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Integration Intelligent Estimators to Disturbance Observer to Enhance Robustness of Active Magnetic Bearing Controller

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Abstract One of the essential components of rotary systems is bearing which is supporting load of rotor. Active magnetic bearings can remove contact point between rotor and supports by magnetic force. Controlling magnetic force is key point of this system to keep mechanical balancing of rotor. Due to high revolution speed of rotors, disturbances produce instability. The Disturbance Observer Algorithm (DO) is an approach to reduce effects of disturbances. The DO Controller was combined to generic PID Controller to improve performance of AMB. In DO, estimation mass is vital to enhance stability and accuracy of that. So, artificial neural network and iterative learning were hybridized to DO as intelligent techniques in estimation mass. Simulation assessment reveals iterative learning showed superior results in terms of accuracy and stability of AMB responses to the disturbances.

Keywords Active Magnetic Bearing, Disturbance Observer, Iterative Learning Algorithm, Neural Network, System Dynamics

1. Introduction

Bearing plays important role in rotary machineries such as pumps, turbines, engines, and compressors etc. one of the bearing family which was introduced recently is Active Magnetic Bearing (AMB). This type of bearing can prepare proper conditions to remove any physical contact between rotor and bearing via magnetic field. So, rotor weight and external loads are supported without contact, and rotational speed can reach to very higher values. To prevent of failure, the air gap between rotor shaft and stator (electromagnetic coils) must be kept constant via controller system. AMBs are nonlinear and unstable naturally, and most of controller designs are based on linear dynamic models [1]. The PD controller for an AMB evaluated and compared to fuzzy controller [2]. They were success to reduce instability of AMB. Using PID controller in low frequency range showed that AMB has low damping property [3]. In other hand, based on a research finding, the PID controller is not suitable for AMB [4]. Moreover, LQR was exploited in AMB, and results demonstrated better performance compared to PID [5, 6]. Generally, PID controllers are not suitable for high speed disturbances. One of the control schemes which were used to face on this problem is Disturbance Observer (DO). Current paper is aimed to develop Disturbance Observer Algorithm with using Iterative Learning (IL) and Neural Network (NN) to cancel disturbances effect.

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2. Dynamic Model of AMB

As stated previous, the major duty of control system is stabilizing rotor motion around balancing point. Thus, controller must supply return force for rotor to balancing point like as spring force. Besides, force control must present damping to decrease vibration around balancing point.

The magnets forces are related to electrical current according to bellow equation:

$$\overline{\mathrm{F}} = \frac{\mu_0 N^2 A_g i^2}{4 g_0^2} \tag{1}$$

As can be seen in equation (1), force has inverse relationship to square of air gap. Moreover, force equation is nonlinear. Normally, Linearization techniques are utilized to make it linear equation. Typically two magnets are employed front of together and work to have positive and negative forces. Refer to Fig.1 magnet force, f_x, can be reached as following:

$$f_x = f_+ - f_- = k\left(\frac{(i_0+i_x)^2}{(s_0-x)^2} - \frac{(i_0-i_x)^2}{(s_0+x)^2}\right)\cos\alpha \tag{2}$$

By simplification and linearization previous equation we have:

$$f_x = \frac{4ki_0}{s_0^2}(\cos\alpha)i_x + \frac{4ki_0^2}{s_0^3}(\cos\alpha)x = k_i i_x - k_s x \quad (3)$$

$$k_i \equiv \frac{4ki_0}{s_0^2}(\cos\alpha)\,, \quad k_s \equiv \frac{4ki_0^2}{s_0^3}(\cos\alpha) \quad (4)$$

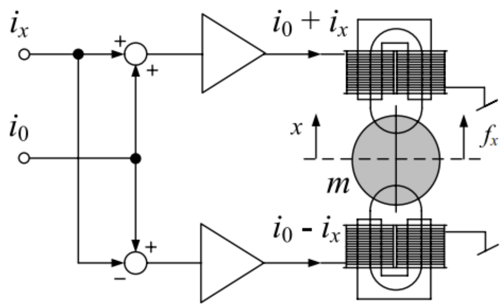

Figure 1. Mode of differences in AMB actuator [1]

The magnetic force around balance point can be considered as bellow:

$$f_x(x,i) = k_i i_x - k_s x \quad (5)$$

The rotor revolution in magnetic field produces voltage in bearing stator like as electrical motor. This induced voltage is related to rotor revolution speed (x). So, the total voltage of amplifier to face on inductance will be [1]:

$$u = Ri + L\frac{d}{dt}i + k_u\frac{d}{dt}x \quad (6)$$

3. Design Position Control

Firstly, a generic controller from PID family was designed to control position of rotor in balancing point. Fig.2 and 3 present block diagram of AMB controller and simulated that in MATLAB/Simulink, respectively. Also, AMB parameters are listed in Table 1. The PID parameters were reached by crude method.

