Optimize Control Current in Magnetic Bearings Using Automatic Learning Control

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Abstract

How to solve the unbalance problem in active magnetic bearings (AMB) is always concerned. In this paper a new unbalance control method, automatic learning control, is proposed to solve this problem. Using the method, the rotor can be forced to rotate about its inertial axis. The synchronous compensation current of the AMB is optimized through iterative "learning". The learning gain and learning cycle of the controller are automatically determined according to the rotational speed. Experiments are carried out to examine its control effect at fixed rotational speed and variable speed, respectively, and results prove that the proposed compensation scheme is effective in AMB control.

1. Introduction

Mass unbalance effect is a common problem in rotating machinery. When the rotor's geometric axis is not coincident with its inertial axis, the imbalance happens and it could cause undesirable vibrations, acoustic noise and rotor position runout. The conventional method of balancing is realized by employing mechanical approaches, for example, the addition or removal of small amount of mass from the rotor to reduce the residual imbalance, and this is a time consuming and costly procedure. In addition, imbalance often changes during operation in some machines, so mechanical balancing has limited benefit in this case [1]. Recently active magnetic bearing is proven to be a good solution to this unbalance problem. Through effective control methods, the unbalance effect can be greatly attenuated in machines using AMB.

Usually, in AMB, the unbalance compensation is implemented in two kinds of approaches,

(1) Rotation about rotor's geometric axis, and

(2) Rotation about its inertial axis.

Using the second kind of approaches is logical and they have been applied in many cases. This kind of approaches can give us the following benefits:

1. Reduced transmission of synchronous force to the bearing housing. When the rotor rotates, the centrifugal force caused by acceleration of the inertial axis is reacted by the bearing and transmitted to the housing. One approach to solve this problem is to make the rotor rotate about its inertial axis so that the centrifugal force is much reduced. Elimination of synchronous current in AMB coils means the mass unbalance has no influence on AMB actuator, so the rotor is well balanced and rotates about its inertial axis.

2. In vertical Permanent-Magnet-Biased AMB, synchronous control currents caused by unbalance contribute to the major portion in AMB coil currents. As a result, eliminating synchronous current can substantially reduce the copper loss in this kind of AMB.

Mass unbalance technique in AMB has become a hot topic since last decade. Some control methods have been worked out to solve this problem [1]-[9]. These methods can be classified into two categories. The first type of the methods tries to modify the loop gain of the AMB closed-loop system by inserting filters in the control loop [2]-[4] or using observer-based state feedback controller [5]-[6]. The other type does not change the stability or performance of the existing closed-loop system. Instead, it tries to generate synchronous compensation signals with an additional controller [1], [7]-[9].

In this paper, automatic learning control (ALC) is proposed to make rotor rotate about its system inertial axis. The control strategy involves time-domain iterative learning control with gain scheduling. The length of learning cycle and learning gain can be automatically determined according to the rotational speed. The performance of the proposed ALC scheme has been evaluated through experiments.

2. AMB model

In AMB, usually two electromagnets are oppositely located to control the rotor motion in one degree-of-freedom (DOF) as shown in Fig.1. Currents in the two opposite electromagnet coils are $i_1 = i_0 + i_c$, $i_2 = i_0 - i_c$ respectively, where i_0 is the bias current and i_c is control current. The EM force in this axis is therefore

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$$f_m = K_m \cdot \left(\frac{i_1^2}{(s_0 - s)^2} - \frac{i_2^2}{(s_0 + s)^2} \right) \tag{1}$$

where K_m is a constant related to the parameters of the electromagnet, s_0 is length of the air gap when the rotor is in the center position, s is the rotor displacement with respect to the bearing center in this axis. Thus $(s_0 - s)$ and $(s_0 + s)$ are respectively the lengths of the air gaps for the two electromagnets.

