PID Controller Design for a Magnetic Levitation System using an Intelligent Optimisation Algorithm

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Abstract **– Magnetic Levitation System (MLS) parameters can be tuned using different controlling techniques. Magnetic levitation systems are used to levitate objects by using attraction force or repulsive force between magnetic force and ferromagnetic material. The levitation of an object is possible using a control system to help stabilize the magnetic force. This paper investigates a controlling technique for a MLS. The numerical model of the system shows that it has high non-linearity and inherent instability. Different Controlling Methods were applied. A Proportional-Integral-Derivative (PID) controller is tuned using Neural Network (NN) and Genetic Algorithm (GA) due to their ability to control nonlinear plants. The results show better performance of the MLS when NN and GA are used, compared to other classical methods.**

Keywords - MLS model, PID controller, LQR controller, IMC controller, NN controller, GA controller, Matlab/Simulink.

I. INTRODUCTION

MLS is very useful system that can be connected to many applications, such as, fast transportation, magnetised bearing systems, vibration disengagement, levitation of wind control, and combination Energy Materials preparing in magnetised levitation furnaces [1]. MLS is an electromagnetic gadget, which suspends ferromagnetic components using the rule of electromagnetism. MLS has the capacity to work in vacuum condition. Due to the steady need for levitation, an MLS is subjected to constant change in its parameters, and consequently the numerical model becomes highly non-linear and unstable. Despite the fact that magnetic levitation is nonlinear behaviour and it is described by nonlinear differential equation, mostly design approaches are based on linear model [2].

Non-linearity occurs due to electromechanical dynamics [3]. Different methods are proposed to control the MLS in the literature, like PID, Linear-Quadratic Regulator, and Internal Model Control. However, all these methods still suffer from the problems of tuning and optimisation for stability, overshoot and settling time. In spite of the fact that PID control is a capable procedure for dealing with of non-linear plant yet. In this way, utilizing an established controller isn't appropriate for nonlinear control application [4, 5, 6]. NN –and GA based controllers are proposed to control non-linear system in [7].

The NN controller has the ability of self-learning to cope with complicated environments and requirements of multi-objectives control, and approach to non-linear function with any precision [8]. A feedback error learning PID controller with NN is presented in [9] to control an MLS. A single multiplicative neuron model is proposed to control an MLS, which derived from the computation model of a single neuron. Particle Swarm Optimisation is used for offline training of network weights and biases [10]. Different combinations of NN and nonlinear method are presented in [11]; Lyapunov method is considered to insure stability. The authors in [12] suggest Back-propagation NN to improve the behaviour of the MLS and obtain the required response.

A method based on NN and GA to control MLS is presented in [13], GA is used to adjust the NN parameters, frequently updates the control signals, where they are computed using the back propagation technique. In [14] GA is used to tune a PID controller for MLS. The results claim that the response of the system of GA-PID is better than traditional PID controller. An Integral-Tilted-Derivative (I-TD) controller for MLS is proposed in [15], and compared with traditional Tilted-Integral-Derivative (TID) controller, the parameters of controller are optimised by using GA, the results show that the I-TD controller is better than TID controller.

The remainder of the paper is organised as follows: Section 2 presents the dynamic model of the MLS. Section 3 explains the design of classical and modern controllers for MLS. Section 4 presents the intelligent algorithms which considered to enhance the response of the system. Section 5 addresses the results and discussion, with a comparison between the proposed and traditional controllers based on simulation results. Finally, Section 6 contains the main conclusions.

II. MLS DYNAMIC MODEL

MLS model [16] relies upon the ball kinematics and electrodynamics conditions. The Dynamic Equation of the Control ball is given in (1), steel ball is moved upward or descending as indicated by compel connected on it by the attractive power F and gravity drive mg, as appeared in figure(1). Applying Newton's second law of development vertical way.

