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NEURAL NETWORKS CONTROL OF MAGNETIC BEARINGS FOR LOW SPEED ROTOR SYSTEMS

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Abstract

In this paper the application of neural networks to the control of magnetic bearings for a low speed rotor system is examined. The application of the neural network control method to a magnetic bearing system with self-excited and forced disturbances is reviewed. In modelling the system, the shaft is first discretized into eighteen finite elements and then four levels of condensation are applied. This leads to a system with six masses and six compliant elements which can be described by twelve state variable. A PD controller was designed first and then used to train the neural network controller. The trained neural network controllers show better results than the original PD controller after three training sessions. For the neural network control scheme discussed, two-layers neural networks have been used in the simulation work. The reinforcement, error-propagation, and temporal-difference methods have been used in the neural network controller. The simulation results show low sensitivity to external periodic disturbances can be achieved for speeds up to 2500 rpm using the proposed neural network controller.

1. Introduction

Magnetic bearing systems are inherently unstable when the shaft and rotor turn at speeds above the first critical speed. In this case the shaft bends from the axis of rotation when either transient or external periodic disturbances are applied. In such systems with a long slender shaft both self-excited and forced instabilities can often lead to severe rotor vibrations. The usual control task for these systems is to ensure that these vibrations are minimised rapidly and the location of the rotor is controlled accurately. This problem has been studied using H^{∞}, root locus, PID, and LQR, methods. In addition the neural network methods have been studied, and it has been shown that good stability can be achieved when transient disturbances are applied [1, 2]. However when external periodic disturbances are applied to the magnetic bearing system the above approaches have proven to give poor robustness.

In this paper we study the operation of a rotor supported on two magnetic bearings. The rotor is assumed to be operating at speeds up to and above the first critical speed, but below speeds where gyroscopic effects are significant. Four classes of neural network control have been identified, depending upon how the controller interacts with each bearing and its axes. In this paper we examine the case where each plane of the bearing system has its own neural network controller, and study the effect of external periodic disturbances on the system operation using computer simulation.

The computer simulation of the control system uses two-layer artificial neural networks. In this scheme one neural network is the *evaluation network* while the other is the *action network*. The three algorithmic methods of error back-propagation, temporal difference, and reinforcement learning are used for the neural network controller. The software package MATLAB is used for carrying out the simulation of the neural network control system.

The operation of the magnetic bearing system with external periodic disturbances is also studied by using computer simulation. Disturbances in terms of different initial displacements and external periodic disturbance inputs are imposed. The training sessions are used for testing the algorithms. Simulation shows that initially many iteration are required for the controller to converge. The effect of rotor speed changes on the neural network controller operation is investigated. Simulation investigation of the system stability and robustness is carried out for various types of applied disturbances.

2. Model of the Magnetic Bearing System

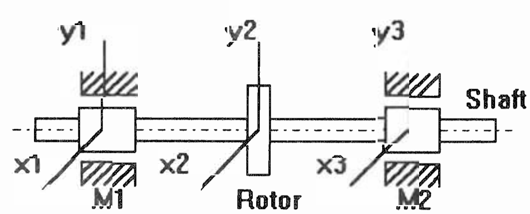

Figure 1. The rotor system general arrangement.

The magnetic bearing suspension system being considered has a flexible shaft as shown in Fig. 1. The shaft is supported at the left and right ends by two magnetic bearings M_1 and M_2 with the rotor being positioned on the shaft as shown in the above figure. The displacements of the bearing journals are defined to be x_1, y_1, x_3 and y_3. In the system model, the rotor flywheel structure was divided into eighteen elements. The finite element method was used to calculate the mass and stiffness of the shaft [7]. Four levels of condensation were applied to the eighteen finite elements. This leads to a mathematical model of the shaft having twelve state variables

$$x = [x_1, x_2, x_3, y_1, y_2, y_3, \dot{x}_1, \dot{x}_2, \dot{x}_3, \dot{y}_1, \dot{y}_2, \dot{y}_3]$$

In this system the bearing forces are generated by electro-magnet coils and the shaft position is detected by a displacement sensor. The sensor signals are fed through the controllers to the power amplifiers which finally supply the excitation currents to the electro-magnet coils.