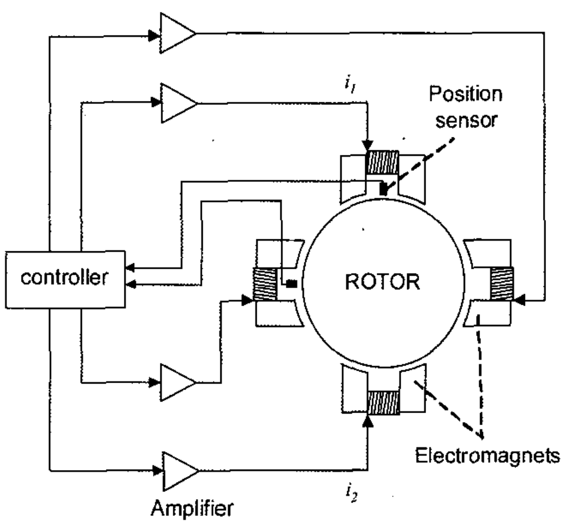

Fig.1. The structure of a closed-loop radial magnetic bearing system.

This electromagnetic force can be linearized at the working point ($i_c = 0$, $s = 0$), and the equation becomes

$$f_m = \frac{4K_m \cdot i_0}{s_0^2} i_c + \frac{4K_m \cdot i_0^2}{s_0^3} s = K_i \cdot i_c + K_s \cdot s \tag{2}$$

If the AMB is Permanent-Magnetic-Biased, there is no bias current i_0, but its electromagnetic force formula has the same format as (2). The difference is that for a Permanent-Magnetic-Biased bearing the force-current factor K_i and force-displacement factor K_s in (2) are related to permanent magnet parameters instead of bias current.

According to Newton's law, the motion of the rotor is

$$\ddot{s} = f_m / m = (K_i \cdot i_c + K_s \cdot s) / m \tag{3}$$

Therefore the state equation for AMB plant can be described by (4).

$$\begin{cases} \begin{pmatrix} \dot{s} \\ \ddot{s} \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ \frac{K_s}{m} & 0 \end{pmatrix} \begin{pmatrix} s \\ \dot{s} \end{pmatrix} + \begin{pmatrix} 0 \\ \frac{K_i}{m} \end{pmatrix} i_c \\ y = \begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} s \\ \dot{s} \end{pmatrix} \end{cases} . \tag{4}$$

A feedback controller is used to stabilize the AMB plant, thus the closed-loop AMB system can be realized. After discretization, a discrete closed-loop AMB system model can be described as in (5).

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k) = Cx(k) \end{cases} \tag{5}$$

The synchronous disturbance force f_u, induced by mass unbalance, produces synchronous position disturbance s_u to the AMB system, which can be described as

$$s_u = R \sin(\omega t + \theta) , \tag{6}$$

where R is the runout amplitude, ω is the synchronous angular speed, and θ is the initial angle. The feedback controller responds to the unbalance position disturbance by providing control current, which is synchronous with the motor speed.

3. Automatic learning control scheme

ALC is based on time-domain iterative learning control and gain-scheduled control. Iterative learning control (ILC) has been applied to AMB to perform unbalance compensation. The adaptive vibration control in [1], [9] is based on Multi-Input-Multi-Output (MIMO) frequency-domain ILC. In adaptive vibration control, complicated gain matrices are employed, which requires large amount of computation and much memory space, especially for the AMB operating in a wide range of speed. To overcome this problem, ALC scheme is proposed in this paper to achieve unbalance control. Implemented in decentralized mode and in time domain, ALC has a simple control algorithm and does not require much memory space. Learning gains are used in ALC instead of gain matrices, so it relieves the computation load and memory space requirement of digital controllers.

