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Design and Simulation of Type two fuzzy Logic based PD controller for Variable Speed Rotation Active Magnetic Bearing System Subject to Random Disturbance

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Abstract – In this paper the design of type-2 fuzzy logic based PD controller for an active magnetic bearing system (AMB) is presented. Such a system is known to be inherently unstable. The logic techniques of the proposed method continuously observes the error signal and it's change in order to modify the parameters of a PD controller. An improved tracking performance has been achieved. Robustness against disturbance effects with various rotation speeds has also been noticed. Comparison with a regular fuzzy like PD controller shows a noticeable improvement in the tracking performance of the system, especially in the presence of disturbances. In order to ensure the stability of the system, a pole placement controller is designed first before applying the type-2 fuzzy logic PD controller.

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Keywords: – Type-2 Fuzzy logic, Active magnetic bearing system, PIDcontroller.

1. Introduction

(AMBS) are being increasingly used in industrial applications where minimum friction is desired or in severe environments where traditional bearings and their associated lubrication systems are considered unacceptable [1] Magnetic bearings have some advantages in relation to the mechanical and hydrostatic levitation. The obvious benefits are contactless operation, absence of lubrication and contamination wear. The rotor can be allowed to rotate at high speed; the high circumferential speed is only limited by the strength of the rotor material. At high operation speeds, the friction losses were decreased 5 to 20 times compared to the conventional ball bearings. Due to the lack of mechanical wear, magnetic bearings have higher life time and lower maintenance costs. However, active magnetic bearings have also disadvantages (the design of a magnetic bearing system for a specific application requires previous information in mechatronics, specifically in mechanical and electrical engineering and in information processing, because of the complexity of the magnetic bearing system, the costs of purchase are several times higher compared to the conventional bearings). Although active magnetic bearings are commonly used in many industrial applications, such as turbo-molecular vacuum pumps, flywheel energy storage systems, compressors, machine tools[2]. Such open loop systems are inherently unstable and need to be stabilized; this is generally done by using a closed loop system with an appropriate controller in which it brings flexibility to the dynamic response that can also add an effect in dealing with noises and vibrations. In [3] robust fuzzy logic-based control scheme for a rotating (AMBS), in which it represent the nonlinear magnetic bearing by means of a Takagi–Sugeno–Kang (TSK) fuzzy model to overcome the position sensitivity, This control scheme is used to obtain robustness with respect to harmonic disturbances and modeling error without estimating perturbations by adaptively adjusting the stiffness of magnetic bearing, while in [4], Model predictive robust controller has been considered to enhance the AMB system tracking through observing and prediction control strategy and find out that MPC is optimally estimated the right positions to track the specified desirable signal that were chosen. The Authors in [5] presented a design for a fuzzy gain tuning mechanism dealing with the problem of unbalanced vibration problem in an (AMBS), a replacement of the conventional proportional-integral-derivative controller with a self-tuning fuzzy PID-type controller have been succeeded in suppressing unbalanced vibration in an AMBS. In [6], an intelligent estimation of uncertainty bounds for robust LMI control of AMB systems had been developed to provide systematic representation of uncertainties through robust control theory. Other researchers like Castillo *et al* in [7] presented that fuzzy controller with an increasing number of membership functions will increase the effectiveness of Fuzzy logic used to control the actuator which is an AMB system. As demonstrated in [8] using FLC for magnetic levitation system proved that it could reduce the overshoot, settling time and produced a small overshoot and a small steady-state error when an external disturbance occurred. In this paper a proportional Derivative based intelligent logic controller have been introduced by incorporates of type two fuzzy set to tune the gains of PD control to control the behavior of AMB systems with and without disturbance and compare the results to a type-1 regular fuzzy based PD controller with the same external effects.

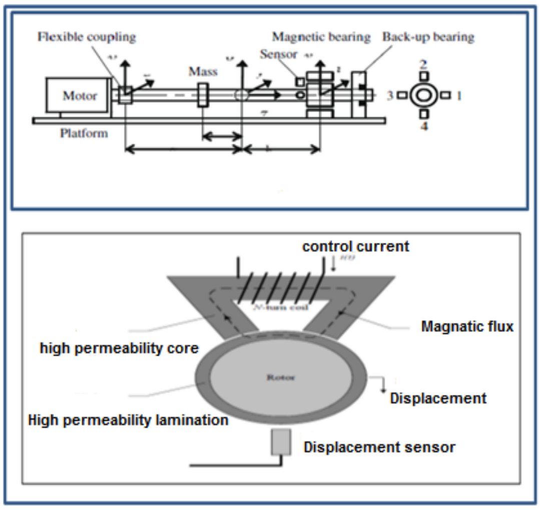
2. Theoretical AMB Model

The force generated by an electromagnetic actuator (as shown in Figure 1) can be derived using magnetic circuit analysis and conservation of energy technique[9][[10].

$$f_{em} = \frac{1}{4}\mu_0 N^2 A_g \frac{i^2}{z^2} \quad (1)$$

The resulting nonlinear magnetic force Equation (1) is proportional to the square of the coil current i and inversely proportional to the square of the air gap between the actuator and the rotor z. $\mu_0$is the permeability of free space $(4\pi.10^{-7}H/m)$,in which it is the measure of the ability of a material to support the formation of a magnetic field within itself. Hence, it is the degree of magnetization that a material obtains in response to an applied magnetic field. $N$is the number of turns in the coil, and $A_g$is the area of the air gap. In order to develop a model based control of the system, the electromagnetic force Equation (1)is linearized about a nominal operating point and an accurate dynamical model is formulated [9], [10]. Despite its highly nonlinear nature, the dynamics of this AMB are represented using a linear model with parameters that vary with rotor set point; the result is an improved tracking performance. Linearization of (1) by Taylor series expansion about the operating point 2*10^{-3}they were represented using a state vector x composed of the rotor displacements and their time derivatives. Therefore by defining $x_1 = z$and$x_2 = \dot{z}$, the model in state space form become [10];

$$\left.\begin{aligned} \dot{x} &= f(x,u) \\ y &= Cx \end{aligned}\right\} \quad (2)$$



Figure(1): Basic Structure and operating principles of an AMB System [9].

3. Systems dynamical equations

Nonlinear state equations for AMB system can be derived using magnetic circuit analysis and conservation of energy techniques. Using actual system parameters, Figure (1) (mass = 0.067 kg, coil inductance = 1.1 mH, coil resistance = 0.35 Ω, the system dynamics can be modeled [9], [4]:

$$\dot{\mathbf{x}}_1 = x_2$$
$$\dot{\mathbf{x}}_2 = -5.162e^{-6}\frac{i^2}{x_1^2} + 9.807 \quad (3)$$

where$x_1$is the rotor position (m) and x_2 is the rotor velocity (m/s).

