Optimization of PID Controller Parameters based on Genetic Algorithm for non-linear Electromechanical Actuator

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ABSTRACT

The servo motors system have been widely used in industrial robotics and electronics due to its excellent speed control characteristics even though its maintenance costs are higher than the induction motor. In this paper, the genetic algorithm were used for non-linear electromechanical actuator to determine the optimal parameters of the PID controller to improve the transient response of the system. The designed parameters which were optimized are rise time, peak time, settling time and maximum overshoot. The Simulation results show that the genetic algorithm is a fast and flexible tuning method to determine the optimal parameters of PID controller for wide range of requirements to achieve satisfied performance for stable system. Genetic Algorithm applied in PID controller improves transient response, the average percent overshoot reduction about 80% compared to the conventional methods such as optimized fuzzy supervisory PID, while keep the delay time, rise time and peak time almost unchanged and improves the settling time

Keywords: Electromechanical Actuator, Genetic Algorithm, PID controller, Optimization.

1-INTRODUCTION

The use of electromechanical actuation is becoming increasingly popular in the aerospace industry as more importance is placed on maintainability. Electromechanical actuators (EMAS) are being used in the actuation of flight critical control surfaces and in thrust vector control [1]. Electrical motor servo systems are indispensable in modern industries. Servo motors are used in a variety of applications in industrial electronics and robotics that includes precision positioning as well as speed control [2]. Servomotors use feedback controller to control the speed or the position, or both. The basic continuous feedback controller is PID controller which possesses good performance. However is adaptive enough only with flexible tuning. Although many advanced control techniques such as self-tuning control, model reference adaptive control, sliding mode control and fuzzy control have been proposed to improve system performances, the conventional PI/PID controllers are still dominant in majority of real-world servo systems [1].To implement a PID controller the proportional gain *KP*, the integral gain *KI* and the derivative gain *KD* must be determined carefully. Many approaches have been developed to determine PID controller parameters for single input single output (SISO) systems.

2-MATHEMATICAL SYSTEM MODEL

A-Linear model

Consider a DC servo motor as shown in figure(1). A simple mathematical relationship between the shaft angular position and voltage input to the DC motor may be derived from physical laws. In the point of control system, DC servo motor can be considered as SISO plant [3]. Therefore, complications related to multi-input system are discarded. DC servo motors have the field coil in parallel with the armature. The current in the field coil and the armature are independent of one another. As a result, these motors have excellent speed and position control [4]

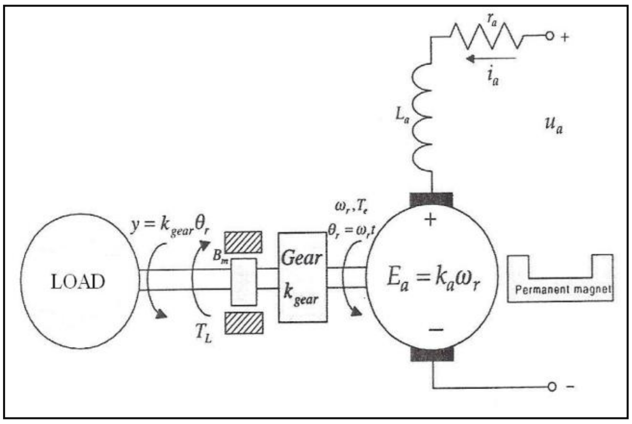

Fig. 1 Schematic diagram of the DC motor.

To find the transfer function for the block diagram of the open and closed loop system a differential equation used to describe the system dynamic. In the begging

Kirchhoff's voltage is use to map the armature circuitry dynamic of the motor.

$$\frac{di_a}{dt} = -\frac{r_a}{L_a} i_a - \frac{k_a}{L_a}\omega_r + \frac{1}{L_a}u_a \quad (1)$$

Then using Newton's 2nd law

$$\sum \bar{T} = J\bar{\alpha} = J\frac{d\bar{\omega}}{dt} \quad (2)$$

The electromagnetic torque developed by the permanent-magnet DC motor

$$T_a = k_a i_a \quad (3)$$

The viscous friction torque

$$T_{viscous} = B_m \omega_r \qquad (4)$$

The load torque is denoted as T_L. Use the Newton's second law, we have

$$\frac{d\omega_r}{dt} = \frac{1}{J}(T_a - T_{viscous} - T_L) = \frac{1}{J}\,(k_a i_a - B_m \omega_r - T_L) \qquad (5)$$