Table 1. AMB parameter [1]

Symbol	Value	Units
m	0.1	Kg
k_s	-10^4	N/m
k_i	10	N/A
$f_e\Delta$	100	N
r	0	m

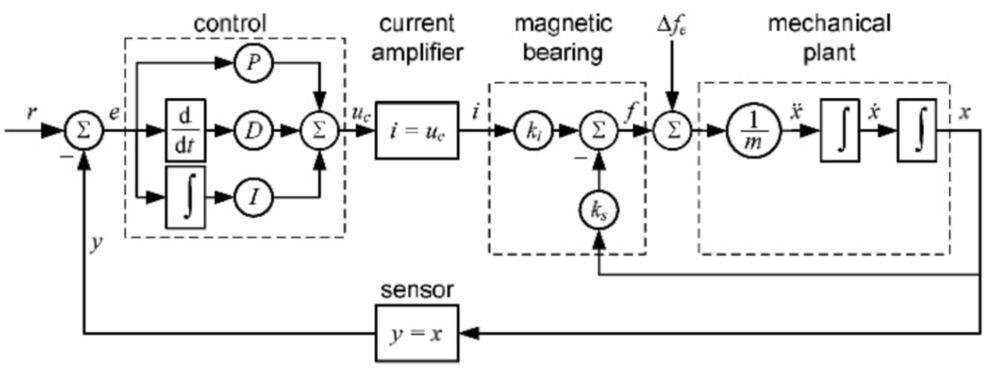

Figure 2. Block diagram of AMB controller [1]

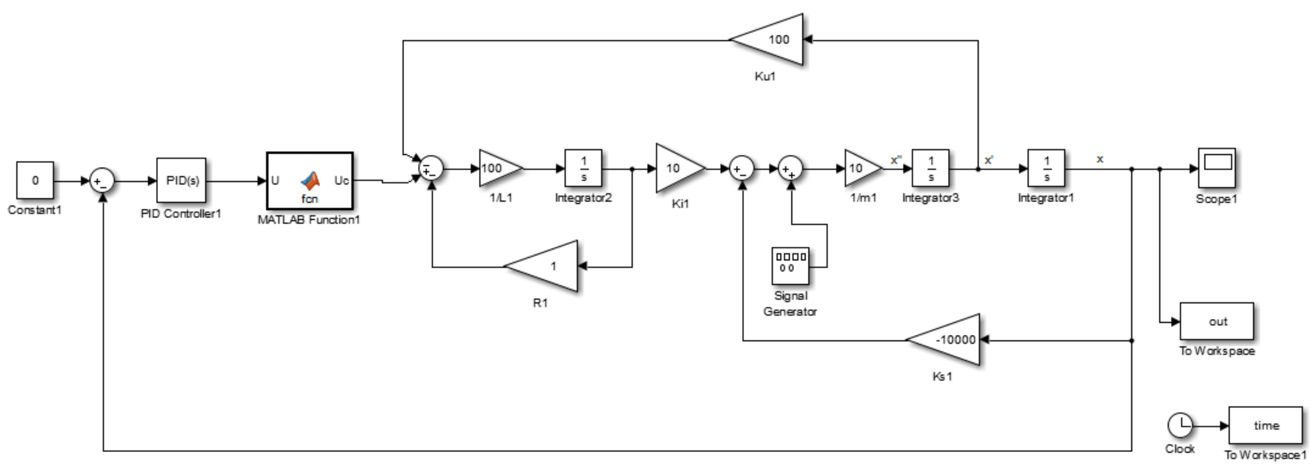

Figure 3. The schematic PID designed for AMB

4. Integration Disturbance Observer to AMB Position Controller

The main concept of the DO scheme is exemplified in Fig.4. The output of system can be mentioned in terms of the reference control input, the external disturbance, and the measurement noise. In fact, the DO prepares compensation force calculated from disturbance, and it is returned to actuator to face to disturbances. This outer loop increases stability of the system by force control.