After linearization, the system

fter linearization, the system′s equations yield the following linear model [9]:

$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\end{bmatrix} = \begin{bmatrix}0 & 1\\ 7263.56 & 0\end{bmatrix}\begin{bmatrix}x_1\\ x_2\end{bmatrix} + \begin{bmatrix}0\\ -5.495\end{bmatrix}u + g(x) = Ax + Bu + g(x)$$

$$y = [1 \quad 0]\begin{bmatrix}x_1\\ x_2\end{bmatrix} = Cx \quad (4)$$

The nonlinear term $g(x)$ appears in the linearized model of AMB system consists of the difference between the nonlinear model and the linear one. Indeed it equals two;

$$g(x) = f(x,u) - (Ax + Bu)$$

In a small neighborhood of the origin we can approximate the nonlinear system (Eq. (2)) by the linear model (Eq. (4)) where $g(x) \to 0$ [11]. Moreover $g(x)$ may also include the perturbation term which comes from the uncertainty in system model and the external disturbances.

Due to the high nonlinearity of the AMB system, the parameters of the linearized model (4) vary with rotor position. Accordingly the resulted Eigen values for the selected operating point are 98.8 and -98.8 clearly, the AMB linearized system is locally unstable [11]. Thus to perform system tracking control properly it had to be stabilized first via pole placement control as follows:

$$u = u_s + u_f = -kx + u_f \qquad (5)$$

where u_s is the stabilizing control term while u_f is the fuzzy control term. The system dynamics with stabilizing controller becomes;

$$\dot{x} = (A - Bk)x + Bu_f + g(x)$$
$$\dot{x} = \breve{A}x + Bu_f + g(x) \qquad (6)$$

where $k = (-2.7177e + 03, -31.8884)$ is the linear state feedback parameter, $\breve{A}$ is the modified A matrix after applying pole placement technique. After stabilization the closed loop eigenvalues (the roots of $\breve{A}$) became -90 and -85 respectively. Consequently the stabilization term increases the area of attraction for the system model which represents the main task of u_s . If the state initiated in the area of attraction it goes asymptotically to the origin.

The second term in the control law (Eq.(5)) is devoted mainly to reject the effect of $g(x)$ at least locally using Fuzzy type-1 $\boldsymbol{u_{f1}}$and Fuzzy type-2 $\boldsymbol{u_{f2}}$. Definitely the fuzzy controller will also enlarge the area of attraction.

4. Type-2 Fuzzy Logic Controller Description

The control objective for this single-input single output system is to manipulate the input voltage *v(t)* of the rotor so that the Position of the rotor $x_1(t)$ tracks the desired signal $x_d(t)$.The chosen controllers in this case study are type-1 fuzzy logic based PD controller and type -2 fuzzy logic based PD controller. A traditional fuzzy logic system consists of 4 components— the rule base, the fuzzy inference engine, the fuzzifier and the defuzzifier. Knowledge is embedded within the rule base in the form of rules whose antecedent (proportional gain (K_P) multiplied by the error while the derivative gain multiplied by the differentiation of error), the consequent (the control action signal (u)) are fuzzy sets that partition the input and output domains. Although type-1 fuzzy logic has a name that reveal the implication of uncertainty, researches have shown that type-1 fuzzy logic systems have difficulties in modeling and minimizing the effect of uncertainties. Hence, in the this work " having difficulties in minimizing the effect of the Random noise that have been applied as compared to type-2 fuzzy logic", The main reason is that a type-1 fuzzy set is certain in the sense that for each input, there is a crisp membership grade. Recently, a type of

fuzzy sets characterized by membership grades that are themselves fuzzy have been reviewed as type-2 fuzzy sets As illustrated in Figure (2), a type-2 fuzzy MF can be obtained by starting with a type- 1 MF and blurring it. The extra mathematical dimension provided by the blurred area, referred to as the footprint of uncertainty (FOU), and represents the uncertainties in the shape and position of the type-1 fuzzy set. The FOU is bounded by upper and lower MFs, and points within the "blurred area" have membership grades given by type-1 MFs. The most frequently used type-2 fuzzy sets are interval fuzzy sets [3], [12].
the major difference being that at least one of the fuzzy sets is type-2 and a type-reducer is needed to convert the type-2 fuzzy output sets into type-1 sets so that they can be processed by the defuzzifier to give a crisp output as shown in Figure (3).

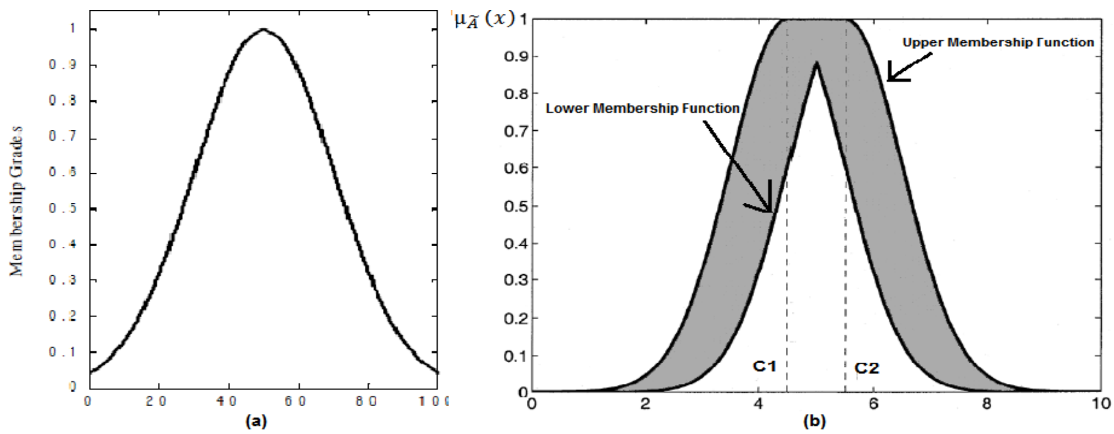


Figure (2): a)Gaussian membership function for Type-1Fuzzy sets b): Gaussian membership function for Type-2Fuzzy sets

4.1 Type-2 fuzzy inference engine:

In this work: [type-1 and type-2] fuzzy inference engine implement the PD controller to manipulate the error for the membership functions used as follows[13], [14]:

- Gaussian Type-1, 2, see Figure (2), Fuzzy logic are used for input MFs $\boldsymbol{F_1^l}$ and $\boldsymbol{F_P^l}$,$\widetilde{\boldsymbol{F_1^l}}$and $\widetilde{\boldsymbol{F_P^l}}$ respectively where '~' implies that the fuzzy set is a type-2 fuzzy set as will be shown in the next Paragraph.

