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DESIGN OF A NONLINEAR SELF-TUNING PARAMETERS ALGORITHM FOR DIFFERENT TYPES OF PID CONTROLLERS BASED ON ARTIFICIAL INTELLIGENT

Khulood E. Dagher
Al-Khwarizmi Collage of Engineering, University of Baghdad, Baghdad, Iraq
E-Mail: dagherkhulood@yahoo.com

ABSTRACT

A new nonlinear self-tuning parameters algorithm for two types of the PID controllers is designed, the first type is traditional PID controller and the second is nonlinear PID controller, with intelligent algorithm for nonlinear magnetic levitation system (MagLev) is presented in this study. The proposed scheme of the on-line self-tuning control algorithm is based on neural network and PSO algorithm to make both controllers are an on-line adaptive PID controllers by calculating the optimal nonlinear values of the PID parameters in order to generate the best or near optimal value of the control action that will guarantee the output of the actual model accurately represents the desired position output of the magnetic ball. From numerical simulation results, the nonlinear adaptive PID controller is the best from the traditional adaptive PID controller with the proposed nonlinear self-tuning parameters algorithm in terms of fast on-line learning and tuning the nonlinear parameters of the controller with best voltage control action that generated to precisely track the motion of magnetic ball and reach to the desired position with convergence of the position error to zero value.

Keywords: PID controller, neural networks, self-tuning, nonlinear mag lev system, PSO algorithm.

INTRODUCTION

In general, the aim of the magnetic levitation (MagLev) system is provided that a ferromagnetic ball to be levitated and/or held in a reference position in the air without any friction problems because the suspension depends on an electromagnet technique. Therefore, there are many industrial applications for MagLev system such as high-speed rail transportation, vibration isolation in sensitive devices, and magnetic frictionless bearings (Yaseen, 2017). However, MagLev systems consider a high nonlinear dynamic structure with unstable behavior therefore, MagLev system has a challenging problem to control it that leads to make the MagLev system a good test bed for self-tuning control strategies such as a self-tuning robust full-state feedback controller (Bidikli and Bayrak, 2018), parameters self-adjusting fuzzy PID controller (Ma, *et al.,* 2008), auto-tuning PID controller (Cetin and Iplikci, 2015), an adaptive backstepping controller (Adıguzel, *et al.*, 2017). Also, many types of control algorithms have been used to build the modelling of MagLev system and controlling it, such as PID controllers (Yaseen, 2017, Hypiusová, and Osuský, 2017, Hypiusová and Kozáková, 2017, Bojan-Dragos, *et al.*, 2017), fuzzy logic controller (Sahoo, *et al.*, 2018), neural network controller (Rubio, *et al.*, 2016), high-order sliding mode controller (Goel and Swarup, 2016), model predictive controller (Sgaverdea, *et al.,* 2015) and robust H_∞ controller (Khan, *et al.*, 2016). In this study, the nonlinear self-tuning control parameters algorithm has been designed based on neural network and PSO algorithm for obtaining the optimal control gains k_p, k_i, k_d of the two different types of the adaptive PID controllers in order to stabilize and improve the dynamic behavior of the magnetic ball position of the MagLev system through generating an optimal voltage control action. The motivation of this work is to make the PID controller as on-line adaptive PID controller that leads to generate the best or near to optimal value of the control action that will improve the dynamic behavior of the closed loop feedback system through guaranteed the magnetic ball position of the MagLev system is accurately represented the desired position. The main contribution of this study is the proposing a nonlinear self-tuning parameters algorithm of the two types of PID controllers for nonlinear MagLev system in order to fast find and tune the optimal nonlinear values of the PID parameters that leads to design an on-line adaptive PID controller that will stabilize the closed loop system and to generate the optimal value of the control action that generated to precisely track the motion of magnetic ball and reach to the desired position with convergence of the position error to zero value.

This paper is organized as follows: Section 2 describes the mathematical MagLev model. Section 3 explains the proposed self-tuning parameters algorithm for two different types of PID controllers. Section 4 demonstrates the performance of the on-line adaptive PID controllers through numerical Matlab simulation results. Finally, Section 5 gives the conclusions for the proposed self-tuning control algorithm.

NONLINEAR MAGLEV MODEL

In general, the schematic diagram of a one dimensional magnetic levitation system is shown in Figure (1) which considers a highly nonlinear dynamic behavior and unstable system and the physical parameters are given in Table-1 (Al-Araji, 2016).

The mathematical mode of the nonlinear MagLev system can be analysed into two parts, 1) electrical part and 2) mechanical part.

The electrical part is based on the magnetic field voltage as seen in equation (1) that responsible on the operation of the magnetic ball levitation.

