Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 8 (14): 2561-2568, 2008
ISSN 1812-5654

Hybrid Control of Magnetic Levitation System Based-on New Intelligent Sliding Mode Control

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Abstract: This study has developed classical and hybrid controllers for control of magnetic levitation system. Sliding mode and PID controllers are proposed as a classical controllers and neural network based controller is used for controlling a magnetic levitation system. Adaptive neural networks controller needs plant's Jacobain, but here this problem solved by sliding surface and generalized learning rule in case to eliminate Jacobain problem. The simulation results show that these methods are feasible and more effective for magnetic levitation system control.

Key words: Radial basis function, sliding mode, feedback error learning, PID controller

INTRODUCTION

One of the ways that non-contact surfaces are maintained is via magnetic suspension. This system is commonly referred to as Magnetic Levitation system (Maglev) which has been used in the vehicle suspension system and magnetic bearing system by B.A. Holes of University of Virginia in 1937 for the first time. In 1954 this system was utilized by Laurencean and Tournier at ORENA in France for the purpose of aerodynamic testing in wind tunnels (Covert, 1988). Furthermore, the system have practical uses in many industrial systems such as in high-speed maglev passenger trains, levitation of wind tunnel models, vibration isolation of sensitive machinery, levitation of molten metal in induction furnaces and levitation of metal slabs during manufacturing.

In recent years, a lot of works have been reported in the literature for controlling magnetic levitation systems. The feedback linearization technique has been used to design control laws for magnetic levitation systems (Jing-Chung, 2002; Trumper *et al*., 1997; Hajjaji and Ouladsine, 2001). Other types of nonlinear controllers based on nonlinear methods have been reported by Yang and Tateishi (1998), Tanaka and Torii (2004), Huang *et al*. (2000) and Teng and Qiao (2008). Control laws based on phase space (Zhao *et al*., 1999), linear controller design (Rifai and Youcef-Toumi, 1998) and neural network techniques and fuzzy controllers have also been used to control magnetic levitation systems (Lairi and Bloch, 1999; Anh and Timothy, 2008; Muñoz-Gómez *et al*., 2006). One of the first applications of Sliding Mode Control (SMC) to magnetic levitation systems was carried out by Cho *et al*. (1993). Chen *et al*. (2001) designed an adaptive sliding mode controller for a rather different type of magnetic levitation systems called dual-axis maglev positioning system. Muthairi and Zribi (2004) designed static and dynamic sliding mode controller for the magnetic levitation system and Chao-Lin *et al*. (2005) designed a novel Fuzzy sliding-mode controller for magnetic ball levitation system.

In this study, we consider a magnetic levitation system and propose classic controllers like sliding mode, PID controller and new hybrid controllers. In proposed hybrid controllers the Feedback Error Learning (FEL) based-on sliding mode is used to train the neural network with Radial Basis Function (RBF). The proposed methods demonstrate the advantages of the adaptive neural network and sliding mode control strategies with achieving better performance.

MATHEMATICAL MODEL OF THE SYSTEM

Figure 1 is shown a diagram of the magnetic levitation system. Note that only the vertical motion is considered. The dynamic model of the system can be written as (Barie and Chiasson, 1996; Muthairi and Zribi, 2004):

$$\begin{aligned}&\frac{dp}{dt} = v\\ &Ri + \frac{d(L(p)i)}{dt} = e\\ &m\frac{dv}{dt} = mg_c - C\left(\frac{i}{p}\right)^2\end{aligned} \qquad (1)$$

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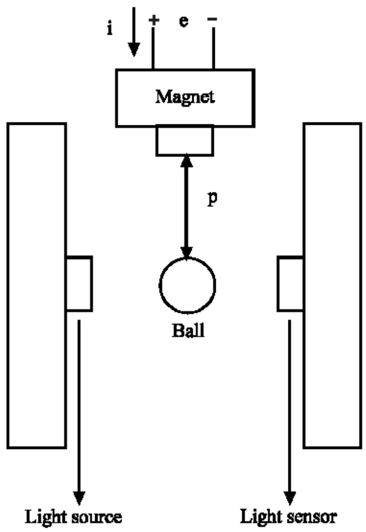

Fig. 1: Diagram of the magnetic levitation system

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 is the gravitational constant, C is the magnetic force constant and m is the mass of the levitated ball. The inductance L is a nonlinear function of ball's position p. The approximation of L is:

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

where, L_1 is a parameter of the system.