The dynamics of the rotor angular displacement

$$\frac{d\theta_r}{dt} = \omega_r \qquad (6)$$

To find the transfer function, the derived three first-order differential equation

$$\frac{di_a}{dt} = -\frac{r_a}{L_a} i_a - \frac{k_a}{L_a}\omega_r + \frac{1}{L_a} \qquad (7)$$

$$\frac{d\omega_r}{dt} = \frac{1}{J}(k_a i_a - B_m \omega_r - T_L) \qquad (8)$$

and

$$\frac{d\theta_r}{dt} = \omega_r \qquad (9)$$

Using the Laplace operator

$$s = \frac{d}{dt} \qquad (10)$$

$$s + \frac{r_a}{L_a})i_a(s) = -\frac{k_a}{L_a}\omega_r(s) + \frac{1}{L_a}u_a(s) \qquad (11)$$

$$\left(s + \frac{B_m}{J}\right)\omega_r(s) = \frac{1}{J}k_a i_a(s) - \frac{1}{J}T_L(s) \qquad (12)$$

$$s\theta_r(s) = \omega_r(s) \qquad (13)$$

A simple model that could describe an actuator 's dynamics is a linear second – order system with demping ratio zeta (ζ) and natural frequency omega (**ω_n**). The transfer function of a second – order system is given below, where (ω_r) is the output and (u_a)is the input[5].

$$\omega_r(s) = G(s) \,.\, u_a(s) = (\omega_n^2 / s(s^2+2\zeta\,\omega_n s+ \omega_n^2)) \qquad (14)$$

B- Nonlinear Model

The nonlinear model equations [6]:

$$R(s) = u_a(s) - \omega_r(s)Lim \qquad (15)$$

$$Y(s) = R(s)[Kp + Ki/s + s\,Kd] \qquad (16)$$

$$s^2\,\omega_r(s) = \omega_n^2\,[Y(s) - RATEFB - s\omega_r(s)\frac{2\zeta}{\omega n}] - HM \qquad (17)$$

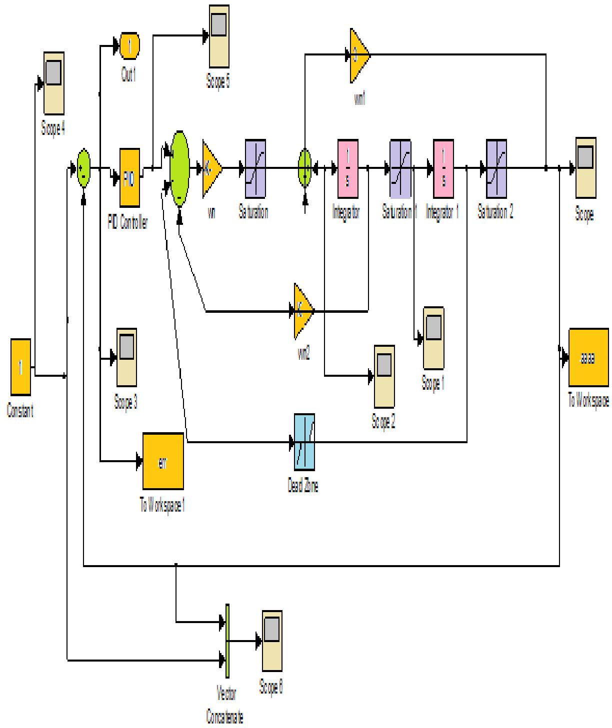

Fig.2 Block diagram of non-linear electromechanical servo motor to adjust PID parameters via GA.

3- GENETIC ALGORITHIMS (GAs)

Genetic algorithms are automated method for solving problems. GAs operate on a population of potential solutions applying the principle of survival of the fittest to produce better and better approximations to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation as shown in figure (3) [7].

The GAs differ from traditional search and optimization methods by four differences, they are:

• GAs search not a single point but a population of points in parallel,

• GAs do not require an auxiliary knowledge;

just the objective function and corresponding fitness levels influence thedirections of search.

• GAs, do not use deterministic ones but only probabilistic transition rules.

• GAs work on an encoding of the parameter set rather than the parameter set

itself (except in where real-valued individuals are used)[8].

4-METHODOLOGY [9]

In a genetic algorithm, a population of strings (called chromosomes or the genotype of the genome), which encode candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem, is evolved toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. A typical genetic algorithm requires:

- ♦ a genetic representation of the solution domain,
- ♦ a fitness function to evaluate the solution domain.