In this work, we have type-1 Gaussian MFs with a center c and σ has been considered to determine the membership function width and defined as

Gaussian (x; c,σ)= $e^{-\frac{1}{2}(\frac{x-c}{\sigma})^2}$ (7)

Referring to Figure (2), (a) which represent the type-1 Gaussian (x;50,20) listed as an example.
Having interval type-2 Gaussian MFs ***with a uncertain center, c, and an fixed standard deviationσ,*** i.e. [13];

$$\mu_A(x) = e^{-\frac{1}{2}(\frac{x-c}{\sigma})^2} \quad c\epsilon[c_1, c_2] \qquad (8)$$

In terms of the upper and lower membership functions, for upper membership function $\overline{\mu}_{\tilde{A}}(x)$

$$\bar{\mu}_{\tilde{A}}(x) = \begin{cases} N(c_1, \sigma; X) & x < c_1 \\ 1 & c_1 \le x \le c_2 \\ N(c_2, \sigma; X) & x > c_2 \end{cases}$$

And for the lower membership function $\underline{\mu}_{\tilde{A}}(x)$

$$\underline{\mu}_{\tilde{A}}(x) = \begin{cases} N(c_2, \sigma; x) & x \le \frac{c_1+c_2}{2} \\ N(c_1, \sigma; x) & x > \frac{c_1+c_2}{2} \end{cases} \quad (9)$$

Where:

$N(c_1, \sigma; x) = e^{-\frac{1}{2}\left(\frac{x-c_1}{\sigma}\right)^2}, N(c_2, \sigma; x) = e^{-\frac{1}{2}\left(\frac{x-c_2}{\sigma}\right)^2},$

5. Type Reduction

The outputs corresponding to the fired rules are type-2 fuzzy sets which must be type-reduced before the defuzzifier can be used. Things are somewhat more complicated for an interval type-2 FLS, because; to go from an interval type-2 fuzzy set to a number (usually) requires two steps The first step, called type-reduction, is where an interval type-2 fuzzy set is reduced to an interval-valued type-1 fuzzy set. There are as many type-reduction methods as there are type-1 defuzzification methods. Many algorithms have been developed can be reviewed in [15], [16] known as the KM Algorithm is used for type-reduction. Although this algorithm is iterative, it is very fast. The type-reducer generates a type-1 fuzzy set output, which is then converted to a numeric output through running the defuzzifier. This type-1 fuzzy set is also an interval set, concerning this work using 'center of sets method' (cos) type reduction hence, this is the main structural difference between the type-1 and type-2 FLCs.

6. Defuzzification

Once the type reduction is completed the procedure begins by calculating the crisp output from an interval set type reduction's obtained values. So the result will be similar to a type-1 fuzzy set but more often enhanced ones. While type-1 fuzzy logic differs in the entire inference engine solver steps as shown in Figure (3).

Shared principles between the two types are as follows

In this section the basic principles that the two types may be sharing has been investigated:

As for The inputs($e, \dot{e}$) and output (u) for fuzzy type-1; are called linguistic variables. participate in the construction of membership functions which are chosen to be seven Gaussian membership functions in this work which are enough to offer sufficient description for the input fuzzy sets and that is the common information with the output membership functions which are Gaussian too, The range of values of the inputs that can be quantified with the fuzzy sets (universe of discourse) is [-1, 1] and of output is [0, 1]. The operator used to represent the rules is the minimum operator 'AND' in premises and implication and centroid method for defuzzification, to calculate number of rules = (number of fuzzy MF's)^(number of fuzzy inputs). Since the fuzzy system has two inputs each one with 7 membership functions then there will be 72 = 49 rule in order to reduce the complex computations and gain less simulation time only the 7 diagonal fuzzy rules were chosen as for the 49 rule were used and it has been concluded that it will not affect the response that much only increasing the simulation time. hence, for the type-2 fuzzy sets the information above is repeated but for another shape of Gaussian membership function shown in Figure (2), as well as the further stage that invented which is 'type reduction' as discussed in the type reduction paragraph, hence, those should be the main differences.

7. Formulation of the rule base for Fuzzy Type-1 based PD controller verses fuzzy type-2 based PD controllers:

Although Type-2 Fuzzy logic uses another type of tool box that differs from type-1 fuzzy logic, Ozek et al [17], introduced Type-2 Fuzzy logic systems toolbox written in MATLAB programming language, the toolbox is very useful and used in the simulations of the control systems in this paper

Hence,

A linear PD control law is usually implemented as [18]

$$u_{PD} = k_p e + k_d \dot{e} \tag{10}$$

Where: u is the actuating signal e is the feedback error, $\dot{e}$is the change of error, and k_p and k_d are the Proportional and Derivative gains, respectively. A Type-1 FLC with Rule base

If e is $\boldsymbol{F_1^l}$ and $\dot{\boldsymbol{e}}$is $\boldsymbol{F_P^l}$ then $\boldsymbol{u_{pd}}$is$\boldsymbol{u_{PD}^l}$ (11)

The consequents of the rules are crisp numbers defined

As $u_{PD_{IJ}}$=$k_p e_i + K_d \dot{e}_j$ (12)

where e and $\dot{e}$ are apexes of the antecedent Type-1 MFs.

AType-2 fuzzy PD controller can be constructed by blurring the Type-1 Fuzzy Sets to Type-2 Fuzzy Sets, The rule base for the resulting Type-2 FLC [18]

$\boldsymbol{\widetilde{R}^l}$: If e is $\boldsymbol{\widetilde{F_1^l}}$ and$\dot{\boldsymbol{e}}$ is $\boldsymbol{\widetilde{F_P^l}}$ then $\boldsymbol{u_{pd}}$ is$\boldsymbol{u_{PD}^l}$ (13)

Where $\boldsymbol{\widetilde{F_1^l}}$&$\boldsymbol{\widetilde{F_P^l}}$are Type- 2 Fuzzy logic obtained by blurring $\boldsymbol{F_1^l}$ and $\boldsymbol{F_P^l}$ respectively, and $\boldsymbol{u_{PD}^l}$ is the same as that defined in (11). Where it is assumed that the number of “negative” MFs equals the number of “positive” MFs, which is a common practice for FLCs.