Let the states and control input be chosen such. Thus, the state-space model of the magnetic levitation system can be written as:

$$\begin{aligned} \frac{dx_1}{dt} &= x_2 \\ \frac{dx_2}{dt} &= g_c - \frac{C}{m}\left(\frac{x_3}{x_1}\right)^2 \\ \frac{dx_3}{dt} &= -\frac{R}{L}x_3 + \frac{2C}{L}\left(\frac{x_2x_3}{x_1^2}\right) + \frac{1}{L}u \end{aligned} \tag{3}$$

Consider the following nonlinear change of coordinates:

$$\begin{aligned} z_1 &= x_1 - x_{1d} \\ z_2 &= x_2 \\ z_3 &= g_c - \frac{C}{m}\left(\frac{x_3}{x_1}\right)^2 \end{aligned} \tag{4}$$

The dynamic model of the magnetic levitation system in the new coordinates system can be written as:

$$\begin{aligned} \dot{z}_1 &= z_2 \\ \dot{z}_2 &= z_3 \\ \dot{z}_3 &= f(z) + g(z)u \end{aligned} \tag{5}$$

Where:

$$\begin{aligned} f(z) &= 2(g_c - z_3)\left(\left(1 - \frac{2C}{L(z_1 + x_{1d})}\right)\frac{z_2}{(z_1 + x_{1d})} + \frac{R}{L}\right) \\ g(z) &= \frac{-2}{L(z_1 + x_{1d})}\sqrt{\frac{C}{m}(g_c - z_3)} \end{aligned} \tag{6}$$

The function f (z) and g (z) correspond in the original coordinates to the following functions, respectively:

$$\begin{aligned} f_1(x) &= \frac{2C}{m}\left(\left(1 - \frac{2c}{Lx_1}\right)\frac{x_2x_3^2}{x_1^3} + \frac{R}{L}\frac{x_3^2}{x_1^2}\right) \\ g_1(x) &= -\frac{2Cx_3}{Lmx_1^2} \end{aligned} \tag{7}$$

The relationship between the input and the output of the system can be found as:

$$y^{(3)} = f_1(x) + g_1(x)u \tag{8}$$

The parameters of the magnetic levitation system are as follows (Barie and Chiasson, 1996). The coil's resistance R = 28.7 Ω, the inductance L_1 = 0.65 H, the gravitational constant g_c = 9.81 $msec^{-2}$, the magnetic force constant $C = 1.24\times10^{-4}$ and the mass of the ball m = 11.87 g and x_{1d} = 0.01 is the desired value of x_1.

MATERIALS AND METHODS

Sliding mode controller: Sliding mode control is a variable structure control utilizing a high-speed switching control law to drive a system state trajectory onto a specified and user chosen surface, so called sliding surface and to maintain the system state trajectory on the sliding surface at subsequent times (Slotin and Li, 1991). In this paper, the sliding surface on the phase plane can be defined as:

$$\begin{aligned} e_1 &= x_1 - x_{1d} \\ S &= \left(\frac{d}{dt} + \lambda\right)^n e_1 \end{aligned} \tag{9}$$

In case n = 2:

$$S = \left(\frac{d}{dt} + \lambda\right)^2 e_1 \quad \Rightarrow \quad S = \ddot{e}_1 + \lambda_1\dot{e}_1 + \lambda_2 e_1 \tag{10}$$

Based on the Lyapunov theorem, the sliding surface reaching condition is:

$$V = \frac{1}{2}S^2 \Rightarrow \quad \dot{V} = S\dot{S} < 0 \tag{11}$$

Using Eq. 10 and 3, the switching surface can be written as:

$$S = g_c - \frac{C}{m}\left(\frac{x_3}{x_1}\right)^2 + \lambda_1 x_2 + \lambda_2 (x_1 - x_{1d}) \tag{12}$$

Note that the choice of the switching surface guarantees that $x_1 - x_{1d}$ converges to 0 as $t \to \infty$, when we have $S = 0$.

