Fuzzy and Online Trained Adaptive Neural Network Controller for an AMB System

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Abstract

In this paper, an intelligent control method to positioning an active magnetic bearing (AMB) system is proposed, using the emerging approaches of the fuzzy logic controller (FLC) and on-line trained adaptive neural network controller (NNC). An AMB system supports a rotating shaft, without any physical contact by using electromagnetic forces. In the presented controller system, the FLC is first designed to identify the parameter of an AMB system. Then the initial training data with two inputs, the error and derivative of the error, and one output signal from FLC can be obtained. Finally, a NNC with on-line training features is designed by using S-function in Matlab/Simulink to achieve better performance. The results of the AMB system indicated that the system responds with satisfactory control performance, without a small overshoot, and obtains better transient and steady-state responses under various operating conditions. Moreover, this method has been experimentally verified on the AMB system. The proposed controller can be feasibly applied to AMB systems exposed to various external disturbances, demonstrating the effectiveness of the NNC with self-learning and self-improving capacities is proven.

Key Words: Active Magnetic Bearing, FLC, On-Line Training, Adaptive Control

1. Introduction

Magnetic bearings are electromechanical devices that use magnetic forces to completely levitate a rotor without physical contact. They use magnetic force to suspend the rotor in an air gap. No mechanical contact is made between the rotor and the stator. Because the system does not undergo friction or wear, it requires no lubrication. In addition, magnetic bearings do not produce pollution, they have a long working life, and they can be used for a wide range of potential applications in the aerospace, energy, transportation, and other high-technology fields, as well as in high-speed ultra-precision machine tools [1–5]. This paper presents an active magnetic bearing (AMB) system that supports a ventilator rotor to ensure the absence of friction between the rotor and the stator. This prevents wear, thereby improving the life of the ventilator and its rate of rotation. Several limits constrain the conventional mechanical rotary bearings while they perform these tasks. Because the bearings are in contact with the shaft, friction occurs between the shaft and the bearings. At high rotating speeds, this friction substantially increases the temperature, resulting in considerable energy loss. Bearings may also be worn or broken. Designing active controls for magnetic bearing systems is difficult because they are highly nonlinear and exhibit open-loop unstable electromagnetic dynamics. When AMB technology was introduced, the main controllers used for AMBs in most practical installations were traditional proportional-integral-derivative (PID) controllers [6–8].
The PID controller exhibits satisfactory performance for most practical applications; however, the controller becomes ineffective when the rotor displacements in AMB systems are inherently unstable, and the relationship between the current and the electromagnetic force is highly nonlinear. In practice, a precise mathematical model cannot be implemented. Therefore, several nonlinear control techniques have been proposed to address the nonlinear dynamics of the AMB. This study proposes a method for controlling the position of the actuator by using an online trained adaptive neural network controller (NNC). NNCs have recently been successfully applied to numerous nonlinear systems. NNC-based methodologies have recently been used to effectively solve nonlinear control problems [9-11]. The proposed design used an online trained adaptive NNC to control magnetic bearings and reduce the rotor displacement of an AMB system. The controller also satisfied the real-time response and stability during disturbance requirements of the control system. This paper is organized as follows. Section 2 introduces the structure, principle of the AMB system and describes the AMB system magnetic forces. Section 3 describes the rotor dynamics of the AMB system. The motion of equation presented in this section was used to analyze the characteristics of the rotor motion and the relationship between the horizontal and vertical directions of rotor displacement. Section 4 presents the structure of an online training adaptive NNC based on the FLC to identifying the parameters of the AMB system. The results and discussion of AMB system are described in section 5 and conclusion to the paper present in section 6.

2. Structure and Magnetic Forces of the Active Magnetic Bearing System

An AMB system proposed in this paper is shown in Figure 1. The system consisted of a ventilator, a rotor shaft, a magnetic bearing, a coupling device, a driving motor, and other components. The drive system of the AMB system included differential driving mode power amplifiers and an analog digital (A/D) converter, as shown in Figure 2. Two sensors were positioned to measure the displacement of the rotor from the reference position. The A/D converter converted the analog signal from the position sensors into a digital signal. This signal was used as the input for the NNC, which generated a control effort according to measurements, conducted using power amplifiers. The control signals were transformed into magnetic forces by four actuating magnets around the rotor, which held the rotor at the reference positions. Two pairs of electromagnetic coils were installed perpendicularly on the E-shaped stators. These coils produced perpendicular attractive electromagnetic forces in response to direct currents. All coils installed in the AMBs have the same turns and were considered symmetrical and uncoupled. Two opposing electromagnets operated in a differential driving mode [12].

