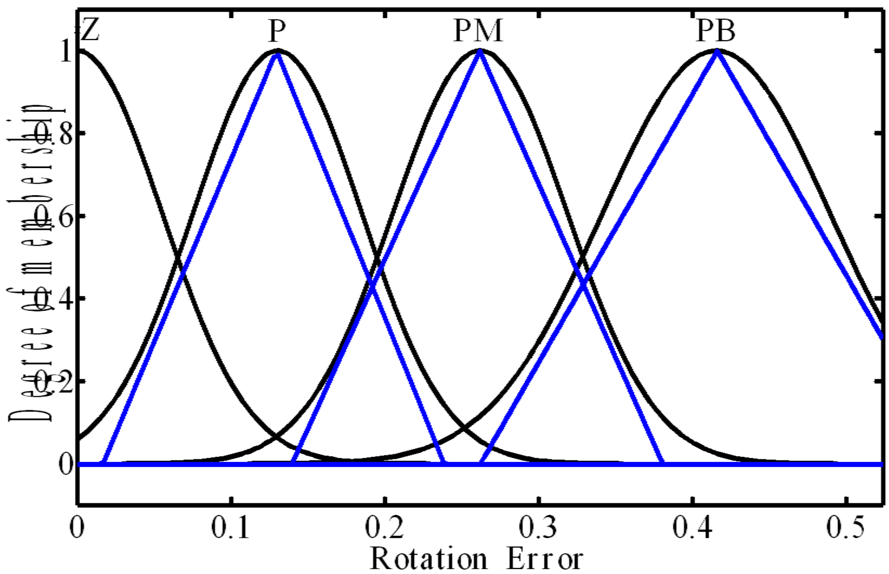

Figure 13. Membership functions of IT-2FL controller for flexible link carrying pendulum system.

RESULTS AND DISCUSSION

The effectiveness of the proposed controller has been tested by simulations. The objective in first simulation was to tune controllers for swing-up control of double inverted pendulum system. The proposed controller allowed us to command a desired angle position and eliminate oscillations while maintaining a fast response. Objective of control was chosen to get pendulums to vertical position. Position angles were chosen 90° and 0° for first pendulum and second pendulum, respectively. Simulations were done in respect to this task. In this way step reference input was given for desired input signal of control system. Feedback signal of first pendulum angle was used to tune controllers. PID (Proportional-Derivative-Integral) control technique was tried and used to compare with the performance of IT-2FL controller. The performance criterions of designed controller are chosen as:

1. Maximum oscillation angels of the pendulums $\leq 30°$
2. Pendulum's settling time is 2 s.

Performances of PID controller were given in Figures 14 and 15. From these results, it can be said that the PID controller is effective over the system. But according to performance criterions PID controller is not appropriate. The IT-2FL controller increased the PID control performance on the double inverted pendulum system. Figures 16 and 17 show performances of IT-2FL controller.

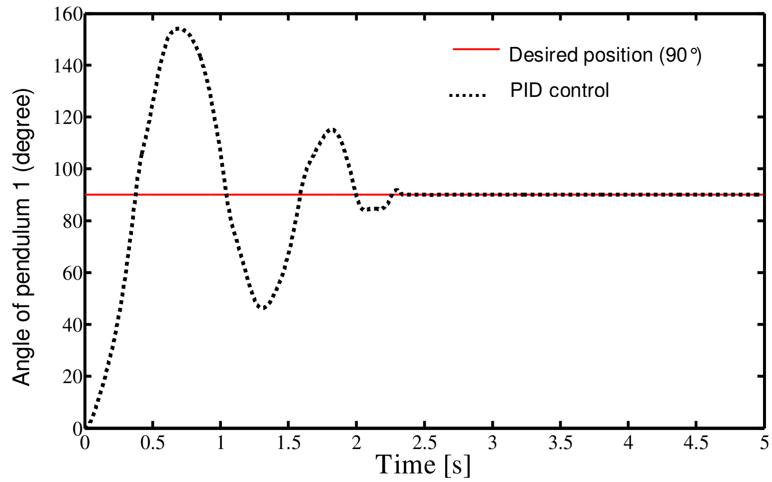

Figure 14. PID control of pendulum 1 angle.