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$$v_{in}(t) = L_{coil}\frac{di(t)}{dt} + R_{coil}i(t) \quad (1)$$

Where, i :is the input current value to the electromagnetic coil. v_{in} :is the variable voltage control action. L_{coil} : is the coil inductance. R_{coil} : is the resistance of the circuit

The relationship between the current *i(t)* that flows in the coil and the voltage $v_{in}(t)$ can be expressed as given in Equation. (2)

$$i(t) = C_1 \times v_{in}(t) \quad (2)$$

Where, C_1: is the control voltage to the coil current gain.

The mechanical part can be illustrated the electromagnet force based on Newton's 2nd law:

$$F_a = F_g - F_m \quad (3)$$

Where: F_a : is the magnetic ball's acceleration force. F_m :is the electromagnetic attraction force. F_g :is the magnetic ball's gravity force.

The dynamic behaviour of the electromagnetic force is nonlinear behaviour as equation (4) (Qin, *et al.*, 2014).

$$F_m = k_f(\frac{i}{z})^2 \quad (4)$$

Where, k_f :denotes the magnetic force constant. z : denotes the variable position of the ball in the magnetic field.

So we can describe the mathematical mode of the second part as equation (5) that represents the open-loop nonlinear and unstable system.

$$\ddot{z}m = mg - k_f(\frac{v_{in} \times C_1}{z})^2 \quad (5)$$

Where, m: is the ball mass g :gravitation constant value 9.81m.sec^{-2}. $\dot{z}$: is the ball velocity $\ddot{z}$: is the ball acceleration.

CONTROLLER DESIGN

The proposed nonlinear self-tuning parameters algorithm of the adaptive PID controller for nonlinear MagLev system is described in this section that it consists of two parts, as shown in Figure-2.

First part: a feedback PID controller such as linear or nonlinear scheme uses to minimize the error value of the performance index by tracking the actual position of the magnetic ball, so the discrete time tracking position error is described as in follows:

$$e_1(k) = z_{ref}(k) - z(k) \quad (6)$$

$$\dot{e_1}(k) = \frac{z_{ref}(k) - z_{ref}(k-1)}{Ts} - \frac{z(k) - z(k-1)}{Ts} \quad (7)$$

$$e_2(k) = \dot{e_1}(k) + \alpha e_1(k) \quad (8)$$

Where: z_{ref} *(k)* denotes the reference position of the magnetic ball; α denotes a constant positive gain.

The general scheme of the traditional or linear PID controller can be represented as shown in Figure-3, and the proposed discrete control law equation is represented as in equation (9):

$$V(k) = k_p e_2(k) + k_i(e_2(k) + e_2(k-1)) + k_d(e_2(k) - e_2(k-1)) + V(k-1) \quad (9)$$

Where, k_p denotes the proportional gain; k_i denotes the integral gain; k_d denotes the derivative gain; *V(k)* denotes the voltage control action and $e_2(k)$ denotes the error signal as in equation (9).

The structure of the proposed nonlinear PID controller is shown in Figure-4. So the discrete control law can be described as follows:

H1: denotes bipolar nonlinear node, H2**:** denotes unipolar nonlinear node, G: denotes a gain function in the output of the control action.

$$V(k) = G \times O_2 \quad (10)$$

O_2 is the output of the unipolar activation function *H2(-)* as in equation (11) (Zurada, 1992):

$$H2(-) = \frac{1}{1 + e^{-(O_1 + V(k-1))}} \quad (11)$$

O_1 is the output of the bipolar activation function *H1(-)*as in equation (12) (Zurada, 1992):

$$H1(-) = \frac{2}{1 + e^{-net(-)}} - 1 \quad (12)$$

$net(-)$ is calculated from equation (7):

$$net(-) = kp \times (e_2(k) + ki \times (e_2(k) + e_2(k-1) + kd \times (e_2(k) - e_2(k-1)) \quad (13)$$

Second part: a nonlinear self-tuning parameters algorithm uses to obtain and tune the on-line control parameters of the PID controller in order to find optimal or near optimal control effort that will lead to minimizing the cost function and will achieve excellent tracking of the desired output. The proposed structure of the nonlinear self-tuning parameters algorithm based on multi-layer perceptron neural network (Nells, 2001) is shown in Figure-5.

The proposed structure constructs of the multi-inputs multi outputs neural network for nonlinear self-tuning parameters algorithm and it consists of three layers:

The first layer is scaling or buffering layer which has proposed four inputs are Z=[$e_1(k)$, $\dot{e}_1(k-1)$, *v(k),* and

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$v(k-1)$] in order to improve the dynamic behavior of the neural network structure.