3.1. Process synchronous signals in ALC

Generally in ILC, a low-pass filter is required because the high-frequency noise can make the learning process be unstable. In ALC, the controller works in a wide range of motor speeds, so the filter should be able to obtain the synchronous current ripple signal from original signals at different speeds. Fourier analysis theory is used in ALC to process synchronous signal. The synchronous control current signal can be obtained according to (7-9).

$$a = \frac{2}{T}\int_{t0}^{T+t0} y_o(t)\sin\omega t dt, \tag{7}$$

$$b = \frac{2}{T}\int_{t0}^{T+t0} y_o(t)\cos\omega t dt, \tag{8}$$

$$y_\omega(t) = a\cdot\sin\omega t + b\cdot\cos\omega t, \tag{9}$$

where $y_o(t)$ is the original signal, $y_\omega(t)$ is the synchronous signal, ω is the rotational angular velocity, T is the rotational period, a is the amplitude of sine wave, and b is the amplitude of cosine wave.

The process of obtaining synchronous control current signal is shown in Fig. 2.

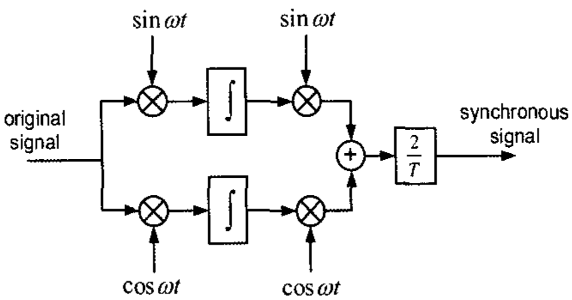

Fig.2. Functional block diagram of the digital filter.

3.2. Time-domain iterative learning control

As a relatively new control method, iterative learning control is firstly invented for better motion control performance in repetitive tasks of robots [10]. In the previous two decades much research work has been done on its theories and applications [10]-[13]. In time-domain ILC, the controller calculates $e_j(t)$, the difference between the system output $y_j(t)$ and the desired tracking target $y_d(t)$. Then the controller computes a new input $u_{j+1}(t)$ for the next cycle according to the learning law, and the new input is stored in the memory. In this process, the new input is the addition of the old input in previous cycle and an error correction item. Through this learning process cycle by cycle, the error can be minimized eventually.

A general iterative learning law in time domain can be described by

$$u_{j+1}(t) = u_j(t) + \Phi\cdot e_j(t+1), \quad t\in 0,1,2,...,t_f-1 \tag{10}$$

where t_f is the number of time steps in one cycle, $u(t)$ is the controller output, k is iteration number, the Φ is defined as the learning gain. The error is

$$e_j(t) = y_d(t) - y_j(t) = -i_{c,j}(t) \tag{11}$$

where $i_{c,j}(t)$ is the synchronous control current in time t of the j^{th} cycle. In (10) and (11), all the values are scalars rather than vectors or matrices. To ensure convergence of learning process, the learning gain should satisfy

$$|1 - C\cdot B\cdot\Phi| < 1, \tag{12}$$

$$\text{thus for all } t\in[0,t_f-1], \lim_{j\to\infty} e_j(t) = 0 \tag{13}$$

Actually, the system model parameter could be ignored in the process of determining the learning gain. A suitable learning gain can be easily obtained by tuning on-line like tuning a PID controller. The detail method of choosing learning gain is discussed in [13].

Note that the output of the controller only provides the compensation current for the rotor's balancing. A feedback position controller should be used to stabilize the AMB system. The whole control scheme is shown in Fig. 3, where i_c is the control current, i_{fb} is the current provided by feedback position controller, and i_{alc} is the compensation current provided by ALC.

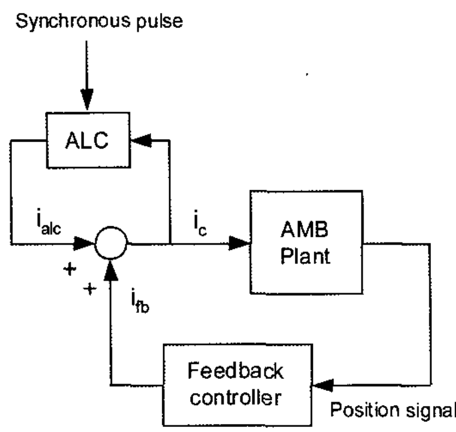

Fig.3. Unbalance Control scheme for AMB

3.3. Variable learning gains and learning cycle

The limitation of the ILC controller in (10) is that it is designed for working at a fixed speed, so motor speed variation may attenuate its control effect. In ALC the controller is improved so that it can adjust itself to different rotational speeds by changing learning gains and length of learning cycle. Therefore motor speed variation has little negative influence on its control effect.