In this configuration, electromagnetic force was exerted on the rotor in arbitrary directions along the x or y axes to maintain the rotor in the center position. Variable \( i_b \) represents the bias current, and \( i_x \) and \( i_y \) are the control currents at the center along the x and y axes, respectively. To clarify the operating principles of the AMB, the structure in Figure 3 of an electromagnet and the main geometrical characteristics of the electromagnet must be considered to calculate the AMB force of a single actuator. The magnetic flux, \( \Phi \), through stator cross-section \( A_{fe} \) was assumed to be constant throughout the loop. Furt-
thermore, it was assumed that $A_{fe} = A_a$ (where $A_a$ is the cross-section of air gap $x_g$). Therefore,

\[ \Phi = B_k A_{fe} = B_a A_a \]  
\[ B_k = B_a = B \]  

Magnetic flux density $B$ was calculated using the following relationship:

\[ B = \mu_r \mu_0 H_s \]  

where $\mu_0$ represents the permeability of air ($\mu_0 = 4\pi \times 10^{-7} \text{ [H/m]}$) and $\mu_r$ is the relative permeability of the iron core. The magnetic circuit in Figure 3 is calculated using the following equation:

\[ \int H ds = ni \]  
\[ ni = H_s I_{fe} + 2H_s x_g \]  

where $ds$ is the differential length of the flux path, $n$ is the number of coil turns on the magnetic actuator, $i$ is the total current in the magnet coils, and $x_g$ is the air gap between the stator and the rotor. The average magnetic path length in the laminate is $I_{fe}$; and $H_{fe}$ and $H_g$ are the magnetic field in the stator and the air gap, respectively. After solving (3) and (5), the flux density from (6) was obtained.

\[ B = \mu_0 \frac{ni}{(\mu_r + 2x_g)} \]  

The permeability of iron is $\mu_r >> 1$; consequently, the magnetization of iron is often neglected. Equation (6) can then be simplified to

\[ B = \mu_0 \frac{ni}{2x_g} \]  

The AMB force was obtained by using (8).

\[ f = \frac{B_k^2 A_a}{\mu_0} \]  

The angle between the direction of the force and the center of cross-section $A$ was determined by $\alpha$ (Figure 3). A common four-pole radial AMB has eight actuator teeth. Equations (7) and (8) yield the force for one actuator.

\[ f = k \frac{i^2}{x_g^2} \]  
\[ k = \frac{1}{4} \mu_0 n^2 A_a \cos \alpha \]  

A radial AMB consisted of two pairs of controlling opposing electromagnets in the differential driving mode. Each electromagnet was fed with the same bias current, and a control current was added to the current that was fed to one magnet and subtracted from the current that was fed to the other magnet, depending on the direction of the desired force. Figure 4 presents a three-dimensional plot of the magnetic force, which was nonlinearly related to the current and rotor displacement. The force produced by one electromagnet increased while the force produced by the other magnet decreased, demonstrating that two forces simultaneously acted on the rotor. The nominal air gaps of the magnetic bearing in the $x$ and $y$ axes were defined by variables $x_g$ and $y_g$, and the deviations from the nominal air gaps to inside the stator were defined by variables $x_1$ and $y_1$. The rotor position in the $x$ and $y$ axes for the right and left air gaps were measured by $x_g + x_1$ and $x_g - x_1$, respectively; and the position for the upper and lower air gaps were measured by $x_g + y_1$ and $x_g - y_1$, respectively. Bias current $i_b$ was supplied to
both pairs of electromagnets to produce the same basic attractive forces in the $x$ and $y$ axes [13]. Therefore, the total currents supplied to both pairs of electromagnets in the right and left coils were $i_b - i_i$ and $i_b + i_i$ for the $x$ axis, respectively; and the total currents supplied to both pairs of electromagnets in the upper and lower coils were $i_b + i_i$ and $i_b - i_i$ for the $y$ axis, respectively. The total non-linear attractive electromagnetic forces for the $x$ and $y$ axes were obtained using (11) and (12).