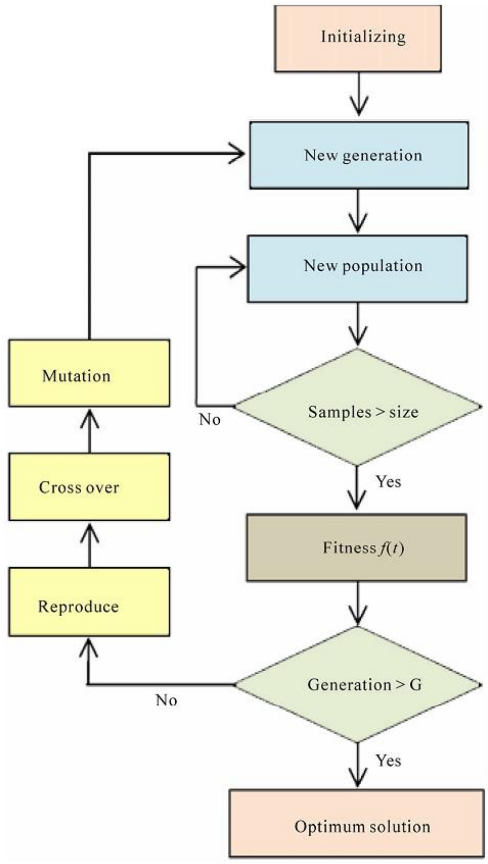

Fig.3 Genetic algorithm – program flow chart.

5- SIMULATION RESULTS

PID controller parameters will be optimized by applying GA. Here we use Matlab Genetic Algorithm to simulate it. The first and the most crucial step is to encoding the problem into suitable GA chromosomes and then construct the population. Each chromosome comprises of three parameters, Kd, Kp, Ki, with value bounds varied depend on objective functions used.

There are several variables used as the standard to measure systems performance. In general, unit step input is used to test the systems, and the output signals is characterized by some standard performance measures: delay time, rise time, percent overshoot, peak time, settling time, and error signal. All these measures are defined in time domain response.

Figure(4) below describes standard performance measures of a typical system driven by unit step input. The delay time is measured as the time needed by systems to reach from 50% of final value. There are several criteria for the rise time, actually in general, is measured as the time needed by systems to reach from 0 to 100% of final value or from 10% to 90% of final value. But, for measurement simplicity, we use 0 - 100% criterion. Percent overshoot is defined as the point where the system response reaches the peak. Peak time is the point where the maximum value reached (overshoot) at 3.2 second. settling time, for example 1% criterion, 2% criterion,

and 5% criterion. Here we use 5% criterion settling time. And error signal is the difference between the input signal magnitude and system response final magnitude. In this work four cases are taken :

The first case when Δ =0.75 for deadzone (RAETFE) and ζ is variable from (0.1-1.0) as shown in table (1).While the second case when Δ =0. 5 for deadzone (RAETFE) and ζ is variable from (0.1-1.0) as shown in table (2).

The third case when ζ =0.3 and Δ is variable from (0.1-1.0) as shown in table (3).While the fourth case when ζ =0.6 and Δ is variable from (0.1-1.0) as shown in table (4)

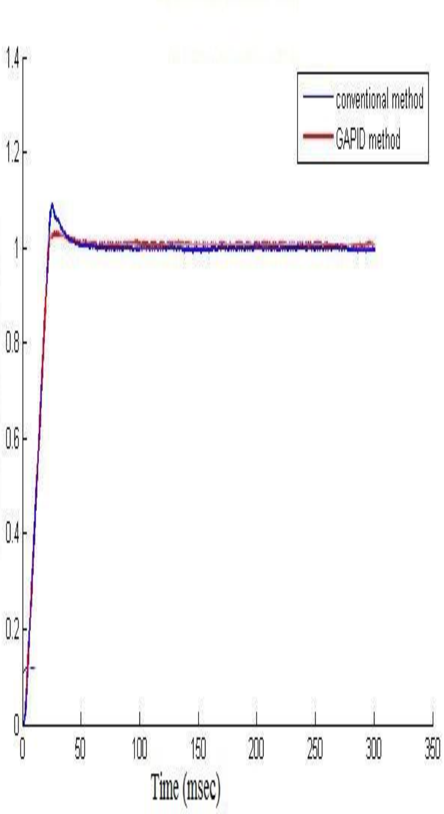

Fig.4 Standard performance measures of a typical system driven by unit step input for PID controller.

There are four tables for the four mentioned cases, which are in Table 1 shows the genetic algorithm optimum results for different gain values of PID and transient performance when Δ =0.75 for dead zone (RAETFE) , ULIM = 200 for saturation, ΩN = 144, HM = 3 (HUGE MOMENT).

Table 1 Genetic Algorithm Optimum Results

Z	Kp	Ki	Kd	Mp	Tp (msec)	Td (msec)	Tr (msec)	Ts (msec)
0.1	754.5818	99.2441	75.3450	1.0132	38	12.241	29.35	180
0.2	754.5818	99.2441	75.3450	1.0132	38	12.241	29.35	140
0.3	677.6254	87.9769	67.3549	1.0132	38	12.241	29.35	140
0.4	885.7227	90.0066	89.8315	1.02495	25	12.241	22.51	80
0.5	915.9792	107.0014	93.1275	1.0132	38	12.241	29.35	140
0.6	908.2300	116.6521	97.2499	1.0024	52	12.241	49.72	80
0.7	951.0498	113.3742	98.5224	1.0132	38	12.241	29.35	140
0.8	757.2700	101.2939	75.0834	1.0249	25	12.241	22.51	80
0.9	733.3928	100.4799	76.4113	1.0132	38	12.241	29.35	140
1.0	982.6898	91.4726	90.1229	1.0884	25	12.241	22.245	80