2.1 Model of the Shaft

The finite element method was used to calculate the mass matrix M_s and stiffness matrix K_s of the shaft. From Fig. 1 these matrices were calculated to be

$$Ms_1 = \begin{bmatrix} 0.7743 & -0.2619 & 0.0651 & 0 & 0 & 0 \\ -0.2619 & 1.7413 & -0.2186 & 0 & 0 & 0 \\ 0.0651 & -0.2186 & 0.7835 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.7743 & -0.2619 & 0.0651 \\ 0 & 0 & 0 & -0.2619 & 1.7413 & -0.2186 \\ 0 & 0 & 0 & 0.0651 & -0.2186 & 0.7835 \end{bmatrix}$$

$$Ks_1 = \begin{bmatrix} 45.792 & -79.524 & 38.039 & 0 & 0 & 0 \\ -79.524 & 157.69 & -76.209 & 0 & 0 & 0 \\ 38.039 & -76.209 & 46.656 & 0 & 0 & 0 \\ 0 & 0 & 0 & 45.792 & -79.524 & 38.039 \\ 0 & 0 & 0 & -79.524 & 157.69 & -76.209 \\ 0 & 0 & 0 & 38.039 & -76.209 & 46.656 \end{bmatrix}$$

2.2 Model of the Magnetic Force

The magnetic force can be modelled as a nonlinear function of the journal displacements and the control currents. In this model, the journal displacements have four directions x_1, x_3, y_1, and y_3 as shown in Fig. 1 and the control currents are defined as i_1, i_3, i_2, and i_4. A pair of general variables (x, i) are used for modelling of the magnetic force, $(x, i) \in \{(x_1, i_1), (x_3, i_3), (y_1, i_2), (y_3, i_4)\}$. The force has been shown by Krodkiewski and Zmood [7] to be

$$f(x,i) = k\{\phi_1(i)\varphi_1(x) + \phi_2(i)\varphi_2(x)\} \qquad (2\text{-}1)$$

In Eq. (2-1), the coefficient can be written as

$$\phi_1(i) = (F+ni)^2, \qquad \phi_2(i) = (F-ni)^2$$

$$\varphi_1(x) = \frac{1}{1-(x/c)^2}\frac{\sin\alpha}{1+(x/c)\cos\alpha} - \frac{2x/c}{\left(1-(x/c)^2\right)^{3/2}} \times \arctan\left(\sqrt{\frac{1-x/c}{1+x/c}}\tan(\alpha/2)\right)$$

and

$$\varphi_2(x) = \frac{-1}{1-(x/c)^2}\frac{\sin\alpha}{1-(x/c)\cos\alpha} - \frac{2x/c}{\left(1-(x/c)^2\right)^{3/2}} \times \arctan\left(\sqrt{\frac{1+x/c}{1-x/c}}\tan(\alpha/2)\right)$$

where

- $f(x, i)$ is the magnetic force [N]
- k is the bearing actuator force coefficient ($1.49 \times 10^{-4} N/(A\text{-}t)^2$).
- F is the permanent magnet air-gap MMF (F=299 A-t).
- n is the control winding turns (n = 140 *turns*).
- c is the stator-rotor air-gap (c = 0.15 *mm*).
- x is the displacement of the shaft ($-0.15\ mm \le x \le 0.15\ mm$).
- i is the control current ($-2\ A \le i \le 2\ A$).
- α is the pole face angle (α = 45 degree).

From above equations, the magnetic force can be plotted as shown in Figs. 2 and 3.