The changing of rotational speed could lead to the variation of AMB plant parameters [14], so a learning gain effective in one rotational speed may lead to instability in another speed. Therefore, in ALC the controller should be able to adjust its learning gain to different rotational speeds. Gain-scheduled control is used to achieve different learning gains under different speeds. Suitable learning gains for a set of speeds covering the operating speed range are obtained beforehand. Operated with a decentralized mode, the proposed ALC scheme needs only one learning gain for each DOF at one speed. The tuning process is very simple and no identification process is required. The learning gains for these rotational speeds are then stored in a look-up table. Because learning gains rather than gain matrices are stored in the memory, this control method requires very little memory space. During operation the controller can automatically adjust its learning gains according to rotor speeds. For a particular rotational speed, the learning gain can be calculated by linear interpolation between the learning gains for the two nearest speeds in the table.

The controller in (10) has a fixed length of learning cycle, which limits the function of ILC to a specific rotational speed. An iterative learning controller designed for one rotational speed cannot work at another rotational speed. Furthermore, because the controller cannot adapt itself to speed variation, it is sensitive to the motor speed disturbance. In ALC, the length learning cycle is not a fixed one. Variable learning cycle is used to adapt the controller to the changing speed. The length of learning cycle varies with rotational speed during operation and it equals the rotational period of AMB.

The learning law of ALC can thus be described by

$$u_{j+1}(t) = u_j(t) + \Phi(\omega) \cdot e_j(t+1), \quad t \in 0,1,2,\dots,t_f(\omega)-1 \tag{14}$$

$$t_f(\omega) = 2\pi/\omega \tag{15}$$

4. Experimental results

An AMB system is used to examine the ALC effects in optimizing the synchronous control current. The AMB system is composed of two identical radial bearings and a thrust bearing. The radial bearings control the shaft motion perpendicular to the shaft and the thrust bearing controls the motion along the shaft. Because the unbalance effect mainly occurs in radial directions, only the unbalance control in radial bearings is concerned. Variable reluctance sensors are used in magnetic bearings to detect rotor position. The rotor is supported using decentralized PID control in the experiment.

A dSPACE DS1103 controller board was used to perform real-time digital control on the AMB system. Control algorithms are programmed in the SIMULINK environment, and are then compiled and loaded to the DS1103 board. In the experiment the sampling frequency for capturing current values is 10 kHz.

4.1. Constant motor speed at 2800 RPM

46.67Hz (2800 RPM) is approximately the first critical frequency of the rotor. As a result, the control currents in AMB coils have large fluctuation around 2800 RPM. The experiment is firstly carried out at this constant speed. In the experiment, ALC presents required performance in optimizing the synchronous current. Without ALC the peak-peak value of the control current is nearly up to 0.8A. When ALC is working, the fluctuation of the control current is effectively reduced and its peak-peak value is no more than 0.1A. Fig.4 and 5 show the comparison of the control current waveform between ALC turned off and ALC turned on. It could be seen that the unbalance control effect is very obvious.

