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Robot manipulator position control using hybrid control method based on sliding mode and ANFIS with fuzzy supervisor

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Abstract: Industrial robots are manipulators with high precision and repeatability making them proper alternatives to humans. In common industrial robots proportional-Integral controllers are exploited owing to their simplicity; however, they cannot guarantee appropriate and robust operation. To obtain suitable performance nonlinear controller is recommended. Sliding mode controller is a state feedback controller with fast transient response which is robust against uncertainties. Despite its advantages sliding mode controller is not a good choice for steady states due to chattering phenomenon. On the other hand, adaptive neuro-fuzzy controllers have been successful, though they have not acceptable performance when encountering uncertainties. It is a consequence of inevitable training phase in such controllers. In this study a hybrid controller is proposed combining sliding mode and adaptive neuro-fuzzy controller with variable weights to take advantage of both structures. A fuzzy supervisor is tasked with optimal adjustment of the weights. Besides, it facilitates switching between two controllers.

Keywords: robot manipulator position control, sliding mode control, ANFIS, fuzzy supervisor

1. INTRODUCTION

Robots are more helpful as they provide safety, precision, speed, boosted production capability and flexibility. They are utilized to perform costly, dangerous, repetitive and boring tasks in industrial environments with hard conditions such as space, under water projects, nuclear reactors and so on. In such cases humans are responsible for controlling robots to achieve the determined goals. These tasks include planning joint movement so that proper paths could be generated. They may also consist of calculating and generating joint torques to precisely track the planned paths.

In case of robot manipulator control, complete and precise control of all joints is crucial to avoid obstacles and to reach the desired destination. Nevertheless, in practical situations disturbances, uncertainties, mismatched parameters and higher order dynamics lead to variations in model parameters, lack of proper control and system instability. Furthermore, robot manipulator is a severely nonlinear, time variant, Multiple-Input Multiple-Output (MIMO) system with heavy coupling between inputs and outputs. These issues must be addressed to obtain a reliable control.

Methods which have been proposed for robot manipulator control can be divided into two groups. The first one includes classic control methods such as linear control, sliding mode control, robust H-infinity control method and adaptive control. The second group of methods consists of intelligent control methods among which fuzzy control and neural control might be mentioned. Generally speaking, the former group is based on classic control theory while the latter is based on intelligent methods using artificial intelligence and soft computations.

Linear control is insufficient when the system faces uncertainty. Sliding mode control, however, is the robust version of linear control which can efficiently overcome uncertainties, disturbances, nonlinearity and higher order

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dynamics as well as providing simplicity. Moreover, its fast transient response makes it even more beneficial. Nonetheless, it suffers from a major drawback which is a discontinuous control signal leading to chattering phenomenon which may stimulate high frequency dynamics. Sliding mode control is considered as a robust controller owing to discontinuous control signal generated in the vicinity of sliding surface satisfying sliding condition; however, the same characteristic is its shortage as this discontinuous term may generate high frequency oscillations known as chattering. Using boundary layers or fuzzy sliding mode control have proposed which are able to increase efficiency of sliding mode control and mitigating (or eliminating) chattering; yet, they adversely affect transient response of the system [1]. In [2] sliding mode control is designed for a robot manipulator and tested in practical condition. A sliding mode control is designed and simulated in SIMULINK environment for a mechanical manipulator in [3]. A fuzzy sliding mode control in which chattering is eliminated is presented in [4]. Some examples of sliding mode control designed for mechanical manipulators can be found in [5-7]. Robust H_∞ control is used in robot manipulators to mitigate external disturbances and stabilize the system. Unfortunately, the robust control obtained using H_∞ is of high orders which make its implementation difficult. To solve this problem the constraints in the highest order of controller (whose order is less than system order) might be set; however, in such circumstance the problem is not convex anymore leading to more difficult solution. To overcome problems associated with this method various order reduction methods have been proposed. To summarize, most of these methods do not include polynomial complexity and they are Non-deterministic Polynomial-time hard (NP-hard) which requires high computational time. Although local methods are fast, they do not guarantee total system convergence [8].

In recent decades artificial intelligence has emerged as a control method for robot manipulators. Conventional artificial intelligence methods include neural network based control methods and fuzzy logic based control methods. The main advantage of neural and fuzzy methods over their classic counterparts is that they do not need precise information about mathematical model or system dynamics which are usually difficult to derive.

Neural networks have inherent capability to train, learn and estimate a nonlinear function with desired precision. This feature helps them model complicated procedures and compensate for unstructured uncertainties. However, inevitable training process (self-training feature) decreases its transient performance in presence of disturbances. Thus, for systems similar to robot manipulator which encounter uncertainties and model information is not sufficiently used, this system does not provide proper transient performance.Additionally, conventional neural networks utilize global activation functions and local learning methods which, in turn, cause shortcomings including low speed learning, failing to obtain suitable solution and high sensitivity to initial values of network weights.

