ISSN: 2688-8645

Vibration Suppression of Active Magnetic Bearings Based on Reinforcement Learning Optimized ADRC

Zhenyu Huang [1], Xiaohu Wang [1], Teng Hu [1,*], Guilin Li [2] and Yanjun Li [3]

[1] School of Mechanical and Engineering, Southwest Petroleum University, Chengdu Sichuan, 610500, China

[2] Taihang National Laboratory, Chengdu Sichuan, 610213, China

[3] AECC Sichuan Gas Turbine Establishment, Chengdu Sichuan, 610500, China

* Corresponding author: Teng Hu

Abstract

To enhance the robustness and stability of active magnetic bearing (AMB) rotor systems under complex disturbances and nonlinear operating conditions, this paper proposes an adaptive active disturbance rejection control (RLADRC) strategy based on reinforcement learning. Traditional ADRC compensates for unbalanced forces through an extended state observer (ESO), but its key parameters (observer gains) rely on empirical tuning, making it difficult to adapt to dynamically changing environments. This study introduces reinforcement learning algorithms to optimize observer gains online through real-time interaction with the system environment, thereby achieving adaptive optimal estimation and compensation for unbalanced disturbances. Simulation results indicate that, compared with traditional ADRC, the proposed method reduces the amplitude of unbalanced forces in each degree of freedom by 90% at a constant speed and results in smaller rotor vibrations when subjected to external impacts. Experimental verification demonstrates that the controller significantly improves anti-interference capability compared to traditional PID control.

Keywords

Active Magnetic Bearing Rotor; Active Disturbance Rejection Control (ADRC); Reinforcement Learning; Extended State Observer (ESO); Anti-interference.

1. Introduction

Active Magnetic Bearings (AMBs) have become ideal supporting components for high-speed rotating machinery due to their advantages of being contact-free, friction-free, and having controllable dynamic characteristics. However, the inherent negative stiffness of AMB systems results in open-loop instability, necessitating closed-loop control to achieve stable levitation[1-3]. While PID control is widely used in industry, its fixed parameters lack adaptability, leading to degraded performance or even instability when facing system perturbations and complex external disturbances. To enhance robustness, researchers have explored control, adaptive LMS algorithms, and composite strategies[4]. Nevertheless, these methods often rely on precise system models or specific frequency measurements, which are difficult to obtain in complex operating environments. Active Disturbance Rejection Control (ADRC) offers a "model-free" advantage by treating internal coupling and external unbalance forces as a "total disturbance," which is then estimated and compensated for by an Extended State Observer (ESO). Despite its effectiveness, the performance of ADRC highly depends on the tuning of observer gains (such as bandwidth). Traditional empirical tuning methods fail to maintain optimal performance under dynamic conditions[5,6]. To address this, this paper proposes a Reinforcement Learning-

ISSN: 2688-8645

based Adaptive ADRC (RLADRC) strategy. By utilizing the TD3 algorithm, the observer bandwidth is optimized online through real-time interaction with the environment. Simulation and experimental results demonstrate that the proposed RLADRC significantly suppresses unbalance vibrations and enhances system robustness compared to traditional PID and standard ADRC.

2. Mathematical Model of 5-DOF Active Magnetic Bearings

Fig. 1 illustrates a simplified magnetic bearing control loop. The rotor is levitated at the geometric center by electromagnetic forces. When the rotor deviates due to disturbances, sensors detect the displacement change and feedback this signal to the controller to generate a corresponding control current.

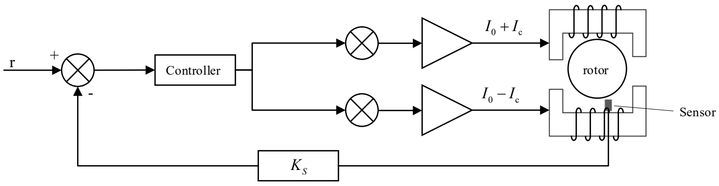

Fig 1. Control loop of magnetic bearing

Specifically, one power amplifier outputs a current of $I_0 + I_c$ magnetic pole pair closer to the rotor axis to increase the electromagnetic force, while another outputs $I_0 - I_c$ to the pair further away to decrease it. The resulting net electromagnetic force returns the rotor to its levitation center.