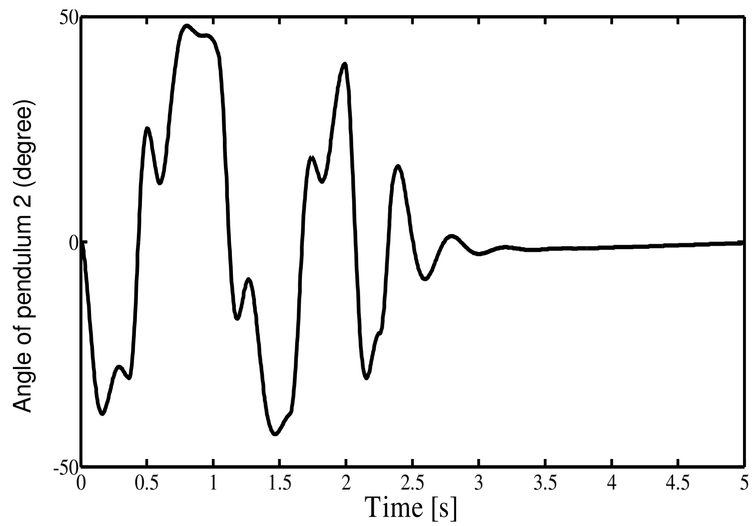

Figure 15. PID control of pendulum 2 angle.

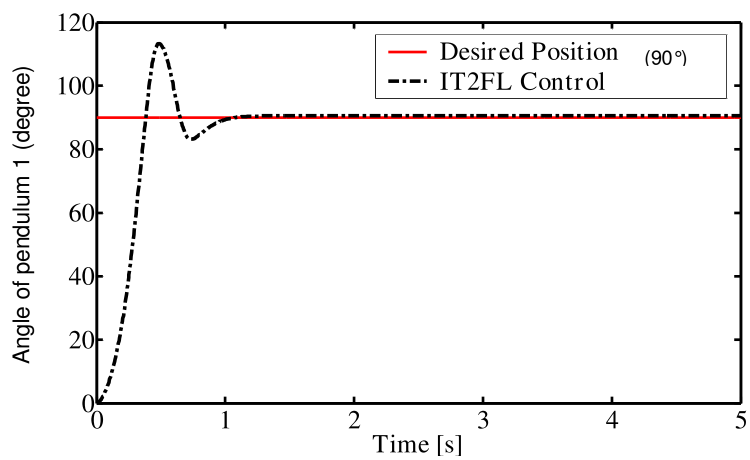

Figure 16. IT-2FL control of pendulum 1 angle.

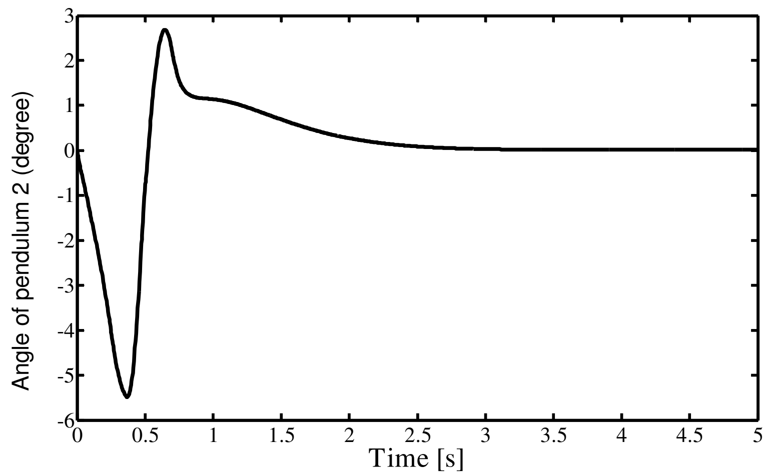

Figure 17. IT-2FL control of pendulum 2 angle.

From these results we can say that IT-2FL controller provides performance criterions and it is effective for swing-up control of double inverted pendulum system. Visual simulation of controlled system was given in Figure 18.

The objective of the second simulation was to tune IT-2FL controller for position and tip deflection control of a single flexible link manipulator. The controller allowed us to command a desired tip angle position and eliminate the link's vibrations while maintaining a fast response. Objective of flexible manipulator was chosen that moving to 30° degree of rotation. Simulations were done in respect to this task. In this way, step reference input was given for desired input signal of control system. Position and tip deflection control responses of IT-2FL controller were given in Figures 19 and 20.