Fuzzy control usually does not require mathematical model of the controlled system; therefore, it is easily employed. It shows exceptional performance in complex, ill-defined, nonlinear and time variant systems. Overall, the superiority of fuzzy control is using human knowledge (knowledge and experience of an expert person) for control procedure. Meanwhile, its most essential shortage is examining stability theory of fuzzy controllers. As a matter of fact, fuzzy control cannot guarantee stability of a system as it lacks an explicit mathematical model of the system. Robot manipulator control is performed using neural networks in [9-12]. In [13] they combined sliding mode control and neural network control with different weights in order to overcome limitations and take advantage of both intelligent and classic controllers simultaneously. The weights are determined by a fuzzy supervisor. It was successful when applied to a robot manipulator with two degrees of freedom.

Adaptive Neuro-Fuzzy Inference System is the realization of Takagi-Sugeno Fuzzy Inference System. It is worth mentioning that Takagi-Sugeno is the most popular type of fuzzy inference system which is capable of locating in an adaptive network (which is general manner of a multi-layer feed forward neural network). Its output is in the form of a linear relationship. Neuro-fuzzy models, such as ANFIS, combine fuzzy logic and artificial neural networks. ANFIS combines advantages of neural networks (learning and adaptivity) with those of fuzzy logic (expert knowledge) to achieve robust control in robot dynamic systems. Fuzzy sets are exploited to formulate human inception level of a physical system while neural networks perform all calculations needed for learning capability. These systems are able to adapt the existing controller to variations in system behaviors through training the system. ANFIS model is capable of estimating every linear or nonlinear function with desired precision in addition to providing high convergence speed and lowerror. It also requires fewer training data. Considering that ANFIS includes capabilities of both neural networks and fuzzy inference systems, it is a proper choice for robot manipulator controller. But, it still suffers from limitations imposed by training phase.

The goal of this study is to combine sliding mode control and ANFIS with different weights to control position of an industrial robot manipulator in such a way that these weights are determined by a fuzzy supervisor. The main idea of this study is inspired by the method proposed in [13] while it is tried to overcome the problems associated with this method. In [13] sliding mode control is used in simulation environment while chattering phenomenon occurs when real time simulation is done (as it is a consequence of the time needed for input signal calculations). In this study all simulations are conducted in real time so as to demonstrate the performance of the proposed controller. Furthermore, to decrease steady state error and improve tracking, on-line training is utilized for ANFIS. In [13] on-line training is not considered. Besides, in [13] the introduced method is not compared to other control methods since in normal simulation (when it is not real time) sliding mode control is the best method with which all other control methods fail to compete.

In the proposed method ANFIS controller is used parallel to sliding mode controller. Sliding mode control is exploited as a robust controller to resist disturbances and to assure system stability. ANFIS controller eliminates chattering. Additionally, it estimates system dynamics and benefits from its self-training capability to compensate for unstructured disturbances. As mentioned in the neural network section, inevitable training phase of ANFIS degrades its transient performance. To address this problem a fuzzy supervisor is employed in external loop. In this scheme during transient states high gain is assigned to sliding mode control to ensure system robustness. In contrast, when the system approaches its steady state, ANFIS becomes the main controller (instead of sliding mode control) to overcome uncertainties and improve reference signal tracking. Fuzzy supervisor can facilitate the switching between two control modes.

2. SLIDING MODE CONTROL AND ANFIS METHODS

2.1. Sliding mode control

Sliding mode control is a state feedback robust control method for nonlinear systems which is able to change its structure to obtain proper performance. To design a sliding mode control it is assumed that controller is able to change its structure spontaneously; nevertheless, it is not possible in practical cases due to computational delay and limitations of operators. This results in chattering phenomenon. To face such challenges high order sliding mode controls or boundary layers might be exploited. The former increases computational complexity while the latter increases steady state error.

When Newton-Euler equation is symbolically evaluated for manipulator, the dynamic equation of the system is derived as shown in equation 1:

$$\tau(t) = D(q)\ddot{q}(t) + H(q,\dot{q}) + G(q) \tag{1}$$

To design sliding mode control robot dynamics is rewritten as denoted by equation 2.

$$\begin{aligned} \ddot{q}(t) &= D(q)^{-1}[\tau(t) - H(q,\dot{q}) - G(q)] \\ y(t) &= q(t) \end{aligned} \tag{2}$$

Where $\left[q^T \dot{q}^T \right]^T$ is the system state vector, $y(t) \in R$ Y is system output and $\tau(t)$ is the control input.

Control objective: *q(t)* outputs tracks $q_d(t)$ bounded reference.

For designing control input it is assumed that system states $q(t)$, $\dot{q}(t)$ are measurable.