\begin{align}
F_3 - F_1 &= k \left( \frac{(i_b + i_i)^2}{(x_e - x_i)^2} - \frac{(i_b - i_i)^2}{(x_e + x_i)^2} \right) \tag{11} \\
F_4 - F_2 &= k \left( \frac{(i_b + i_i)^2}{(y_e - y_i)^2} - \frac{(i_b - i_i)^2}{(y_e + y_i)^2} \right) \tag{12}
\end{align}

where $F_3 - F_1$ and $F_4 - F_2$ are electromagnetic forces of the magnetic bearings along the $x$ and $y$ axes, respectively; $x_1$ and $y_1$ are rotor displacements along the $x$ and $y$ axes; $k$ is the electromagnet constant. In this AMB system, the coil on the $x$ and $y$ axes circulate the same bias current ($i_b$). Because the nominal air gaps along the $x$ and $y$ axes are also the same ($x_g = y_g$).

3. Rotor Dynamics of the Active Magnetic Bearing System

In this study, the rotor was assumed to be a rigid and symmetric body with unbalanced uniform mass. The rotor geometry relationships with the center of gravity ($CG$: $x_c$, $y_c$, $z_c$) in the AMB system is shown in Figure 5.

In Figure 5 $m$ is the mass of the rotor; $g$ is the gravity constant; $x_c$, $y_c$, and $z_c$ are the coordinates of $CG$; $F_1$ to $F_4$ denote the four attractive magnetic forces in the $x$ and $y$ directions; $F_{dx}$, $F_{dy}$, and $F_{dz}$ are the external disturbance forces of the rotor corresponding to the $x$, $y$, and $z$ axes, respectively; $\varphi_x$, $\varphi_y$, and $\varphi_z$ denote the pitch, yaw, and spin angle displacements around the $x$, $y$, and $z$ axes of the rotor, respectively; and $l_1$, $l_2$, and $l_3$ are the distances from $CG$ to the flexible coupling, magnetic bearing, and external disturbances, respectively, where $l = l_1 + l_2$. The rotor was assumed to be perfectly regulated, and $\varphi_x = \varphi_y = 0$ and $\Omega = \varphi_z$ represented the rotational speed of the rotor. The dynamic equations describing the motion of the rotor bearing system about $CG$ are represented by (13) to (16).

\begin{align}
F_{dx} &= m \ddot{x}_c + \frac{\partial V}{\partial x} \\
F_{dy} &= m \ddot{y}_c + \frac{\partial V}{\partial y} \\
F_{dz} &= m \ddot{z}_c + \frac{\partial V}{\partial z}
\end{align}

where $V$ is the potential energy of the rotor system.

![Figure 4. Characteristics of electromagnetic force.](image1)

![Figure 5. Geometry relationships of rotor and an AMB system.](image2)
where $J$ is the transverse moment of inertia of the rigid rotor around its $x$-axis or its $y$-axis; $J_z$ is the polar mass moment of inertia of the rotor; and $J_{zx}$, $J_{zy}$ are the gyroscopic effects when the rotor rotational speed spinning around the $z$-axis is $\Omega$; and $F_{x1}$ and $F_{y1}$ are coupling forces. In this model, the shaft of the AMB system was fixed to the motor shaft through a coupling, therefore the shaft displacement of the $z$-axis was small because it was only caused by the rotor displacement of the motor. Thus, the external disturbance forces of the $z$-axis rotor was approximately zero, and the external disturbance forces acting on the AMB system were exerted by two axes ($x$ and $y$ axes). Figure 6 shows the principle of unbalance force generation. The $x$ and $y$ axes are perpendicular axes in a stationary frame. The unbalanced mass forces, $\mathbf{f}_d = [F_{dx}, F_{dy}]^T$, in the two perpendicular axes are defined using (17) and (18) [14],

\begin{align}
F_{dx} &= m_e \cdot \Omega^2 \cos \Omega \\
F_{dy} &= m_e \cdot \Omega^2 \sin \Omega
\end{align}

where $m_e$ is an additional mass with a radius of $\varepsilon$ in the $\Omega \varepsilon$ direction.