The following proposition gives the U :

$$U = \frac{1}{g_1(x)}\left(-f_1(x) - \lambda_1\left(g_c - \frac{C}{m}\left(\frac{x_3}{x_1}\right)^2\right)\right) - \lambda_2 x_2 - W\mathrm{sign}(S) \tag{13}$$

For eliminating chattering in control signal, we use saturation function instead of sign. So the following proposition gives the U_s:

$$U_S = \frac{1}{g_1(x)}\left(-f_1(x) - \lambda_1\left(g_c - \frac{C}{m}\left(\frac{x_3}{x_1}\right)^2\right)\right) - \lambda_2 x_2 - W\mathrm{sat}(S) \tag{14}$$

Radial basis function neural networks: In this study, we use a type of neural networks which is called the Radial Basis Function (RBF) networks (Powell, 1987). These networks have the advantage of being much simpler than the perceptrons while keeping the major property of universal approximation of functions (Poggio and Girosi, 1987). RBF networks are embedded in a two layer neural networks, where each hidden unit implements a radial activated function. The output units implemented a weighted sum of hidden unit outputs. The input into an RBF network is nonlinear while the output is linear. Their excellent approximation capabilities have been studied in (Park and Sandberg, 1991). The output of the first layer for a RBF network is:

$$\phi_i(x) = \exp\left(-\frac{\|x - c_i\|^2}{2\sigma_i^2}\right), \qquad i = 1, 2, \cdots, n \tag{15}$$

The output of the linear layer is:

$$y_i = f(x) = \sum_{i=1}^{n} w_{ji}\phi_i(x) = w_j^T \phi, \qquad j = 1, 2, \cdots, m \tag{16}$$

where, $x \in R^n$ and $y \in R^m$ are input vector and output vector of the network, respectively and $\phi = [\phi_1, \Lambda, \phi_n]^T$ is the hidden output vector. n is the number of hidden neurons, $W_j = [w_{j1}, \Lambda, w_{jn}]^T$ is the weights vector of the network, parameters c_i and σ_i are centers and radii of the basis functions, respectively. The adjustable parameters of RBF networks are W, c_i and σ_i. Since the network's output is linear in the weights, these weights can be established by least-square methods. The adaptation of the RBF parameters c_i and σ_i is a non-linear optimization problem that can be solved by gradient-descent method.

RBF sliding mode controller: The sliding variable, S will be used as the single-input signal for establishing a RBF neural network model to calculate the control law, u. Then for the single-input and single-output case in this paper, the output of the controller based on RBF networks is:

$$u = \sum_{i=1}^{n} w_i \exp\left(-\frac{\|S - c_i\|^2}{2\sigma_i}\right) = W^T\Phi \tag{17}$$

where, n is the number of hidden layer neurons and u is the final closed-loop control input signal. In order to combine the advantages of sliding mode and adaptive control schemes into the RBF neural network, an adaptive rule is introduced to adjust the weightings between hidden and output layers.

If a control input u can be chosen to satisfy this reaching condition (11), the control system will converge to the origin of the phase plane. Adaptive law is used to adjust the weightings for searching the optimal weighting values and obtaining the stable convergence property. The adaptive law is derived from the steep descent rule to minimize the value of $S\dot{S} < 0$ with respect to W. Then the updated equation of the weighting parameters is:

$$W_{new} = W_{old} - \eta \frac{\partial S\dot{S}}{\partial W}\Big|_{W = W_{old}} \tag{18}$$

Or

$$W_{new} = W_{old} - \eta S \frac{\partial \dot{S}}{\partial W}\Big|_{W = W_{old}} \tag{19}$$

$$\frac{\partial \dot{S}}{\partial W} = \frac{\partial \dot{S}}{\partial u} \times \frac{\partial u}{\partial W} \tag{20}$$

