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Control of Non Linear Two Mass Drive System using ANFIS

K.M.N.Chaitanya Kumar Reddy[1], Dr.B.Rajani[2], Dr.P.Sangameswara Raju[3]

PG Student [ICS], Dept. of EEE, S V University, Tirupati, Andhra Pradesh, India[1]

Associate Professor, Dept. of EEE, Siddarth institute of Engineering & Technology, Puttur, Andhra Pradesh, India[2]

Director (Academic), Siddhartha institute of science & Technology, Puttur, Andhra Pradesh, India[3]

ABSTRACT: This paper presents the application of Adaptive neuro fuzzy inference system (ANFIS) controller to a non-linear system which is made out of an engine where motor is associated with the load machine through a shaft. The state equation that describes the mathematical model of non linear two mass drive system is first developed, based upon which the ANFIS controller is designed. The objective of ANFIS controller is to adjust the parameters of a fuzzy system by applying a learning procedure using input–output training data. The design of ANFIS controller is explained in detail. The regulation of the speed of the two mass drive system using both existing Active disturbance rejection controller (ADRC) and proposed Adaptive neuro fuzzy inference system (ANFIS) controller is observed. At the end, the simulation results of these controllers are compared.

KEYWORDS*:* Adaptive neuro fuzzy inference system (ANFIS); Fractional order controller; Two mass drive system; Active disturbance rejection control (ADRC); Neural networks; Extended state observer (ESO); Tracking differentiator.

I.INTRODUCTION

At present days, requirements for the ideal action in fixed and dynamic states of industrial electrical drives are increasing day by day. The main objective of this sort of systems is to reduce the time delay in the ephemeral process and to achieve the ideal tracking of the given curve of the speed or position while system must be robust to parameter change of the controlled systems. In two mass systems the problem mainly develops due to low resonant frequency in the mechanical part of the system that is caused as a result of existing long shaft between motor and load. The concept of two-mass drive system is used in many industrial electrical drives, practically this phenomena is used in industrial applications like in the drives of rolling mill, machinery of textile and paper manufacturing, conveyors, radio telescopes, drives of the robots, positioning systems of hard disks etc.., Presence of elastic connection between electrical drives creates dynamic oscillations of the drive state variables. Hence due to dynamic oscillations in this type of drive system with elastic joint, it is very difficult to control the speed or position of the shaft. In many cases oscillations can create loss of stability. In order to make sure that the system to be stable we need to evaluate the state variables of the two-mass system. The evaluation process can be done by using artificial methods which include control methodologies like fractional order control and neural network techniques. In order to evaluate the mechanical state variables such as the shaft torque and load-side speed of the two-mass drive system, we use a neural network estimator.

Fig. 1(a) shows a schematic of a two-inertia servo-drive system where ω_1 is the motor speed, ω_2 is the load speed, τe is the motor torque, τs is the shaft (torsional) torque, τL is the disturbance torque, J_m and J_d represents motor and load inertias respectively, K_{md} is shaft of finite stiffness and Fig. 1(b) shows a dynamic block diagram of the system.

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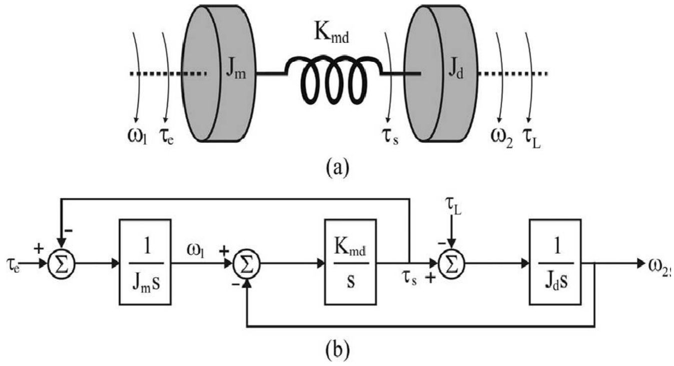

Fig.1. Mechanical schematic of a two-mass system.
(a) Two-mass representation of a servo-drive system.
(b) Block diagram of a two-mass mechanical system.

In this paper, we replace the existing fractional order PID and Active disturbance rejection controllers with ANFIS controller which is a kind of artificial neural network that is based on Sugeno fuzzy inference system. ANFIS can be further described as a data mining methodology based on a combination of fuzzy logic and neural networks by clustering values in fuzzy sets. Since it is a combination of both neural networks and fuzzy logic principles, it has capability to hold the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy if–then rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator. By using ANFIS controller we get speed of response fast and will reach steady state very quickly compared to existing controllers.