The effect of the rotor rotation was ignored, thus the flexible coupling forces corresponding to the $x$ and $y$ axes can be expressed as follows [15].

\begin{align}
F_{x2} &= -d_e \dot{x}_2 - s_e x_2 \\
F_{y2} &= -d_e \dot{y}_2 - s_e y_2
\end{align}

where $d_e$ is the equivalent damping coefficient; $s_e$ is the equivalent stiffness of the coupling; and $x_2$ and $y_2$ are the shaft displacements corresponding to the $x$ and $y$ axes at the flexible coupling, respectively.

Based on (11) and (12), if the four electromagnets exhibit the same static magnetic force, the non-linear electromagnetic forces can be represented by the following simplified linearized electromagnetic force [16],

\begin{align}
F_{x} &= F_{x1} + F_{x2} \\
F_{y} &= F_{y1} + F_{y2}
\end{align}

where $k_i$ and $k_{di}$ are the position and current stiffness parameter of the magnetic bearing, respectively; $x_1$ and $y_1$ are the shaft displacements at the magnetic bearing. The system equations for the designed controller indicate the displacements at the locations of the flexible coupling and magnetic bearing. Moreover, because the rotor was assumed to be rigid and the displacement from the desired position was assumed to be small, the relationships between the shaft positions ($x_1$, $x_2$, $y_1$, $y_2$) and $CG$ ($x_c$, $y_c$, $z_c$) are reflected as follows.

\begin{align}
x_c &= \frac{l_1 x_1 + l_2 x_2}{l} \\
y_c &= \frac{l_1 y_1 + l_2 y_2}{l} \\
x &= \frac{x_2 - x_1}{l} \\
y &= \frac{y_2 - y_1}{l}
\end{align}

Figure 6. Unbalance mass force.
\[ M_c \ddot{X}_c + G_c \dot{X}_c + K_{d0} X_c = K_{i0} u_c + E f_d + D g \] (27)

where \( M_c \) is the mass matrix; \( G_c \) is the gyroscopic matrix; \( K_{d0} \) is the displacement stiffness matrix; \( K_{i0} \) is the current stiffness matrix; \( E \) is the mass unbalanced external disturbance; \( f_d \) is the external disturbance vector; and \( D \) is gravity vector. From equations (11), (12) shown that the relationship between the current rotor displacement and the electromagnetic force in AMB system is highly nonlinear. For a nonlinear system, a new control method is proposed to controlling the position of an AMB system by using an online trained adaptive NNC.

4. Control System Design

4.1 Fuzzy Logic Controller Design

Figure 7 shows the synoptic scheme of the fuzzy controller, which possesses two inputs, the error (\( e \)) and the derivative of the error (\( de \)), and output (\( i \)). The basis of the FLC is the representation of linguistic descriptions as MFs. The MF indicates the degree to which a value belongs to the class labeled by linguistic description. In FLC algorithms, the degree of membership serves as the input. Determining the appropriate degree of membership is a component of the design process. Once the MFs are defined, the input values are transformed into a degree of an MF with the linguistic descriptor values varying from 0 to 1. This process is called fuzzification. The resulting fuzzified data are passed through an inference mechanism that contains the output rules. After the rules are applied, the combined effect of all of the rules is evaluated according to the proper weightage for each rule. The weightage is generally used to fine-tune the fuzzy controller, and this process is called defuzzification.

In this study, two inputs (\( e \)) and (\( de \)) and a single output (\( i \)) were defined for the system. The linguistic levels of these inputs were designated as \( N \): negative; \( Z \): zero; and \( N \): negative. Fuzzy logic was characterized by three fuzzy sets (\( N, Z, P \)) for inputs (\( e \)) and (\( de \)). The linguistic levels of these outputs were designated as \( BN \): big negative; \( SN \): small negative; \( ZE \): zero; \( SP \): small positive; and \( BP \): big positive. Fuzzy logic was characterized by five fuzzy sets (\( BN, SN, ZE, SP, BP \)) for the output (\( u \)) variable. A Gaussian MF was employed as the inputs, and a triangular MF was employed as the output fuzzy sets of the FLC. The MFs are shown in Figures 8 and 9. Implication using a Takagi-Sugeno-type FIS we chose aggregation is Max-Min, and defuzzification was performed using the centroid technique.