And from Eq. 12, we have:

$$\dot{S} = \dddot{e}_1 + \lambda_1 \ddot{e}_1 + \lambda_2 \dot{e}_1 \Rightarrow \quad \dot{S} = \dddot{x}_1 + \lambda_1 \ddot{x}_1 + \lambda_2 \dot{x}_1 \tag{21}$$

Form Eq. 3, we can find that:

Fig. 2: Block diagram of the modified RBF-sliding mode

$$\frac{\partial \dot{x}_1}{\partial u} = 0, \quad \frac{\partial \ddot{x}_1}{\partial u} = 0$$
$$\frac{\partial \dddot{x}_1}{\partial u} \neq 0 \qquad (22)$$

$$\Rightarrow \quad \frac{\partial \dot{s}}{\partial u} = \frac{\partial \dddot{x}_1}{\partial u} \qquad (23)$$

Finally we can find updating rule as follow:

$$W_{new} = W_{old} - \eta S \frac{-2Cx_3}{Lmx_1^2} \times \frac{\partial u}{\partial W}\bigg|_{W=W_{old}} \qquad (24)$$

From Eq. 16, we have:

$$\frac{\partial u}{\partial W} = \Phi(S) \qquad (25)$$

It is clear that we do not need any identifier for magnetic levitation system.

For improve control signal, a modified RBF-sliding mode controller is now designed for the magnetic levitation system. Figure 2 is a block diagram of the modified RBF-sliding mode controller.

Feedback error learning architecture: The structure of FEL is shown in Fig. 3, which is proposed by Kawato *et al.* (1988). In this architecture, the neural network is used as a feed forward controller and trained by using the output of a feedback controller as error signal. The total control input U to the plant is equal to:

$$U(t) = U_C(t) + U_N(t) \qquad (26)$$

where, $U_C(t)$ and $U_N(t)$ are outputs of CFC and NN, respectively.

The feedback-error learning scheme has the following advantages: (1) the teaching signal is not required to train the neural network. Instead, the error signal is used as the training signal, (2) the learning and control are performed simultaneously in sharp contrast to the conventional learn-then-control approach and (3) back-propagation of the error sign through the model of the controlled object or through the model of the controlled object is not necessary.

In this control procedure, the CFC controller is a sliding mode controller and in Fig. 4, modified FEL-sliding mode controller, the CFC controller is a proportional-plus-derivative (PD) controller. The total control input U to the plant is equal to:

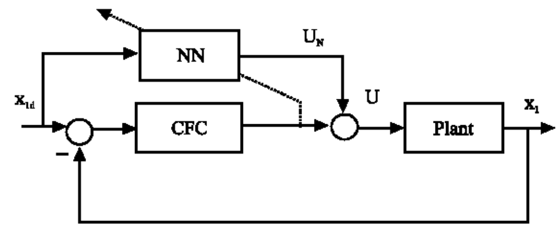

Fig. 3: General structure of FEL

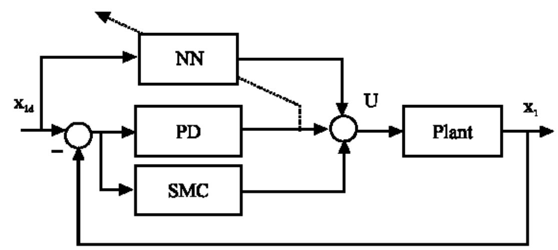

Fig. 4: The modified hybrid control approach

$$U(t) = U_P(t) + U_N(t) + U_S(t) \qquad (27)$$

where, $U_P(t)$, $U_N(t)$ and $U_S(t)$ are PD controller, NN output and sliding mode outputs, respectively.

The PD controller and sliding mode controller guarantees the stability of the overall system and ensures adequate performance prior to convergence of the neural network weights and reduces the steady-state output errors due to disturbance inputs.