Error equations for system 2 are defined as shown by equation 3.

$$\begin{aligned} q(t) - q_d(t) &= \tilde{q}(t) \\ \dot{q}(t) - \dot{q}_d(t) &= \dot{\tilde{q}}(t) \end{aligned} \tag{3}$$

For each degree of freedom sliding surface is defined as follows.

$$\begin{aligned} &s_i = \left(\frac{d}{dt} + \lambda\right)\tilde{q}_i = \dot{\tilde{q}}_i - \lambda_i \tilde{q}_i \\ &i = 1 \ldots n \end{aligned} \tag{4}$$

Where n is the number of system degrees of freedom and λ_i are positive and constant values.

Defining s_i according to above equation, the problem of tracking q_d is changed from a second-order *withn*degrees of freedom to an issue ofsustainabilityof n to s from the first order.

For this purpose a vector consisting of n sliding surfaces is defined as equation 5.

$$S = [s_1, s_2, \ldots, s_n]^T \tag{5}$$

To maintain S vector in zero value, the control input should exist such that:

$$\frac{1}{2}\frac{d}{dt} S^T S \le -\eta \,|\, S \,| \tag{6}$$

, where η is a positive constant. The above condition is known as sliding condition. It means that square of distance to sliding surface is decreasing along all state paths. If the above condition is met starting from non-zero initial condition, states will reach time variant sliding surface in a finite time. As soon as locating on sliding surface, tracking error approaches to zero exponentially (figure 1).

In this step $\tau(t)$ control input is designed such that output is able to track desired path. Besides, tracking error of all its derivatives must approach zero. Sliding surface and its derivative for robot system are as follows:

$$\begin{aligned} &S = \left(\frac{d}{dt} + \Lambda\right)\tilde{q} = \dot{\tilde{q}} + \Lambda\tilde{q} \\ &\dot{S} = \ddot{\tilde{q}} + \Lambda\dot{\tilde{q}} = D(q)^{-1}\left[\tau(t) - H(q,\dot{q}) - G(q)\right] - \ddot{q}_d + \Lambda\dot{\tilde{q}} \end{aligned} \tag{7}$$

In sliding phase where $S(t) = 0$ and $\dot{S}(t) = 0$, $\tau(t)$ is designed to maintain the system on sliding surface. In the approaching phase where $S(t) \# 0$, is designed such that $S(t)$. $\dot{S}(t) < 0$ (condition for reaching to surface) is satisfied. To do so, consider Lyapunov function as equation 8:

$$V = \frac{1}{2} S^T S \tag{8}$$

, which is a continuous and positive definite function. The derivate of this function is derived according to equation 9.

$$\dot{V} = S^T \dot{S} \tag{9}$$

Considering $\dot{S}$ in the form of equation 10, one may demonstrate that equation 9 is negative and, consequently, (8) is descending:

$$\dot{S} = -K sign(S), \forall t, K > 0 \tag{10}$$

, here K is a diagonal matrix that has positive entries. Substituting equation 7 in equation 10 one may write:

$$\begin{aligned} &-Ksign(S) = \dot{S} = \ddot{\tilde{q}} + \Lambda\dot{\tilde{q}} = \\ &D(q)^{-1}[\tau(t) - H(q,\dot{q}) - G(q)] - \ddot{q}_d + \Lambda\dot{\tilde{q}} \end{aligned} \tag{11}$$

Thus, control input is obtained as follows.

$$\begin{aligned} &-Ksign(S) = \dot{S} = \ddot{\tilde{q}} + \Lambda\dot{\tilde{q}} = \\ &D(q)^{-1}[\tau(t) - H(q,\dot{q}) - G(q)] - \ddot{q}_d + \Lambda\dot{\tilde{q}} \\ &\tau(t) = D(q)(\ddot{q}_d - \Lambda\dot{\tilde{q}} - Ksign(S)) + \\ &H(q,\dot{q}) + G(q) \end{aligned} \tag{12}$$

K must be selected such that sliding condition is met. Sliding condition is represented in equation 13.

$$S\dot{S} \le -\eta\,|\,S\,| \tag{13}$$

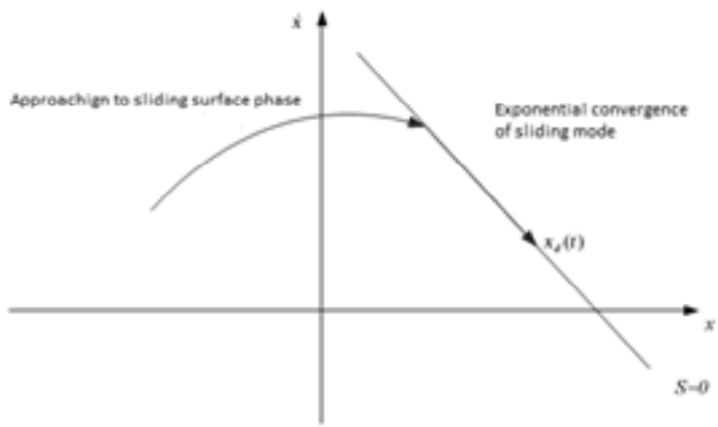

Figure 1: Schematic view of sliding mode for a second order system

In the aforementioned equations feedback control rule is designed so that sliding condition is fulfilled. To overcome modeling imperfections and disturbances, control signal is discontinuous in the vicinity of *S*; therefore, its implementation in practical systems does not lead to acceptable results and chattering may occur in system states. Generally speaking, chattering is an unwelcome behavior. In addition to high control activity, it stimulates high frequency dynamics of the system which are not modeled.