II.MATHEMATICAL MODEL OF TWO MASS DRIVE SYSTEM

A general model of the drive system with elastic coupling as shown in fig.1 is considered where the shaft is put through a torsional torque τs and is excited by a combination of electromagnetic torque τe and load-torque perturbations τL. The state equation of this two mass drive system is as follows:

$$\frac{d}{dt}\begin{bmatrix} w1(t) \\ w2(t) \\ \tau s(t) \end{bmatrix} = \begin{bmatrix} 0 & 0 & -\frac{1}{T1} \\ 0 & 0 & -\frac{1}{T2} \\ \frac{1}{Tc} & -\frac{1}{Tc} & 0 \end{bmatrix} \begin{bmatrix} w1(t) \\ w2(t) \\ \tau s(t) \end{bmatrix} + \begin{bmatrix} \frac{1}{T1} \\ 0 \\ 0 \end{bmatrix} [\tau e] + \begin{bmatrix} 0 \\ -\frac{1}{T2} \\ 0 \end{bmatrix} [\tau L]$$

Where T1 is the mechanical time constant of the motor,T2 is the mechanical time constant of the load machine, Tc is the stiffness time constant,W1 is the motor speed,W2 is the load speed, τe is the motor torque, τs is the shaft torque, τL is the disturbance torque.

From the interpreted system, the system parameters are considered as constant: T1 =74 ms, T2 =74 ms and Tc =5.6ms where the control input of the system is considered as electromagnetic torque of the motor τe, and the output value is considered as the angular speed of the motor ω1 .The damping losses are neglected without significantly affecting the forgoing simulation analysis, since under normal conditions these are contemplated to be relatively low. Furthermore, nonlinear parts of the real drive system like backlash, mechanical hysteresis, and nonlinear friction, were also not taken into account in the simulation study.

III.FRACTIONAL-ORDER CALCULUS AND CONTROLLER DESIGN OF EXISTING CONTROLLERS

In this section we will know about fractional order calculus followed by controller design of existing Fractional order PID and ADRC controllers. Fractional calculus is a concept obtained by inference of integration and differentiation to non integer (fractional)-order fundamental operator a D^r t, where a and t are the limits and (r ∈ R) is the order of the operation . The fractional calculus can be defined by many definitions, but the most commonly used are the Riemann–

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Liouville integral and the Grünwald–Letnikov derivative. The classical form of fractional calculus is given by the Riemann–Liouville integral as given in (1)

$$ {}_aD^r_t\, f(t) = \frac{1}{\Gamma(n-r)}\frac{d^n}{dt^n}\int_a^t \frac{f(\tau)}{(t-\tau)^{r-n-1}}d\tau \qquad (1)$$

By contrast the Grünwald–Letnikov derivative starts with the derivative instead of the integral. The Grünwald–Letnikov derivative is a basic extension of the derivative in fractional calculus that allows one to take the derivative a non-integer number of times. It was introduced by Anton Karl Grünwald (1838–1920) from Prague, in 1867, and by Aleksey Vasilievich Letnikov (1837–1888) in Moscow in 1868. The classical form of fractional calculus is given by the Grünwald–Letnikov as given in (2)

$$ {}_aD^r_t\, f(t) = \lim_{h\to 0} h^{-r}\sum_{j=0}^{\left[\frac{t-a}{h}\right]}(-1)^j\binom{r}{j}f(t-jh) \qquad (2)$$

The discretization of fractional-order differentiator/integrator $s^{\mp r}$ ($r \in R$) can be expressed by the generating function $s \approx w(z^{-1})$ where the generating function formula is as given in (3)

$$ w(z^{-1}) = \left(\frac{1}{\beta T}\,\frac{1-z^{-1}}{\gamma+(1-\gamma)z^{-1}}\right) \qquad (3)$$

Where β and γ are denoted as the gain and phase tuning parameters, respectively.

In order to discretize s^r ($0 < r < 1$), the infinite-impulse response discretization form is used. Raised to power $\mp r$ of the generating function has the following form and is given in (4)

$$ w(z^{-1})^{\mp r} = \left(\frac{1+a}{T}\,\frac{1-z^{-1}}{1+az^{-1}}\right)^{\mp r} \qquad (4)$$

Where a is the ratio term and r is the fractional order.