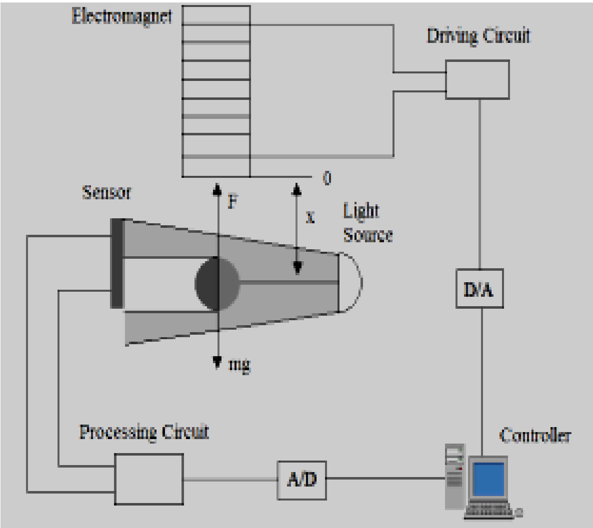

Figure1. MLS Configuration [3].

$$m\frac{d^2x}{dt^2} = F(i,x) + mg \tag{1}$$

Where, (x) is the air hole between the ball and the magnet, (m) is the mass of steel ball, (i) is current in electromagnet and force is generated and can be given using following equation, (g) is acceleration speed of gravity. When the control current goes over the winding, electromagnetic power is created and can be given using the following condition:

$$F(i,x)=K(i/x)^2 \tag{2}$$

Where K is constant, depending on physical parameters. $F(i,x)$ is the attraction power, the current (i) and air hole (x) are nonlinearly related. For the controller configuration, the system can be linearized using linear hypothesis, first at balance point (i0, x0). Now Taylor's expansion of (2), ignore higher order terms, then

$$F(i,x)=F(i_0,x_0)+F_i(i_0,x_0)(i-i_0)+F_x(i_0,x_0)(x-x_0) \tag{3}$$

In which $F(i_0,x_0)$ is the magnetic force equal to the ball gravity force, when the air gap is x_0 and the current is i_0.

$$F(i_0,x_0) = mg \tag{4}$$

$$K_i = F_i(i_0,x_0) = \left.\frac{\delta F(i,x)}{\delta i}\right|_{i=i_0, x=x_0,} = \frac{2K_{i0}}{x_0^2}$$

(5)

$$K_x = F_x(i_0,x_0) = \left.\frac{\delta F(i,x)}{\delta x}\right|_{i=i_0, x=x_0,} = \frac{2K_{i0}^2}{x_0^3} \tag{6}$$

K_i and K_x are the stiffness coefficients of the magnetic force to current and air gap at the equilibrium point respectively. From equations (4), (5), (6), (3) and (1) for the whole system, the (F) is:-

$$F(i,x) = K_i i + K_x x + F_i(i_0,x_0) \tag{7}$$

$$m\frac{d^2x}{dt^2} = K_i(i - x_0) + K_x(x - x_0) \tag{8}$$

The voltage equation of the electromagnetic coil is given by:

$$U(t) = R_i(t) + L(d_i / d_t) \tag{9}$$

Where (L) is the static inductance between the ball and attractive field. In system demonstrating, the input is the control current of the electromagnet, the effect of inductance isn't considered here. Expect the power enhancer yield current is entirely straight with input voltage immediately. The system can be portrayed by following condition, $mg = -K(i_0 - x_0)^2$, subsequent to taking Laplace change and putting limit condition ,the system open mathematical model is:-

$$m\frac{d^2x}{dt^2} = K_i(i - i_0) + K_x(x - x_0) = \frac{2Ki_0}{x_0}i - \frac{2Ki_0^2}{x^3}x \tag{10}$$

$$x(s)s^2 = \frac{2ki_0}{mx_0^2}i(s) - \frac{2ki_0^2}{mx_0^3}x(s) \tag{11}$$

$$\frac{x(s)}{i(s)} = \frac{-1}{As^2 - B} \tag{12}$$

Where $A = {}^{i_0}\!/_{2g}, B = {}^{i_0}\!/_{x_0}$ characterize the input variable as the input voltage of the power amplifier Uin , output variable as the output voltage Uout, the System control object model can be described as:-

$$G(s) = \frac{Uout(s)}{Uin(s)} = \frac{k_s x(s)}{ka_i x(s)} = \frac{-(\frac{k_s}{k_a})}{As^2 - B} \tag{13}$$

Then the system state variables are $x_1 = Uout$, $x_2 = Uout$ and the system state equations are as:-