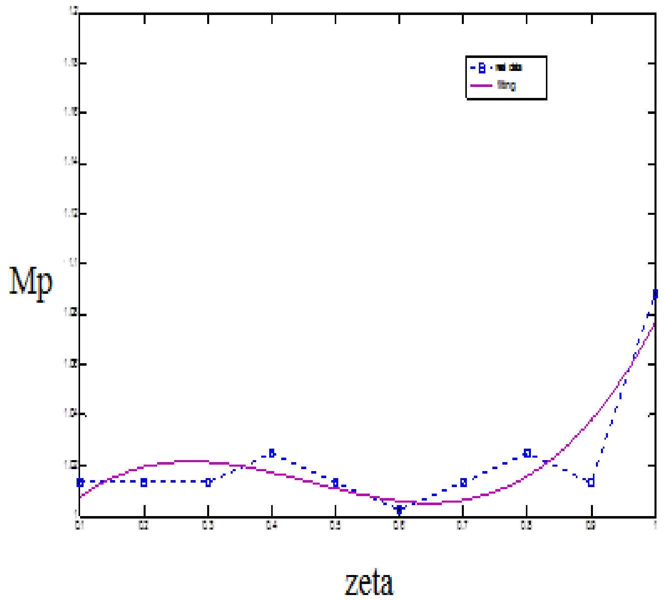

Fig.5 The relation between damping ratio zeta ζ max.peak overshoot M_p when deadzone time delta Δ=0.75

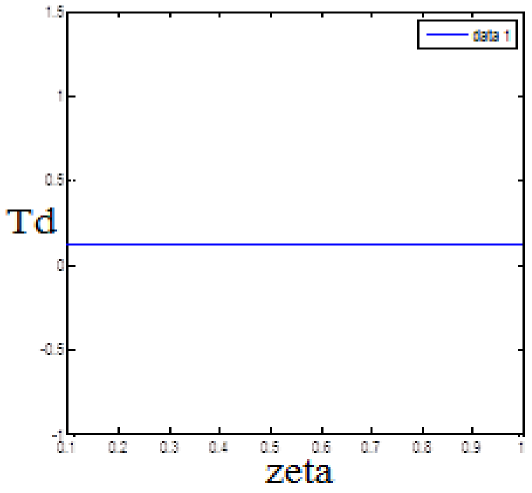

Fig.6 The relation between damping ratio zeta ζ & delay time T_d when deadzone time delta Δ=0.75

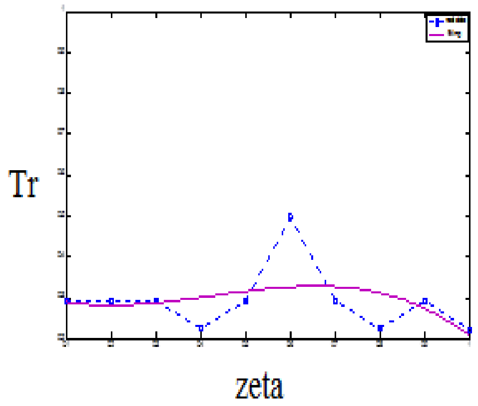

Fig.7 The relation between damping ratio zeta ζ & rise time T_r when deadzone delta Δ=0.75

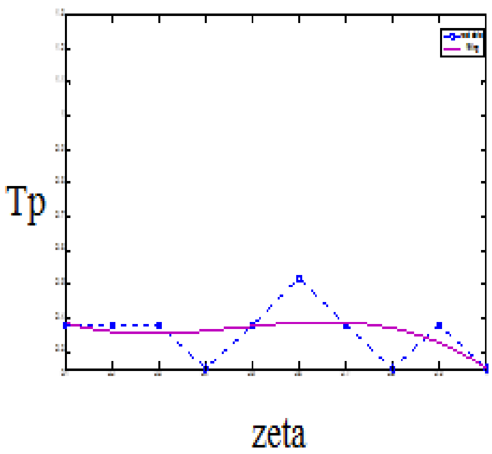

Fig.8 The relation between damping ratio zeta & peak time T_p when deadzone time delta Δ=0.75