PD controller: Considering the following PD control for the Fig. 4 block diagram for eliminate error between x_{1d} and x_1:

$$U_P = -k_p.(x_1 - x_{d1}) - k_d\dot{x}_1 \qquad (28)$$

PID controller: The continuous form of a PID controller, with input e (0) and output u_{PID} (0), is generally given as:

$$u_{PID}(t) = K_P\left[e(t) + \frac{1}{T_i}\int_0^t e(\tau)d\tau + T_d\frac{d}{dt}e(t)\right] \qquad (29)$$

where, K_P is the proportional gain, T_i is the integral time constant and T_d is the derivative time constant. We can also rewrite (28) as:

$$u_{PID}(t) = K_Pe(t) + K_i\int_0^t e(\tau)d\tau + K_d\frac{d}{dt}e(t) \qquad (30)$$

where, $K_i = \frac{K_P}{T_i}$ is the integral gain and $K_d = K_PT_d$ is the derivative gain.

RESULTS AND DISCUSSION

Here, simulation results are presented. The figures show the position versus time (millisec) and the control (the applied voltage) versus time for the system.

First, the sliding mode controller is applied to the magnetic levitation system. The parameters of controllers are chosen such that W = 350, λ_1 in sliding surface is set as 61 and λ_2 = 930. The simulation results are shown in Fig. 5. It can be seen from the Fig. 5 that there is a small steady-state error in the position and some chattering can be seen due to this controller. Figure 6 shows sliding mode controller that we eliminate steady-state and chattering by using saturation function instead of sign function (14).

Second, the RBF-Sliding mode controller of system results are shown in Fig. 7, the control signal has chattering and it is not suitable for voltage source so we proposed modified RBF-Sliding mode controller of magnetic levitation system. The results in Fig. 8 shows that we improve control signal by proposing this new methods.

Third, Fig. 9 shows the FEL-Sliding mode controller of system that there is a small steady-state error in the position and we eliminate it by modified FEL-sliding mode controller. Figure 10 shows the modified FEL-sliding mode controller of magnetic levitation system. For PD controller k_p and k_d are set as 1.4 and 0.5.

Fourth, Fig. 11 shows the PID controller of plant. The parameters of controllers are chosen such that K_P, K_i and K_d are 1990, 9996 and 88.5, respectively.

Finally, in Fig. 12, we compare all results with together. Therefore, the simulation results indicate that the proposed control schemes work well when applied to the magnetic levitation system.

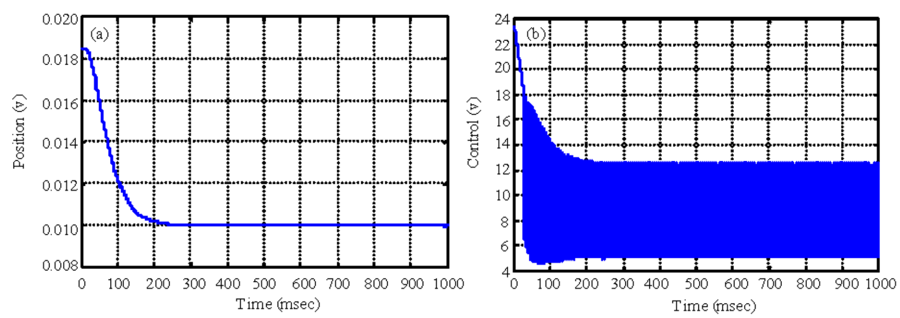

Fig. 5: Classical sliding mode control (a) position of ball and (b) control signal)