According to Figures 19 and 20, the performance of IT-2FL controller was increased gradually by using ANFIS controllers. Neural network base of ANFIS toolbox developed to learning capacity of IT-2FL controller. As shown in Figure 19, the proposed IT-2FL controller brought to flexible link to desired position without maximum overshoot and steady state error. Moreover IT-2FL controller has good tip deflection response in Figure 20. The performance results of the proposed controller were given in Tables 3 and 4 for position and tip deflection control. From these results, it can be said the IT-2FL controller is a more effective controller for control of a single flexible link manipulator system. The reason is that ANNIT2FL controller has two different type membership functions and it is consisted of two ANFIS type controllers. The objective of the scaled tower crane system was chosen that moving to thirty degree of rotation. Simulations and experiments were realized in respect to this task. In this way step reference input was given for desired input signal of the control system. Position and tip deflection performances of the IT-2FL controller were given in Figures 21 and 22. According to Figures 21 and 22, it can be said that simulation results obtained by using SolidWorks modeling technique and Lagrange formulation were close to experimental results. Moreover IT-2FL controller has good control performances over position and tip deflection control. The proposed IT-2FL control decreased position steady state error of flexible link effectively.

In addition IT-2FL control terminated pendulum oscillation effects over position response of the system. The proposed IT-2FL control was applied to scaled tower crane system successfully both simulation and experimental works, because the IT-2FL controller's base depends on the two ANFIS type controllers training data sets. Pendulum swing angles defined as $[\varphi, \phi, \alpha_L]$ of IT-2FL controlled system were simulated according to SolidWorks modeling technique and Lagrange formulation in Figures 23 and 24, respectively. Both simulation and experimental works "ϕ" swing angle of pendulum was defined as critical swing angle which affected position and vibration control more than other swing angles called as "φ, α_L". Because the plane of swing angle "ϕ" was the same with rotary plane "x" of the flexible link. The simulation and experimental results already obtained about swing angles showed that "φ, α_L" angles were observed smaller than swing angle "ϕ". According to Figures 23 and 24, swing angles $[\varphi, \phi, \alpha_L]$ were reduced and ended after 4.5 s in simulations. The results obtained simulations with SolidWorks modeling technique were close to simulation results by Lagrange formulation. In addition, swing angle results in Figure 23 were found smaller than obtained results in Figure 24. So these results showed that SolidWorks modeling technique can be used to obtain dynamic behaviors of the proposed systems without using mathematical