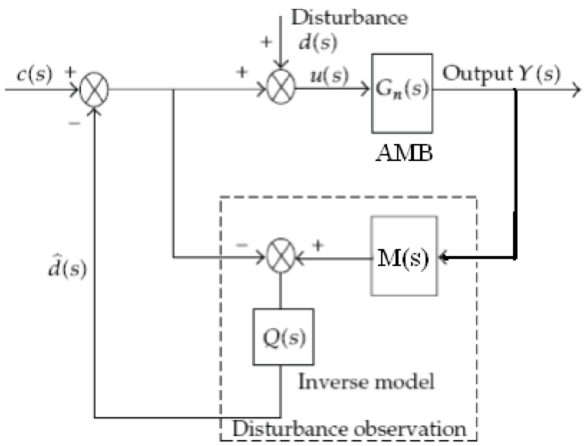

Figure 4. Block diagram of DO

Regards to Fig.4, the u(s) will be as:

$$u(s) = c(s) - \hat{d}(s) + d(s), \quad (7)$$

Where, c(s) is PID control signal, and $\hat{d}(s)$ is disturbance estimation. The position signal, *Y(s)*, is converting to estimated force signal by following equation:

$$M(s)=d/dt[d/dt[Y(s)]]*m \quad (8)$$

Where, *m* is estimated mass of rotor. The result of subtracting actuated force and estimated force the disturbance force, $\hat{d}(s)$, can be acquired. The key part of DO is estimation of mass, and accuracy of controller can be increased by that [9]. Various techniques can be utilized to this purpose such Fuzzy Logic [11], On-line NN [10], IL [12-14], Off-line ANN [15-18]. In this paper, the results of integration NN and IL in predicting estimated mass to AMB controller are compared together.

4.1. Iterative Learning Algorithm in DO Controller of AMB

The iterative learning algorithm (ILA) is an intelligent technique during the performance of a dynamical system be improved and improved as time increased based on reducing the error. Uchiyama first time represented the basic concept of the ILA [19]. Fig.5 reveals a block diagram of the proportional-Integral-Derivative type (PID-type) of ILA.

The input signal, u_k, and the recent output signal, y_k, are stored in memory each iteration of processing. The system error, $e_k = y_d - y_k$, is assessed by the learning algorithm where y_d is the preferred output of the system. Subsequently, algorithm computes a new input signal u_{k+1} refer to this error signal, which is saved for next iteration. The next input command is selected where as it causes to the performance error to be decreased on the subsequently iteration. To have enhanced convergence and stability in output of algorithm, integrator and derivative units were integrated to ILA which is called PID-ILA. The equations explaining PID-ILA is affirmed following:

$$u_{k+1} = u_k + (\Phi + \Gamma \frac{d}{dt}) e_k \quad (9)$$

$$u_{k+1} = u_k + (\Phi + \Psi \int dt) e_k \quad (10)$$

$$u_{k+1} = u_k + (\Phi + \Gamma \frac{d}{dt} + \Psi \int dt) e_k \quad (11)$$

Where Φ, Γ and Ψ are proportional, derivative and integral learning parameters, respectively. The coefficients of ILA “Φ, Γ, and Ψ” were tuned as 0.0001 by Heuristic method. The simulated DO-IL is exemplified in Fig. 6, and results of that is discussed and compared to DO-NN and PID in next section.

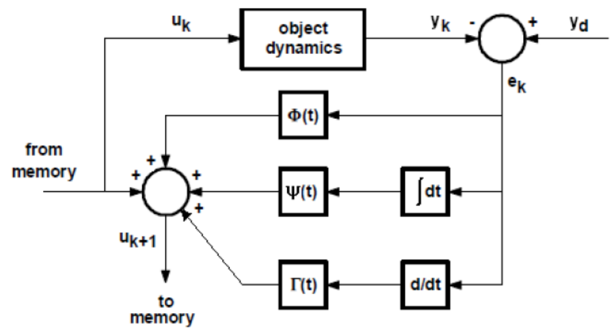

Figure 5. Block diagram of the PID-type of ILA

4.2. Neural Network Algorithm in DO Controller of AMB

A typical NN multilayer feed forward structure involves of neurons as input, hidden and output layers. They are interrelated through weights refreshed as the training process. Threshold or activation functions are applied at the output. The mainly ordinary equation that stated the input/output relationship of a neuron is expressed as following:

$$y = f\left(\sum_{i=1}^{m} w_i I_i + b\right) \quad (12)$$

Where I_i is the set of inputs, w_i is the synaptic weight connecting the j_{th} input to the i_{th} neuron, b_i is a bias, f( ) is the activation function, and y_i is the output of the i_{th} neuron considered. The back propagation error algorithm is normally used as training algorithm. This algorithm tuned the weights and biases during learning process via input-target sets by minimizing the error between target and network output. The NN algorithm were exploited to predict estimated mass and send it to DO algorithm which was hybridized to AMB controller (called NN-DO). The proposed NN includes 6 hidden layers, and each layer has 5 neurons. The input of NN is error signal, and output of that is estimated mass. Training was performed offline with Levenberg-Marquardt (LM) Algorithm. The NN-DO simulated by MATLAB/Simulink is represented in Fig.7.