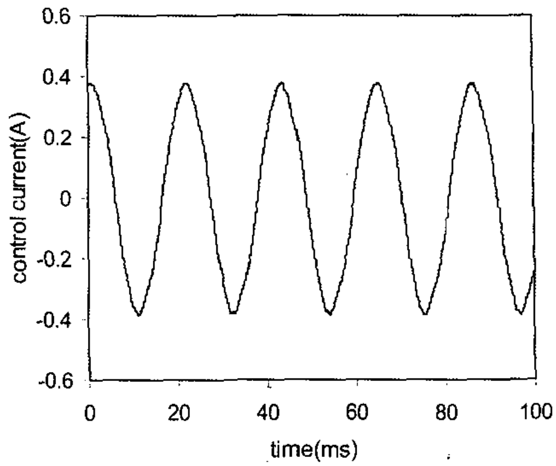

Fig.4. Control current waveform at 2800 RPM without ALC

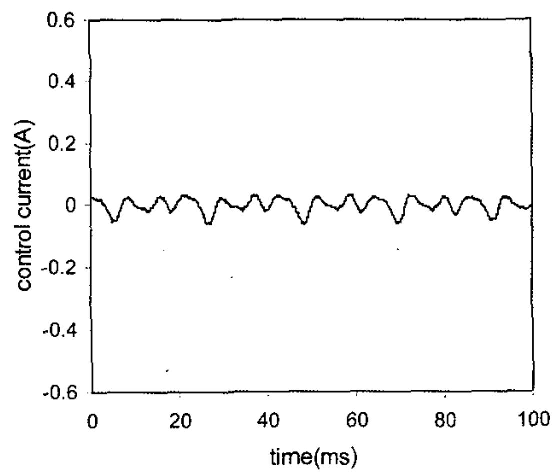

Fig.5. Control current waveform at 2800 RPM with ALC

The control effect of ALC is also shown in frequency domain in Fig. 6 and 7. It can be seen that the major portion in the control current without ALC is the synchronous component. Higher order components contribute only a small amount. With ALC turned on, the synchronous component is almost reduced to zero. On the other hand, other components are not affected because only the synchronous component is extracted by the digital filter.

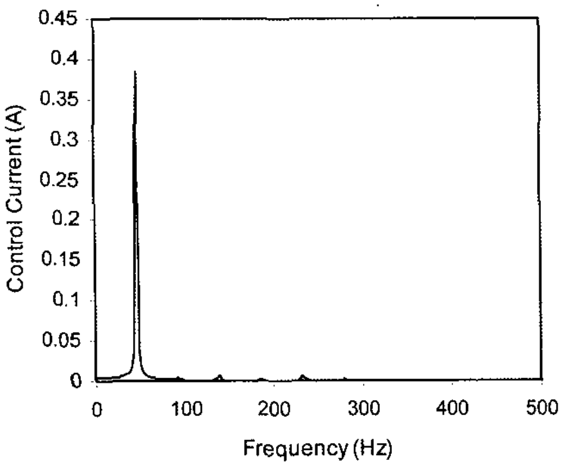

Fig.6. Control current in frequency domain with ALC turned off.

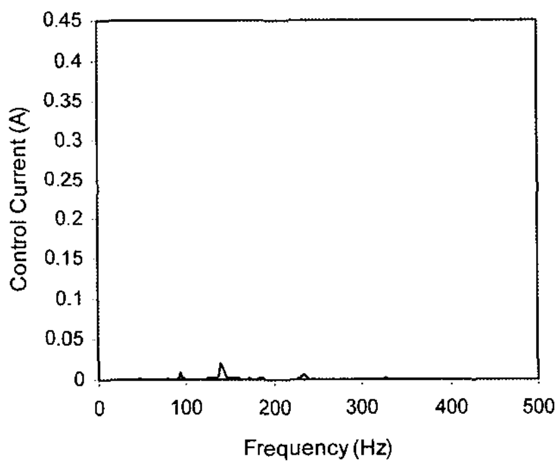

Fig.7. Control current in frequency domain with ALC turned on.

4.2. Change motor speed

To verify its performance with varying rotational speeds, ALC scheme is also examined during a run-up test from 1200 RPM to 3200 RPM. ALC also exhibits satisfactory compensation performance in this experiment.

Figure 8 shows the comparison of effective value of the control current between ALC turned off and ALC turned on. The control current in the latter case can be reduced significantly. This is important to all kinds of AMBs, especially to the vertical Permanent-Magnet-Biased AMB, as the copper loss in this kind of AMB is proportional to square of its effective control current. Thus, its power consumption and generated heat during operation will be reduced significantly by ALC. Smaller control current and less generated heat allow the power electronics to be further integrated, making it possible to put control electronics for small AMB systems in a multichip module (MCM) [15].