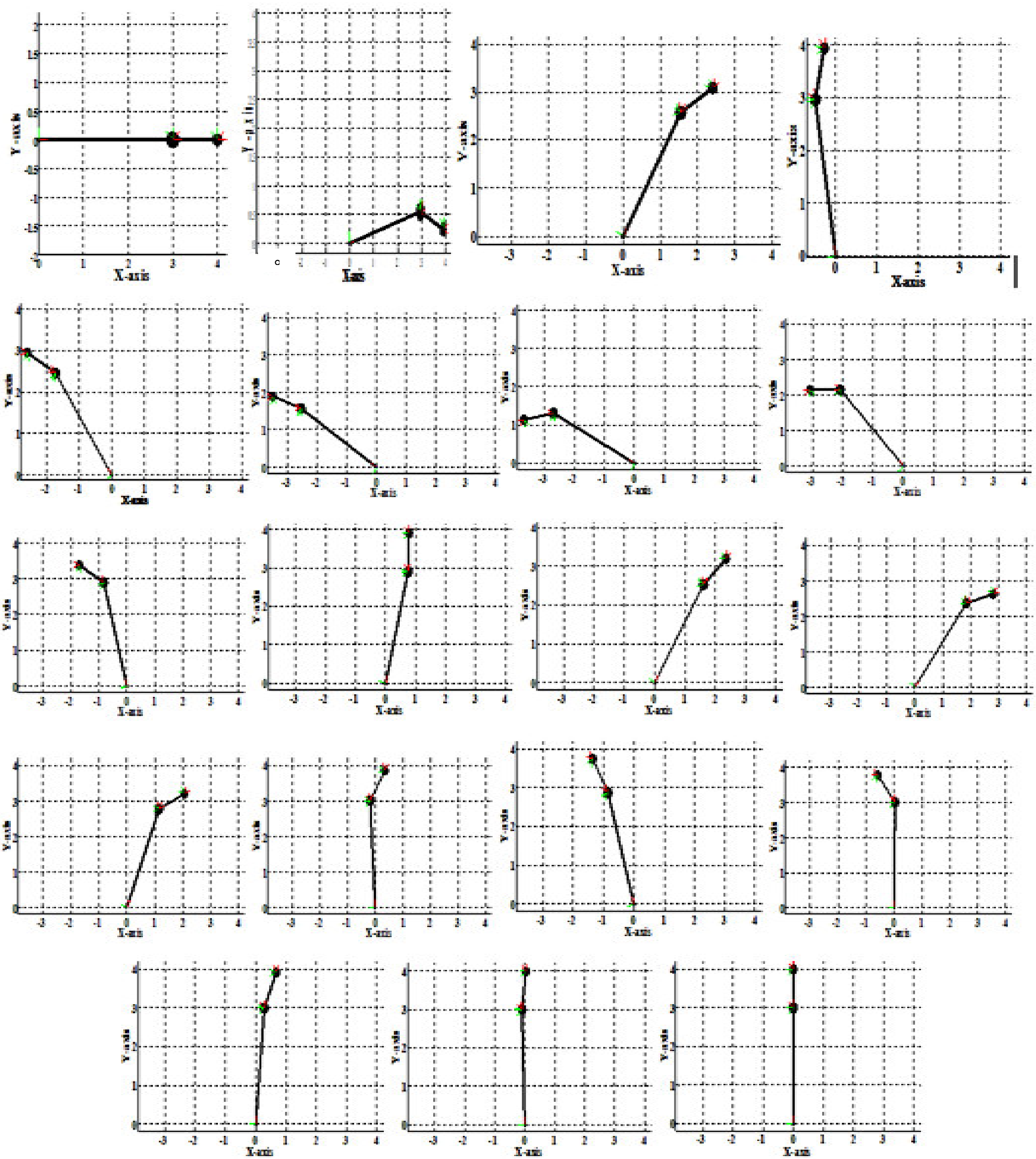

Figure 18. Visual simulation of the double inverted pendulum system (under IT-2FL control).

equations. The critic swing angle "ϕ" results of IT-2FL controlled system were compared experimentally and given in Figure 25. The critic swing angle "ϕ" was measured during experimental works by using image

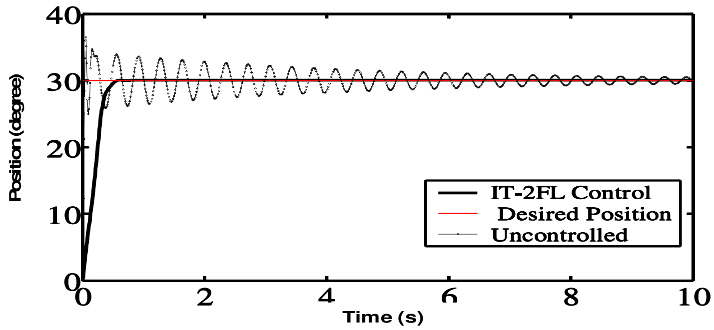

Figure 19. IT-2FL position control response of a single flexible link manipulator.

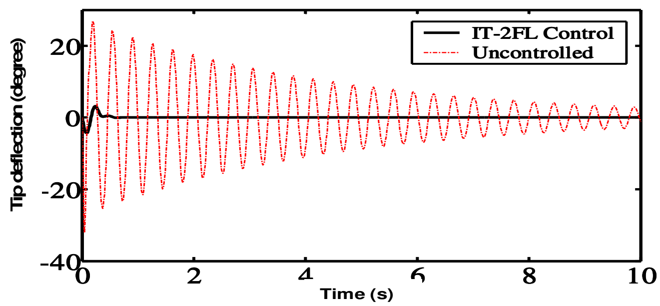

Figure 20. IT-2FL tip deflection control response of a single flexible link manipulator.

Table 3. Performance comparison of proposed controllers for position control.

Controller	Rise time	Settling time	Maximum overshoot	Steady state error
IT-2FL	0.35 s	0.6 s	-	-

Table 4. Performance comparison of proposed controllers for tip deflection control.