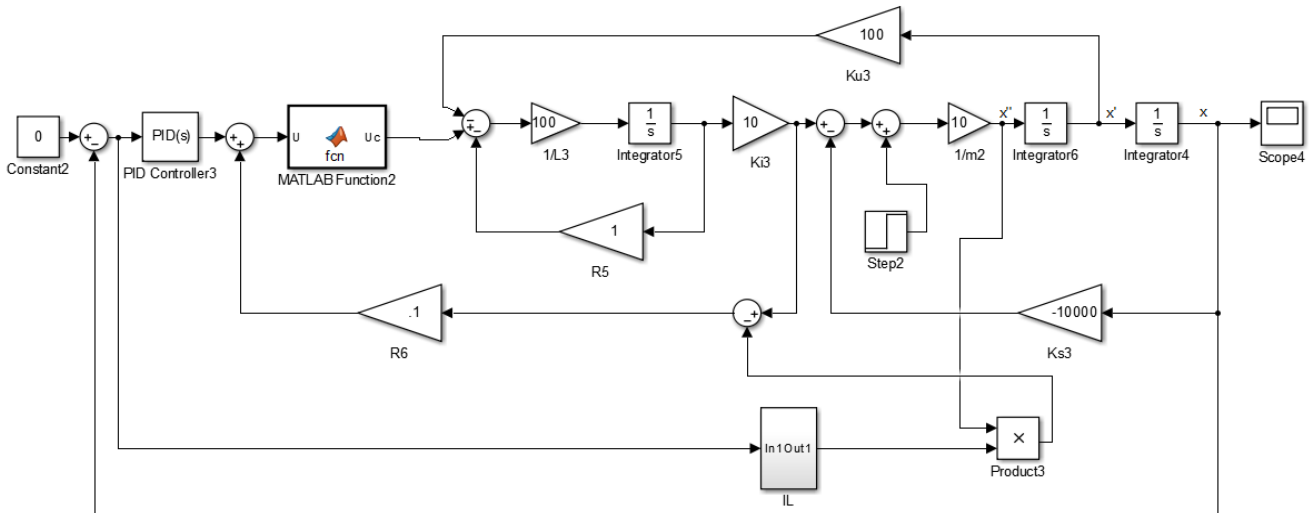

Figure 6. Applied DO-IL in AMB

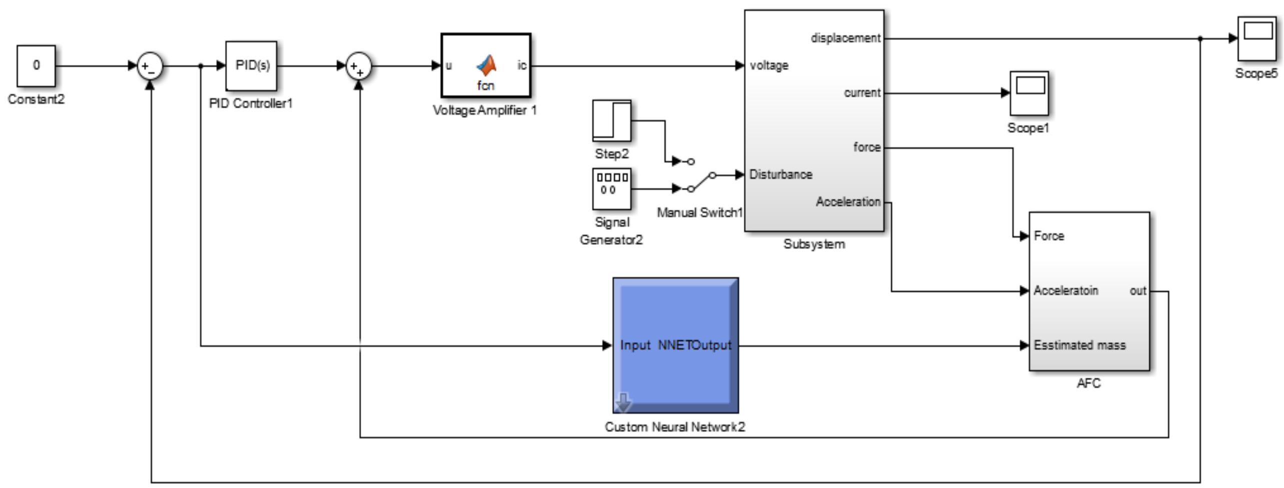

Figure 7. AMB PID controller integrated to NN-DO

5. Results and Discussion

Fig.8 illustrates responses of AMB to the step input via PID Controller, IL-DO, and NN-DO. As can be seen, the overshoot by conventional PID is higher than NN-DO and IL-DO. Moreover, the overshoot of IL-DO is half of NN-DO, and both of them reach to set point faster than PID. In Fig.9, previous result is zoomed to better comparison. The stability of output by IL-DO was increased. Therefore, the robustness of AMB was increased and variation was decreased dramatically by DO Controllers.

Subsequently, white noise random disturbance was exposed to the AMB. The output of three controllers is shown in Fig.10.

Regards to Fig.10, PID Controller generates higher peaks in output while IL-DO and NN-DO peaks are very lower than PID. The notable point is that peaks obtained by IL-DO are lower than NN-DO. For more comparison, these time domain results transformed to frequency domain and unveiled in Fig.11 to 13. As can be observed, the peaks of IL-DO and NN-DO is very lower to PID. In other words, the peaks of DO controllers results is one tenth of PID Controller output.