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{2g}{x_0} & 0 \end{bmatrix} + \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ -\frac{2gK_s}{i_0 K_a} \end{bmatrix} U_{in} \tag{14}$$

$$Y = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = x_1 \qquad (15)$$

After substituting the real system model parameters [17, 18, 19], in equations (14) and (15), then

$Y = x_1$

The sytem state conditions can be written as:

$$\dot{X} = AX + BU_{in}, \qquad Y = CX$$

And the transfer function in equation (13) is:

$$G_0(s) = \frac{Y(s)}{U_{in}(s)} = \frac{77.8421}{0.0311s^2 - 30.5250} \qquad (16)$$

There is an open loop pole at the right of s-plane, by stability basis; stable system ought to have all the open poles on the left plane. Therefore the GML system is unstable. See figure (2).

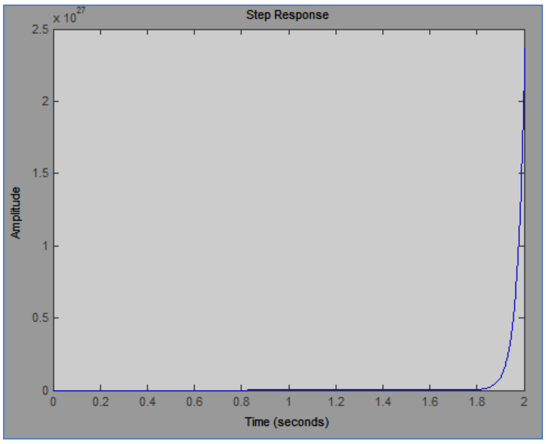

Figure2. Shows unstable transient response of the MLS.

III. MLS CONTROLLERS

There are many controllers for MLS, can be classified between classical and modern approaches:-

A. PID Controller

For unstable systems, the one level of opportunity controller neglects to provide a smooth reference following execution because of proportional and derivative kick. With end goal to improve the overall closed loop performance, it is basic to consider a Two Degree of Freedom (2DOF) PID structure. A detailed examination on different 2DOF structures is illustrated in [20].

In this paper, an endeavour has been made with the Feed Forward (FF) 2DOF PID structures. Figure (3) shows the Feed Forward type controller structure with PD controller in the feed forward loop and a PID controller in the closed-loop. The PID controller responds on error e(t) and the PD controller works on the reference input r(t) .The controller values for this structure are given in the conditions below [21]:

$$C_3(s) = k_p(1 + \frac{1}{\tau_i s} + \tau_d D_f(s)) = k_p + k_i + k_d D_f(s) \qquad (17)$$

$$C_4(s) = k_p(\alpha + \beta\tau_d D_f(s)) = k_p\alpha + \beta k_d D_f(s) \qquad (18)$$

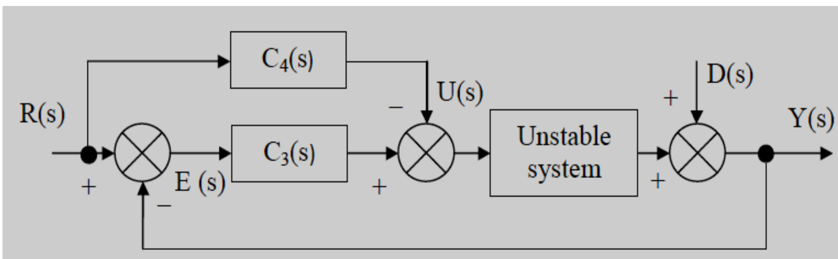

Figure3. Feed forward structure of 2DOF PID [21].

In this structure, the numbers of parameters to be tuned are K_p, K_i, K_d. (α) And (β) are the controller weighting parameters, ranging from 0 to 1, while $D_f(s)$ is the approximate derivative which given by:

$$D_f(s) = \frac{s}{\tau s + 1} \qquad (19)$$

$$\tau = k_d / k_p$$

Where (K_d) is the derivative gain. Using PID tune by MATLAB can be calculated:-

$K_p = 9.07$, $K_i = 32.4$ and $K_d = 0.0753$. Substitute, these values, in equation (17), and for C_4 controller let $\alpha = \beta = 0.6$, Figure (4) shows the SIMULINK block-Diagram, and Figure (5) shows the transient response of (FF) 2DOF PID structure. The response requires more tuning, to reduce the settling time, but this may increase the overshoot.