The second layer is the activation or hidden layer which has proposed five neurons with bipolar activation function in each neuron to make the nonlinear behavior of the control parameters.

The third layer uses a nonlinear unipolar activation function with gain more than 1 in order to limit the range of control parameters between (0 to kp_{max}, ki_{max}, kd_{max}] values for avoiding the negative sign in the parameters that leads to stabilize the acting of the PID controller.

The proposed parameters law can be calculated as in follows:

$$kp(k) = [\frac{1}{1+e^{-net_{kb}}}] \times g_1 \tag{14}$$

$$ki(k) = [\frac{1}{1+e^{-net_{ki}}}] \times g_2 \tag{15}$$

$$kd(k) = [\frac{1}{1+e^{-net_{kd}}}] \times g_3 \tag{16}$$

Where, g_1, g_2 and g_3 are experience gains.

$$net_{kp} = \sum_{b=1}^{B=5} h_b\, w_{b,c} \tag{17}$$

Where, c=1, that means the first output of the neural network.

$$net_{ki} = \sum_{b=1}^{B=5} h_b\, w_{b,c} \tag{18}$$

Where, c=2, that means the second output of the neural network.

$$net_{kd} = \sum_{b=1}^{B=5} h_b\, w_{b,c} \tag{19}$$

where c=3, that means the third output of the neural network.

$$h_b = \frac{2}{1+e^{-net_b}} - 1 \tag{20}$$

$$net_b = \sum_{a=1}^{A=4} Z_a\, V_{a,b} \tag{21}$$

Where, b=1 …5.

To generate the optimal nonlinear values of the control parameters (k_p,k_i,k_d) for the PID controller from the proposed structure of the neural network, PSO algorithm is used to learn and tune the weights parameters of the neural network because PSO is an intelligent algorithm and has fast and stable algorithm. The numbers of weights in each particle are equal to 35 weights that represent all weights in the proposed structure of the neural network as shown in Figure-5.

There are two equations that describe the motion of the particles, the first is updated velocity equation (22) and the second equation (23) is updated the position of the particles, respectively (Mohamed, *et al*., 2017).

$$\overline{\Delta Weight}_i^{k+1} = \Omega \times \overline{\Delta Weight}_i^{k} + c_1 r_1 (pbest_i^k - \overline{Weight}_i^k) + c_2 r_2 (gbest^k - \overline{Weight}_i^k) \tag{22}$$

$$\overline{Weight}_i^{k+1} = \overline{Weight}_i^{k} + \overline{\Delta Weight}_i^{k+1} \tag{23}$$

Where, $\overline{\Delta Weight}_i^{k+1}$ is the i^{th} particle's velocity (*neural network weights*) at k^{th} iteration; $Weight_i^k$ is the i^{th} particle's position (*neural network weights*) at k^{th} iteration; Ω : denotes the value of the inertia weight factor which equals to 0.75 in order to decrease the iterations number of the evaluation function; c_1 and c_2 are the positive values that equal to 1.25 because (c_1 + c_2)< 4 (Sundaravadivu, *et al*., 2016); r_1 and r_2 are random values (0 to 1); $pbest_i$ is the i^{th} particle's best previous weight; $gbest_d$ is the best particle from the overall population.

The on line cost function is described by mean square error as in Eq. (24) .

$$OnLinePI = \frac{1}{K}\sum_{i=1}^{K}[(z_{ref} - z)^2] \tag{24}$$

k: denotes maximum iteration number.

NUMERICAL SIMULATION RESULTS

Matlab package (2017) is used to apply the proposed structure of a nonlinear self-tuning parameters algorithm for the two types of the PID controllers for MagLev system. The 4th order Range Kutta method is used in the numerical simulation with 0. 01 second sampling time.

To investigate the optimal nonlinear values of the control parameters (k_p,k_i,k_d) for the two types of the PID controllers from the proposed structure of the neural network, PSO algorithm requires initialization to learn and tune the 35 weights of the neural network based on equations (22) and (23) as follows:

Total particles size= 30; the number of weights in each particle = 35; the best number of on-line iterations = 25; the maximum number of samples=600; the experience gains g_1, g_2, and g_3 are equal to 3, 2.5, and 2 respectively.
The numerical simulation result for the different types of PID controllers for the variable step steel ball position change of (2.5, 3 and 2) cm of the MagLev is shown in Figure (6) where the actual position of the magnetic ball with respect to nonlinear PID controller behavior was a fast excellent response without any over-shoots and it has a zero steady-state the error value at each step position when we compared with linear PID controller results in terms of the transient response and the steady-state error.
Figure (7) shows the position error of the magnetic ball of the MagLev system when we used two types of PID controllers. The position error has a very small value in the transient region and fast reaches zero in the steady state region when we used nonlinear PID controller with nonlinear self-tuning parameters algorithm. Figure-8 shows the performance of the two types of the adaptive

PID controllers based on an on-line self- tuning parameters neural network PSO algorithm in terms of optimal smooth voltage control action with very small spikes without oscillations that leads to deliver a stable suspension of the steel ball in the desired position.