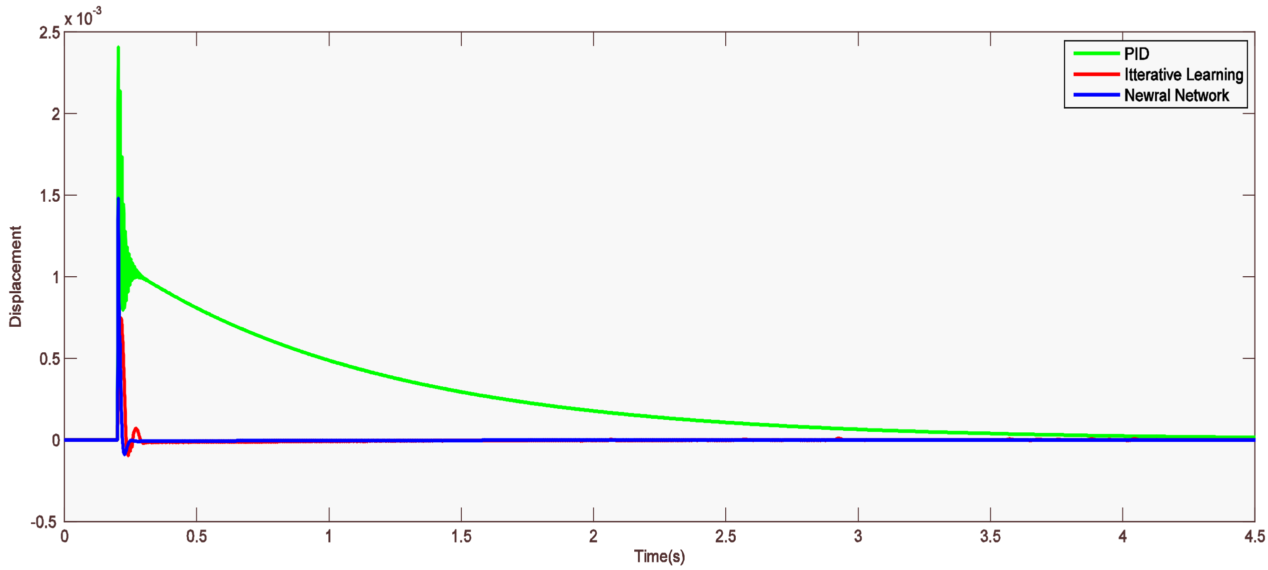

Figure 8. Time responses of AMB with different controllers

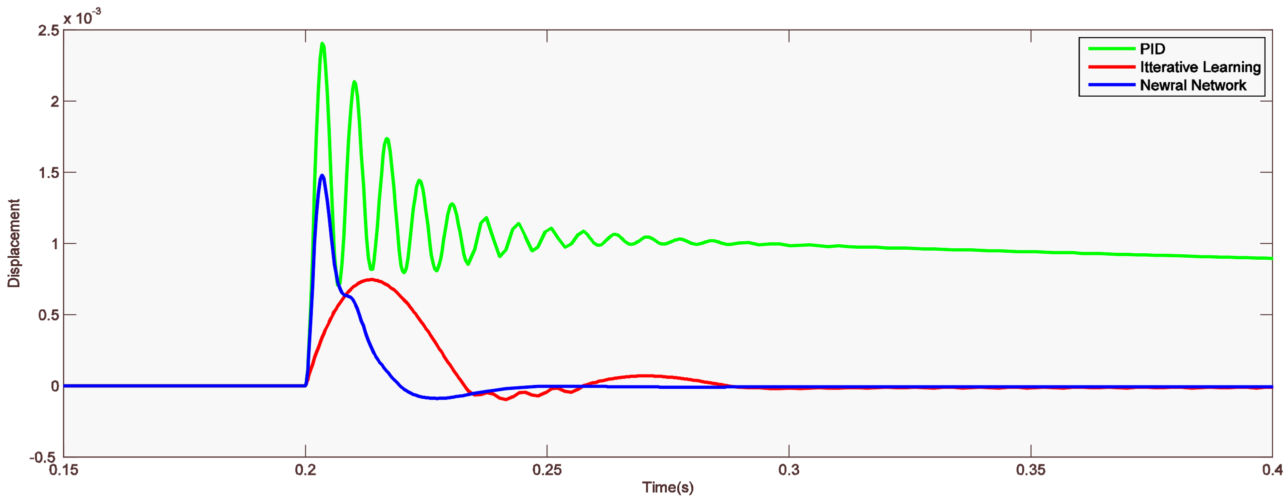