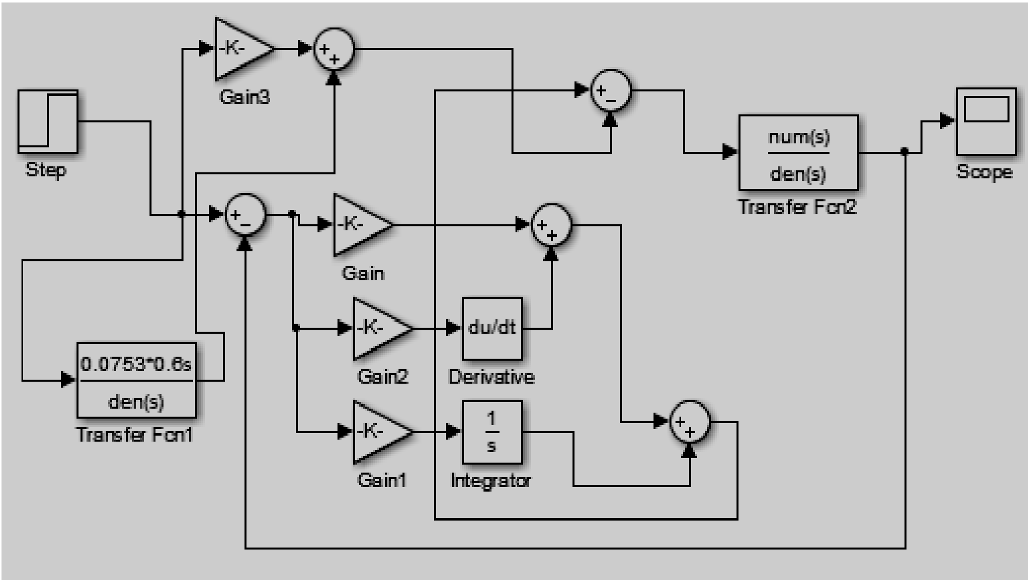

Figure4. SIMULINK (FF) structure of 2DOF PID.

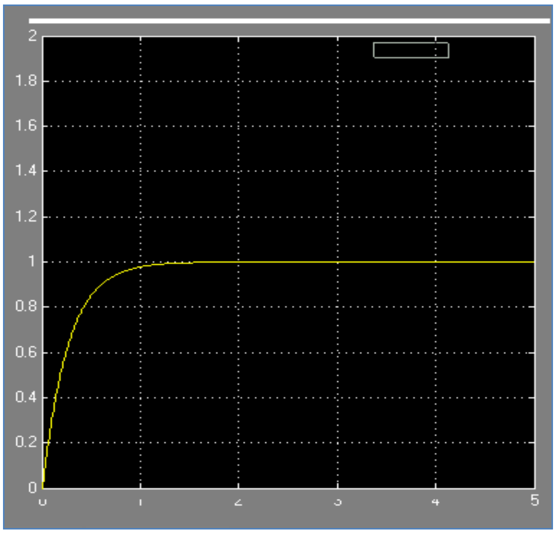

Figure5. Closed Loop Response (2DOF PID Controller).

B. LQR Controller

LQR controller is intended to investigate the system in closed-loop. The controller demonstrated enhanced execution for various tracks [22]. To make the response of the system stable feedback path was used. The LQR controller looks to limit the vitality show in the system, and the control that is gotten by limiting this criterion is linear.The strategy is by finding a K for input in state factors to such an extent that it limits practical cost [23].Using equation (14) and let

$$R = 1; \text{ and } Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Using MATLAB LQR statement, the optimal K is equal to: K= [1.4664 1.0006]. Figure (6) shows closed loop response with (LQR Controller).