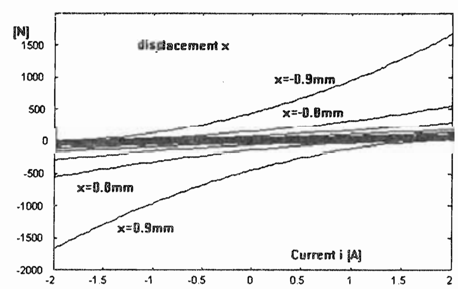

Figure 2. The nonlinear magnetic force.

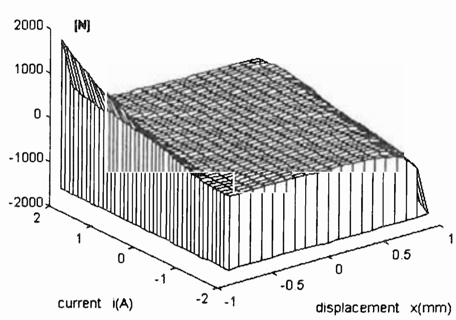

Figure 3. Three dimensional plot of nonlinear magnetic force.

2.3 The Model of the Magnetic Bearing System

The equations of motion used in the simulation of the magnetic bearing system are given in Appendix 1. The magnetic bearing system is modelled using the continuous-time state-space model

$$\begin{cases} \dot{x} = Ax + B(f(x,i) + F_d) \\ y = Cx \end{cases} \tag{2-2}$$

The coefficient matrices for A and B are

$$A = \begin{bmatrix} 0_{6\times 6} & I_{6\times 6} \\ -M_s^{-1}(K_s) & 0_{6\times 6} \end{bmatrix} \quad B = \begin{bmatrix} 0_{6\times 6} \\ M_s^{-1} \end{bmatrix}$$

Expanding Eq. (2-2) into a discrete-time equation gives

$$x(k+1) = A_g x(k) + B_g (f(x,i) + F_d)$$

$$y(k) = Cx(k) \tag{2-3}$$

In this expansion the sample time has been taken as 0.001 seconds.

3. Architecture and Learning Algorithms of Neural Network

In this magnetic bearing system, there are four displacements x_1, x_3, y_1, and y_3 having to be controlled by the neural network controller as shown in Fig. 1. Four classes of neural network control have been identified, depending upon how the controller interacts with each bearing and its axes. In this paper each plane of the bearing system has its own neural network controller. In the present work, the learning system is based on the work by Anderson [3]. The learning system utilizes the temporal difference (TD) method [5], the reinforcement learning method [4], and the connections error back-propagation algorithm. The block diagram of the neural network control system is shown in Fig. 4. This system contains two controller subsystems; these being the *evaluation* and *action networks*. The *action network* functions as a controller where its output is used as an input for controlling the magnetic bearing system operation. The *evaluation network* subsystem is a learning neural network where the evaluation functions are adaptively adjusted during the control system learning phase when both subsystems are simultaneously modified.

During operation a primary objective of the neural network control system is to avoid system 'failure'. This concept can be formalised in terms of the failure signal, which provides information to the evaluation network regarding control system performance during the learning phase. For example this failure signal is given by

$$r(t) = \begin{cases} -1, & \text{if } |x_1| > 0.01mm \\ 0, & \text{otherwise} \end{cases}$$

for the x_1 axis neural network controller. In the *evaluation network* of the output layer, the temporal-difference (TD) method has been used to predict system future behaviour, and thereby provides a solution to the temporal credit-assignment problem.

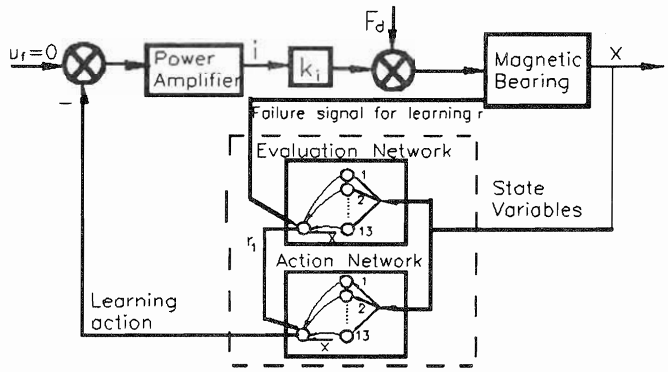

Figure 4. Neural network control system.