The most common form of a fractional order PID (FOPID) controller is the $PI^{\lambda}D^{\mu}$ controller. FOPID controller provides extra degree of freedom for not only the need of design controller gains (k_p, k_i, k_d) but also design orders of integral and derivative. The FOPID controller generalizes the conventional integer order PID controller when $\lambda = 1$, $\mu = 1$ and when $\lambda = 1$, $\mu = 0$, and $\lambda = 0$, $\mu = 1$, respectively corresponds to the conventional PI & PD controllers. All these classical types of PID controllers are special cases of the $PI^{\lambda}D^{\mu}$ controller. This expansion could provide much more flexibility in PID control design. The transfer function of such a controller has the following form as shown in (5).

$$ G_C(s) = k_p + \frac{k_i}{s^{\lambda}} + k_d s^{\mu} \qquad (\lambda, \mu > 0) \qquad (5)$$

In order to estimate the controller parameters k_p, k_i, k_d, λ, and μ, the transfer function of the system is required. With reference to fig.1(b), the transfer function of the analysed two-mass system is given as following expression:

$$ G_{TMS}(s) = \frac{K_{md}}{s(s^2 J_d\, J_m + K_{md} J_m + K_{md}\, J_d\,)} \qquad (6)$$

The discretized form of the transfer function of the two-mass system using (4) was observed and is given by

$$ G_{TMS}\,(z)^{-1} = \frac{18620 - 62.71z^{-1} - 12350z^{-2} - 5509z^{-3} - 696.4z^{-4}}{9.333\;10^7 - 6.222\;10^7\;z^{-2} - 2.765\;10^7 z^{-3} - 2.765\;10^7 z^{-4}}$$

In the ADRC design, the disturbance is estimated using the so called state observer, which is commonly used in the framework of modern control theory to estimate the immeasurable internal states of a system .These states, also known as state variables, refer to physical variables of a system, such as current, voltage, temperature, pressure, etc., and state observer, usually implemented in a computer algorithm, and uses the input and output data of a system, and its model, to reconstruct in real time the values of state variables. The uniqueness of the ADRC design is that the total disturbance, which includes both external disturbances and unknown internal dynamics, is defined as an extended state of the system and is estimated using a state observer, known as the extended state observer (ESO). Unlike the standard state observers, the state in ESO is extended beyond the regular physical variables to include the effects of unknown

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Vol. 5, Issue 12, December 2016

disturbances and dynamics in their totality. Once estimated, the total disturbance can be readily cancelled by the control signal, transforming elegantly the original system to a disturbance-free one, which can easily be controlled.
Let us assume a nonlinear uncertain object with an unknown disturbance

$$x^{(n)} = f\left(x, x^{(1)}, x^{(2)}, \dots, x^{(n-1)}, t\right) + w(t) \qquad (7)$$

Where $f\left(x, x^{(1)}, x^{(2)}, \dots, x^{(n-1)}, t\right)$ is an unknown function and w(t) is an unknown disturbance. Deploying (4), the extended state vector $x(t), x^{(1)}(t), x^{(2)}(t), \dots, x^{(n-1)}(t)$ can be computed by a tracking differentiator. A first-order system is represented as follows

$$\dot{x} = f(x(t), w(t), t) + bu \qquad (8)$$

When x (t) is measurable, the second-order ESO is

$$\begin{cases} \dot{z} = z_2 - \xi_1 \text{func}\,(z_1 - x(t), \gamma 1, \varepsilon_1) + b_0 u \\ \dot{z_2} = -\xi_2 \text{func}(z_2 - x(t), \gamma 2, \varepsilon_2 \end{cases} \qquad (9)$$

Where ξ_i's are observer coefficients and $0 < \gamma 2 < \gamma 1 < 1$

$$\text{func}(z, \gamma, \varepsilon) = \begin{cases} |z|^{\gamma}\text{sgn}(z), & |z| > \varepsilon \\ \frac{z}{\varepsilon^{1-\varepsilon}}, & |z| \le \varepsilon \end{cases} \qquad (10)$$

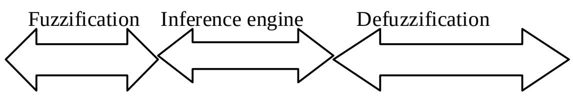
Usually, $\gamma 1 = 1$, $\gamma 2 = 0.5$, $\varepsilon 1 = \varepsilon 2 = dt = 0.001$, $\xi_1 = 120$, $\xi_2 = 47$, and b_0 is the estimated value of b. Assuming z_1=w1, $z_2=\tau L$ and $u=\tau e$, we can estimate the value of τL.