During 600 samples, the parameters k_p, k_i, k_d of the two types of PID controllers are generated from the self-tuning neural network PSO algorithm have stable, smooth, and optimal nonlinear values as shown in Figure (9-a and b) in order to improve the transient response of the feedback control system and achieve the stability. Figure (10-a and b) show the on-line position error convergence for the response of the MagLev's steel ball based on the mean square error function during the carried out 600 samples.

CONCLUSIONS

Two different types of the adaptive PID controllers based on a new on-line self-tuning nonlinear parameters neural network with PSO algorithm for MagLev system have been designed and simulated for different desired magnetic ball positions using Matlab package are presented in this study. From the numerical simulation results, the proposed on-line self-tuning nonlinear parameters algorithm leads to the excellent performance in terms of: i) fast and smooth parameters k_p, k_i, k_d of the PID controller are calculated, ii) Optimal and smooth voltage control action is generated without saturation state and no oscillations control action response, iii) High precision tuning control parameters are obtained for faster tracking the desired ball position and high reduction the on-line tracking position error that reaches zero value.

Table-1. The physical parameters of the MagLev system.

v_{in}	**Control Input voltage level**	**-5 to 5 V**
m	Magnetic ball mass	0.02 kg
k_{mf}	Constant of magnetic force	24.83×10^{-6} kg.m^3/s^2/A^2
g	Constant of gravitation	9.81 m/s^2
C_1	Control voltage to the coil current gain	0.95 A/V
C_2	IR sensor gain	143.48V/m

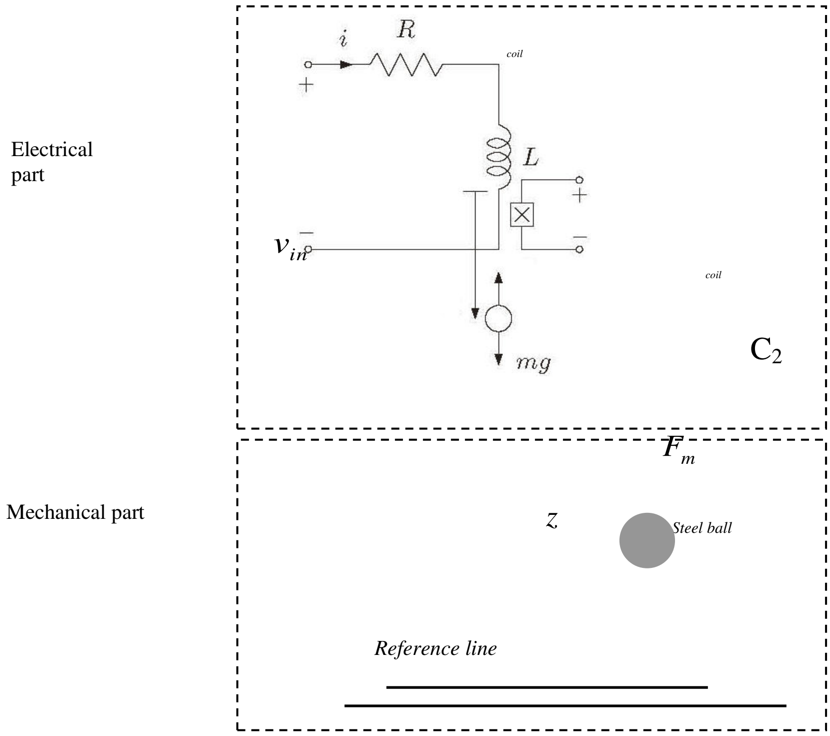

Figure-1. Diagram of magnetic levitation model.