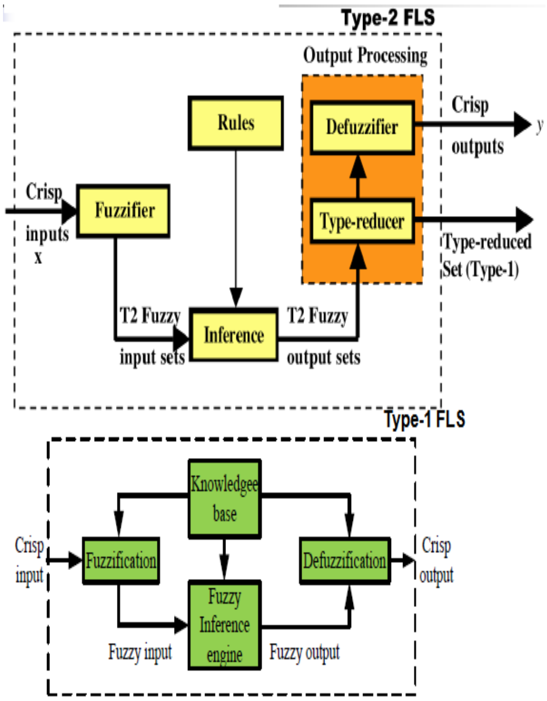


Figure (3): The inference engine representation in- Type-1 and type-2 fuzzy Logic[8]

8. Design a PD-like type (1 and 2) fuzzy logic for AMB system:

In order to feed the inputs of fuzzy Types with the proper KP and Kd Gains 2000,4.3 values were suitable selected respectively by trial and error to acquire an enhanced response as well as amplifying the fuzzy signal by 5.582 and as a result the robust manipulated signal were obtained as far as Type-2 Fuzzy Controller is concerned,

The proposed controller enabled tracking of the square wave reference trajectory [9];

$$\mathbf{x_d = 2 * 10^{-3} + 1 * 10^{-5} sign(sin(\beta\pi t))m} \tag{14}$$

The reference trajectory has a set point of 2.0.e^{-3}m, a square wave amplitude of 1.0 .10^{-5}m, and for 3 Frequencies of 2 π ,10 π and 20π rad / sec that represent the speed of rotation of the bearing rotor.

9. Simulation Results:

An Application program was built using Matlab/Simulink and M-file where the system shown in Figure (4) is simulated after applying the pole placement control and the desired trajectory in (14) in which The reference trajectory has a set point of $2*10^{-3}$m, a square wave amplitude of $1*10^{-5}$, and a frequency of $\beta = 2, 10, 20$. The results shown for the system with no Disturbance in Figures (5-a, b and c) it is clear that the systems response does not suffer from palpable steady state error or any considerable amount of oscillation and The controlled system can perfectly track the desired trajectory with short as a rise time. Moreover, damped oscillations, with a better performance concerned with the response of type-2 fuzzy sets was gained, especially when increasing the speed to 20 π rad/sec. Nevertheless, the controlled system is stable for increased values of the parameter β . it can be noticed that the offset is pretty obvious between the response of fuzzy type 1&2 and the desired signal in terms of micro meter, but it is also important to realize that this offset has been intentionally revealed after zooming the response several times in order to present the enhanced behavior of fuzzy type-2 against fuzzy type-1 and this offset is very small in amount due to the small values of the tracking signal as will be shown in numbers as description analysis for mean and standard deviation of tracking error in Table (1).

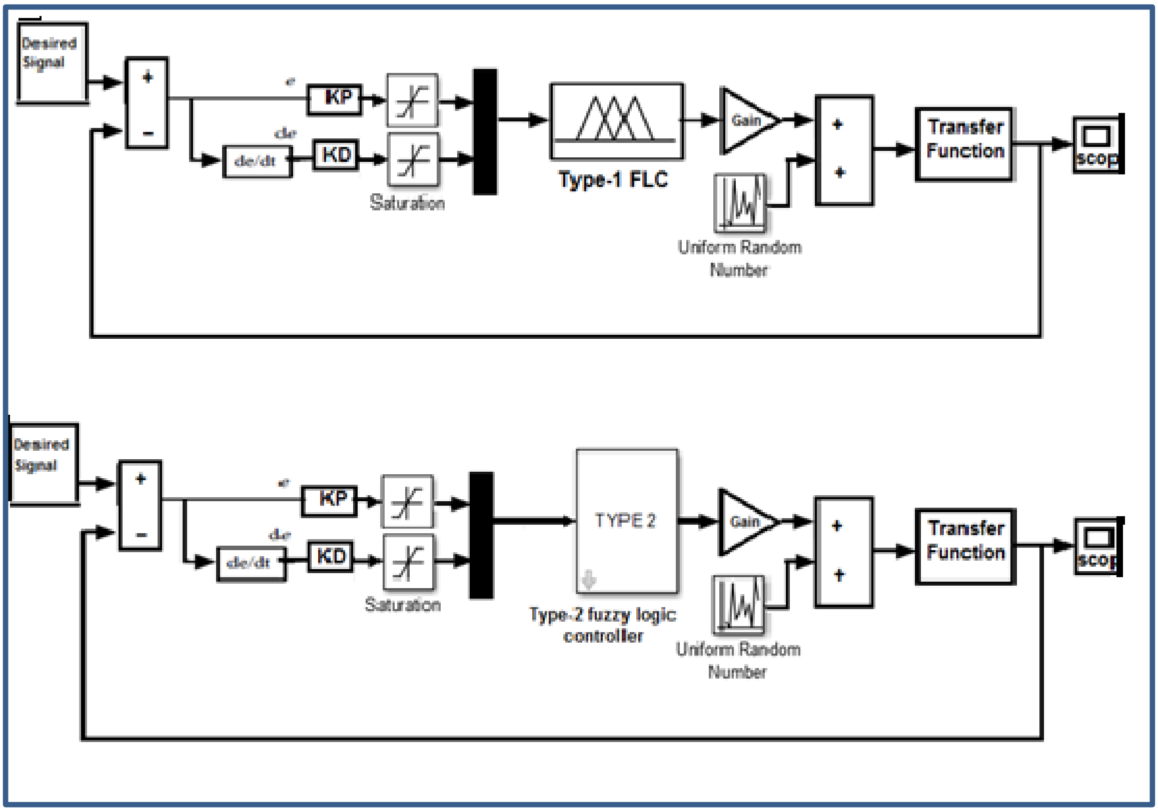


Figure (4): Block Diagram of the system controlled by PD-Like Fuzzy Type-1 and Type-2 Fuzzy sets