IV.PROPOSED CONTROLLER

ANFIS has gain a lot of interest over the last few years as a powerful technique to solve many real world problems. Compared to conventional techniques, they own the capability of solving problems that do not have algorithmic solution. To overcome the drawbacks of neural networks and fuzzy logic, Adaptive neuro fuzzy inference system (ANFIS) was proposed in this paper. The fuzzy inference commonly used in ANFIS is first order Sugeno fuzzy model because of its simplicity, high interpretability, and computational efficiency, built- in optimal and adaptive techniques.
In matlab the main difference between fuzzy controller and adaptive neuro fuzzy controller is that we have in matlab two types of fuzzy controllers, one is mamdani and second one is Sugeno. Mamdani is ordinary fuzzy controller where we provide input and output by using some assumptions, but in Sugeno type we provide inputs and the controller automatically train outputs. This is the main difference between two fuzzy controllers in matlab. Hence I have taken Sugeno type fuzzy controller adaptive neuro fuzzy controller in matlab.
A typical architecture of an ANFIS is shown in fig.2. For a first order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules can be expressed as:

Rule 1: if x is A_1 and y is B_1, then $z_1 = p_1 x + q_1 y + r_1$ (11)
Rule 2: if x is A_2 and y is B_2, then $z_2 = p_2 x + q_2 y + r_2$ (12)

Where A_i and B_i are the fuzzy sets in the antecedent, and p_i, q_i and r_i are the design parameters that are determined during the training process.



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Vol. 5, Issue 12, December 2016

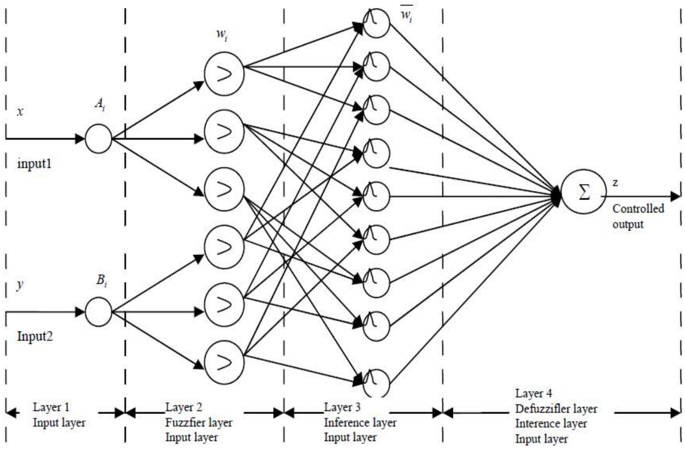

Fig.2.Adaptive neuro fuzzy structure

Layer 1**:** Every node in this layer contains membership functions.

$$o^1{}_i = \mu_{A_i}(x), \ \ i = 1{,}2 \qquad (13)$$

$$o^1{}_i = \mu_{B_{i=2}}(x), i = 3{,}4 \qquad (14)$$

Where μ_{A_i} and μ_{B_i}can adopt any fuzzy membership function.

Layer 2: This layer chooses the minimum value of two input weights.

$$o^2{}_i = w_i = \mu_{A_i}(x)\ \mu_{B_i}(y), \ \ i = 1{,}2 \qquad (15)$$

Layer 3: Every node of these layers calculates the weight, which is normalized.

$$o^3{}_i = \overline{w}_i = \frac{w_i}{w_1+w_2}\ , \ i = 1{,}2 \qquad (16)$$

Where $\overline{w}_i$ is referred to as the normalized firing strengths.

Layer 4: This layer includes linear functions, which are functions of the input signals.

$$o^4{}_i = \overline{w}_i z_i = \overline{w}_i(p_i x + q_i y + r_i), \ i=1{,}2 \qquad (17)$$

Where $\overline{w}_i$ is the output of layer 3, and {pi, qi, ri} is the parameter set. The parameters in this layer are referred to as the consequent parameters.