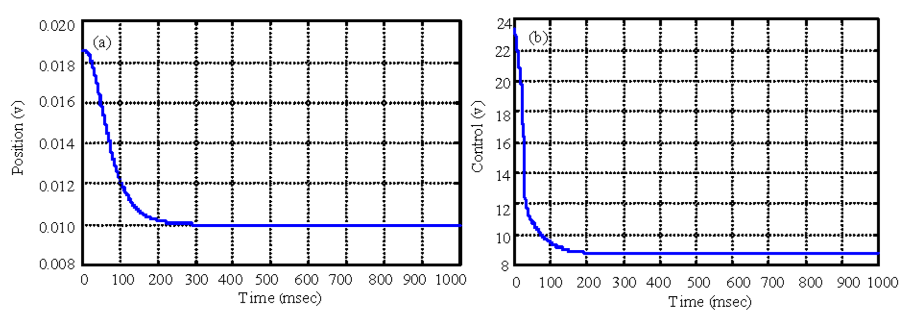

Fig. 6: Sliding mode without chattering (a) position of ball and (b) control signal

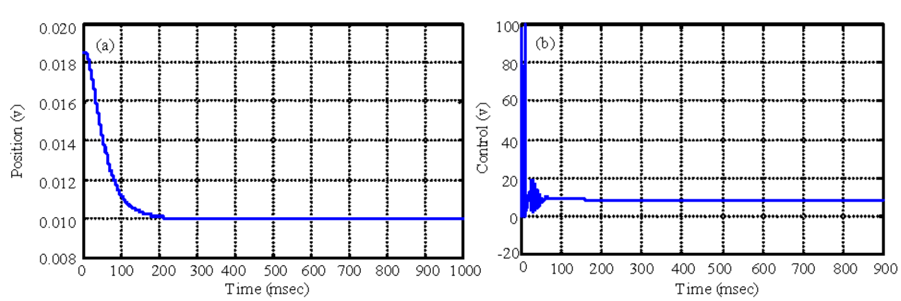

Fig. 7: RBF-Sliding mode controller without low pass filter (a) position of ball and (b) control signal

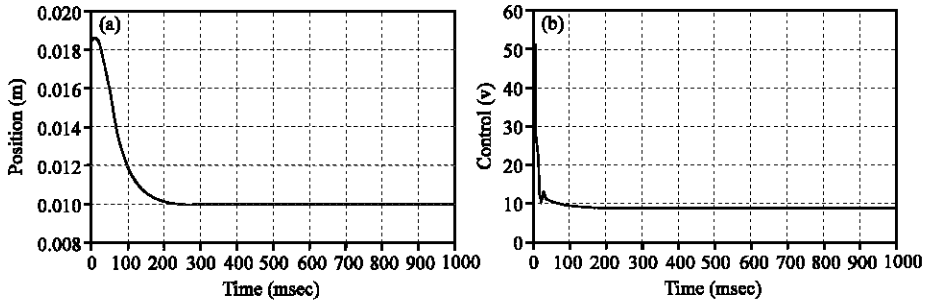

Fig. 8: Modified RBF-Sliding mode controller (a) position of ball and (b) control signal

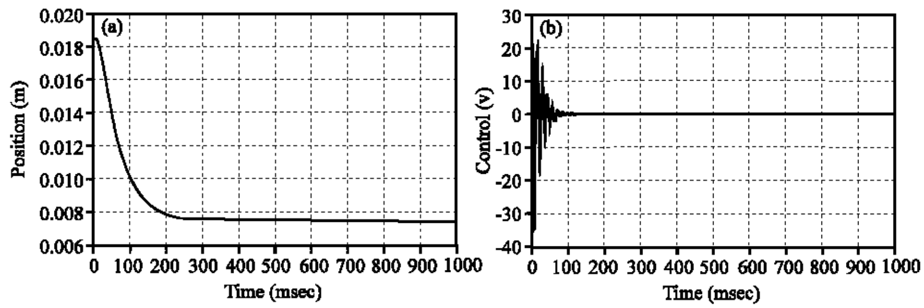

Fig. 9: FEL-Sliding mode controller without PD controller (a) position of ball and (b) control signal