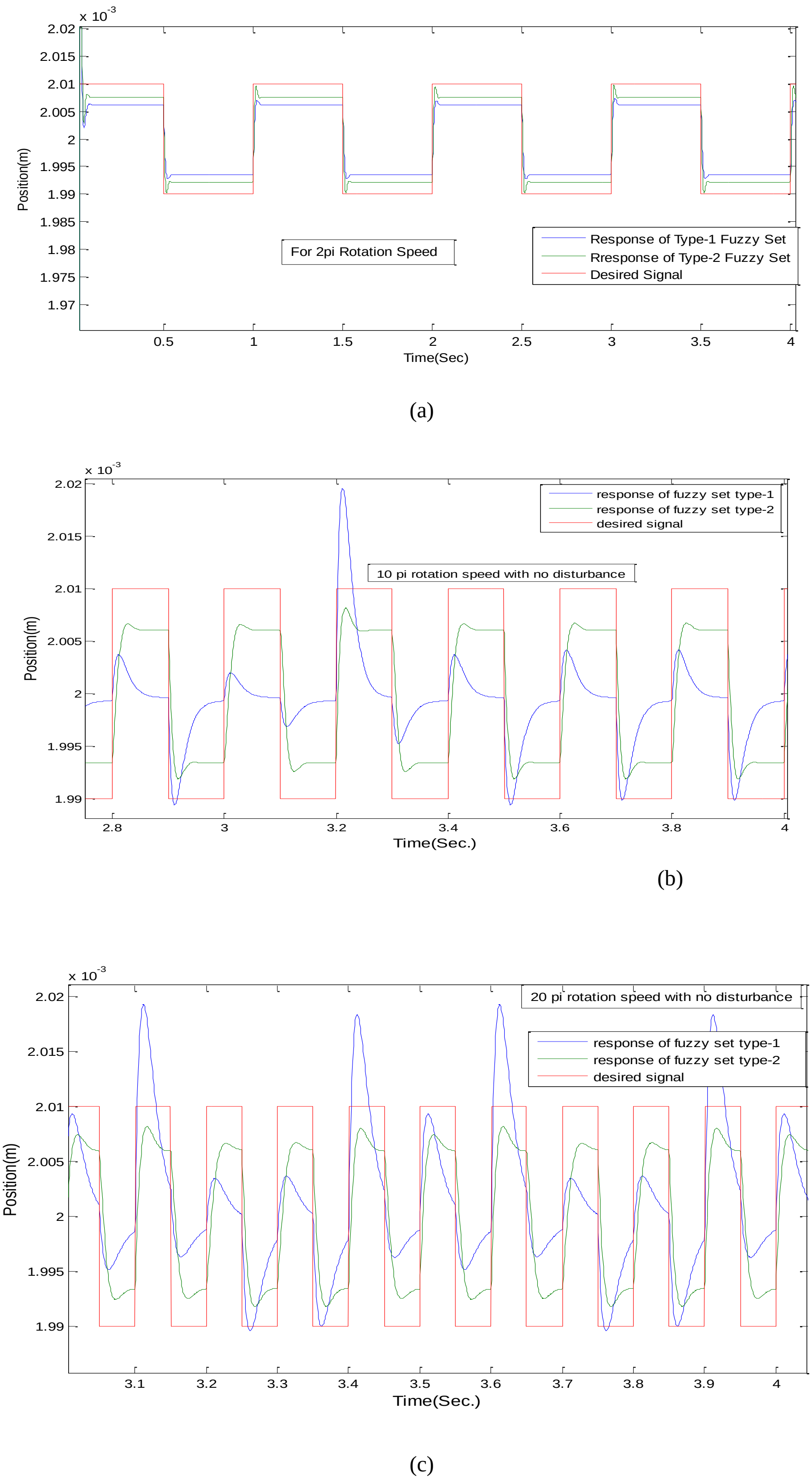
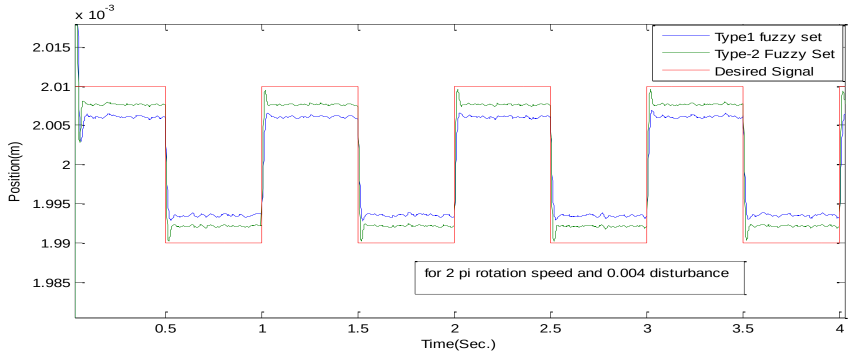


Figure (5): The Simulated Output of type-1 and type-2 fuzzy logic without disturbance for:
a) 2 pi Rotational speed **b)** 10pi Rotational speed **c)** 20pi Rotational speed

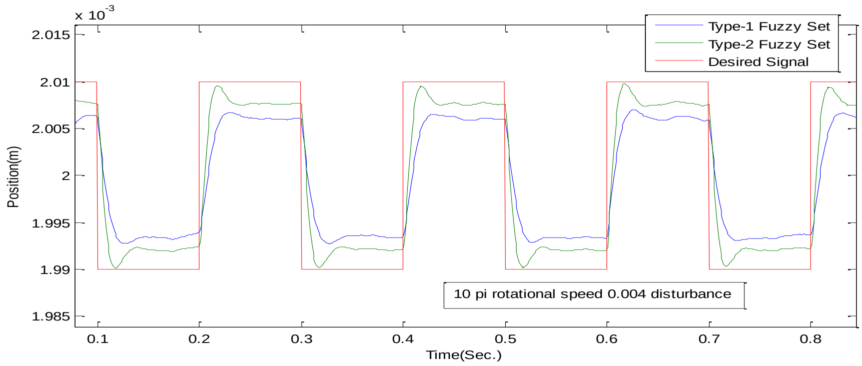
Table(1): Mean and standard deviation of tracking error in fuzzy 1 &2 with no forced disturbance

Type of fuzzy set	Rotational Speed	Mean value of error e-06	∓Standard deviation e-05
Fuzzy type -1	2π	**6.5487**	**∓9.6572**
	$10\ \pi$	**6.4464**	**∓9.5859**
	$20\ \pi$	**6.3480**	**∓9.5021**
Fuzzy Type-2	$2\ \pi$	**6.3861**	**∓9.5696**
	$10\ \pi$	**6.2911**	**∓9.4993**
	$20\ \pi$	**6.1871**	**∓9.4168**

After adding a disturbance of peak values (-0.004, 0.004) shown in Figure (6), to the system of the block diagram shown in Figure (4), the controlled response is shown in Figures (7- a, b and c). This distortion with the speed variations was obviously overcomed by fuzzzy type-2 espicially after increasing the Random Disturbance peaks to(0.08,-0.08) as shown in Figures (8- a, b and c). and the description analysis of the mean value of error was shown in Table(2).