Layer 5: This layer sums all the incoming signals.

$$o^5{}_i = \sum_{i=1}^{2} \overline{w}_i\, z_i = \frac{w_1 z_1 + w_2 z_2}{w_1 + w_2} \qquad (18)$$

The output z in fig.2.can be rewritten as:

$$z = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2 \qquad (19)$$

V. RESULTS

In this paper, performance of the proposed ANFIS controller's motor speed, load speed, electromagnetic torque and shaft torque is evaluated and is compared with those of $PI^{\lambda}D^{\mu}$ controller and ADRC controller. The software environment used for this simulation is Matlab. 7.12, with simulink package. We go for comparison of the wave forms of motor speed, load speed, electromagnetic torque and estimated shaft torques in fractional-order $PI^{\lambda}D^{\mu}$ controller and ADRC controller with proposed ANFIS controller. The simulation results were also presented. The results were taken with respect to time.

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Vol. 5, Issue 12, December 2016

MOTOR SPEED

Fig.3.Fractional order $PI^{\lambda}D^{\mu}$

The above graph shows the motor speed response of the system using Fractional order $PI^{\lambda}D^{\mu}$ controller.

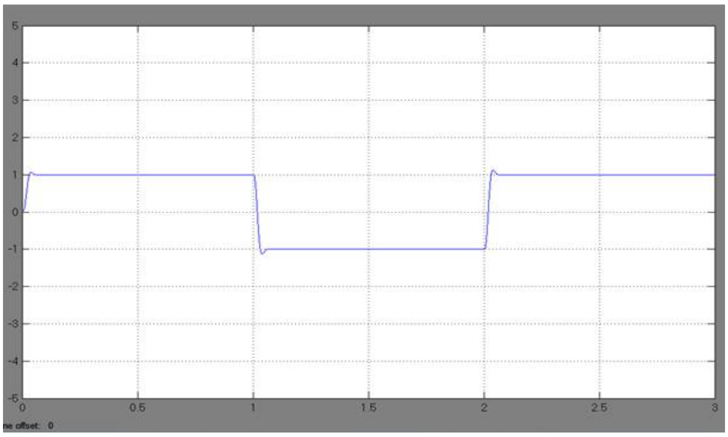

Fig.4.ADRC

The above graph shows the motor speed response of the system using Active disturbance rejection controller.

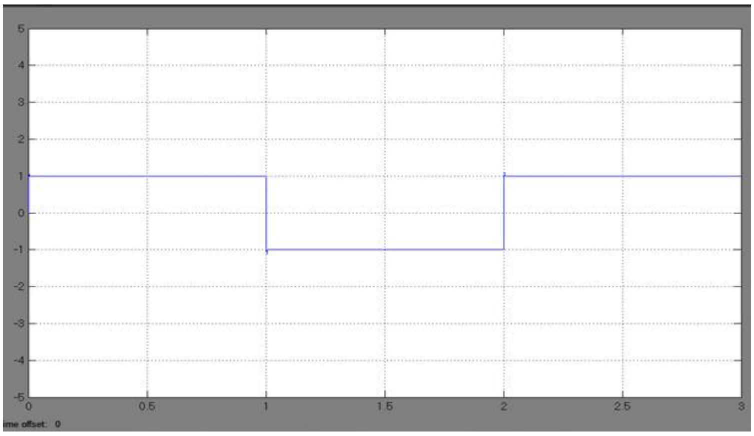

Fig.5.ANFIS

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ISSN (Online): 2278 – 8875

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(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 12, December 2016

The above graph shows the motor speed response of the system using Adaptive neuro fuzzy inference system controller.

LOAD SPEED

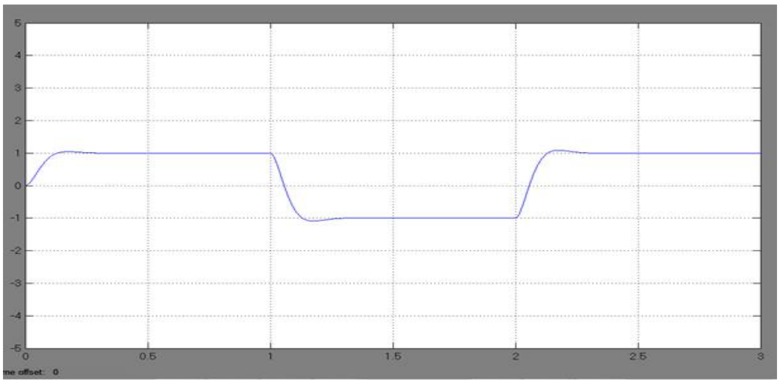

Fig.6.Fractional order $PI^{\lambda}D^{\mu}$

The above graph shows the load speed response of the system using Fractional order $PI^{\lambda}D^{\mu}$ controller.