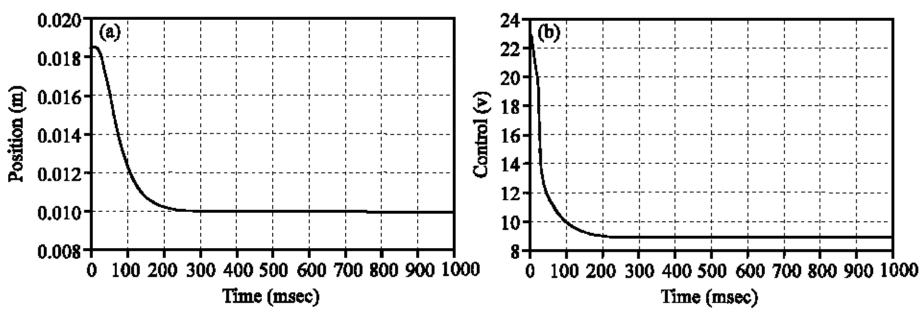

Fig. 10: Modified FEL-sliding mode controller (a) position of ball and (b) control signal

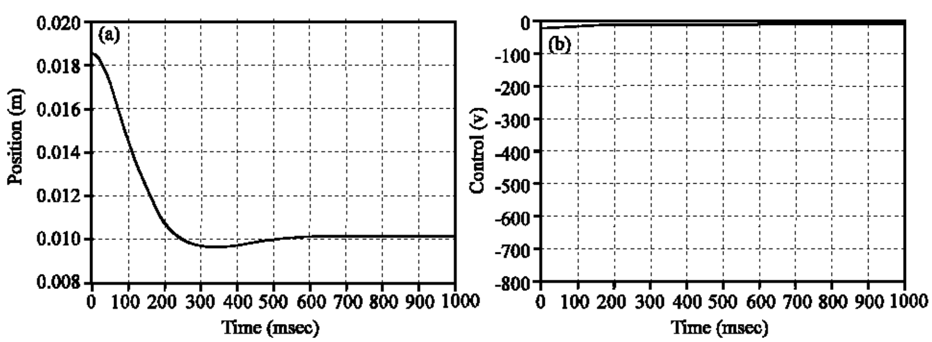

Fig. 11: PID controller (a) position of ball and (b) control signal

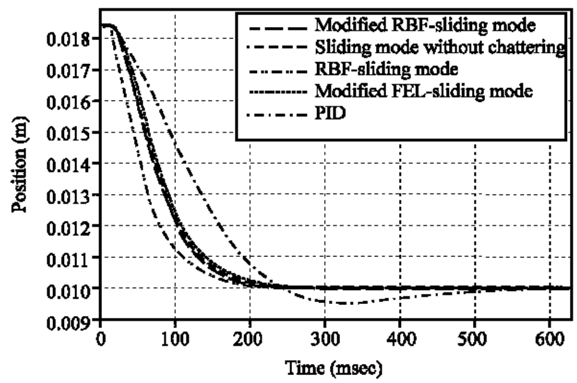

Fig. 12: Comparison of all methods results (Modified RBF-Sliding mode, Sliding mode without chattering, RBF-Sliding mode, Modified FEL-Sliding mode and PID)

CONCLUSION

This study introduced classical and hybrid methods for control the magnetic levitation system which has practical uses in many industrial systems.

In this research, a new RBF-sliding mode control method, a new FEL-sliding mode control method and modified FEL-sliding controller for magnetic levitation is proposed, which combines the merits of adaptive neural network and sliding mode control. Based on the Lyapunov stability theory, a RBF-sliding mode controller is designed for stabilization of magnetic levitation system to the desired point in the state space. The adaptive neural network controller in this new approaches uses generalized learning rule therefore does not need to compute Jacobain of plant which comes more simplicity. Simulation results show that the proposed hybrid controllers are able to control magnetic levitation and the chattering phenomenon of conventional switching type sliding control does not occur any more in control process.

REFERENCES

Anh, P.P. and J.G. Timothy, 2008. Direct adaptive fuzzy control with a self-structuring algorithm. Fuzzy Set Syst., 159: 871-899.

Barie, W. and J. Chiasson, 1996. Linear and nonlinear state-space controllers for magnetic levitation. Int. J. Syst. Sci., 27: 1153-1163.