Indeed, learning to predict is one of the most basic and prevalent tasks in learning. For the *action network* of the output layer, the supervised learning method cannot be used, because the correcting action is not known. Here learning must be based on the inaccurate, time-varying, and delayed evaluations of the adaptive evaluation function. The numerical approach to learning with such performance feedback is called *reinforcement* learning. This is the on-line learning of an input-output mapping through a process of trial and error designed to maximise a scalar performance index called a reinforcement signal r_1. If the value of r_1 is positive, the probability of an action is increased in the output layer of the action network while if the value of r_1 is negative, the probability of an action is decreased. In this paper the weights in the neural networks are updated at each time step in the manner described in [6]. A PD controller for training the neural network controller is given in Appendix 2.

4. Simulation Results

In this section we examine the operation of a magnetic bearing system using neural network controllers where the rotor is subjected to external periodic disturbances. In the simulations a number of cases of periodic disturbances using unbalance eccentricities as shown in Table 1 are examined. At the start of the first training session of the neural network controllers, the magnetic bearing system controller was initialised by assigning random values to all of the connection weighting coefficients. These random values were taken in the range (-0.3, 0.3). During each training session, the weights were adjusted according to the learning rules given in [6]. The simulations have shown that in the first training session 400 iterations were required before the controller converged. However by the third training session the number of iterations required to achieved satisfactory convergence had reduced to thirty. In Figs. 6 to 10 we show the results of the third training session for external periodic disturbances with different initial conditions.

Fig. 6 shows the simulated results for different initial conditions and rotor speed ω = 0 for Test Condition 2 only, as the results for the remaining cases are similar. It can be seen that the shaft returns to its steady state position in approximately 0.03 seconds.

Fig. 5. shows the simulation result for a PD controller and rotor speed ω = 100 for Test Condition 1. It can be seen that the shaft begins to rotate about its principal inertial axis with a magnitude of 0.05 mm. But with neural network control, for Test Condition 3, where ω = 100 rad/sec, the rotor returns to its steady state position in about 0.15 seconds as shown in Fig. 7. For Test Conditions 4 and 5, where ω = 150 rad/sec and ω = 200 rad/sec, the shaft begins to rotate about its principal inertial axis with a magnitude of 0.01 mm as shown in Figs. 8 and 9, respectively. For Test Conditions 6, where ω = 250 rad/sec, the rotor begins to rotate about its principal inertial axis with a magnitude of 0.02 mm as shown in Fig. 10.

However as was observed above, when ω is greater than 150 rad/sec the shaft begins to rotate about its principal inertial axis with a magnitude of 0.03 mm when unbalanced mass m = 0.01 kg and the eccentricity of the unbalance mass μ = 70 μm and when ω is greater than 250 rad/sec the shaft begins to rotate about its principal inertial axis with a magnitude of 0.05 mm when the unbalance mass m = 0.005 kg and the eccentricity of the unbalance mass μ = 60 μm. From the above simulation results it can be seen that good stability and system robustness can be achieved with various types of disturbances when the proposed neural network controller is used.

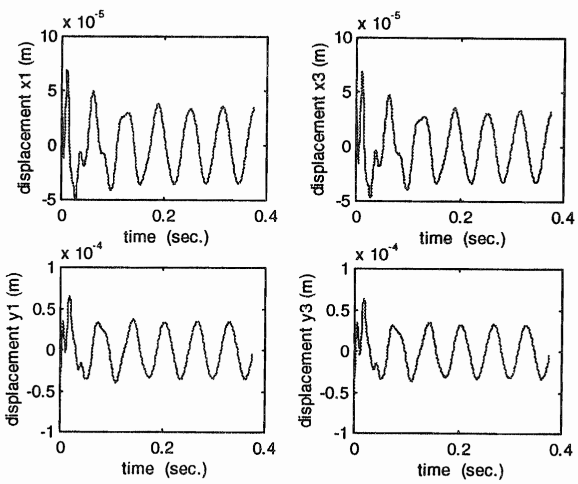

Fig. 5. System response for different initial conditions with Test Condition 1.