As shown in Fig 2, the active magnetic bearing (AMB) utilizes an 8-pole stator coil structure.

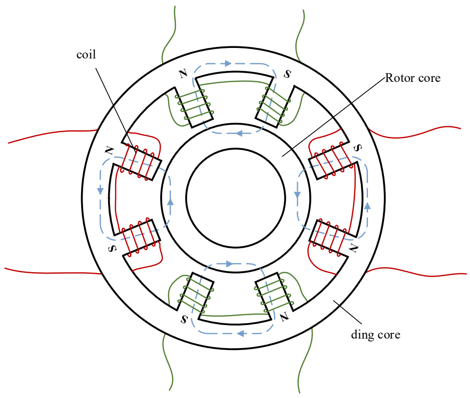

Fig 2. Coil structure of active magnetic bearing

Let n be the number of coil turns, A_a be the effective magnetic pole area, s_0 be the nominal air gap, and i_0 be the bias current. Then we have the electromagnetic force generated by four magnetic poles acting as a differential pair expressed as:

$$f = f_+ - f_- = \frac{1}{4}\mu_0 n^2 A_a \left(\frac{(i_0+i)^2}{(s_0-x)^2} - \frac{(i_0-i)^2}{(s_0+x)^2} \right)\cos\alpha \tag{1}$$

For small displacements where $x \ll s_0$, the equation is linearized by neglecting high-order infinitesimals:

$$f = \frac{\mu_0 n^2 A_a i_0}{s_0^2}(\cos\alpha)i + \frac{\mu_0 n^2 A_a i_0^2}{s_0^3}(\cos\alpha)x = k_i i - k_s x \tag{2}$$

Where $\mu_0 = 4\pi \times 10^{-7}$, represents the vacuum permeability, n is the turns of coils; α=22.5, represents the angle between the magnetic pole and the centerline.

The schematic and force distribution of the 5-DOF AMB-rotor system are shown in Fig 3. O represents the geometric center of the balanced rotor; l_a and l_b are the distances from the origin to the left and right radial displacement sensors, respectively.

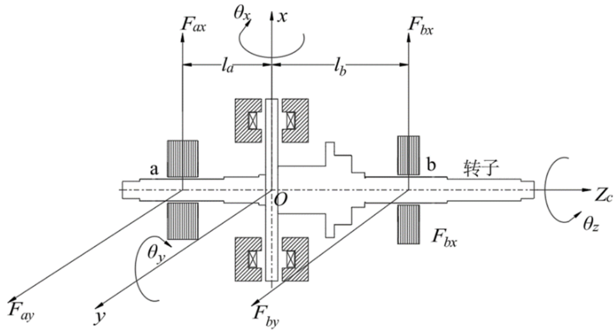

Fig 3. force distribution of the 5-DOF AMB-rotor system

The equations of motion for the 5-DOF AMB-rotor system are defined as follows:

$$\begin{cases} m\ddot{x} = F_{ax} + F_{bx} + F_x' \\ m\ddot{y} = F_{ay} + F_{by} + F_y' \\ m\ddot{z} = F_z + F_y' \\ J_x\ddot{\theta}_x + wJ_z\dot{\theta}_y = -F_{ay}l_a + F_{bx}l_b \\ J_y\ddot{\theta}_y + wJ_z\dot{\theta}_x = -F_{ax}l_a + F_{bx}l_b \end{cases} \tag{3}$$

By defining the state variables , control variables , and output variables , the mathematical model for the radial degrees of freedom is obtained:

$$\begin{aligned} \dot{X} &= AX + BU \\ Y &= CX \end{aligned} \tag{4}$$

3. Optimization Method of ADRC

3.1. Active Disturbance Rejection Control (ADRC)

The AMB is a highly nonlinear system with multi-degree-of-freedom (DOF) coupling. ADRC simplifies the 4-DOF radial control into decentralized single-DOF channels by treating unbalance forces and inter-channel coupling as a "total disturbance". The primary external harmonic interference, the rotor mass unbalance force, is modeled as:

$$\begin{cases} f_{dx} = me_x w^2 \cos(wt) \\ f_{dy} = me_y w^2 \sin(wt) \end{cases} \tag{5}$$

Where e_x and e_y represent mass eccentricity.

