Multiplexed Control of Single Neuron PID and Normal PID of Magnetic Suspension System

Polamraju.V.S.Sobhan[1] , Dr. G.V.Nagesh Kumar[2] , Dr. J.Amarnath[3] and R.S.Srinivas[4]

[1]Vignan University, Vadlamudi, Guntur, Andhra Pradesh, INDIA
[2] GITAM University, Visakhapatnam, Andhra Pradesh, INDIA
[3] JNTUH, Andhra Pradesh, INDIA
[4]Acharya Nagarjuna University, Guntur, Andhra Pradesh, INDIA

Abstract— In this paper, a combined control strategy of Single Neuron PID and normal PID is proposed for the magnetic suspension ball system, which has simple structure, adaptability to environmental changes and strong robustness. The magnetic suspension system (MSS) is a typical nonlinear system, and is unstable with external disturbance. The main function of the Controller is to maintain the balance between the magnetic force and the ball's weight. The traditional control methods of PID can not satisfied the stability requirements of system because the structural parameters of MSS will change at some time. The input of the proposed composite controller is error ,when the error is small , a Single-Neuron controller is adopted, and a PID controller is adopted when the error is big. Simulation results indicate that the proposed controller can solve the problem that normal PID cannot solve because MSS is difficult to describe from an accurately mathematical equation, so the paradox between the response time and overshoot of displacement is managed. The system has shown high control accuracy and good dynamic characteristics are achieved, and the system has better adaptability and good robustness.

Keywords— Magnetic suspension system – Single Neuron-PID Control – Stability and performance.

I. INTRODUCTION

The magnetic suspension systems uses the magnetic force to make the translation and rotation systems in frictionless, oscillation and noise reducing. In recent years, magnetic levitation systems [1-6] have been successfully implemented in many applications, such as

- magnetic frictionless bearings,
- vibration isolation tables,
- high-speed maglev passenger trains and
- fast-tool servo systems.

The magnetic levitation system is an open-loop unstable and nonlinear in electromechanical dynamics. Therefore, it is an interesting and impressive system for engineers and researchers.

Normal PID control is still being used widely in many areas because of its simple structure, high reliability. It works well if model parameters change little. But when the system has a strong interference and uncertainty with a high degree of nonlinearity, only relying on normal PID is not effective. For MSS, because of high nonlinearity the parameters and structure of the entire control system may be changed with time, so it is difficult to describe from an accurately mathematical equation, and normal PID controller with fixed parameters may not be an ideal controller. In order to overcome the disadvantage of normal PID controller, the variety of intelligence methods combining with PID controller are continuously researched, such as self-tuning PID, variable structure PID controller, fuzzy logic control and neural network controller, etc. In order to control the complex system, in recent years, artificial neural networks [6] with its unique advantages has made researchers great certain. It has great potential and has been used widely in many applications in order to solve the nonlinear and uncertain control of the system. So the neural network with a combination of traditional PID control for the SRM is hot research for many scholars.

For these reasons, in this paper, a single neuron-PID composite control method for the magnetic suspension system is proposed. The MSS is controlled by a single neuron-PID with self-learning and self-adaptive capacity. It is not only simple in structure, but also adapts to environmental changes. Simulation results show that high control accuracy and good dynamic characteristics are achieved, and the system has better adaptability and good robustness.

II. MODELING OF MAGNETIC SUSPENSION SYSTEM

The magnetic levitation system is a magnetic ball suspension system which is used to levitate a steel ball on air by the electromagnetic force generated by a voltage-controlled magnetic field. Only the vertical motion is considered. The objective is to keep the ball at a prescribed reference level. The schematic diagram of the system is shown in fig1. The magnetic force, applied by the electromagnet is opposite to gravity and maintains the suspended steel ball levitated.

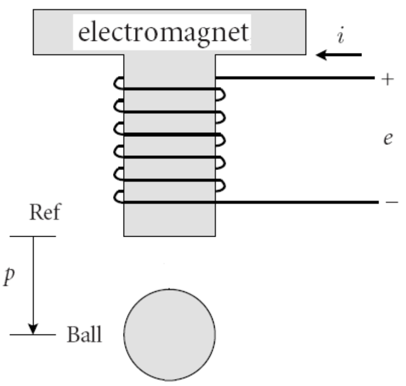

Fig. 1. The principle of a electromagnetic suspension system

The dynamic model of the system can be written as ,

$$\frac{dp}{dt} = v \tag{1}$$

$$Ri + \frac{d(L(p),i)}{dt} = e \tag{2}$$

Where

p denotes the ball's position,
v is the ball's velocity,
i is the current in the coil of the electromagnet,
e is the applied voltage,
R is the coil's resistance,
L is the coil's inductance,
g_c is the gravitational constant, and
m is the mass of the levitated ball