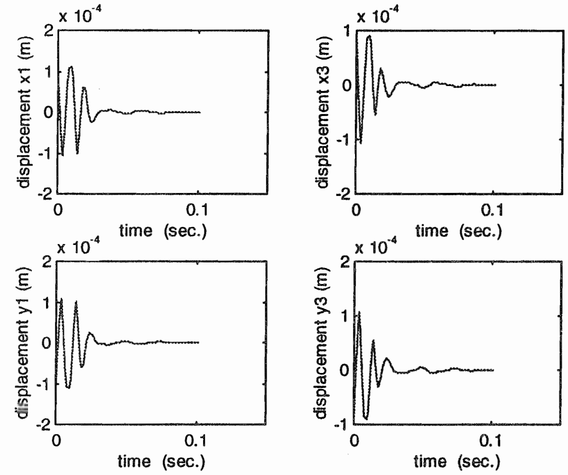

Fig. 6. System response for Test Condition 2 to external periodic disturbances.

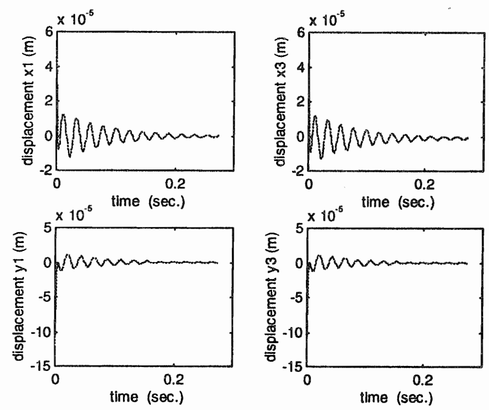

Fig. 7. System response for Test Condition 3 to external periodic disturbances.

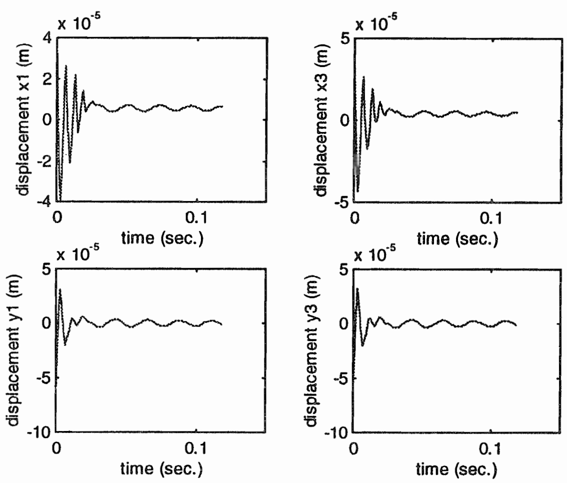

Fig. 8. System response for Test Condition 4 to external periodic disturbances.

Table 1

Test Conditions	Unbalanced Mass *m* (*kg*) Attached To The Rotor	Initial Conditions In All Tests (*mm*)	ω (rad/sec) and μ (μm)
1	0.01	x_1=0.06, y_1=0.06, x_3=-0.06, y_3=-0.06	100, 70
2	0.05	x_1=0.1, y_1=0.1, x_3=-0.1, y_3=-0.1	0, 70
3	0.01	x_1=0.06, y_1=0.06, x_3=-0.06, y_3=-0.06	100, 70
4	0.01	x_1=0.06, y_1=0.06, x_3=-0.06, y_3=-0.06	150, 70
5	0.005	x_1=-0.12, y_1=-0.12, x_3=-0.12, y_3=-0.12	200, 70
6	0.005	x_1=0.06, y_1=0.06, x_3=-0.12, y_3=-0.12	250, 60