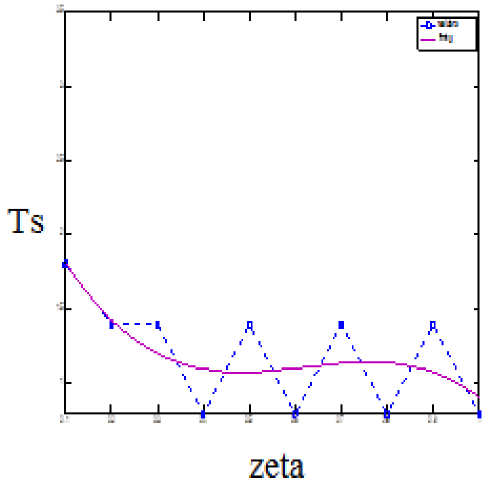

Fig.9 The relation between damping ratio zeta & settling time T_s when deadzone time delta Δ=0.75

Table 2, shows genetic algorithm optimum results for different gain values of PID and transient performance when Δ =0.5 for deadzone (raetfe) , ulim = 200 for saturation, ωn = 144, hm = 3 (huge moment)

Table 2 Genetic Algorithm Optimum Results

Z	Kp	Ki	Kd	Mp	Tp (msec)	Td (msec)	Tr (msec)	Ts (msec)
0.1	721.2435	75.6320	73.5623	1.0132	38	12.242	29.34	150
0.2	637.2281	85.2942	65.5922	1.0132	38	12.242	29.35	150
0.3	678.8693	96.6264	70.2872	1.0132	38	12.243	29.36	150
0.4	707.4107	89.6187	73.3138	1.0132	38	12.242	29.36	140
0.5	890.9687	95.4964	90.1083	1.0132	38	12.242	29.36	140
0.6	970.9693	134.5488	101.8444.	1.0032	45	12.242	37.69	85
0.7	692.3050	108.5041	69.5329	1.0132	38	12.243	29.35	140
0.8	950.2976	125.0130	94.0703	1.0249	25	12.242	22.51	90
0.9	850.9007	124.6650	84.5597	1.0249	25	12.242	22.51	90
1.0	846.0631	120.7570	87.8157	1.0132	38	12242	29.35	140

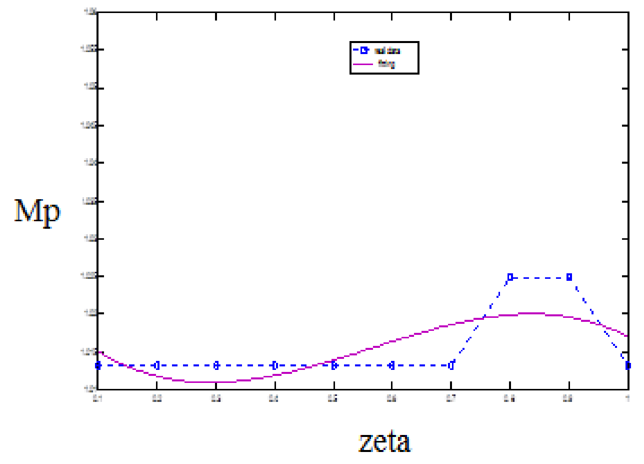

Fig.10 The relation between damping ratio zeta ζ &max.peak overshoot M_p when deadzone time delta Δ=0.5

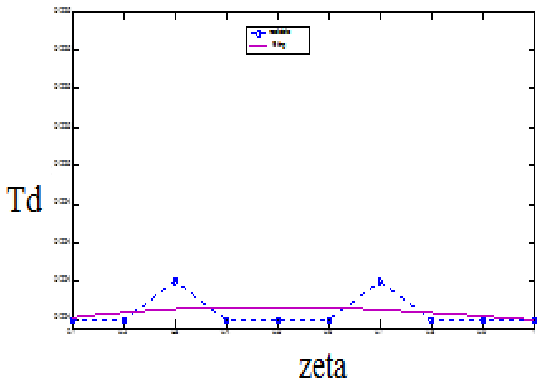

Fig.11 The relation between damping ratio zeta ζ & delay time T_d when deadzone time delta Δ=0.5

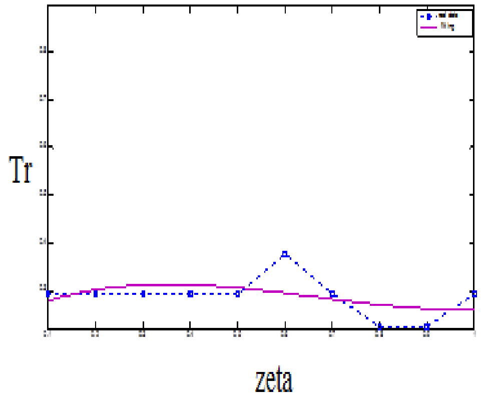

Fig.12 The relation between damping ratio zeta ζ & rising time T_r when deadzone time delta Δ=0.5