(a)



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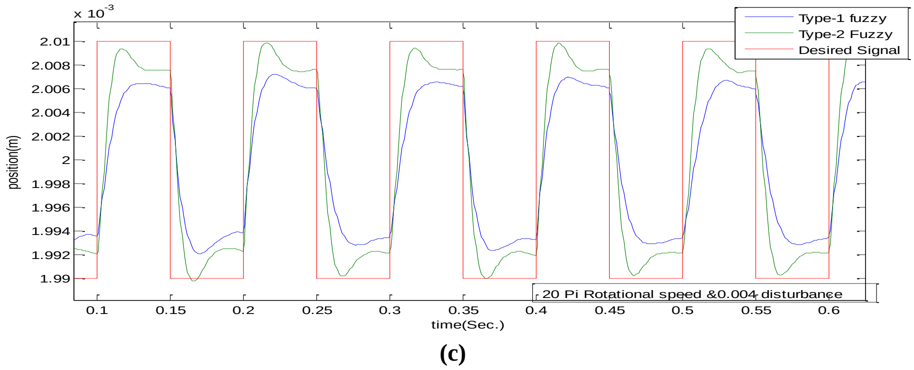


(c)

Figure (6) The Simulated Output of of type-1 and type-2 fuzzy logic with 0.004 peak value disturbance for: **a)**2 pi Rotational speed **b)**10pi Rotational speed **c):**20pi

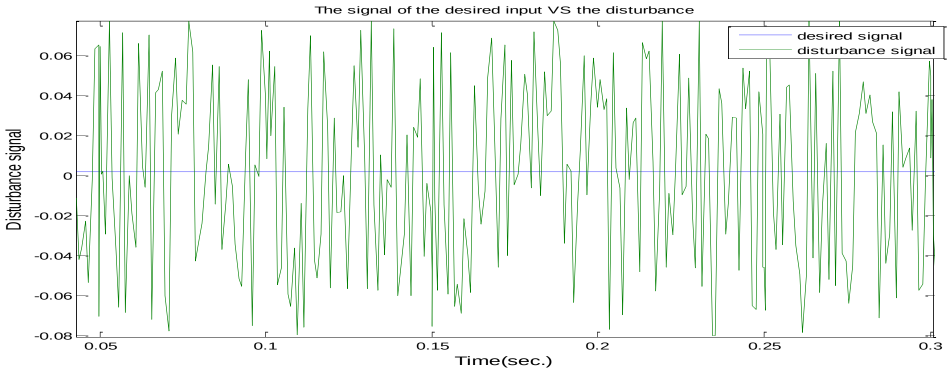
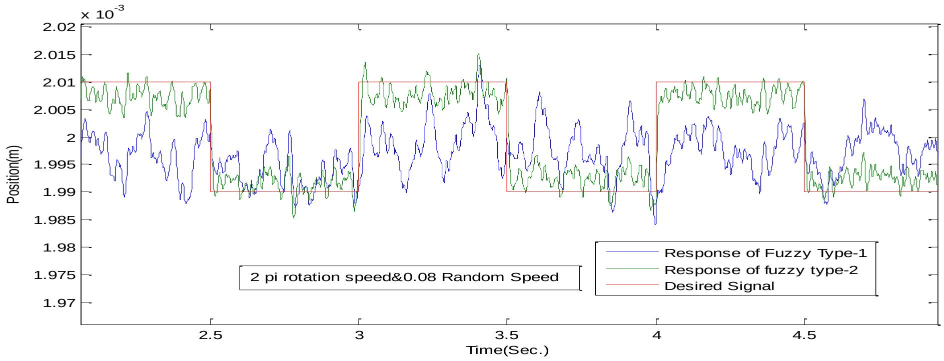
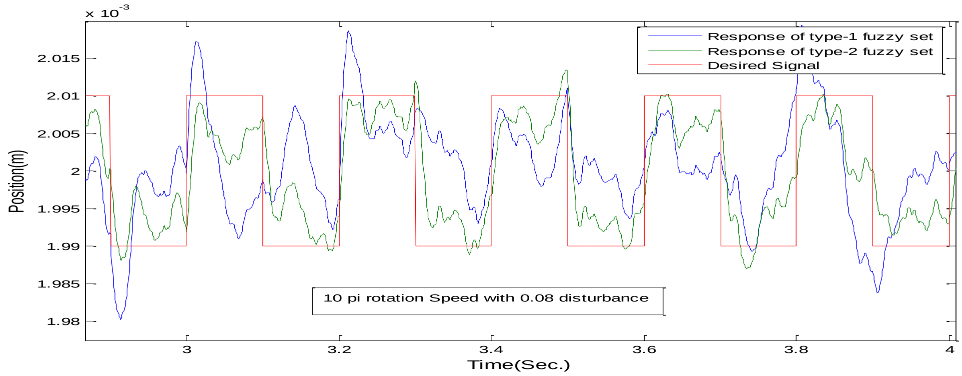


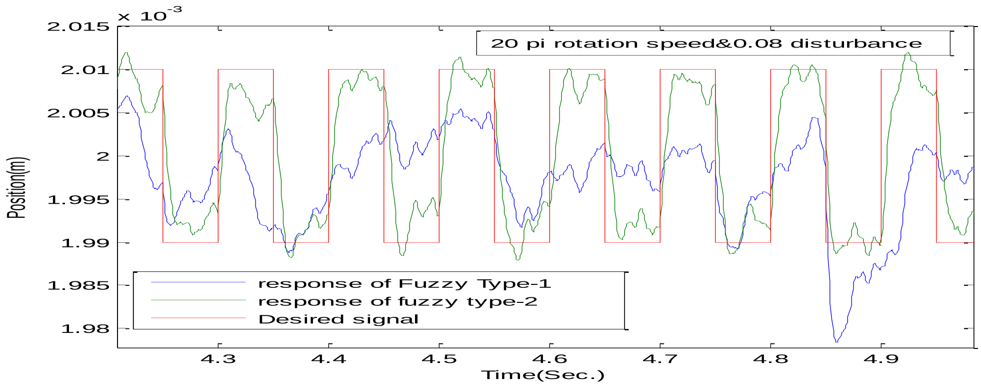
Figure (7) Enlarged Section The Random Disturbance Signal = **0.08** Peak Value VS partition of the desired signal