The coil inductivity L is a nonlinear function depends upon the position "p" of the ferromagnetic ball in accordance to the relationship defined as:

$$L(p) = L_1 + \frac{2k}{p} \tag{3}$$

where L_1 is a system parameter and k is the magnetic force constant,

$$k = \frac{\mu_o N^2 A}{4} \tag{4}$$

The electromagnetic levitation force $F(p,i,t)$ can be determined using the theorems of the generalized forces

$$F(p,i,t) = -\frac{i^2}{2}\frac{\partial L(p)}{\partial p} = \frac{i^2}{2}\frac{\partial}{\partial p}\left(L_1 + \frac{2k}{p}\right) = k\left(\frac{i}{p}\right)^2 \tag{5}$$

$$m\frac{dv}{dt} = m g_c - F(p,i,t) = m g_c - k\left(\frac{i}{p}\right)^2 \tag{6}$$

$$\frac{dv}{dt} = g_c - \frac{k}{m}\left(\frac{i}{p}\right)^2 \tag{7}$$

From equation(2)

$$e = Ri + \frac{\partial(L(p),i)}{\partial L}\frac{\partial L}{\partial t} + \frac{\partial(L(p),i)}{\partial i}\frac{\partial i}{\partial t} \tag{8}$$

$$= Ri + i\frac{dL}{dt} + L\frac{di}{dt} = Ri + i\frac{\partial L}{\partial p}\frac{\partial p}{\partial t} + L\frac{di}{dt}$$

Where

$$\frac{\partial L}{\partial p} = -\frac{2k}{p^2}$$

$$e = Ri - 2k\left(\frac{v\, i}{p^2}\right) + L\,\frac{di}{dt} \qquad (9)$$

III. MULTIPLEXED CONTROL OF SINGLE NEURON PID OF MAGNETIC SUSPENSION SYSTEM

The multiplexed control structure of Single Neuron-PID is shown in figure 2, with an input is e=p^*- p, that is the difference between reference displacement and the actual displacement, and output is a reference voltage to the electromagnet.

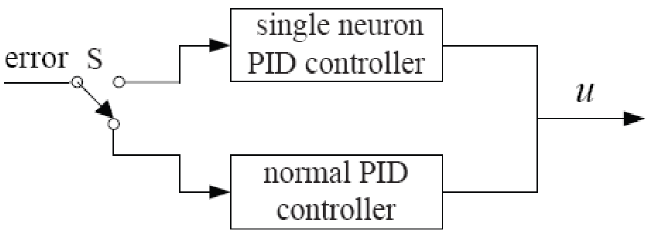

Fig. 2. Combined control of Single Neuron PID structure

A displacement controller consists of combined control which is made up of a Single Neuron-PID controller and a normal PID controller. In order to eliminate static error, when the error of displacement is small, a Single-Neuron controller is adopted, and when the error of displacement is large, a normal PID controller is adopted, and the change between the Single-Neuron controller and normal PID controller can expediently be implemented by a switch S.

When model parameters change greatly and the plant has strong interference and highly nonlinearity, a normal PID controller has obviously disadvantage of bad following characteristic. A single neuron intelligent controller has adaptive and self-learning ability, which can not only overcome disadvantage of normal PID, but retains the advantages of the normal PID controller that is simple, high reliability, easy achievement [3]. Structure of single neuron PID controller structure is shown in Figure 3

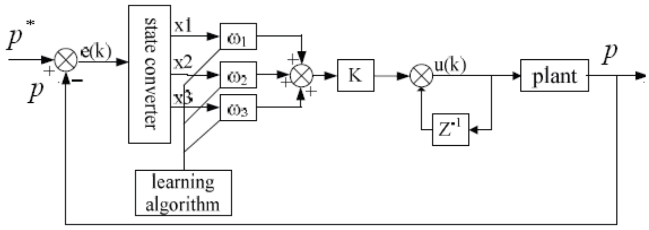

Fig. 3 Structure of single neuron PID controller

In this figure, there is three input x (i), (i=1, 2, 3). The input of state converter is the error between reference and actual displacements .i.e the deviation is *e(k)*; (i=1, 2, 3) is corresponding weight; K is the coefficient of proportionality; u(k) is the output of single neuron PID controller

The functions of self-organization and self-learning are implemented by adjusted weight $w_i(k)$ for the single neuron adaptive controller. Weight $w_i(k)$ is adjusted through a rule of supervised Hebb learning that is combination of Hebb learning and supervised learning. The control action from the tissue and effect of neuron by the neuron under the action of the teacher signals, the control process is obtained by a neuron through self-organizing information on the environment and implies the evaluation of the neuron action signal. The algorithm is as following

$$\begin{aligned} x_1(k) &= e(k) = p^* - p \\ x_2(k) &= e(k) - e(k-1) \\ x_3(k) &= \Delta^2 e(k) = e(k) - 2e(k-1) + e(k-2) \end{aligned} \qquad (10)$$

Where *e(k)* is error;

p^* is input, that is the reference displacement;

p is output, it present the desire displacement.