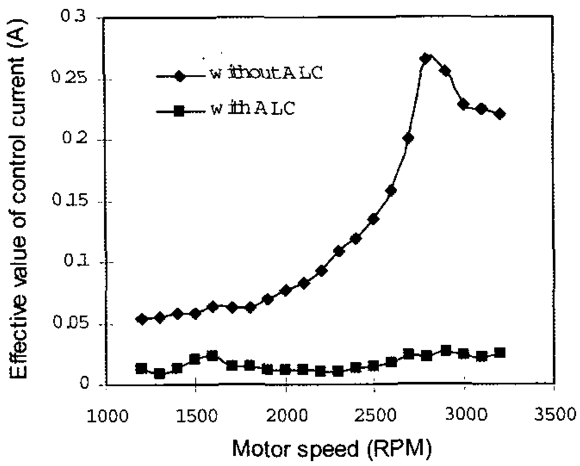

Fig.8. Comparison of effective control current between ALC turned off and ALC turned on.

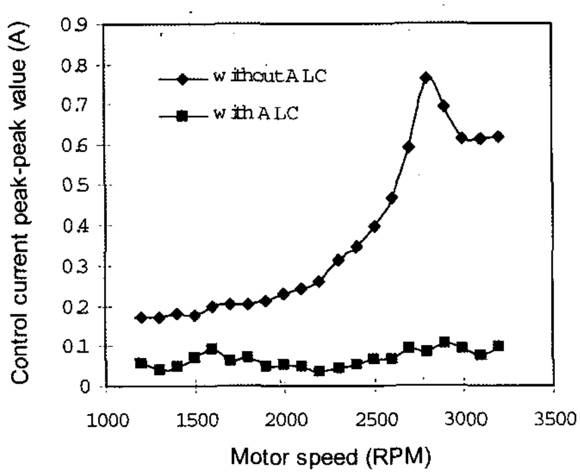

Fig.9. Comparison of control current peak-peak value between ALC turned off and ALC turned on.

Figure 9 shows the comparison of peak-peak value of the control currents between ALC turned off and ALC turned on. It could be seen that the control current fluctuation decreases substantially when ALC is turned on. Reducing the fluctuations of coil currents is helpful in reducing the vibration of the housing [9].

In the experiment, the control current without ALC increases a lot when motor speed is increased, and the maximum point is around 2800 RPM. With the effective control of ALC, control current is almost constant in a very wide speed range.

5. Conclusions

In this paper, a new unbalance compensation scheme, automatic learning control, is introduced, analyzed, and verified in the experiments. The rotor is forced to rotate about its inertial axis. By achieving this, the transmitted force due to the acceleration of the inertial axis is reduced. At the same time, the synchronous control current in AMB coils decreases, resulting in much less copper loss in vertical Permanent-Magnet-Biased bearings.

ALC is based on the combination of time-domain iterative learning control and gain-scheduled control. The learning cycle and learning gain can be automatically adjusted to different rotational speeds. A digital filter is used in order to obtain synchronous control current signals. Because the iterative learning control is employed in time domain instead of frequency domain, learning gain in ALC is a scalar rather than complicated gain matrix. Therefore, large amount of memory space and computation are not required. In comparison with existing unbalance compensation methods in AMB, ALC has advantages of easy implementation, simple control algorithm, less computation load, and good controlling effect. Because of these advantages, it is very suitable for different applications.

ALC can work together with a conventional feedback controller without changing system stability. The feedback controller, which has been already designed for optimum transient response, is responsible for stabilizing the AMB system, while ALC provides the optimized unbalance compensation current.

Experiment results prove that ALC is very effective in unbalance compensation in AMB. The synchronous control current is reduced significantly in experiments. In addition, the ALC scheme can work at different rotational speeds and has good performance during motor speed variation.

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