(a)

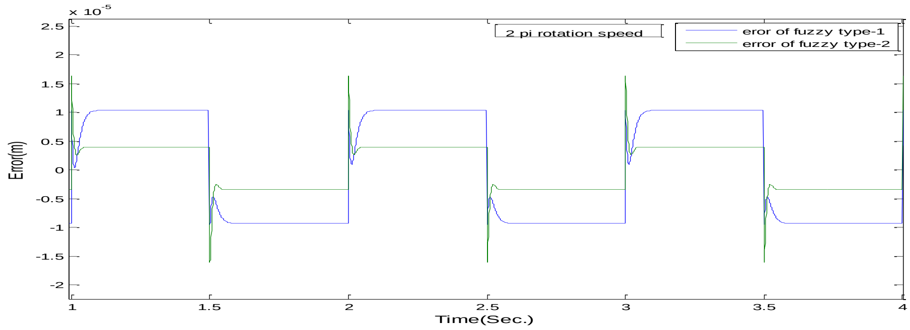


(b)

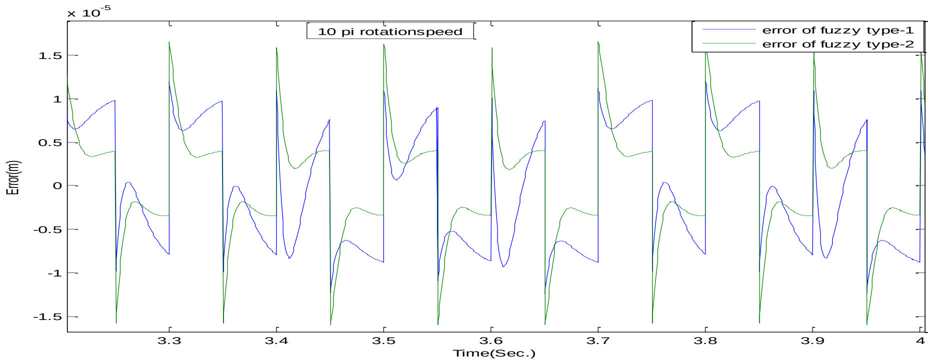


(c)

Figure (8): The Simulated Output of type-1 and type-2 fuzzy logic with 0.08 peak value disturbance for:
a) 2 pi Rotational speed **b)**10 pi Rotational speed **c)** 20 pi Rotational speed**.**



(a)



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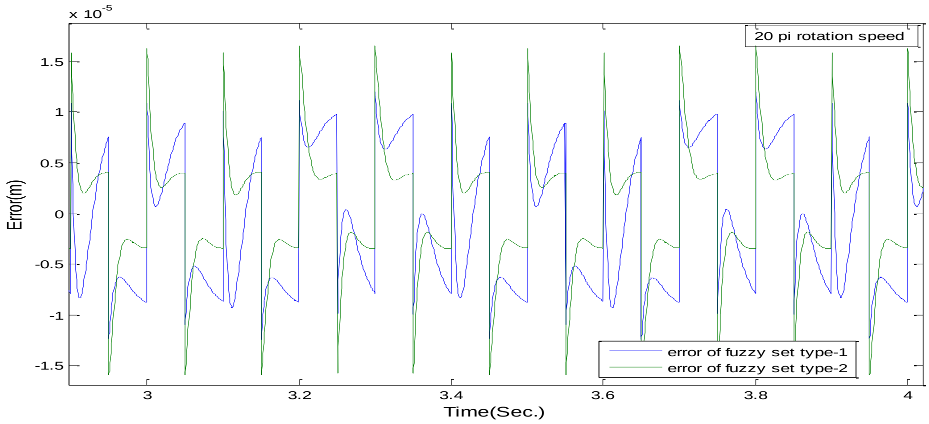


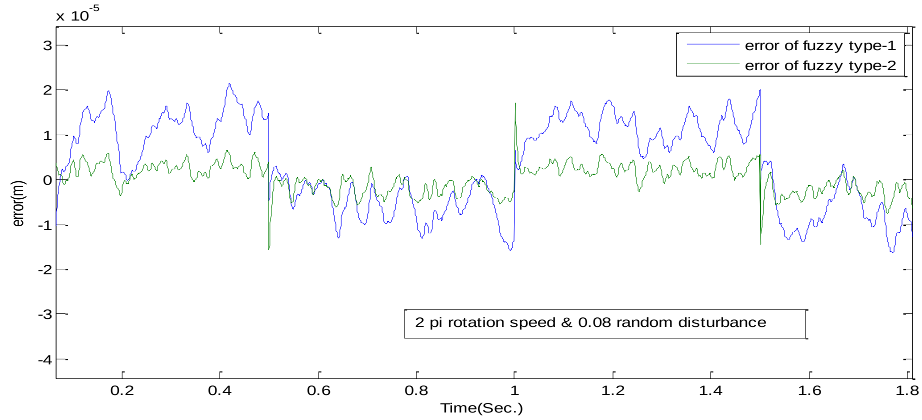
(c)

Figure (9) The mean value of error of type-1 and type-2 fuzzy logic for the system without disturbance
a) 2 π rotation speed **b)** 10 π rotation speed **c)** 20 π rotation speed

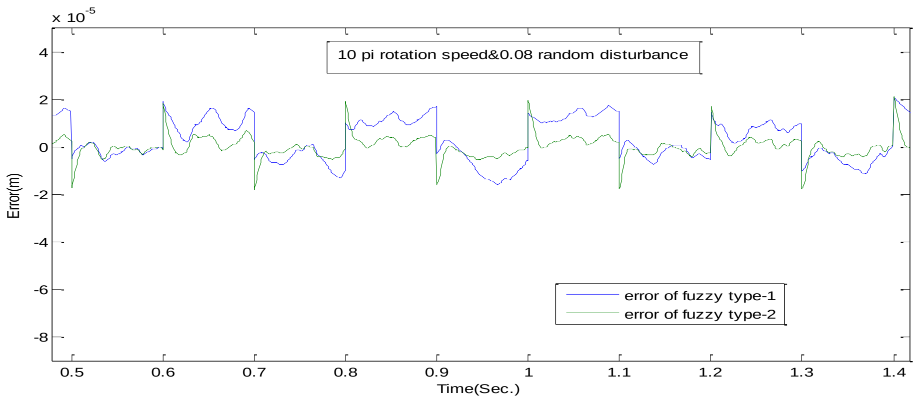
Table(2):Mean and standard deviation of tracking error in fuzzy 1 &2 subject to random disturbance=0.08

Type of fuzzy set	**Rotational Speed**	**Mean value of error* e-06**	**∓Standard deviation e-04**
Fuzzy type -1	2π	**11.506**	**∓1.1418**
	10 π	**11.530**	**∓1.0505**
	20 π	**11.450**	**∓1.1115**
Fuzzy Type-2	2 π	**7.4416**	**∓1.0617**
	10 π	**7.3325**	**∓1.0505**
	20 π	**7.1146**	**∓1.0355**

Figures (9) and (10) show the diffrence between the mean value of error with and without disturbance for fuzzy type-1 and type-2.The control action of PD like fuzzy set type-2 control can be notied in Figures (11) and (12) with and without disturbance. Further performance improvement and project cost reduction may call for adaptively choosing the membership functions factors. Another new direction worth considering is the use of particle swarm optimization in such a procedure.