Chao-Lin, K., T.H.S. Li and N.R. Guo, 2005. Design of a novel fuzzy sliding-mode control for magnetic ball levitation system. J. Intel. Robotic Syst., 42: 295-316.

Chen, M.Y., C.C. Wang and L.C. Fu, 2001. Adaptive sliding mode controller design of a dual-axis maglev positioning system. Proceeding American Control Conference, Virginia, 5: 3731-3736.

Cho, D., Y. Kato and D. Spilman, 1993. Sliding mode and classical controllers in magnetic levitation systems. IEEE Control Syst. Mag., 13: 42-48.

Covert, E.E., 1988. Magnetic Suspension and balance systems. 1st Edn. IEEE AES Magazine, pp: 14-22.

Hajjaji, A. El and M. Ouladsine, 2001. Modeling and nonlinear control of magnetic levitation systems. IEEE Trans. Ind. Elect., 48: 831-838.

Huang, C.M., J.Y. Yen and M.S. Chen, 2000. Adaptive nonlinear control of repulsive maglev suspension systems. Control Eng. Pract., 8: 1357-1367.

Jing-Chung, S., 2002. H_∞ control and sliding mode control of magnetic levitation system. Asian J. Control., 4: 333-340.

Kawato, M., Y. Uno, M. Isobe and R.A. Suzuki, 1988. Hierarchical model for voluntary movement and with application to robotics. IEEE Control Syst. Mag., 8: 8-16.

Lairi, M. and G. Bloch, 1999. A neural network with minimal structure for maglev system modeling and control. Proceeding 1999 IEEE international symposium on intelligent control/intelligent systems and semiotics, October, Massachusetts, pp: 40-45.

Muñoz-Gómez, J.A., P. González-Casanova and G. Rodríguez-Gómez, 2006. Domain decomposition by Radial Basis Functions for time dependent partial differential equations. Proceedings of the International Conference Advances in Computer Science and Technology, January 23-25, IASTED. pp: 105-109.

Muthairi, N. and M. Zribi, 2004. Sliding mode control of a magnetic levitation. Math. Problem Eng., 2: 93-107.

Park, J. and J.W. Sandberg, 1991. Universal approximation using radial basis functions network. Neural Comput., 3: 246-256.

Poggio, T. and F. Girosi, 1987. Networks for approximation and learning. Proceedings of IEEE, Sep, IEEE. pp: 1481-1497.

Powell, M., 1987. Radial Basis Functions for Multivariable Interpolation. In: A Review, Mason, J.C. and M.G. Cox (Eds.). Algorithms for Approximation, pp: 143-167.

Rifai, O. El and K. Youcef-Toumi, 1998. Achievable performance and design trade-offs in magnetic levitation control. Proceeding 5th International Workshop on Advanced Motion Control (AMC'98), July, Coimbra, Portugal, pp: 586-591.

Slotin, J.J.E. and W. Li, 1991. Applied Nonlinear Control. 1st Edn. Prentice Hall, New York .

Tanaka, A. and S. Torii, 2004. Magnetic levitation control with real-time and fewer sensors using finite element method. Int. J. Applied Elect. Mech., 19: 679-683.

Teng, N.G and B.P. Qiao, 2008. Vibration analysis of continuous maglev guideways with a moving distributed load model. J. Phys. Conf. Ser., 96: 1-6. 10.1088/1742-6596/96/1/012117

Trumper, D.L., M. Olson and P.K. Subrahmanyan, 1997. Linearizing control of magnetic suspension systems. IEEE Trans. Control Syst., 5: 427-438.

Yang, Z.J. and M. Tateishi, 1998. Robust nonlinear control of a magnetic levitation system via backstepping approach. Proceeding of 37th SICE Annual Conference (SICE '98), July, Chiba, Japan, pp: 1063-1066.

Zhao, F., S.C. Loh and J.A. May, 1999. Phase-space nonlinear control toolbox: the maglev experience. 5th International Hybrid Systems Workshop, September, Lecture Notes in Computer Science, Springer-Verlag, London, pp: 429-444.