The output signal of single neuron *u (k)* is expressed by following

$$u(k) = u(k-1) + K\sum_{i=1}^{3} w_i'(k)x_i(k) \qquad (11)$$

And its learning algorithm is

$$w_i'(k) = \frac{w_i(k)}{\sum_{i=1}^{3}|w_i(k)|} \qquad (i = 1,2,3) \qquad (12)$$

Here $w_i(k)$ is the weighting coefficient of corresponding to $x_i(k)$. K is single neuron coefficient of proportionality. To ensure the convergence of the control strategy, the weight $w_i(k)$ is normalized, it has obvious physical meaning compared with traditional PID controller, $w_i(k)$ is equivalent to proportional, integral and differential item of the traditional PID controller.

Single neuron adaptive controller is adjusted by weighting factors to achieve functions of self-adaptive and self-organizing, weight adjustment is based on a supervised Hebb learning rule to achieve. And therefore,

$$\begin{aligned} w_1(k) &= w_1(k-1) + \lambda_I\, z(k)u(k)x_1(k) \\ w_2(k) &= w_2(k-1) + \lambda_P\, z(k)u(k)x_2(k) \qquad (13) \\ w_3(k) &= w_3(k-1) + \lambda_D\, z(k)u(k)x_3(k) \end{aligned}$$

Where $\lambda_I, \lambda_P, \lambda_D$ respectively is the rate of proportional, integral and differential. When different learning rates are selected, weights will be adjusted then the response of the system will be adjusted. K ($K > 0$) presents the neuron proportional coefficient, it is important to choice the value of K. K is the bigger, fast is the better, but overshoot is large, and if K is too big, the system may be unstable. When the delay of the plant is increased, value of K must be reduced to ensure stability of the system. If the value of K is too small, the system response will be slow.

The single neuron controller and normal PID controller are switched by switch S. When $e(t) = \left|\frac{p^* - p}{p^*}\right| \le 2\%$ (p^* is the desire displacement, p is the real displacement), single neuron PID is used; When $e(t) = \left|\frac{p^* - p}{p^*}\right| > 2\%$ normal PID is used. In this way, not only the steady-state error and the integral switch delay are eliminated, but also the system dynamic overshoot is reduced.

TABLE I
SPECIFICATIONS PARAMETERS OF THE MAGNETIC SUSPENSION SYSTEM

Symbol	PARAMETER	Optimum values
m	Mass of the steel ball	0.014 kg
g_c	Acceleration due to gravity	9.81 m/s^2
p	Equilibrium distance	0.009 m
i	Equilibrium current	1.5 A
K	Force constant	4.94 x10^{-6} Nm^2/A^2
R	Coil resistance	5.2 ohm
L	Coil inductance	0.027 H
L_o	Coil inductance when the ball is absent	0.0011 H

Table I summarizes the variables and parameters use in this problem. Here the problem is to maintain the ball at its operating point (position) of 0.05 meters from the coil.

IV. SIMULATION RESULTS OF THE MULTIPLEXED CONTROL OF SINGLE NEURON PID CONTROLLER

The proposed control scheme is simulated using MATLAB. Magnetic suspension system and force control using Combined Single Neuron PID And Normal PID Controller is shown in Figs. 4 and 5

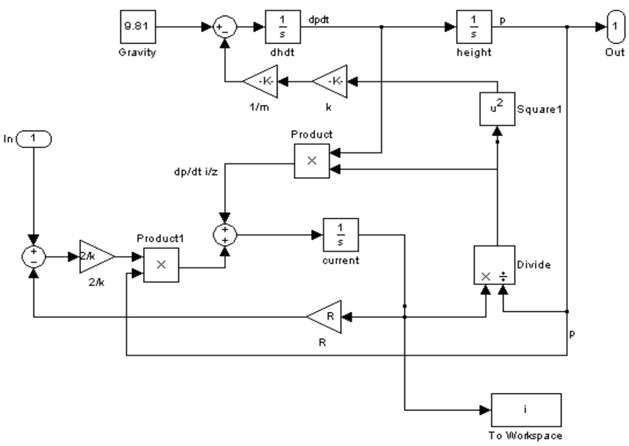

Fig. 4. Magnetic suspension system

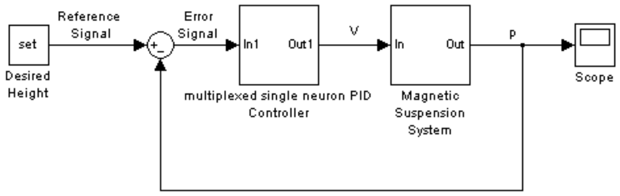

Fig. 5. Magnetic Suspension System With Combined Single Neuron PID And Normal PID Controller