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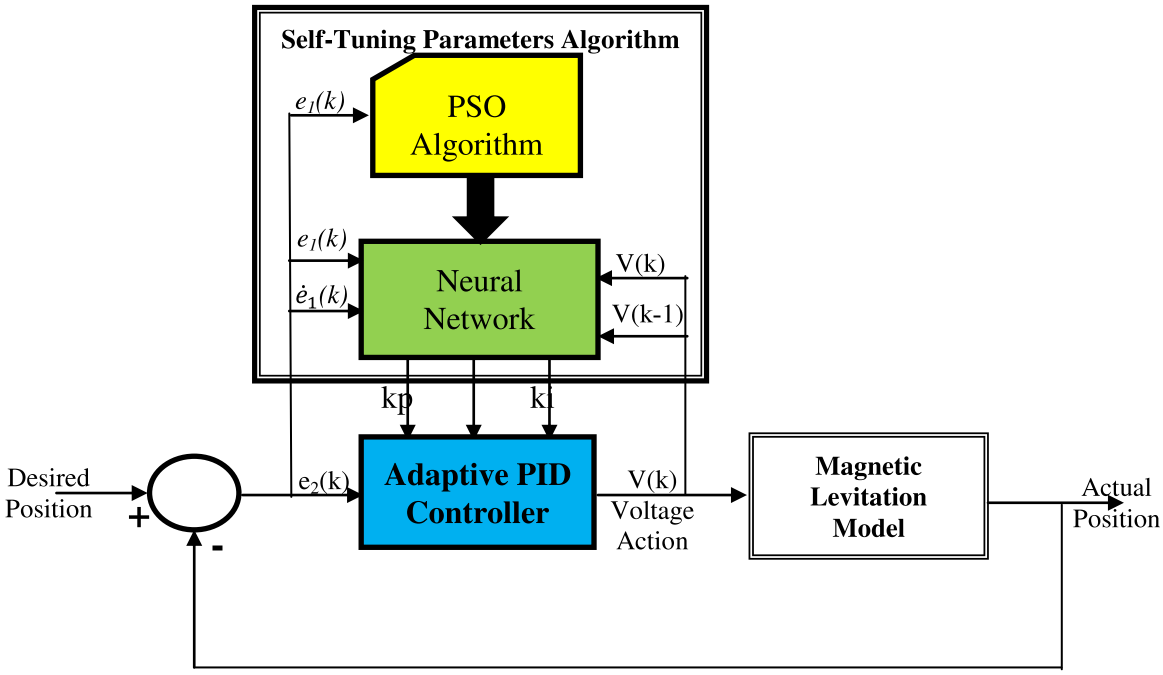

Figure-2. The general structure of the proposed controller.

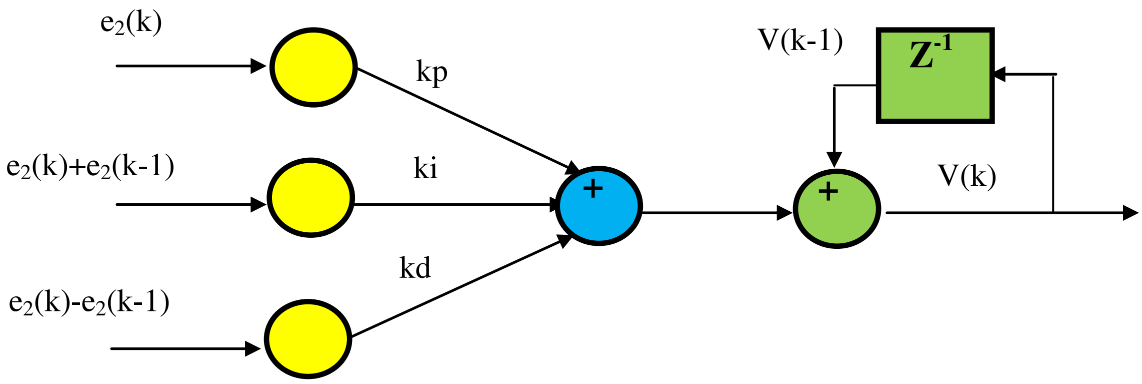

Figure-3. The traditional or linear PID controller structure.

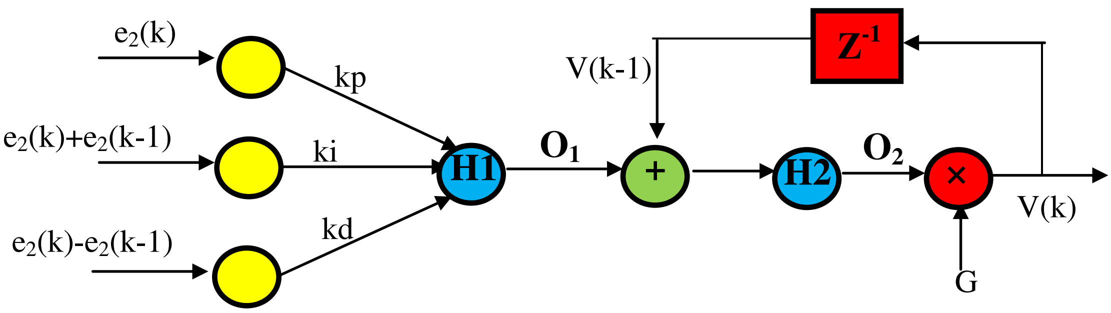

Figure-4. The proposed nonlinear PID controller structure.