2.2 Anfis

Fuzzy systems and neural networks have pros and cons. Fuzzy systems are capable of using linguistic rules which enables them to exploit human experience and expert people; whereas, they cannot learn. That is to say, fuzzy system cannot be trained using observed data while neural networks have self-training capability. Meanwhile**,** neural networks cannot use linguistic rules and they are implicit [4]. In 1993, for the first time, Jang utilized linguistic power of fuzzy systems together with training capability of neural networks to introduce a system called fuzzy systems based on adaptive neural networks [15]. Such systems are known as ANFIS which stands for Adaptive Neuro-Fuzzy Inference Systems. To identify nonlinear systems ANFIS is used. In the following ANFIS and its learning algorithm for Sugeno fuzzy model are explicated.

Assume that the discussed fuzzy inference system has two inputs (*x*, *y*) and one output (*f*). A sample rule set with to if-then fuzzy rules might be described as follows:

Rule1: if x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$
Rule2: if x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

To correct Sugeno fuzzy model it is suitable to apply it in the form of adaptive networks which are able to systematically calculate gradient vectors. This model is illustrated in figure 2. Figure 2 depicts the mechanism of Sugeno model fuzzy inference for obtaining *f* from two input vectors; *X* and *Y*. Firing strength of W1 and W2 are usually derived through multiplying membership degrees of inputs. The *f* is a weighted average of both rules. The architecture of equivalent ANFIS is depicted in figure 3. Nodes in the same layer have similar roles.

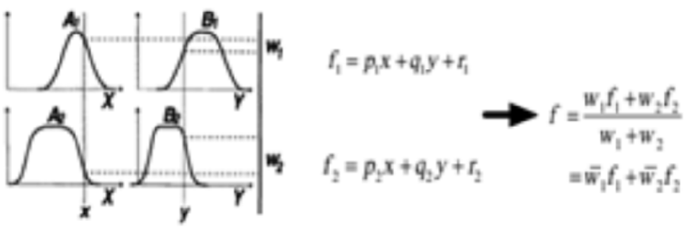

Figure 2: First order fuzzy inference system

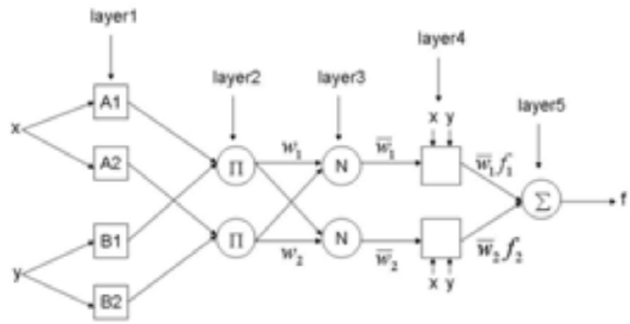

Figure 3: ANFIS structure associated with first order inference system

All nodes in the first layer are adaptive. In this layer input node membership degrees in various fuzzy intervals are determined using membership functions. In the second layer input signals are multiplied and transferred to the next layer where (in third layer) normalization is applied. The fourth layer which is an adaptive layer calculates shares resulted from rules. Fifth layer is the output layer and returns sum of inputs and the output of the network.

2. THE PROPOSED METHOD

As mentioned before, in the proposed method sliding mode control and adaptive neuro-fuzzy inference system with different weights are combined to take advantage of both system capabilities while overcoming their drawbacks. A fuzzy supervisor is responsible for determining the weights in accordance with the current situation. Moreover, using fuzzy supervisor avoids sudden switching between two controllers and provides a smooth transition. The main structure of a fuzzy control is composed of four segments; fuzzifier, fuzzy inference system, fuzzy rule base and defuzzifier. More specifically, a fuzzy controller with if-then rule base, minimum inference engine, singleton fuzzifier and center of gravity defuzzifier is represented according to equation 14.

$$f(x) = \frac{\sum_{m=1}^{M} y^{-m} \left(\min_{i=1}^{n} \mu A_i^m (x_i) \right)}{\sum_{i=1}^{M} \min_{i=1}^{n} \mu A_i^m (x_i)} \tag{14}$$

Fuzzy supervisory control is a two level control method (Figure 4). Typically, a low level controller is tasked with rapid and direct control operation. In contrast, the high level controller (supervisor) is a low speed control section aiming to improve performance or ensure stability. One of the advantages of two level control systems is that different controllers might be designed to reach various control objectives, though; they are problematic due to their complicated control structure.