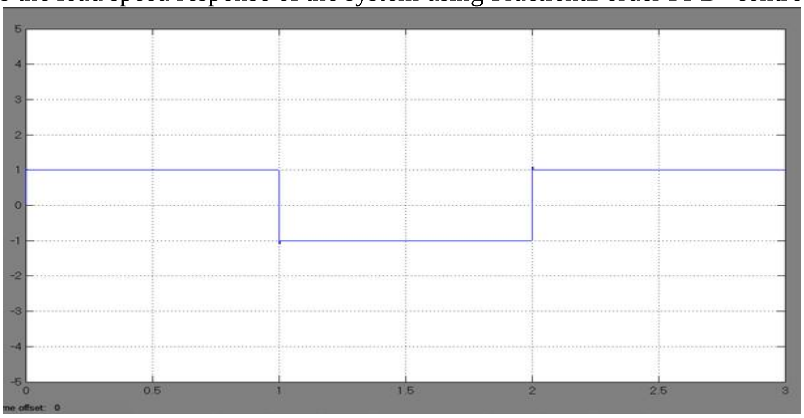

Fig.7.ADRC

The above graph shows the load speed response of the system using Active disturbance rejection controller.

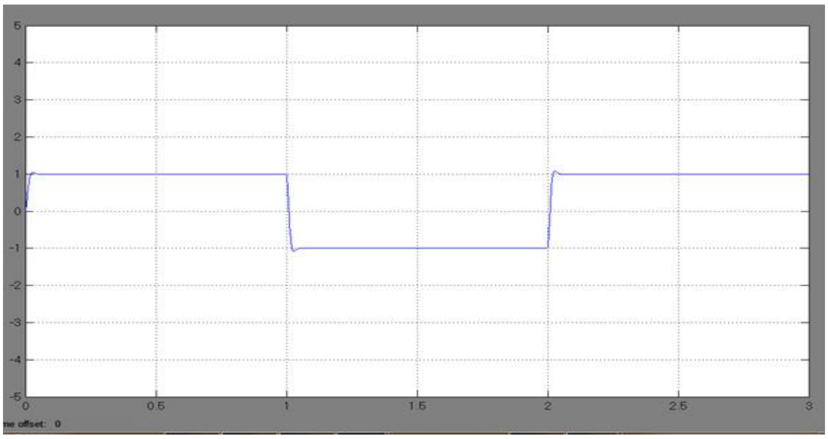

Fig.8.ANFIS

The above graph shows the load speed response of the system using Adaptive neuro fuzzy inference system controller.

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ELECTROMAGNETIC TORQUE

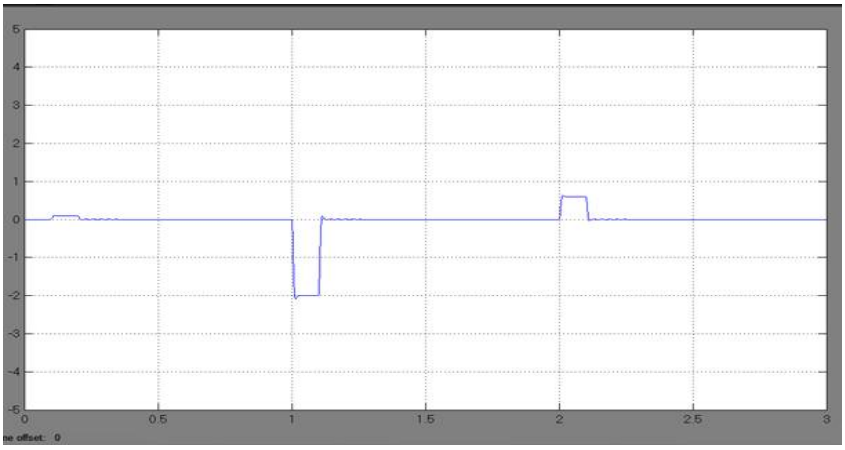

Fig.9.Fractional order $PI^{\lambda}D^{\mu}$

The above graph represents electromagnetic torque response of the system using Fractional order $PI^{\lambda}D^{\mu}$ controller.