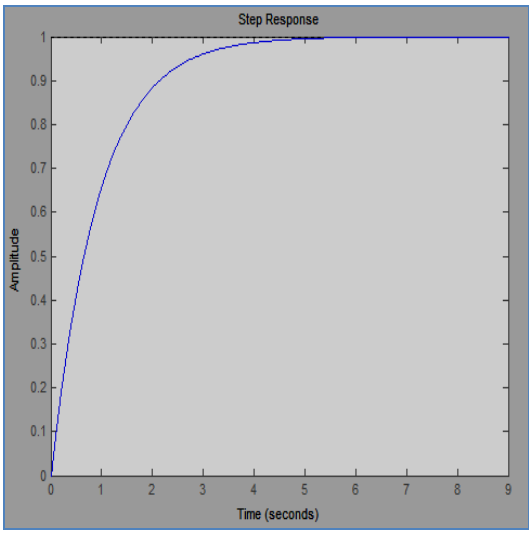

Figure6. Shows Closed Loop Response LQR Controller.

C. IMC

The IMC is a notable procedure and a successful strategy for planning and actualizing robust controllers. IMC structure is a contrasting option to the classic feedback structure .The input setup is appeared in Figure (7). In the IMC plan, the controller, Gc(s), is construct specifically with respect to the "great" some portion of the system under control[24].The transfer function of controller Gc(s) is:-

$$G_o(s) = \frac{1}{(\mu s+1)^n} G_p(s)^{-1} \tag{20}$$

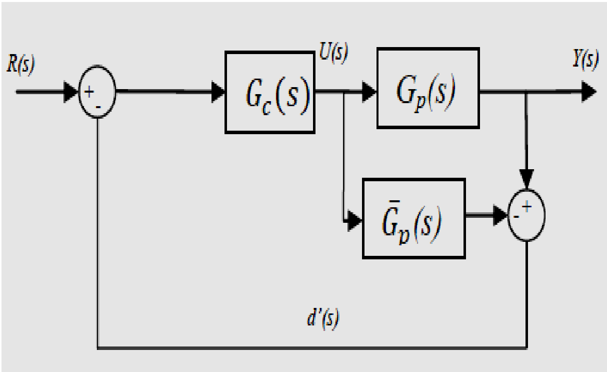

Figure7. The IMC feedback configuration [24].

The IMC detailing for the most part results about just a single tuning parameter, the closed loop time constant (μ), the IMC filter factor. The filter order (n) is selected large enough to achieve proper Gp(s). Choose n=2 and μ =0.01. Figure (8) shows the closed-loop response for (IMC), the response is satisfactory, but at one second the response is out of control, due to unstable poles at high frequency. (μ) can be adjusted to obtain the bandwidth and the stability required for the closed loop system.

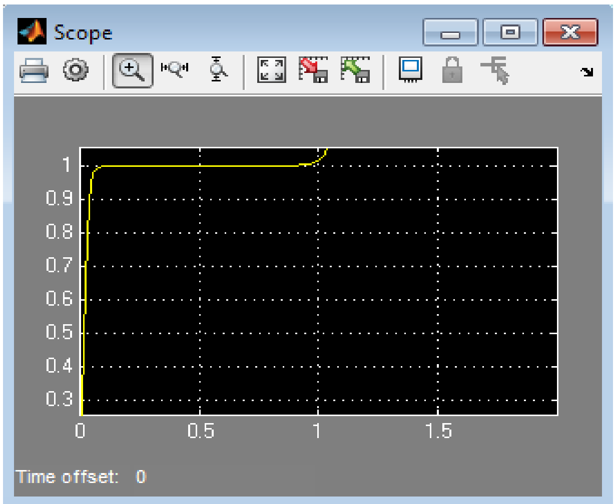

Figure 8. Closed-loop response IMC.

IV. THE INTELLIGENT ALGORITHMS FOR ENHANCING THE RESPONSE OF THE SYSTEM

NN and GA are used to optimise the attributes of the PID controller, to obtain the required response for the (MLS).The two methods are explained in follows.

A. *NN Algorithm*

The NN processes the information of the system with many properties as biological NN [25]. The intelligent controller can estimate the behaviour of the system to produce the desired response .The most familiar network used is feed forward NN [26].

The NN is divided into three main layers:

1- The input layer: It takes the data to be processed through the network. The required output of the MLS at a time is input to the NN controller during different time.

2- The hidden Layer: In this layer by the activation functions processing the data that take from input layer.