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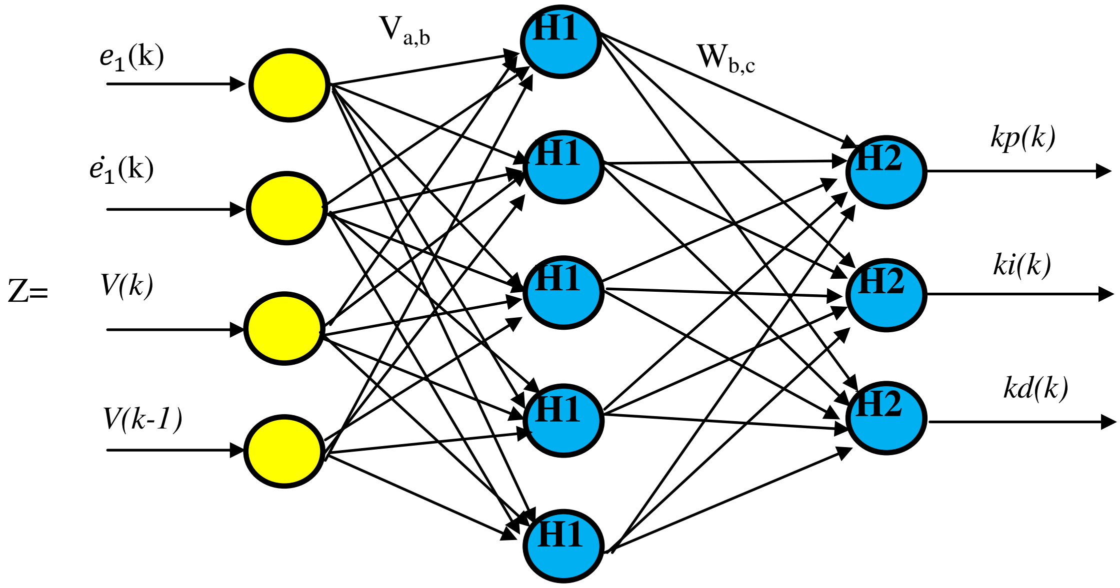

Figure-5. The proposed structure of the nonlinear self-tuning parameters algorithm.

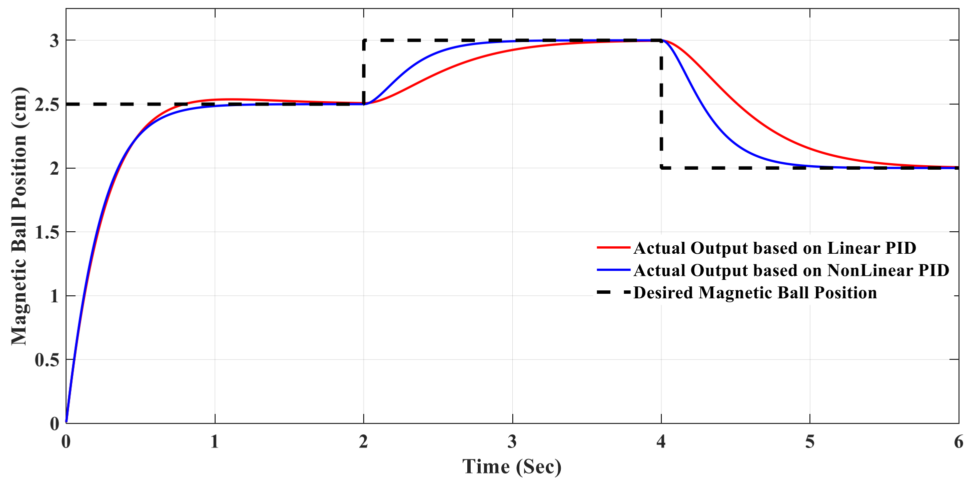

Figure-6. The magnetic ball actual position response.