In the literature fuzzy supervisory control guaranteeing system stability is presented. The main idea is that the supervisor switches to idle mode if the supervised system works properly; otherwise, if the system approaches instability, the supervisor will start operation and avoid system instability. This makes the control process discontinuous. To achieve continuous control, gain-scheduling fuzzy supervisory control has been introduced such as PID fuzzy supervisory control, sliding mode fuzzy supervisory control and PI [16]. Obviously, if the supervised controller is a linear one, it would not be sufficient in presence of uncertainties [17]; hence, in this study a nonlinear intelligent controller is used to effectively overcome uncertainties.

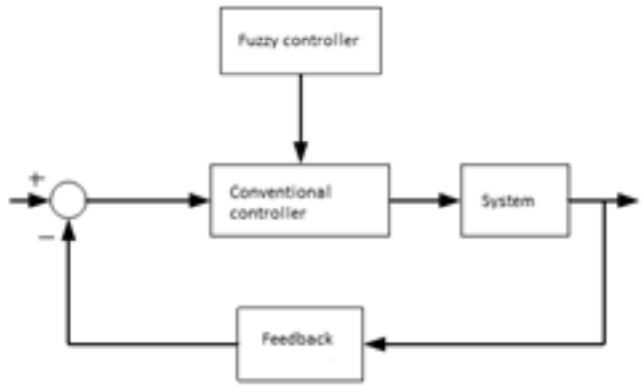

Figure 4. Fuzzy supervisory control

One of the main advantages of sliding mode control is fast and robust performance in presence of disturbances. It still has some disadvantages including chattering, bounds estimation requirement and conservative determination of larger coefficient. On the other hand, ANFIS controller is able to overcome structural uncertainties; however, it suffers from undesirable transient response which is a consequence of parameter update. To compensate for aforementioned drawbacks a novel method is proposed called sliding mode and adaptive neuro-fuzzy networks fuzzy supervisory control. The proposed strategy is using a fuzzy inference system to adjust gain of sliding mode and ANFIS control in presence of disturbance and considerable tracking error.

High sliding mode control signal guarantees system stability and leads error to sliding surface. When error gets close to the sliding surface, chattering might be decreases using smaller gain coefficient. In this circumstance, system is still prone to unstructured uncertainties which cause the system to have improper steady state. In this condition ANFIS plays the main role in confronting unstructured uncertainties relying on its self-training capability. Furthermore, delay in calculating control signal results in discontinuity in control signal of sliding mode controller. Fuzzy supervisor determines gain coefficient of each low level controller based on system behavior and rule base. Fuzzy controller is also able to smooth switching between sliding mode and ANFIS controllers. Fuzzy supervisor is a behavior oriented supervisory controller. It is used to obtain α and $1-\alpha$ coefficients respectively for sliding mode and ANFIS controllers. The sum of gain coefficient of sliding mode and ANFIS controllers equals to one; thus, the range of fuzzy supervisor output (α) is considered to be between 0 and 1. The block diagram of final control system is demonstrated in figure 5.

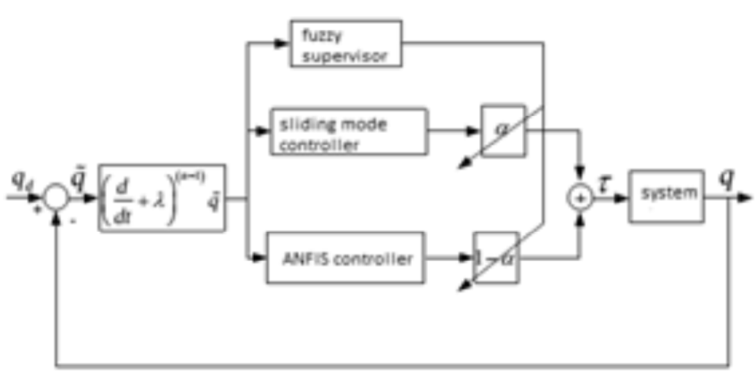

Figure 5: Block diagram of the proposed control method

Where n, q, $\tilde{q}$ and $\left(\frac{d}{dt}+\lambda\right)^{(-1)}\tilde{q}$ are system order, system output, reference signal and output error and sliding surface, respectively.

Since sliding mode controller is utilized, S and its derivative values ($\dot{S}$) are considered as fuzzy supervisor inputs. Fuzzy rules are based on analyzing the movement toward sliding surface associated with sliding mode controller. In this manner, only two inputs are required for supervisor while if the main output was used the number of fuzzy supervisor inputs had been equal to the number of system states. Therefore, using sliding surface and its derivative as inputs of fuzzy supervisor, results in a simple design of fuzzy supervisor and reduction of fuzzy rule based dimensions. Moreover, using sliding surface and its derivative provide a unique design which might be applied to all types of systems with minor changes in supervisor parameters.