3-The output layer: Each neuron at the hidden layer is connected with weights to all neurons at the output layer. The tan sigmoid (tansig) activation function is considered here for the MLS is. The structure of NN is shown in Figure (9).

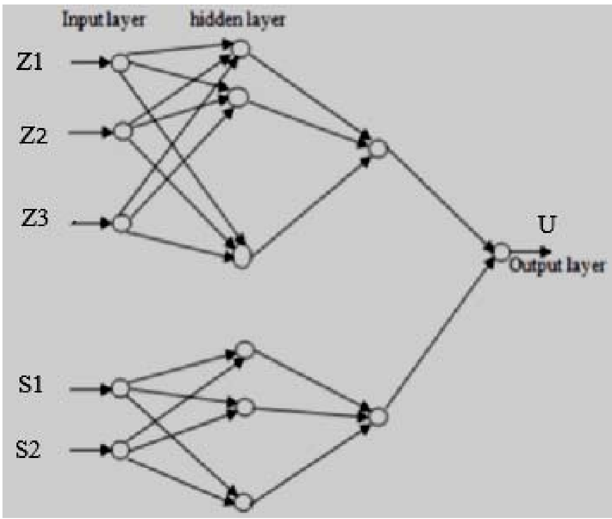

Figure 9. Structure of NN [25].

The input to the hidden neurons can be expressed as follows:

$$net_i^2 = \sum_{k=0}^{n} w_{ik}^2 * I_k^1 \tag{21}$$

$$net_j^2 = \sum_{q=0}^{n} w_{jq}^2 * I_q^1 \tag{22}$$

Where: net_i^2 and net_j^2 are the inputs to the hidden layer, w_{ik}^2 and w_{jq}^2 represent the hidden layer weights , I_k^1 and I_q^1 are the output of the K^{th} and q^{th} inputs of the input

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layer, k and q represent the number of input layer neurons.

The control action (U) represents the output of the NN, which applied to the plant (MLS). In this structure, the input signals to the NN are Z1, Z2 and Z3 from the PID controller. S1 and S2 are fed from the NN. The block diagram of the PID-NN controller for the MLS is shown in Figure (10). The NN is used to control the MLS directly. The NN controller has two inputs, the first input is the feedback from the NN and second input is the output of the PID controller .The optimized control action is applied to the plant to obtain the required response with small values of overshoot and settling time.

Figure (11) shows the Simulink model of the PID - NN controller for the MLS. This NN is self-learning, there is no need to modify the activation function or neural block, if the reference input is changed. The NN controller receives data from the output of same block with the output of the PID controller as inputs to controller. In this structure, the same parameters of the PID controller are used, which are obtained from using 2DOF PID controller. Figure (12) shows the response of the system using the proposed NN controller.

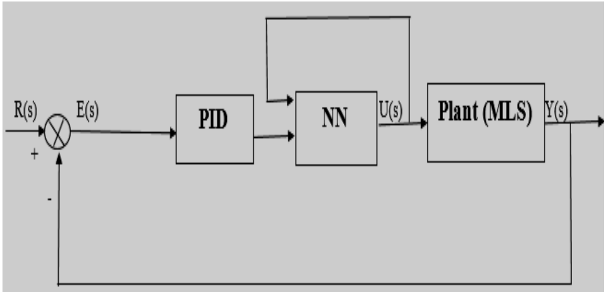

Figure 10. A block diagram of PID - NN controller for MLS.

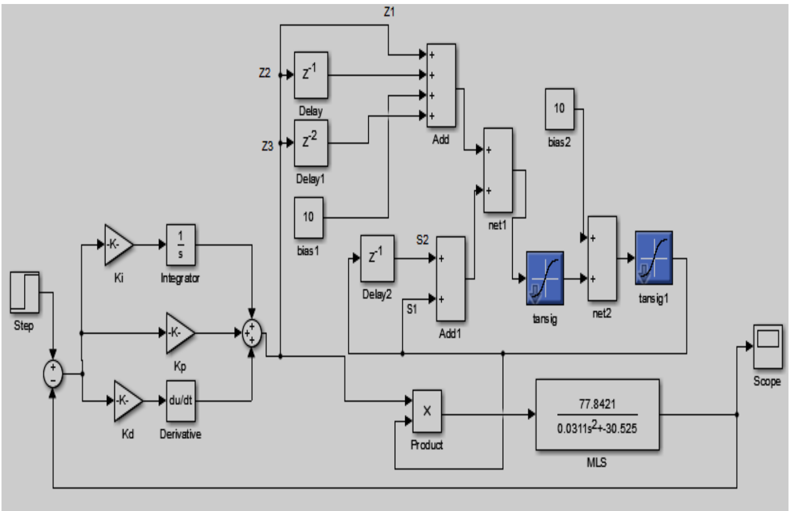

Figure 11. Simulink model of PID-NN controller.