Figure 9. Magnification of Fig.7 for more comparisons

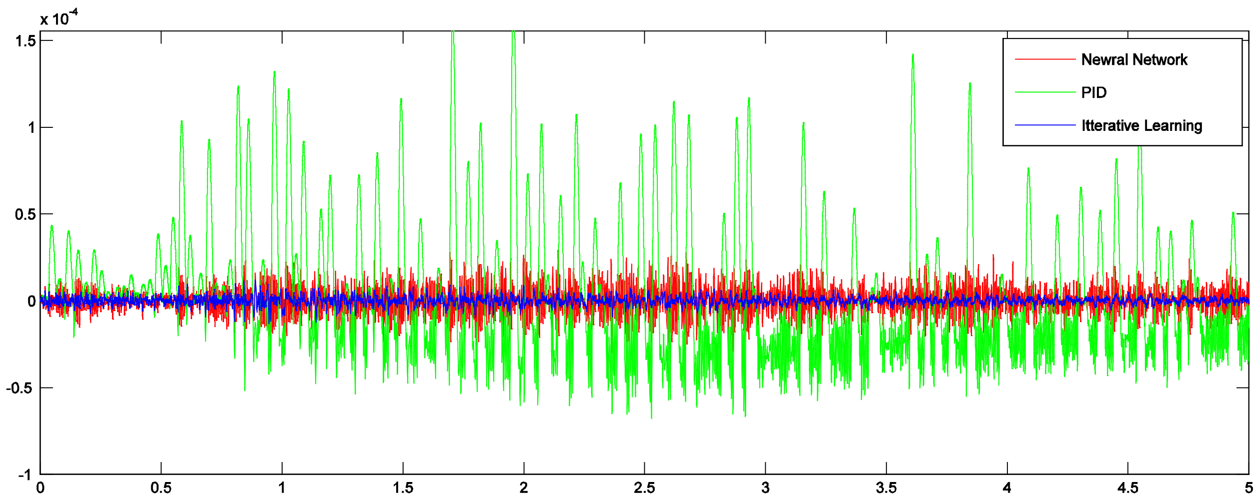

Figure 10. AMB responses to the White Noise Random disturbance with three controllers