Each input includes five fuzzy sets; NB, NS, ZE, PS and PB. They respectively denote Negative Big, Negative Small, Zero, Positive Small and Positive Big. Input range is determined via predicting *S* in presence of disturbance. For the output three membership functions are considered (zero, LM, M, HM and one) which are singleton.

Membership functions of fuzzifier are Gaussian. Only two membership functions including NB and PB are considered to be *z* and *s* type, respective. Fuzzy rule base is specified based on an intuitive perspective of *S* & $\dot{S}$. For instance, if in a long distance from sliding surface (large *S* value) system is getting further away from sliding surface, a significant weight is assigned to sliding mode control so as to effectively decrease *S*. inversely, when *S* decreases weight of sliding mode control is reduced and that of adaptive neuro-fuzzy control increases. While *S* approaches to zero adaptive neuro-fuzzy controller plays the main role. Hence, fuzzy rule base is defined as presented in table1.

Table 1
Fuzzy rule base

${}_{S}\alpha^{\dot{S}}$	*NB*	*NS*	*ZE*	*PS*	*PB*
PB	**HM**	**HM**	**1**	**1**	**1**
PS	**0**	**LM**	**M**	**HM**	**1**
ZE	**M**	**LM**	**0**	**LM**	**0.5**
NS	**1**	**HM**	**M**	**LM**	**0**
NB	**1**	**1**	**1**	**HM**	**Hm**

For example if *S* acquires NB and $\dot{S}$ is ZE inference system returns one for α. The output is derived using equation 14.

3. CASE STUDY

In October 2009 the smallest multipurpose robot, IRB-120, was introduced by ABB company. It has 6 degrees of freedom and includes all features associated with modern design of large robots of ABB; meanwhile, it is very light

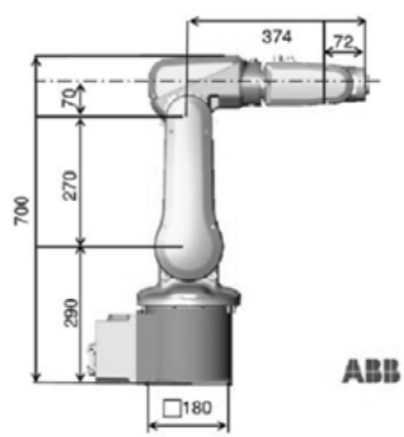

Figure 6: Important dimensions of IRB-120 robot

and cost efficient. Its reach is 580 mm and it may access 112 mm underneath its base. IRB-120 is a cost efficient choice for manipulating materials and assembling small devices. It can be employed in several industries such as electronics, solar industry, food industry, machineries, pharmaceutical and medical industry and research works. The important dimensions of the robot are illustrated in figure 6.

Since this study focuses on position control, three first joints are used and three joints belonging to wrist are assumed to be constant. Characteristics related to dynamic specifications of links are summarized in table 2.

The mentioned problems regarding sliding mode and ANFIS controllers encourage us to use a combination of these methods for robot position control. The control signal is a weighted sum of these controllers in which the weights are determined by the supervisor. To smooth transition between two controllers a fuzzy supervisor is utilized.

Table 2
Dynamic characteristics of IRB-120 components

Link3:	*Link2*:	*Link1*:
Mass = 15.55kg	*Mass* = 16.9kg	*Mass* = 8.4kg
Center of Mass(m) = $\begin{bmatrix} 0.058 \\ 0.024 \\ 0 \end{bmatrix}$	*Center of Mass(m)* = $\begin{bmatrix} 0.124 \\ 0 \\ 0 \end{bmatrix}$	*Center of Mass(m)* = $\begin{bmatrix} 0 \\ 0 \\ -0.05 \end{bmatrix}$
Moments of inertia: (kg * square mitter)	Moments of inertia: (kg * square mitter)	Moments of inertia: (kg * square mitter)
Taken at the center of mass and aligned with the output coordinate system.	Taken at the center of mass and aligned with the output coordinate system.	Taken at the center of mass and aligned with the output coordinate system.
Lxx = 0.89 Lxy = 0.59 Lxz = 0	Lxx = 0.16 Lxy = 0 Lxz = 0	Lxx = 0.031 Lxy = 0 Lxz = 0.00037
Lyx = 0.59 Lyy = 0.46 Lyz = 0	Lyx = 0 Lyy = 0.3 Lyz = 0	Lyx = 0 Lyy = 0.028 Lyz = 0
Lzx = 0 Lzy = 0 Lzz = 0.94	Lzx = 0 Lzy = 0 Lzz = 0.16	Lzx = 0.00037 Lzy = 0 Lzz = 0.025
Moments of inertia: (kg * square mitter)	Moments of inertia: (kg * square mitter)	Moments of inertia: (kg * square mitter)
Taken at the output coordinate system.	Taken at the output coordinate system.	Taken at the output coordinate system.
Lxx = 0.094 Lxy = 0.028 Lxz = 0	Lxx = 0.16 Lxy = 0 Lxz = 0	Lxx = 0.053 Lxy = 0 Lxz = 0.0008
Lyx = 0.028 Lyy = 0.099 Lyz = 0	Lyx = 0 Lyy = 0.56 Lyz = 0	Lyx = 0 Lyy = 0.049 Lyz = 0
Lzx = 0 Lzy = 0 Lzz = 0.016	Lzx = 0 Lzy = 0 Lzz = 0.42	Lzx = 0.0008 Lzy = 0 Lzz = 0.025