The structure in simulation of combined single neuron PID and normal PID is shown in figure 6

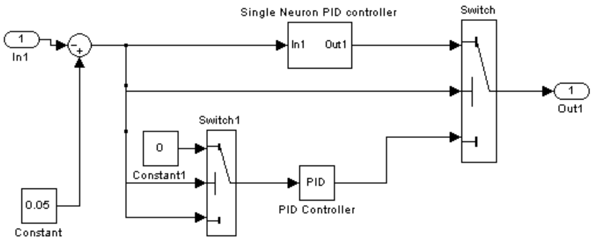

Fig. 6. The structure of combined controller

Single neuron PID controller structure is shown in Figure 6, system input is *e(k),e(k-1),e(k-2),u(k-1)*,where *e(k)=p*-p* , *u(k)* is the output voltage i.e voltage applied to electromagnet . Singlehebb is written with S-function using supervised Hebb algorithm. Saturation block is added to prevent overflow of the out voltage.

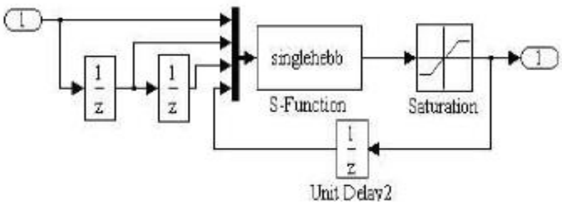

Fig. 7. structure of neuron PID controller

The simulation results of the ferromagnetic ball position control using Combined Single Neuron PID And Normal PID Controller of the magnetic suspension system is shown in Fig. 8. It can be seen that the position converges to its desired value with less time.

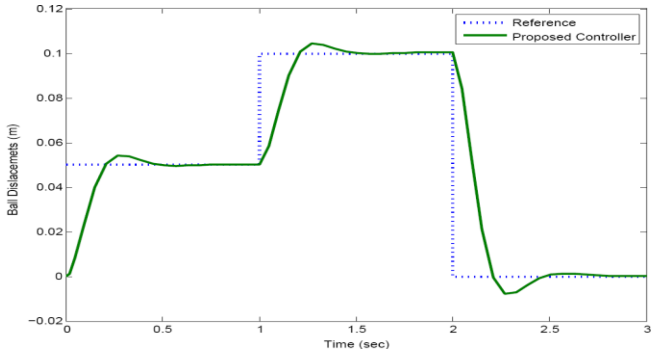

Fig. 8.The position versus time for the Proposed Combined Controller

It can be observed that from fig 9. the Proposed controller has better transient response than the classical PID controller. The overshoot of the Proposed controller is 8% compared to 60% in the classical PID case. Furthermore, Proposed controller has a faster transient response; it reaches to steady state in 0.7 second to that of 1.6 sec in PID. In comparison to the steady state value, both controllers satisfactorily attain the steady state value .

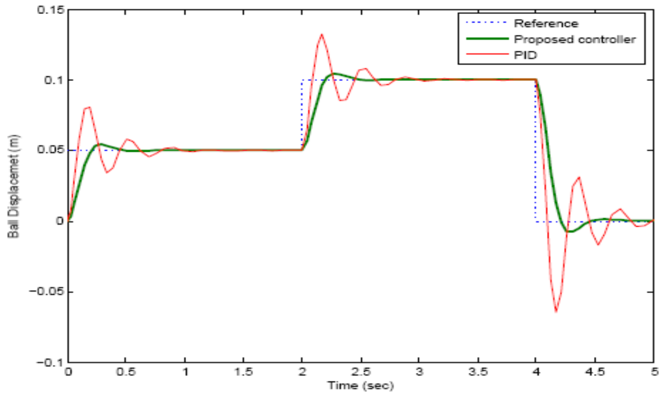

Fig. 9.The position versus time for the Proposed Combined Controller Vs Normal PID

V. CONCLUSIONS

An strategy for controlling the magnetic suspension system based on multiplexed control of Single Neuron PID and normal PID has been presented. General PID controller has characteristics of simple structure, less adjustable parameters, wide application, etc. but its parameters of K_P K_I and K_D are constant and cannot be changed according to the load change. Neural network controller is particularly suitable for nonlinear adaptive control. No matter how object parameters changed, neural network can be changed by learning to adjust its weights to control the system.

The performance of the proposed combined controller in trajectory tracking is superior for step signal applied to the ball. Analysis indicates that better operating results can be achieved by self-learning single neuron PID, and simulation results verifies that the system of combined single neuron PID and normal PID has high precision, fast dynamic characteristics, better adaptability and strong robustness.These features make this control technique a valid alternative for standard control approaches like speed and position control.

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