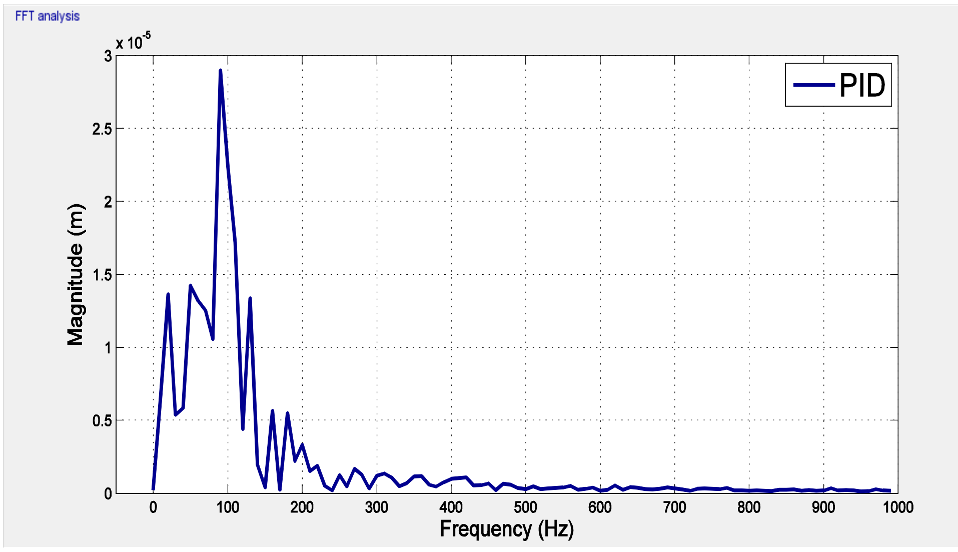

Figure 11. PID responses to the White Noise Random disturbance in frequency domain

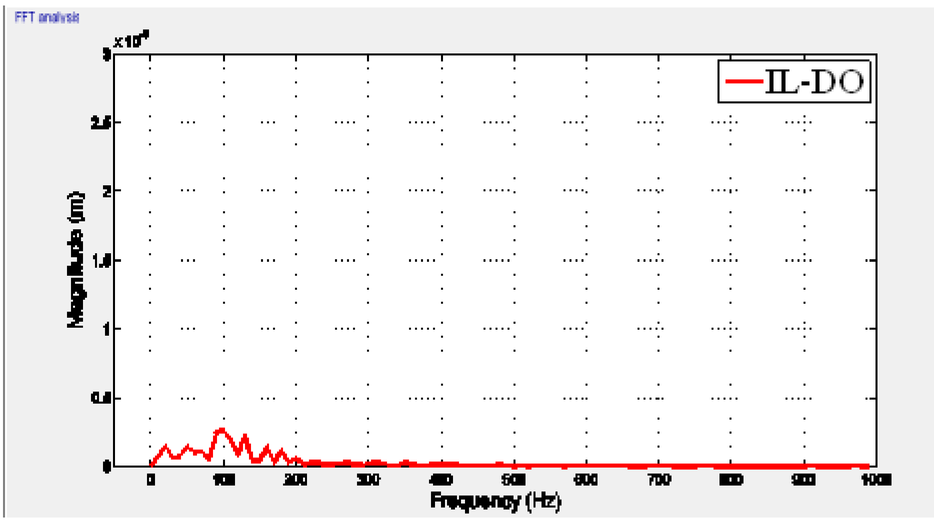

Figure 12. IL-DO responses to the White Noise Random disturbance in frequency domain

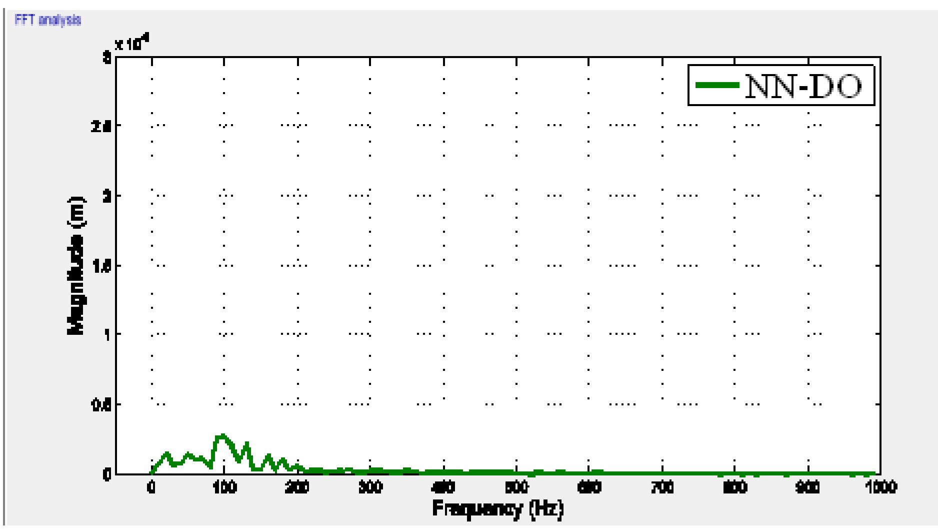

Figure 13. NN-DO responses to the White Noise Random disturbance in frequency domain