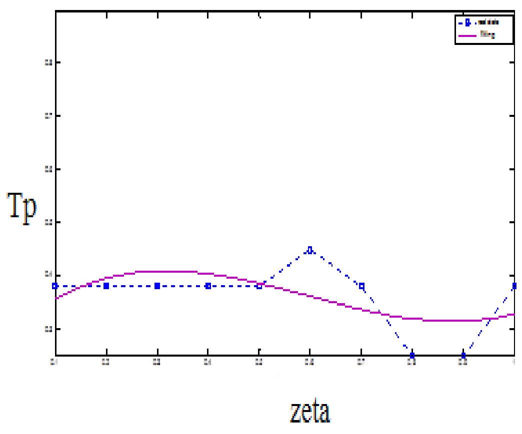

Fig.(13) The relation between damping ratio Zeta ζ & Peak time T_p when deadzone time delta Δ=0.5

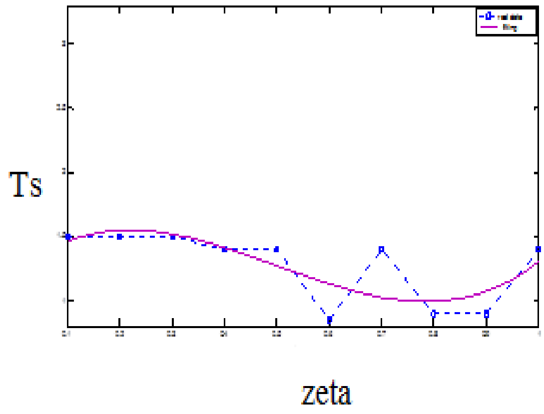

Fig.14 The relation between damping ratio zeta ζ & settling time T_s when deadzone time delta Δ=0.5

Table 3 shows the genetic algorithm optimum results for different gain values of pid and transient performance when ζ =0.3, ulim = 200 for saturation,ωn= 144, hm = 3 (huge moment)

Table 3 Genetic Algorithm Optimum Results

Δ	Kp	Ki	Kd	Mp	Tp (msec)	Td (msec)	Tr (msec)	Ts (msec)
0.1	776.8372	106.0846	80.3730	1.0132	38	12.242	29.35	120
0.2	785.7835	98.7298	81.7990	1.0132	38	12.242	29.35	120
0.3	616.9086	109.9305	61.6555	1.02965	31	12.222	22.51	80
0.4	749.4216	108.4152	78.5293	1.0132	38	12.242	29.35	120
0.5	812.1277	121.7033	84.3297	1.0132	38	12.241	29.35	120
0.6	896.7755	163.9519	88.1837	1.02965	31	12.241	22.51	80
0.7	925.1863	116.7138	98.7058	1.0024	52	12.241	49.7	80
0.8	890.0490	221.5051	96.8994	1.0151	52	12.241	37.69	80
0.9	962.1358	212.8717	101.4063	1.024	38	12.241	26.55	150
1.0	912.1743	161.3187	93.8667	1.0132	38	12.241	28.93	120

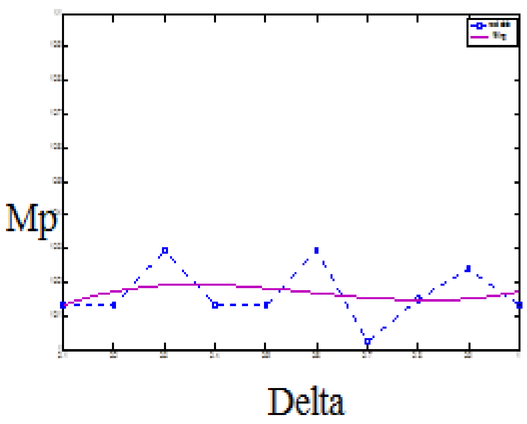

Fig.15 The relation between deadzone time delta Δ & max. peak overshoot(M_p) when damping ratio Zeta ζ =0.3

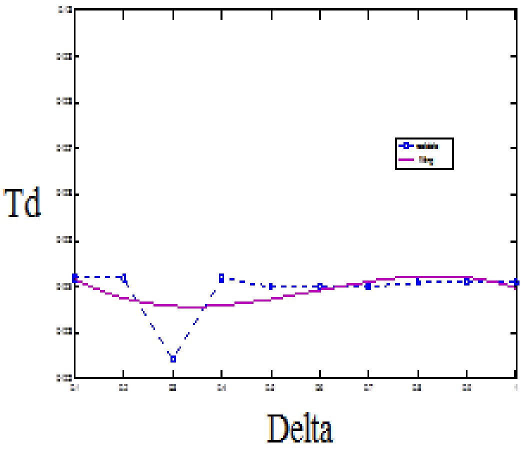

Fig.16 The relation between deadzone time delta Δ & delay time T_d when damping ratio zeta ζ =0.3