S and $\dot{S}$ signals are used as inputs of supervisor respectively denoting sliding surface and its derivative. As far as these two values are zero the output of fuzzy supervisor is zero as well ($\alpha = 0$) i.e. ANFIS controller dominates the control system. Otherwise, both controllers are involved in the control process proportional to their corresponding weight. When S is far from zero, sliding mode controllers plays the main role ($\alpha = 1$).

PID is known as a popular controller in robot position control in industries; however, it cannot overcome limitations. In this section a PID controller is used for initial training of ANFIS controller. For this purpose, first off, system response with a PID controller for a reference input is derived. Afterwards, the measured data is used to train adaptive neuro-fuzzy controller. To adjust PID coefficients Zeigler- Nichols method is utilized. After obtaining initial model, the ANFIS controller parameters are updated to decrease errors. To design sliding mode control Eigen values matrix and control gain matrix are considered to be $A = diag\,[10, 10, 10]$ and $K = diag\,[200, 200, 200]$, respectively. They are obtained via a simple search method. To validate the proposed method a second order path composed of two segments is used for all three joints. Diagram of joint positions together with reference position using sliding mode, ANFIS and the proposed controllerare depicted in figure 7. Besides, tracking error and control torque for all controllers are respectively shown in figures 8 and 9. As can be seen, the proposed controller is able to effectively follow reference signal and to facilitate transition between different operating points. Furthermore, the output of the system with the proposed controller is similar to sliding mode controller which illustrates superiority of sliding mode controller to other controllers. In the proposed controller control signal and system states chattering are completely eliminated which is a significant advantage of the proposed method over sliding mode control.

4. CONCLUSION

The results revealed that the proposed controller provides acceptable time response as well as error performance. The chattering of system states and control signal were eliminated. Furthermore, transient behavior of the system

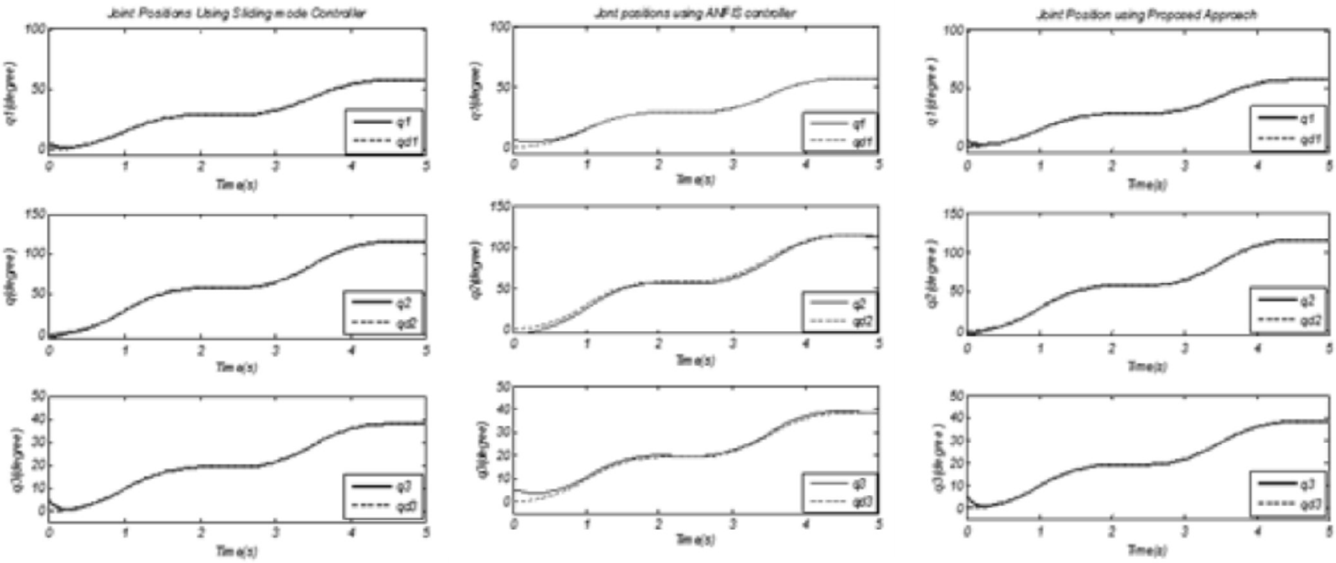

Figure 7: Joint positions using sliding mode controller, ANFIS and the proposed controller