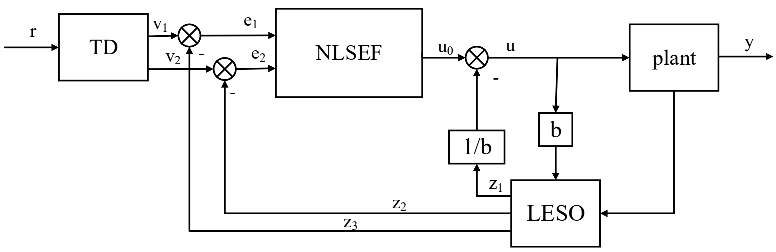

Fig 4. Structure of ADRC

As shown in Fig. 5, the ADRC consists of three core modules: the Tracking Differentiator (TD), the Extended State Observer (ESO), and the Nonlinear State Error Feedback (NLSEF). TD generates a smooth transition signal and its derivative to prevent setpoint overshoot. ESO is the core unit, designed to estimate the system states and the total disturbance in real-time for active compensation.

NLSEF utilizes the fal function to compute the control law.

The fal function is defined as:

$$fal(e,\alpha,\delta)=\begin{cases}|e|^{\alpha}\cdot\text{sign}(e),\text{if }|e|>\delta\\ \dfrac{e}{\delta^{1-\alpha}},\text{if }|e|\leq\delta\end{cases} \tag{6}$$

This function follows the principle of "small error, large gain; large error, small gain". At large errors, it avoids control saturation and overshoot; at small errors, the high gain ensures high steady-state precision and eliminates chattering.

3.2. Parameter Optimization via Reinforcement Learning

To enhance AMB performance under varying speeds and external disturbances, this paper proposes an RL-based ADRC (RLADRC) strategy. The core idea is to utilize the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm to adaptively tune the observer bandwidth ω_0 — the critical parameter determining the disturbance estimation and rejection capability of the LESO.

TD3, an advanced Actor-Critic framework, addresses the overestimation bias common in continuous action spaces by employing twin critic networks and delayed policy updates. The agent learns the optimal control strategy through real-time interaction with the AMB environment. The specific reinforcement learning components are designed as follows:

State Space (S): The state includes the rotor displacement deviations at both bearings in x and y directions: $s=\left(e_{xa},e_{xb},e_{ya},e_{yb}\right)$.

Action Space (A): The agent directly outputs the optimized observer bandwidth ω_0. During training, the controller bandwidth ω_c is maintained within a stable range.

Reward Function (R): A normalized weighted reward function is designed to balance control precision with system safety. It considers position errors, system response speed, and penalties for control currents that approach the physical limits of the electromagnets to avoid saturation:

$$R=w_1r_1+w_2r_{error}+w_3r_{set}+w_4r_{final}+w_5de \tag{7}$$

where r_1 is the safety reward and r_{error} is the error-based reward.

By maximizing the cumulative reward, the TD3 agent enables the ADRC to self-adjust its parameters dynamically, ensuring robust vibration suppression across various operating conditions.

4. Simulation Analysis

4.1. Experimental Setup and Parameters

To verify the effectiveness of the reinforcement learning-based ADRC (RLADRC), a 4-degree-of-freedom (DOF) magnetic bearing-rotor experimental platform was modeled. The physical parameters of the system, including rotor mass and stiffness coefficients, are detailed in Table 1.

The TD3 agent was trained over 150 episodes with specific hyperparameters, such as a discount factor of 0.9 and a learning rate of times 10^{-3}, to ensure optimal parameter convergence.