The control rules of the fuzzy controllers were a set of heuristically selected fuzzy rules. The processing time required when using an FLC depends upon the number of rules that must be evaluated. Large systems containing numerous rules require extremely powerful and fast processors to perform computations in real time. The fuzzy controller rule base was composed of 9 rules for the output (\( i \)) variable, as shown in Table 1.

![Figure 7. Fuzzy logic controller synoptic diagram.](image)

![Figure 8. Membership functions of input e.](image)

![Figure 9. Membership functions of input de.](image)
4.2 Online Trained Adaptive Neural Network Controller Design

In this paper, the proposed online trained adaptive NNC was designed to control an AMB system, as shown in Figure 10. The system consisted of the NNC, a reference model, and a delta adaptation law. The operating principle of the controller was based on engineering experience of AMB dynamics, and control knowledge was incorporated into the NNC [17,18]. The rotor displacement output of the AMB system ($x_p$) was expected to share the same reference input ($x^*$). Both signals were compared to the generated error ($e$) as inputs for the online trained adaptive neural controller. $K_1$ to $K_4$ are positive constants. The variable, $i_N$, was the output of NNC, and its signal controls into power amplifier of the AMB system.

The three-layer neural network structure shown in Figure 11 is adopted to implement the proposed NN controller. The hidden and output layers contain several processing units with a hyperbolic tangent function [19,21].

The net input to node $j$ in the hidden layer is calculated according to the following equations.

$$ \text{net}_j = \sum (W_{ji} \cdot O_i) + \theta_j \quad (28) $$

The output of node $j$ is

$$ O_j = f(\text{net}_j) = \tanh(\beta \cdot \text{net}_j) \quad (29) $$

where $O_j$ represents the output of units in the hidden layers; $\text{net}_j$ is the summed input for the units in the hidden layers; $W_{ji}$ is the connective weight between the input layers and hidden layers; $\beta > 0$ is a constant; $f$ denotes the activation function, which is a hyperbolic tangent activation function,

$$ f(\text{net}_j) = \frac{2}{1 + e^{-\beta \cdot \text{net}_j}} - 1; \quad (-1 < f(\text{net}_j) < 1) \quad (30) $$

the net input to node $k$ in the output layer is,

$$ \frac{\partial \text{net}_k}{\partial O_i} = K_i e + K_4 \dot{e} \quad (31) $$

Table 1. Rules base of FLC

<table>
<thead>
<tr>
<th>$i$</th>
<th>$e$</th>
<th>$N$</th>
<th>$Z$</th>
<th>$P$</th>
</tr>
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<tbody>
<tr>
<td>$e$</td>
<td>$N$</td>
<td>$BP$</td>
<td>$SP$</td>
<td>$BN$</td>
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<td>$Z$</td>
<td>$BN$</td>
<td>$ZE$</td>
<td>$SN$</td>
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<tr>
<td>$P$</td>
<td>$ZE$</td>
<td>$SN$</td>
<td>$BP$</td>
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</table>

Figure 10. Block diagram neural network controller for MB system.

Figure 11. Schematic diagram of the proposed NNC.
where $W_{kj}$ is the connective weight between the hidden layers and output layer. And the corresponding output of the neural network is,

$$O_k = f(\text{net}_k) = \tanh(\beta \cdot \text{net}_k)$$

The terms $\theta_j$ and $\theta_k$ are the threshold values for the units in the hidden layers and output layer. Variables $\text{net}_j$ and $\text{net}_k$ were used to differentiate $O_j$ and $O_k$, respectively.