Controller	Maximum deflection	Damping time	Permanent vibration
IT-2FL	2.5°	0.9 s	-

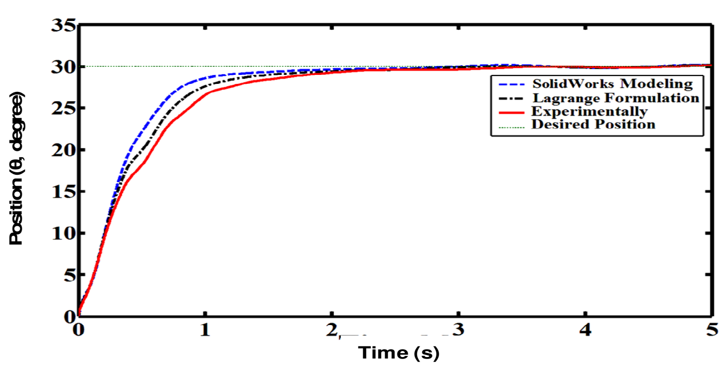

Figure 21. IT-2FL position control response of flexible link carrying pendulum system.

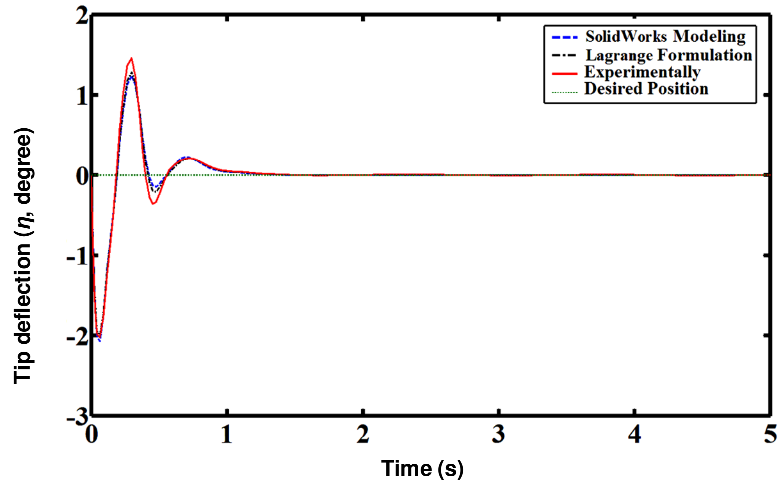

Figure 22. IT-2FL tip deflection control response of flexible link carrying pendulum system.

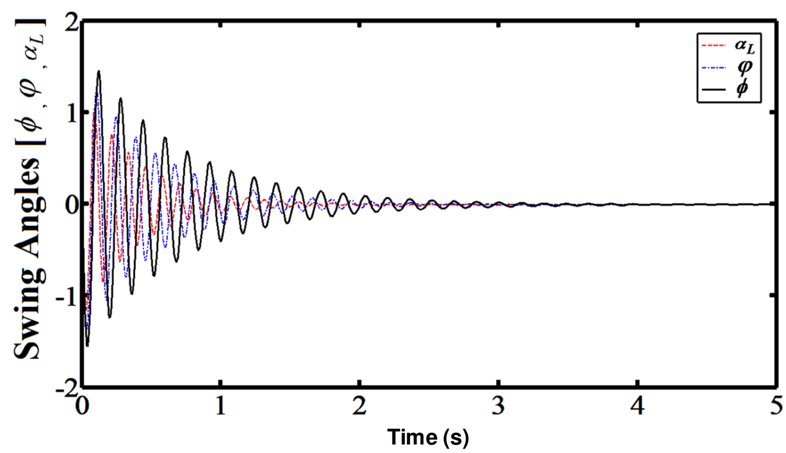

Figure 23. Swing angles responses of IT-2FL controller by SolidWorks modeling.

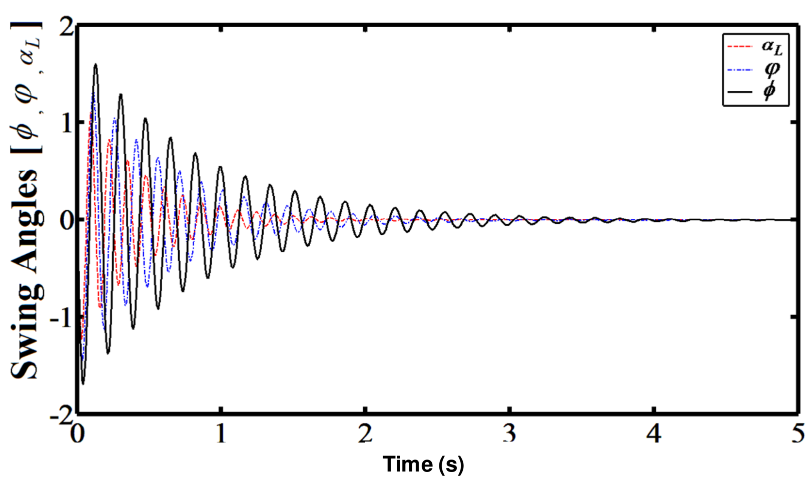

Figure 24. Swing angles responses of IT-2FL controller by Lagrange formulation.