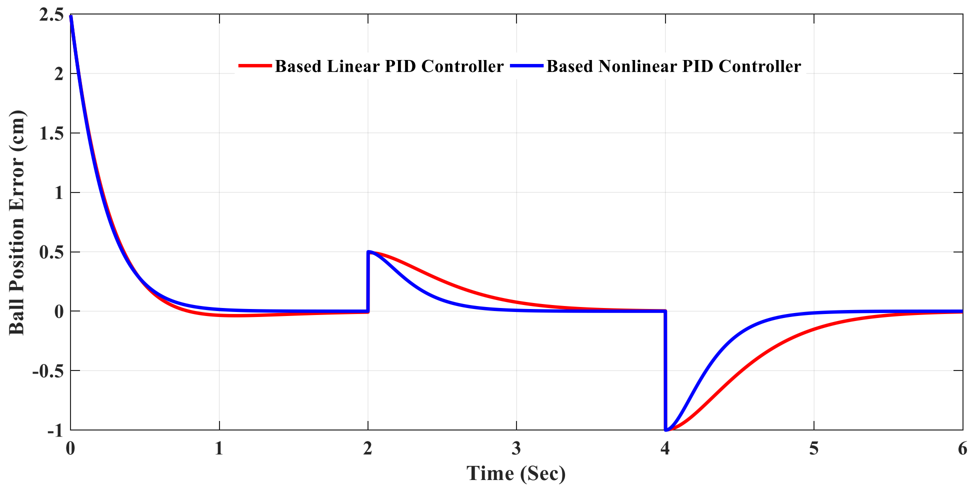

Figure-7. The magnetic ball position error response.

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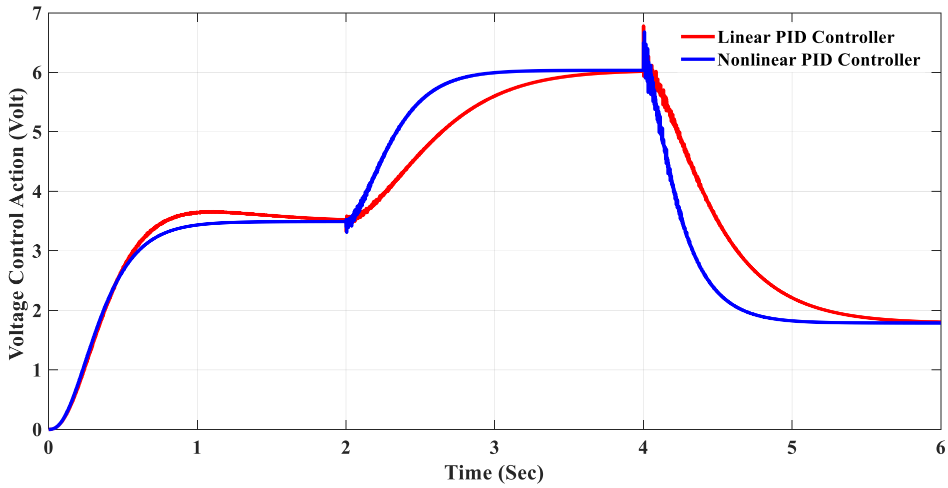

Figure-8. The voltage control action response.

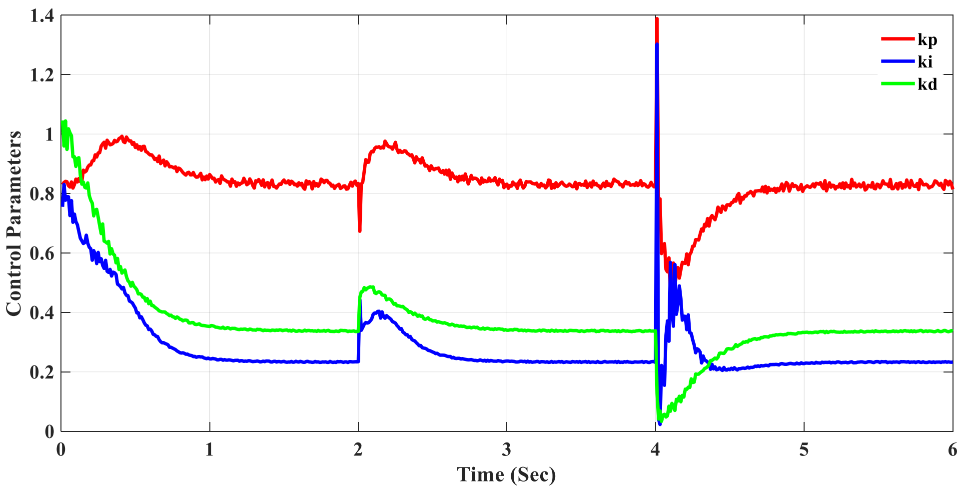

Figure-9-a. The on-line self-tuning control parameters of the nonlinear PID controller.