$$\frac{\partial O_j}{\partial \text{net}_j} = \beta(1 - O_j^2)$$

$$\frac{\partial O_k}{\partial \text{net}_k} = \beta(1 - O_k^2)$$

To describe the online learning algorithm of the proposed NNC, energy function $E_N$ was defined as

$$E_N = \frac{1}{2}(x_{rm} - x_p)^2 = \frac{1}{2}e^2$$

where $x_{rm}$ and $x_p$ represent the outputs of the reference model and the plant at the $N$th iteration, respectively. Within each interval from $N$ to $N+1$, the back-propagation algorithm was used to update the connective weights in the NNC according to the relationship in (38),

$$W_{i,j}^{N+1} - W_{i,j}^N = -\eta \frac{\partial E_N}{\partial W_{i,j}} + \alpha \Delta W_{i,j}^{N+1}$$

where $\eta$ is the learning rate, $\alpha$ is the momentum factor, $N$ indicates the number of training iterations, and $\Delta W(N-1)$ is the difference between $W(N)$ and $W(N-1)$. Based on the chain rule, the required gradient of $E_N$ in (38) is determined using

$$\frac{\partial E_N}{\partial W_{i,j}} = \frac{\partial E_N}{\partial \text{net}_i} \frac{\partial \text{net}_i}{\partial W_{i,j}} = \delta_i O_j$$

$$\delta_i = \frac{\partial E_N}{\partial \text{net}_i} = \sum_n \frac{\partial E_N}{\partial x_p} \frac{\partial x_p}{\partial O_n} \frac{\partial O_n}{\partial \text{net}_i} = \sum_n \frac{\partial E_N}{\partial O_n} \beta(1 - O_n^2);$$

$$n = 1, 2, ..., K$$

The gradient of $E_N$ between the hidden layers and input layers is determined by

$$\frac{\partial E_N}{\partial W_{i,j}} = \frac{\partial E_N}{\partial \text{net}_i} \frac{\partial \text{net}_i}{\partial W_{i,j}} = \delta_i O_j$$

with

$$\delta_i = \frac{\partial E_N}{\partial \text{net}_i} = \sum_n \frac{\partial E_N}{\partial x_p} \frac{\partial x_p}{\partial O_n} \frac{\partial O_n}{\partial \text{net}_i} = \sum_n \frac{\partial E_N}{\partial O_n} \beta(1 - O_n^2);$$

$$m = 1, 2, ..., L$$

The exact value of $\frac{\partial E_N}{\partial x_p}$ is difficult to determine because of the unknown plant dynamics. To overcome this problem and to increase the online learning rate of the connective weights, a delta adaptation law was proposed as follows,

$$\frac{\partial E_N}{\partial x_p} = K_1 e + K_2 \dot{e}$$

where $K_1$ and $K_2$ are positive constants. Based on (38), the matrix weight update of the output layers and hidden layers, and the $N$th iteration of the input layers and hidden layers are shown in (44) and (45), respectively.

$$\Delta W_{i,N} = -\eta \frac{\partial E_N}{\partial W_{i,N}} + \alpha \Delta W_{i,N-1}$$

$$\Delta W_{i,N} = -\eta \frac{\partial E_N}{\partial W_{i,N}} + \alpha \Delta W_{i,N-1}$$

The synaptic weighting matrix interval from $N$ to $N+1$ is updated using (46) and (47).

$$\Delta W_{i,N+1} = \Delta W_{i,N} + \Delta W_{i,N-1}$$

$$\Delta W_{i,N+1} = \Delta W_{i,N} + \Delta W_{i,N-1}$$

5. Results and Discussions

The experimental setup of this study is presented in Figure 12. The device included a horizontal shaft magnetic bearing that was symmetrical and controlled by two axes. The system was driven by an induction motor with a flexible coupling to isolate the motor vibration. The magnetic bearing included four identical electromagnets that were equally spaced radially around a rotor composed of laminated stainless steel, as indicated in Figure...
13(a). An experimental for the AMB system has been verified by the current-control loop using current amplifier, as shown in Figure 13(b). The current responses of four electromagnetics in current-control loop at the same time are presented in Figure 14. This figure, we can see that the current response (four electromagnetic) is very close the reference signal and setting time about 0.01s. This is favorable for position control loop in AMB system. The rotor displacement along the vertical y and horizontal x axes of the geometric center of the shaft were measured using a pair of eddy current sensors, as indicated in Figure 15. A photograph of the experimental setup is presented in Figure 16. The AMB system and a