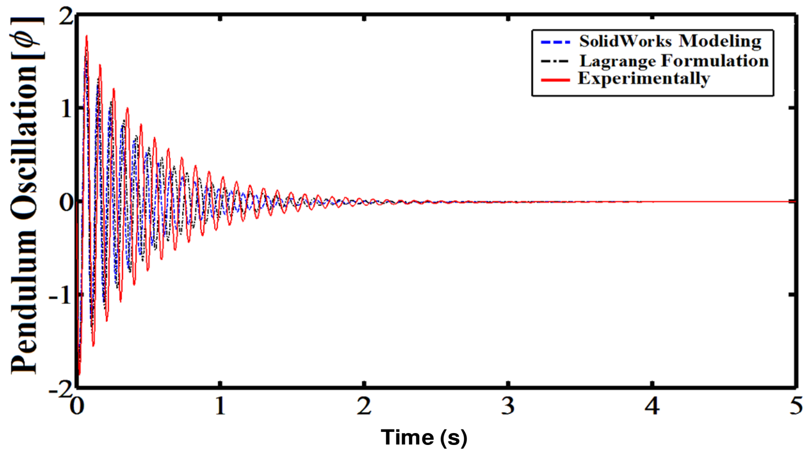

Figure 25. The critic swing angle "ϕ" results of IT-2FL controlled system by experimentally.

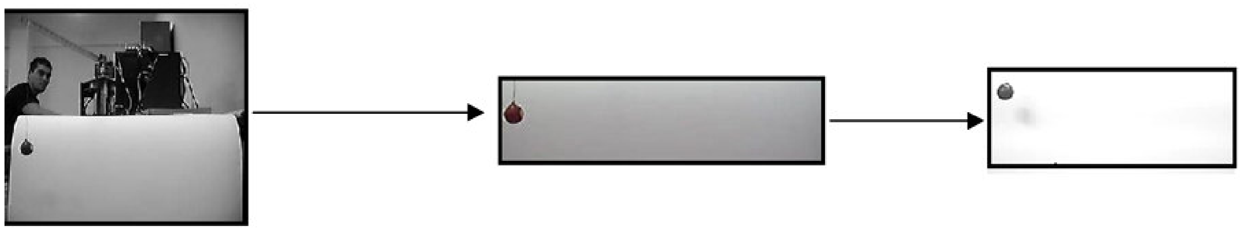

Figure 26. Image processing of the critic swing angle "ϕ".

processing method (Hagras, 2004) and given in Figure 26.

Conclusions

In this paper, adaptive network based fuzzy inference system (ANFIS) was used in control applications of different type nonlinear systems as interval type-2 fuzzy logic controller (IT-2FL). Two adaptive network based fuzzy inference systems were chosen to design type-2 fuzzy logic controllers for each control applications. The double inverted pendulum, a single flexible link and a flexible link carrying pendulum systems were used to test the performances of designed interval type-2 fuzzy logic controllers. System behaviours were defined by Lagrange formulation and MATLAB/SimMechanics computer simulations. The performances of the proposed controllers were evaluated and discussed on the basis of the simulation and experimental results.

The proposed IT-2FL controller has good performance over different type nonlinear systems according to its structure. ANFIS type controllers were used to obtain IT-2FL controller and different type membership functions were used together to determine ideal fuzzy logic controllers in terms of interval type-2 fuzzy logic. Owing to this new approach different ANFIS type controllers can be used with their different types of membership functions into one IT-2FL controller. In this manner IT-2FL controller has two ANFIS type controllers' performances and their adaptive capacities. Another result of this study is that SolidWorks modeling technique can be used instead of Lagrange formulation to obtain dynamic system behaviour. It was verified with the results of Lagrange formulation and experimental results. In the future, more effective approaches to the realtime performance of the interval type-2 fuzzy logic control will be investigated. Moreover the proposed type-2 control will be used in the control strategy of different nonlinear systems such as position and vibration control of the earthquake platform (with single and double storey), feedback position control of the flexible robot over earthquake platform and exo-skeleton motion control.

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