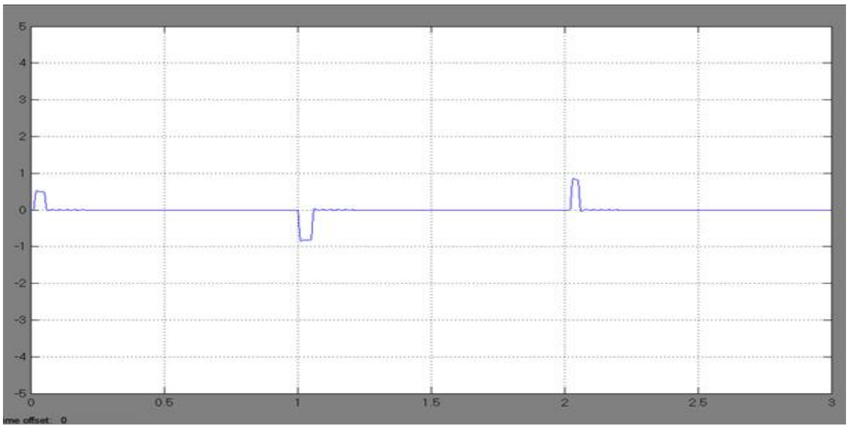

Fig.10.ADRC

The above graph represents electromagnetic torque response of the system using Active disturbance rejection controller.

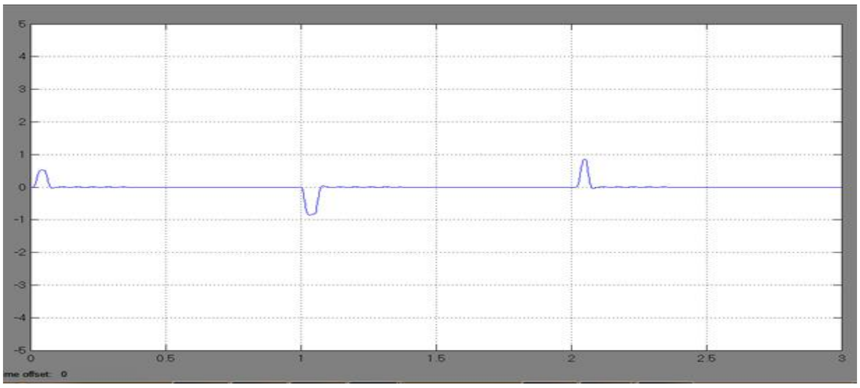

Fig.11.ANFIS

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Vol. 5, Issue 12, December 2016

The above graph represents electromagnetic torque response of the system using Adaptive neuro fuzzy inference system controller.

SHAFT TORQUE

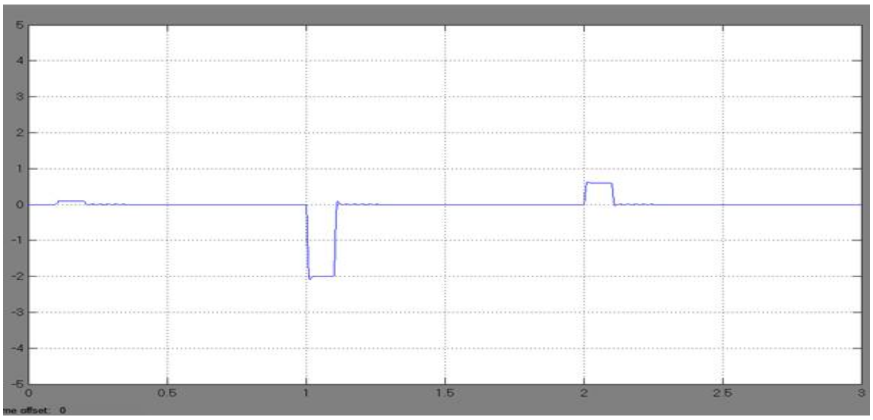

Fig.12.Fractional order $PI^{\lambda}D^{\mu}$

The above graph represents shaft torque response of the system using Fractional order $PI^{\lambda}D^{\mu}$ controller.