![Figure 12. The experimental setup of the AMB system.](image)

![Figure 13. Photograph of inside view of magnetic bearing (a), current amplifier (b).](image)

![Figure 14. Current loop control of magnetic bearing with x and y axes.](image)

![Figure 15. Eddy sensor and driver power.](image)

![Figure 16. Photograph of the experimental setup.](image)
NNC were implemented using Matlab/Simulink; the parameters are listed in Table 2. The requisite interface was a PCI-1716L card comprising an A/D part with 16 channels and a digital input and output part with 16 channels. The conversion time of the 16-bit A/D converter was 10 μs. The sampling rate of the 16-bit converter was 100 kHz and the control cycle was approximately 0.1 ms. Matlab/Simulink was used to code the proposed controllers. The training results of the desired output and practical output, as shown in Figure 17(a), indicate that the practical output almost tracked the desired output. Figure 17(b) displays the error converged to zero. Figures 18–20 summarizes the results for the rotor displacement and the orbit of rotor center on x and y axes. Figures 18(a)–20(a) indicates that the rotor displacement of x and y axes in the AMB system. The rotor displacement is small about 0.12–0.19 mm, as shown in Figures 18(a) and 19(a). In general, the rotor displacement in the horizontal direction was smaller than the rotor displacement in the vertical direction, because of the effects of gravity on the y axis. The rotor displacement is increase at rotating high speed about 0.28 mm, as shown in Figure 20(a); but the rotor displacement is small at steady-state, about 0.1 mm. Figures 18(b)–20(b) show the orbit of the rotor center is using a NNC at rotating speeds from 3600–9600 rpm. Figure 18(b) presents the AMB system rotating speeds the rotor displacement is small about 0.1–0.12 mm; at rotational speeds from 7200–9600 rpm, the rotor displacement about 0.21–0.28 mm, as shown in Figures 19(b)–20(b), but it is still in the permitted limits of nominal length of air gap (xg = 0.5 mm). To evaluate the performance and characteristics steady state of system, an AMB system controlled by a NNC; it is unstable system before the first 0.1–0.27 s display in Figures 18(a)–20(a). It can be seen that the proposed scheme can

Table 2. Parameters of an AMB system

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<tbody>
<tr>
<td>1</td>
<td>Mass of shaft (m)</td>
</tr>
<tr>
<td>2</td>
<td>Nominal length of air gap (x_g)</td>
</tr>
<tr>
<td>3</td>
<td>Transverse moment of inertia of rotor (J)</td>
</tr>
<tr>
<td>4</td>
<td>Polar moment of inertia of rotor (J_θ)</td>
</tr>
<tr>
<td>5</td>
<td>Displacement stiffness (k_d)</td>
</tr>
<tr>
<td>6</td>
<td>Current stiffness (k_is)</td>
</tr>
<tr>
<td>7</td>
<td>Bias currents to be used (i_b)</td>
</tr>
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![Figure 17. Desired output and practical output (a); Error after training (b).](image1)

![Figure 18. Rotor displacement x, y axes (a); orbits of rotor center (b) with 3600 rpm.](image2)
noticeably reduce the rotor displacement. The parameters of a NNC are adjusted to the unbalanced vibration in an AMB system into effect after short time. The results further demonstrate that a short rise time implies a short settling time, and a small steady-state error with external disturbance.

6. Conclusions

In this study, an NNC was developed to dampen shaft displacement in a highly unstable AMB system. The results indicated that the online trained adaptive NNC allowed the AMB system to achieve more satisfactory performance at various running rotor speeds and existing unbalanced masses. The experimental results also demonstrated that the AMB system achieved satisfactory dynamic and steady-state responses with rotor rotational speeds between 3600 and 9600 rpm. The proposed control method can be used in complex model of AMB systems and other nonlinear systems. Since an experimental for the AMB system has been verified by the current-control loop and position control loop; furthermore an AMB system is used in flywheel energy storage system (FESS), we hope develop an NNC for AMB using on FESS in the future.

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References


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