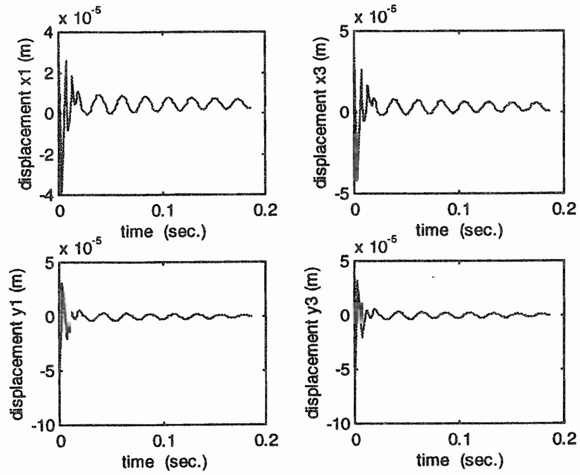

Fig. 9. System response for Test Condition 5 to external periodic disturbances.

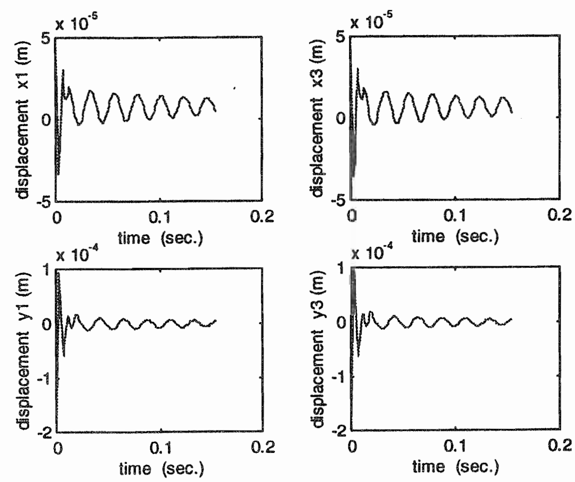

Fig. 10. System response for Test Condition 6 to external periodic disturbances.

5. Conclusions

A neural network control technique has been successfully tested for the control of a magnetic bearing suspension system subjected to external periodic disturbances. Both the system modelling and some simulation results have been presented in this paper. In the case where the system has external periodic disturbances it can be seen that it has good robustness when operating at speeds up to 250 rad/sec.

Acknowledgments

In this work the shaft mass and stiffness for the rotor system were calculated using the software package developed by Dr. J. Krodkiewski, from the Department of the Mechanical Engineering, University of Melbourne, Australia.

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Appendix 1

The equations of motion for a magnetic bearing system can be shown to be

$$[M_s]\{\ddot{x}\}+[K_s]\{x\}=[f(x,i)]+[F_d]$$

In the above equation the displacement vector *x* is defined to be $x=[x_1,x_2,x_3,y_1,y_2,y_3]$. *f(x,i)* is the magnetic bearing force in Newtons. The power amplifier output current $i=[i_1,0,i_3,0,i_4,0,i_6]$. F_d is the external periodic disturbance force produced by an unbalance mass *m* attached to the rotor so that $F_d=[0,m\omega^2\mu,0,0,0,0,0,0]'\cos\omega t + [0,0,0,0,0,m\omega^2\mu,0,0]'\sin\omega t$. In the expression for F_d the rotor angular velocity is denoted by ω while μ is the eccentricity of the unbalance mass.

Appendix 2

The equation of a PD controller was designed as

$$i=-200x-2\dot{x}$$

where

i is the controller current, ($i=i_1$, i_3, i_4, i_6).
x is the displacements of the shaft, (x_1, x_3, y_1, y_3).
$\dot{x}$ is the velocities of the shaft, ($\dot{x}=\dot{x}_1,\dot{x}_3,\dot{y}_1,\dot{y}_3$).

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