Table 1. Main design parameters of AMB-rotor system

Parameters	Symbols	Values	Unit
Distance from electromagnet 1 to geometric center	l_a	254	mm
Distance from electromagnet 2 to geometric center	l_b	220	mm
Rotor mass	m	13	kg
Equatorial moment of inertia	J	123565×10^{-6}	Kg ▪ m^2
Polar moment of inertia	J_z	42300×10^{-6}	Kg ▪ m^2
Bias current	I_0	1.5	A
Current stiffness coefficient	k_i	53.498	N/A
Displacement stiffness coefficient	k_x	-1.0710^5	N/m

4.2. Static Levitation Performance

The static levitation performance was evaluated at 0 r/min using a 0.25 mm step signal, as shown in Fig 5. The results indicate that RLADRC achieves a faster response time and significantly lower overshoot compared to traditional PID and standard ADRC.

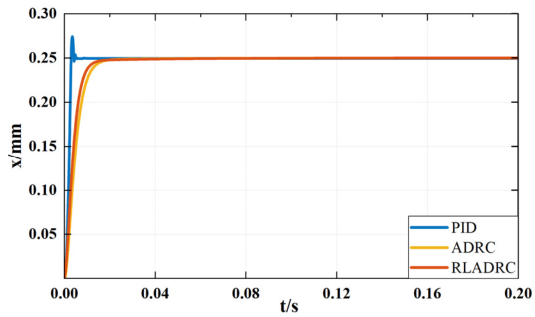

Fig 5. Simulation of rotor static levitation

During the initial levitation phase, RLADRC required a lower peak current than PID to achieve the same levitation force. Also when subjected to a 500 Hz sinusoidal external disturbance, the displacement vibration peak of RLADRC was 50% lower than that of PID control, demonstrating superior disturbance rejection.

5. Summary

This paper proposes an RLADRC strategy for a 4-DOF AMB-rotor system, utilizing the TD3 algorithm to optimize the observer gains online. The key findings are:

Optimization Efficiency: The RL agent successfully automates the tuning of LESO gains, which is typically the most challenging aspect of ADRC design.

High Precision: Compared to PID, the RLADRC reduced average tracking errors by 90% and suppressed unbalance vibration peaks by 50% at 6500 r/min.

Engineering Value: The RLADRC demonstrates exceptional performance in both static levitation and dynamic high-speed operation, making it a high-performance alternative to traditional PID for industrial AMB applications.

Acknowledgments

This work was supported by Taihang National Laboratory of China (A2063).

ISSN: 2688-8645

References

[1] Lusty, Christopher,Keogh,et al. Active Vibration Control of a Flexible Rotor by Flexibly Mounted Internal-Stator Magnetic Actuators[J]. IEEE-ASME TRANSACTIONS ON MECHATRONICS, 2018, Vol. 23 (6): 2870-2880.

[2] F.Y. Saket,P.S. KeoghCA1. Force-based feedforward control of persistent synchronous rotor/ touchdown bearing contact in active magnetic bearing systems[J]. Mechanical Systems and Signal Processing,2023,Vol.201: 110657.

[3] Van-Nam Giap,Shyh-Chour Huang. Effectiveness of fuzzy sliding mode control boundary layer based on uncertainty and disturbance compensator on suspension active magnetic bearing system[J]. Measurement + Control,2020,Vol.53: 934-942.

[4] Gui-Ping Ren,Ziheng Yu,Yue Wu,. The analysis of similarities and differences between ADRC and PID controller for AMB system[C]. 2021-07-26.

[5] Zhihao Ma, Gai Liu,Yichen Liu,et al. Research of a Six-Pole Active Magnetic Bearing System Based on a Fuzzy Active Controller[J]. Electronics,2022,Vol.11(11): 1723.

[6] Scott Fujimoto, Herke van Hoof,Dave Meger. Addressing Function Approximation Error in Actor-Critic Methods[J]. Statistics,2018.