6. Conclusions

A novel controller called the disturbance observer (DO) was integrated to the active magnetic bearing. The DO Controller can eliminate effect of disturbances by simple inner control loop. This DO controller was combined to artificial neural network and iterative learning algorithm named NN-DO and IL-DO, respectively. The designed controllers were simulated for the suppression of disturbances inserted to AMB balance point. The results of simulations illustrate that the performance of DO is better than traditional PID Controller. In addition, combining NN and IL to DO generates different responses of AMB with higher stability. IL-DO shows superior efficiency in suppression of overshoot compared to NN-DO. However, complementary study should be conducted to investigate the effects of other forms of disturbances, uncertainties and parametric changes in practical condition.

REFERENCES

[1] Bleuler, H., et al., Magnetic bearings: theory, design, and application to rotating machinery. 2009: Springer Science & Business Media.

[2] Hartavi, A., O. Ustun, and R. Tuncay. A comparative approach on PD and fuzzy control of AMB using RCP. in Electric Machines and Drives Conference, 2003. IEMDC'03. IEEE International. 2003. IEEE.

[3] Keith, F., et al., Digital control of magnetic bearings supporting a multimass flexible rotor. Tribology transactions, 1990. 33(3): p. 307-314.

[4] Habib, M.K. and J.I. Inayat-Hussain. Control of dual acting magnetic bearing actuator system using fuzzy logic. in Computational Intelligence in Robotics and Automation, 2003. Proceedings. 2003 IEEE International Symposium on. 2003. IEEE.

[5] Kim, H.-Y. and C.-W. Lee, Design and control of active magnetic bearing system with Lorentz force-type axial actuator. Mechatronics, 2006. 16(1): p. 13-20.

[6] Grega, W. and A. Pilat, Comparison of linear control methods for an AMB system. International Journal of Applied Mathematics and Computer Science, 2005. 15(2): p. 245.

[7] Somad, F., System identification and control of magnetic bearing systems. 2007, Victoria University.

[8] Rosli, R. and M. Mailah, Active Force Control with Iterative Learning Control Algorithm Applied to Vehicle Suspension System. Recent Advances in Electrical Engineering Series, 2013(11).

[9] Hewit, J. and J. Burdess, Fast dynamic decoupled control for robotics, using active force control. Mechanism and Machine Theory, 1981. 16(5): p. 535-542.

[10] Mailah, M., Intelligent active force control of a rigid robot arm using neural network and iterative learning algorithms. 1998, University of Dundee.

[11] Priyandoko, G. and M. Mailah, Simulation of suspension system with adaptive fuzzy active force control. To all Intelligent Active Force Control Research Group, 2007: p. 30.

[12] Tahmasebi, M., et al., Sprayer Boom Active Suspension Using Intelligent Active Force Control. Journal of World Academy of Science, Engineering and Technology, 2012. 68: p. 1277-1281.

[13] Gohari, M., et al., Structure Isolation of Base Excitation by Active Force Control Method.

[14] Mailah, M., J. Hewit, and S. Meeran, Active force control applied to a rigid robot arm. Jurnal Mekanikal, 1996. 2(2): p. 52-68.

[15] Gohari, M., & Tahmasebi, M. (2015). Active off-road seat suspension system using intelligent active force control. Journal of Low Frequency Noise, Vibration and Active Control, 34(4), 475-489.

[16] Tahmasebi, M., Rahman, R. A., Mailah, M., & Gohari, M. (2013). Active force control applied to spray boom structure. In Applied Mechanics and Materials (Vol. 315, pp. 616-620). Trans Tech Publications.

[17] Gohari, M., Rahman, R. A., Raja, R. I., & Tahmasebi, M. (2012). A novel artificial neural network biodynamic model for prediction seated human body head acceleration in vertical direction. Journal of Low Frequency Noise, Vibration and Active Control, 31(3), 205-216.

[18] Tahmasebi, M., Rahman, R. A., Mailah, M., & Gohari, M. (2013). Roll movement control of a spray boom structure using active force control with artificial neural network strategy. Journal of Low Frequency Noise, Vibration and Active Control, 32(3), 189-201.

[19] Arimoto, S., Kawamura, S. and Miyazaki, F., Bettering operation of robots by learning, J. Robotic Syst (1984), Vol.1, pp. 123140.