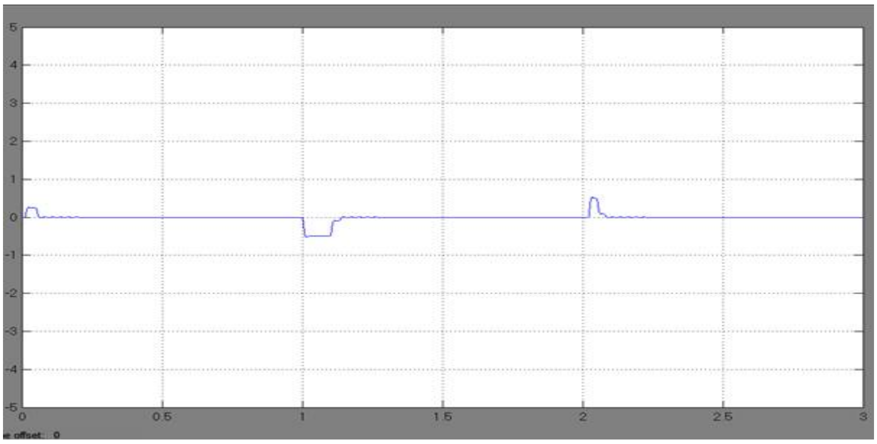

Fig.13.ADRC

The above graph represents shaft torque response of the system using Active disturbance rejection controller.

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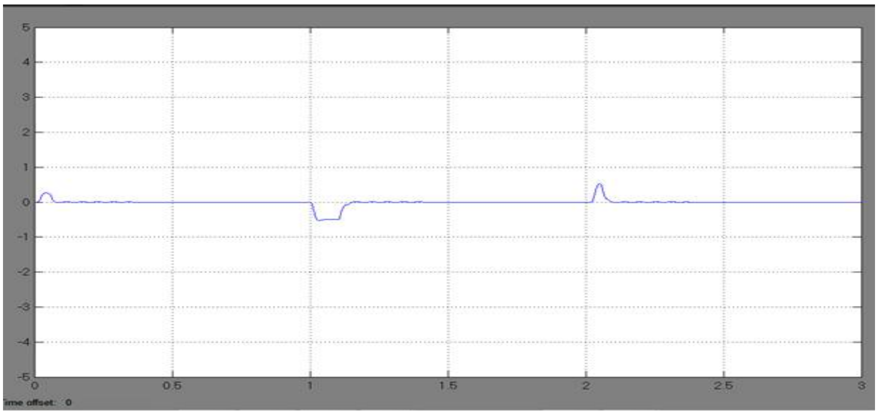

Fig.14.ANFIS

The above graph represents shaft torque response of the system using Adaptive neuro fuzzy inference system controller.

From the above results the comparison is made between existing controllers and proposed controller. The parameters we have chosen are overshoot and settling time of electromagnetic torque, shaft torque, load speed and motor speed. A comparison among $PI^{\lambda}D^{\mu}$, ADRC and ANFIS controllers regarding these parameters is given in table.1. From comparison table we observed that proposed ANFIS controller gives better performance when compared to existing ADRC and $PI^{\lambda}D^{\mu}$ controllers. It was also observed that by using ANFIS controller we get speed of response fast and will reach steady state very quickly compared to Fractional order PID controller and Active disturbance rejection controller. Hence from the simulated work we can say that the ANFIS controller provides robust control for the non linear two mass drive system when compared with the existing Fractional order PID controller and Active disturbance rejection controller.

Controller method	**Overshoot**	**Electromagnetic Torque Settling Time (s)**	**Shaft Torque Settling Time (s)**	**Load Speed Settling Time (s)**	**Motor Speed Settling Time (s)**
$PI^{\lambda}D^{\mu}$ Controller	0.8666%	0.12	0.125	0.28	0.1
ADRC	0%	0.035	0.045	0.08	0.085
ANFIS Controller	0%	0.014	0.016	0.045	0.006

TABLE.1.Comparison table for $PI^{\lambda}D^{\mu}$, ADRC and ANFIS controllers

VI.CONCLUSION

The different controller design techniques for the intensified performance of two mass servo drive systems have been demonstrated in this paper. The fractional-order calculus based $PI^{\lambda}D^{\mu}$ controller and ADR controller have been scrutinized with regard to both the closed loop robustness and the control of the process variable to a step reference

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speed. And we proposed an ANFIS controller in place of existing controllers. By using this ANFIS controller we get fast and good dynamic response. The harmonic distortion in the system using ANFIS controller is less compared to system using existing controllers. Under divergent operating conditions for different speed levels, the drive system performance has been analysed. The secured results have established a very good dynamical performance and state variable estimation quality for the drive system with an elastic joint. The proposed controller also establishes very robust control for the considered two mass drive systems.

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