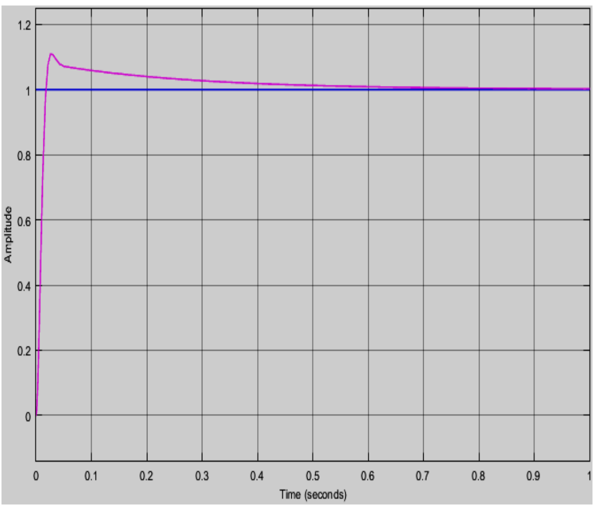

Figure 12.The Response of MLS with NN controller.

B. GA

GA follows the natural evolution for Drawin theory "The survival of the fittest". In 1975 John Holland proposed the GA for the first time In GA, the smallest unit of data is the gene, the data which carried by a set of genes is called individual, and population is a set of individuals, synonyms are chromosome and individual [27]. GA is used to choose the optimum parameters of the PID controller to obtain the desired response of the system. The process of optimisation is calculated by maximisation of the fitness function (F) which is the mean error between the current value of the system output and the desired reference:

$$\mathrm{MSE} = \frac{1}{\tau} \int_0^T (e(t))^2 dt \tag{23}$$

$$\mathrm{Fitness} = 1 / \mathrm{MSE} \tag{24}$$

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A block diagram of PID-GA is shown in Figure (13), to apply GA, the chromosome elements (Kp, Kd, Ki) of PID controller is set.

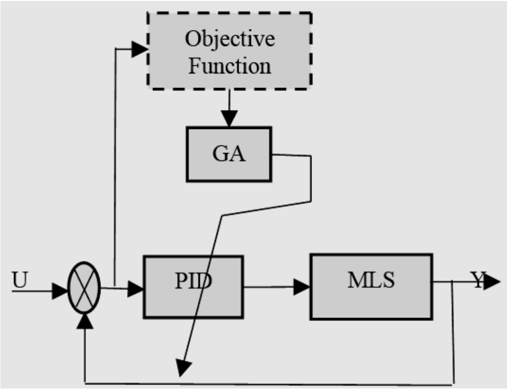

Figure 13. A block diagram of PID-GA controller for MLS.