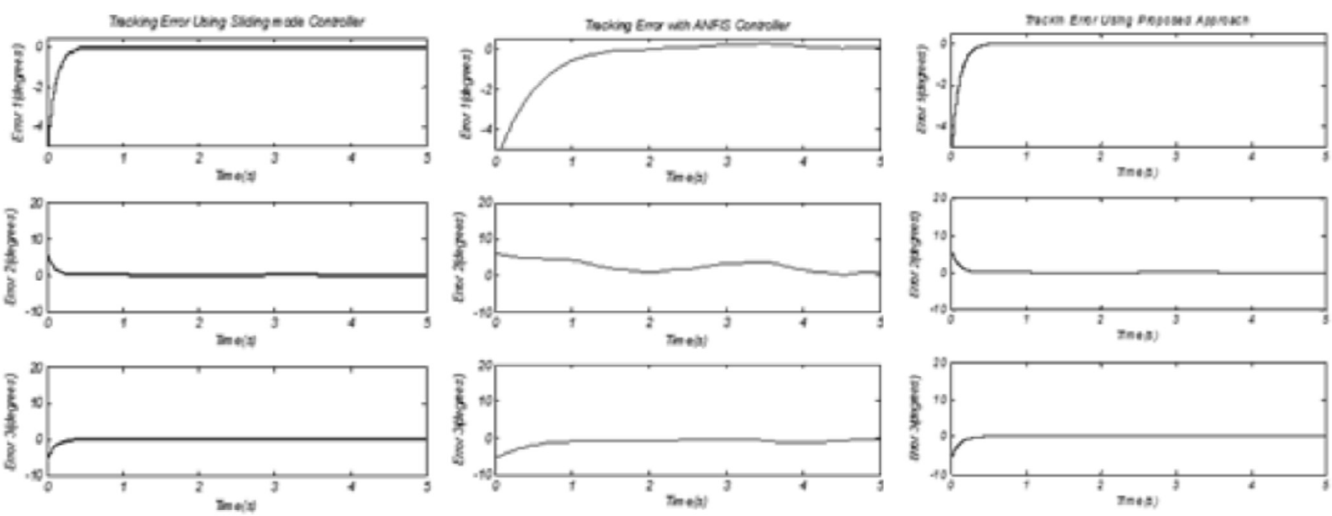

Figure 8: Tracking error for sliding mode controller, ANFIS and the proposed controller

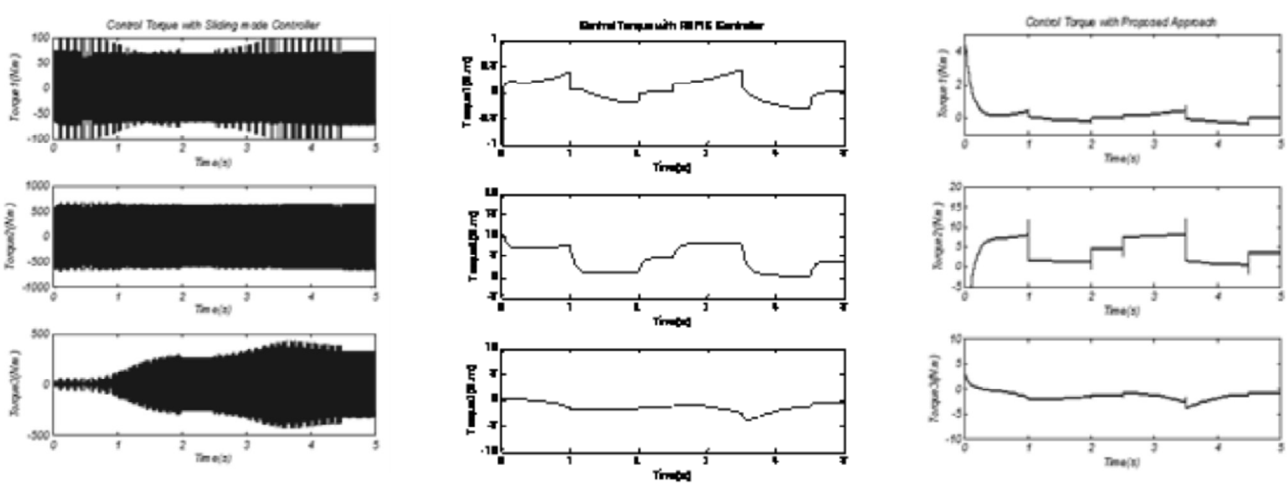

Figure 9: Control torque with sliding mode controller, ANFIS and the proposed controller

was considerably improved comparing to controllers without chattering such as neuro-fuzzy controller. To sum up, the designed controller uses the advantages of both sliding mode and adaptive neuro-fuzzy controller to overcome their shortages leading to a significant improvement in system behavior.

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