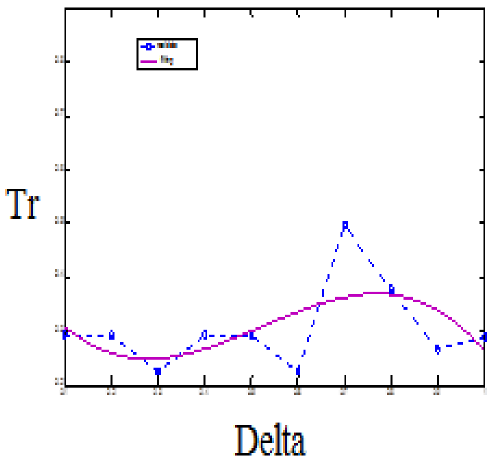

Fig.17 The relation between deadzone time deltaΔ & rising time(T_r) when ζ=0.3

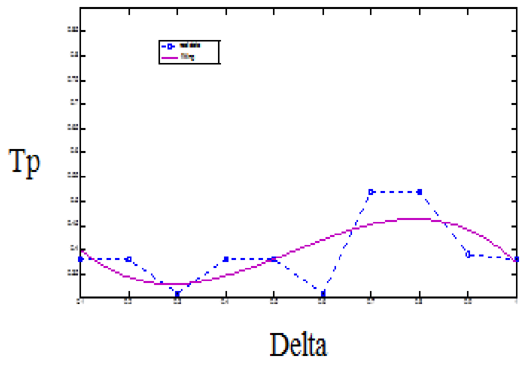

Fig.18 The relation between deadzone time delta Δ & peak time T_p when damping ratio zeta ζ =0.3

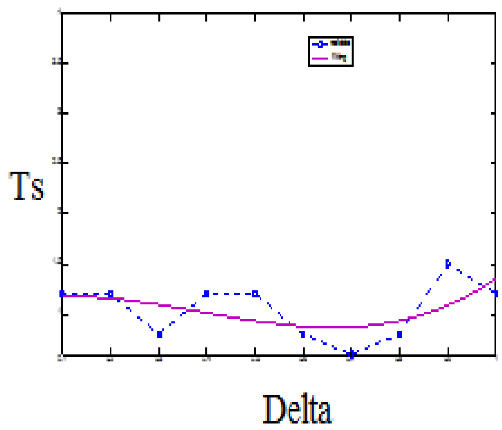

Fig.19 The relation between deadzone time delta Δ & settling time T_s when damping ratio zeta ζ =0.3

Table 4 shows the genetic algorithm optimum results for different gain values of pid and transient performance when ζ =0.6, ulim = 200 for saturation, ωn = 144,hm= 3 (huge moment).

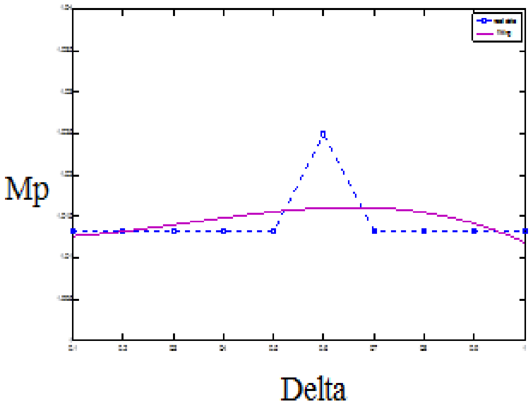

Fig.20 The relation between deadzone time delta ∆ &max. peak overshoot (M_p) when ζ=0.6

Table 4 Genetic Algorithm Optimum Results

∆	Kp	Ki	kd	Mp	Tp (msec)	Td (msec)	Tr (msec)	Ts (msec)
0.1	626.7801	89.5452	64.4189	1.0132	38	12.245	29.36	160
0.2	959.8850	176.5927	101.2775	1.0132	38	12.25	29.36	160
0.3	857.4701	133.5264	86.0727	1.0132	38	12.245	29.36	170
0.4	916.1705	98.1728	91.1001	1.0132	38	12.245	29.36	170
0.5	949.8885	156.1254	96.3753	1.0132	38	12.242	29.36	170
0.6	695.2232	72.945	68.8030	1.0249	25	12.242	22.51	125
0.7	727.0700	85.9769	75.8768	1.0132	38	12.242	29.36	160
0.8	973.6226	129.6789	97.6081	1.0132	38	12.245	29.36	170
0.9	807.6227	83.1211	81.8213	1.0132	38	12.245	29.36	170
1.0	894.7265	126.0383	92.6512	1.0132	38	12.245	29.36	170