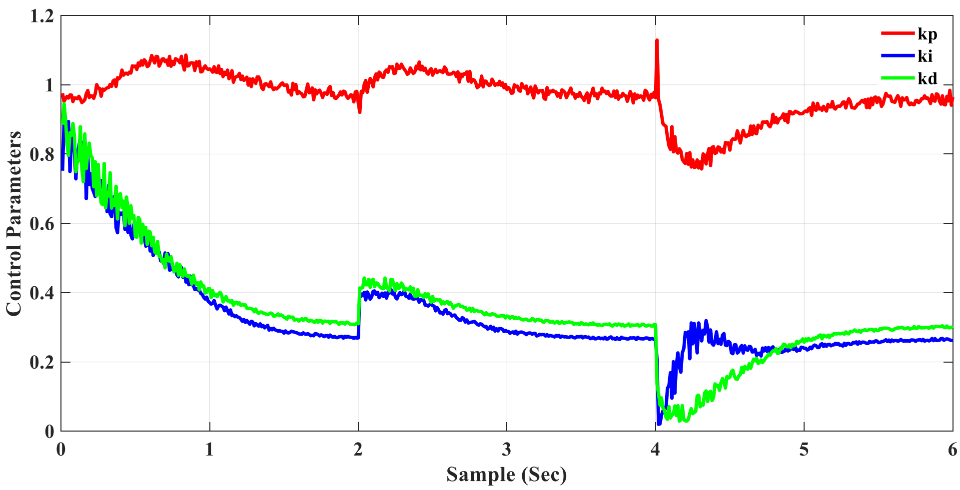

Figure-9-b. The on-line self-tuning control parameters of the linear controller.

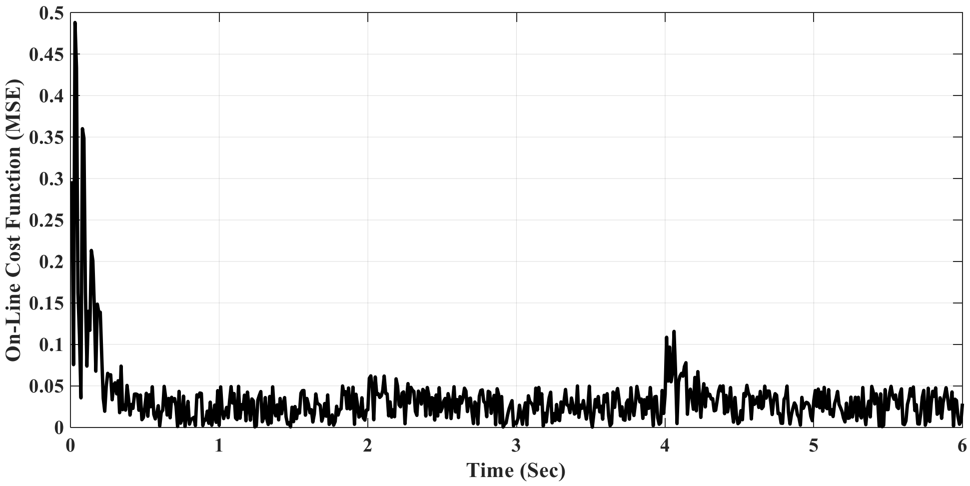

Figure-10-a. The on-line MSE for nonlinear PID controller.

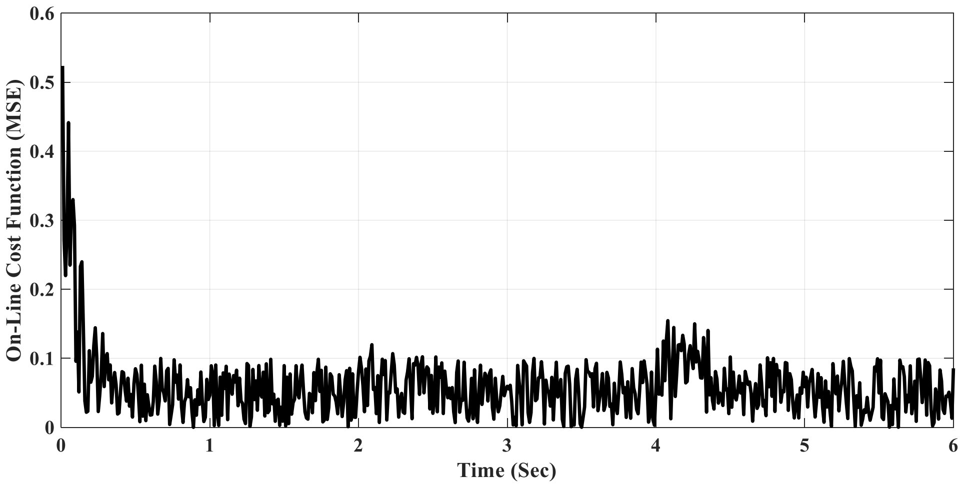

Figure-10-b. The on-line MSE for linear PID controller.

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