(a)



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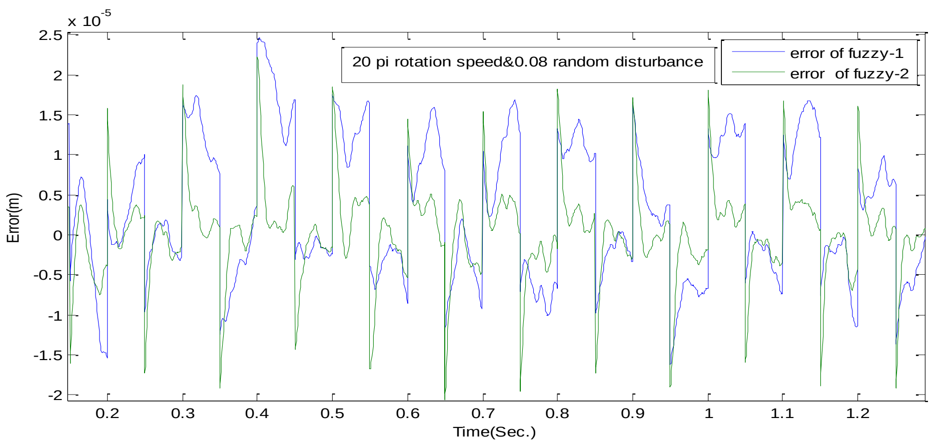

(c)

Figure (10) The mean value of type-1 and type-2 fuzzy logic for the system with0.08 peak value disturbance
a) 2 π rotation speed **b)** 10 π rotation speed **c)** 20 π rotation speed

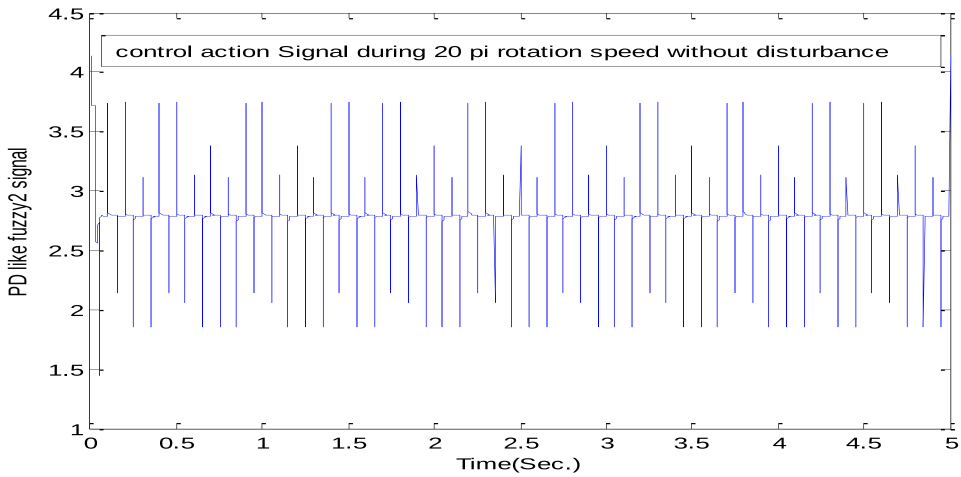

Figure (11) Control action Signal during 20 pi rotation speed without disturbance

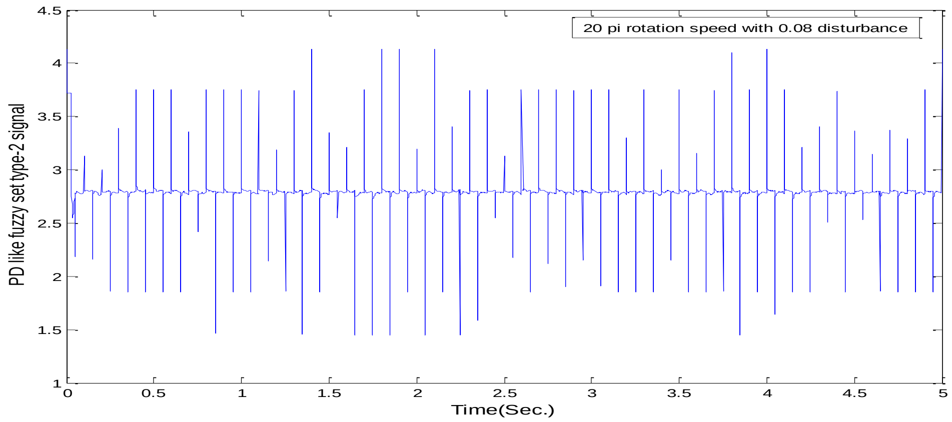

Figure (12) Control action Signal during 20 pi rotation speed with 0.08 random disturbance

Through examining the tables above it is obvious that these kinds of systems considers precision, accuracy and higher sensitivity are an essential requirement, especially that precision positioners are in in Nano and micro scales

10. Conclusion

A PD like fuzzy type-2 and type-1 control were designed for an AMB system after stabilizing it using pole placement method, to control the changing in position and displacement sensitivity under high disturbance through three different amounts of speed, it has been shown that; this controller PD like fuzzy type-2 robustly trace the right positions to track the specified desirable signal that were chosen compared to PD like Fuzzy type-1. Type-2 can ensure safe work of the mechanical system with various amounts of Random Disturbance and changeable parameter of speed and this is not achievable in type-1 fuzzy set although it succeeded to almost track the desired signal for smaller amounts of disturbance and speed parameter but with higher amounts of Random disturbance the rotor lost the reference trajectory and tracking is deteriorated. It should be noted that this robustness of fuzzy controller could be obtained by overcoming the inherent characteristics of displacement sensitivity.

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