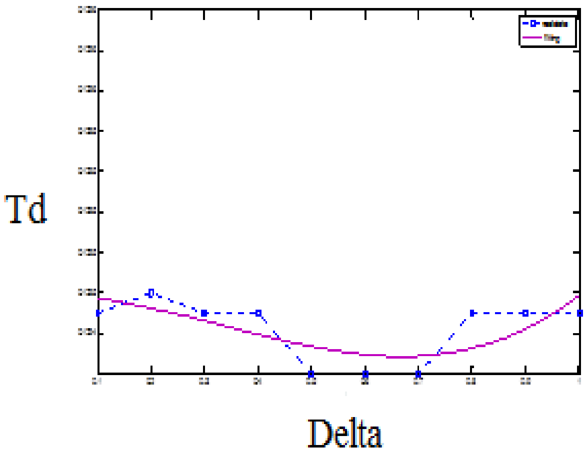

Fig.21 The relation between between deadzone time delta ∆ & delay time (T_d) when ζ=0.6

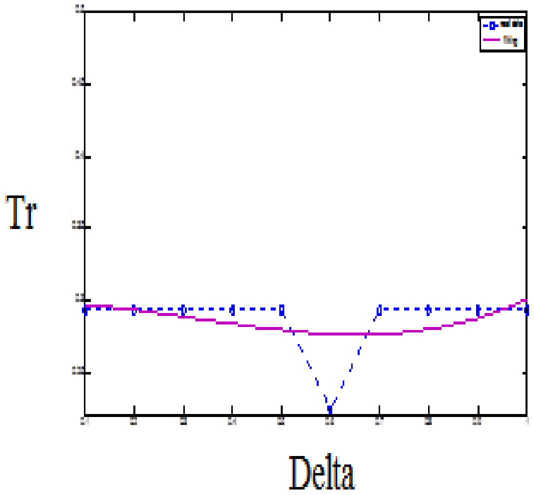

Fig.22 The relation between between deadzone time delta ∆ &rRising time (T_r) when ζ=0.6

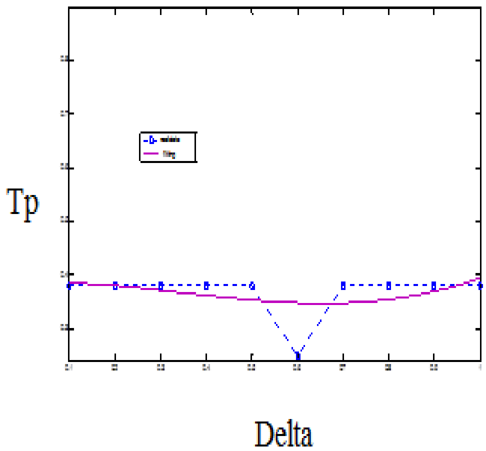

Fig.23 The relation between between deadzone time delta ∆ & peak time (T_p) when ζ=0.6

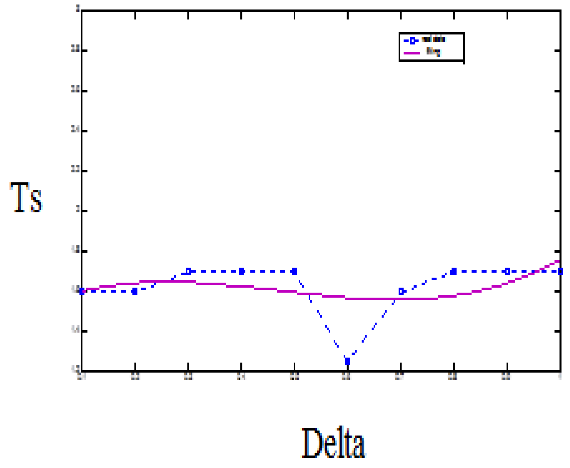

Fig.24 The relation between between deadzone time delta Δ & sittling time (T_s) when ζ=0.6

6- CONCULUSION

- The genetic algorithm based PID tuning provides much better results compared to the conventional methods as shown in figure (4).

- The conventional method is good for getting the initial values of the PID tuning which needs to be modified.

- In the designed PID controller tuning with GA, the actual response was found to be satisfying the required value. PID controller gain values depend upon the range selected for the initial population. The range of requirement can be widened by increasing the range of initial population but the number of generations required to converge to optimal value may increase.

- Genetic Algorithm applied in PID controller improves transient response. This is shown by average percent overshoot reduction about 80% compared to the conventional methods such as genetic PID optimization and genetic algorithm optimized fuzzy supervisory PID, while keep the delay time, rise time and peak time almost unchanged and improves the settling time as shown in figures (6) to figure (24).

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8- NAMENCLATUR

Symbol	Meaning	Unit
ξ	Damping ratio	-------------
ωn	Natural Frequency	Rad /sec
Kp	Proportional gain	
Ki	Integral gain	-----------
Kd	Derivative gain	
Δ	Deadzone delay time	Sec.
Mp	Maximum peak overshoot	
Td	Delay time	Sec.
Tr	Rising time	Sec.
Tp	Peak time	Sec.
ts	Settling time	Sec.