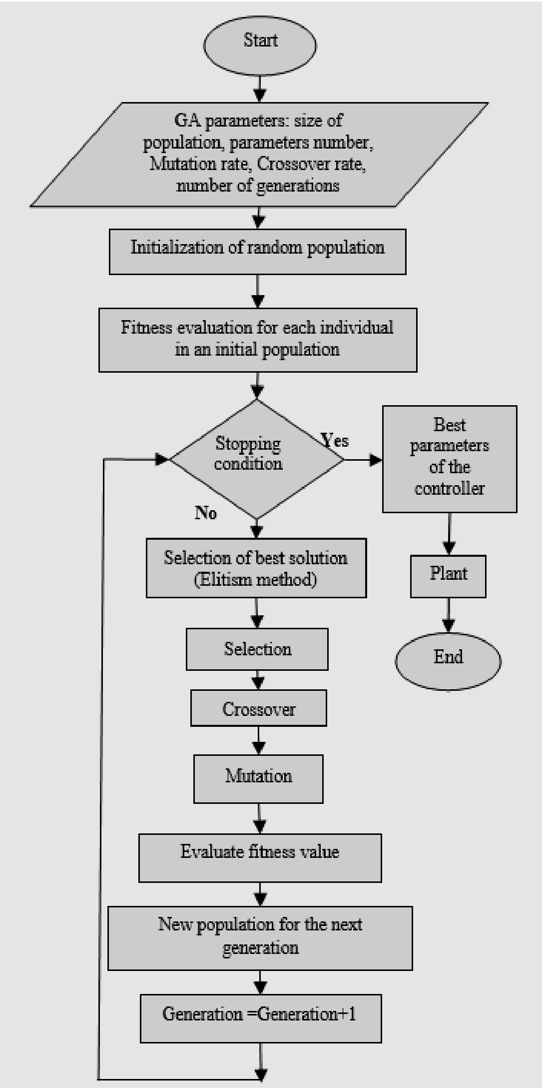

Figure 14. The flowchart for the PID –GA system design.

The optimisation is achieved in iterations form called generations, and creates a new set of chromosomes at each generation through crossover and mutation and the best chromosomes are allowed to the next generation. In this work GA parameters are chosen according to the trial and error method as follows:

Population size=80; Crossover rate= 0.4;

Mutation rate=0.01; Maximum generation = 100.

Roulette wheel selection method is considered with uniform mutation and arithmetic crossover. The Elitism strategy is applied to keep the best solution over generations, and the stopping condition is accomplished when the maximum number of generation is reached. Figure (14) shows the flowchart of the PID –GA system design. Figure (15) shows the response of the MLS system of PID-GA controller.

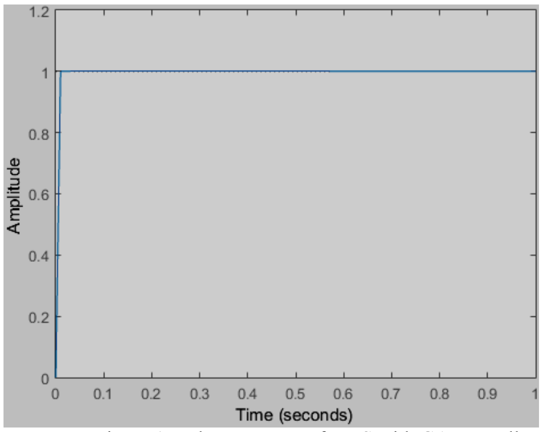

Figure 15. The Response of MLS with GA controller.

V. DISCUSSION

The responses of all presented controllers are compared with respect to settling time, maximum overshoot, and steady-state error, as shown in Table (1).

TABLE I. COMPARSION BETWEEN ALL CONTROLLERS

Controller Types	Settling Time (sec)	Max. Overshoot %	Steady-State Error
PID	1.3	0	0
LQR	5.3	0	0
IMC	0.1	Infinity(after1sec)	infinity
PID - NN	0.378	0.108%	0
PID - GA	0.009	0	0

It is noticed that GA provides better results than other methods, but GA requires 45.74 seconds computational time to tune the PID controller. The parameters of the PID controller which are optimised by using the GA are:

Kp = 155.7678, Kd = 28.9475, and Ki = 489.8021.

When comparing the proposed method PID-GA, with the same system equation. (16) in [1] and [19], using intelligent controller (fuzzy logic controller), it is clear that the design specifications (Max. overshot, settling time, and rise time) are better.

VI. CONCLUSIONS

This paper presents a controlling method for the (MLS), where different approaches are proposed. The proposed methods are PID, state-space approach, LQR and IMC, are measured, in every one of these techniques, the transient plan details are not met, exceptionally in settling time (response speed), as shown in Table (1).

The NN controller system for the MLS is proposed. The neural system structure is self-learning and straightforward. The response of the MLS with the NN controller is better than the traditional PID, providing fast response, with small estimation of overshoot. There is no need to compare the proposed methods with the IMC since the steady-state error and overshot are infinity after one second. The PID-GA method results are the best among other methods. However, the PID-GA improvement is sensitive to the reference which used. PID-GA appears to offer the most encouraging result.

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