Active Magnetic Bearing PID Tuning With Model-Free Analysis Based Modified Hebb Learning Rule

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Abstract

Active Magnetic Bearings (AMBs) are critical for high-speed rotating machinery, yet their PID controller tuning remains heavily reliant on manual calibration and precise system models, limiting efficiency and adaptability. This paper proposes a novel model-free PID tuning framework that integrates a modified Hebb learning rule with adaptive disturbance rejection to overcome these limitations. The methodology employs a two-phase approach: During static levitation, heuristic offline calibration guided by directional analysis of displacement-current correlations optimizes initial P and D parameters to ensure baseline stability. In rotational operation, an adaptive notch filter (ANF) isolates synchronous disturbances from sensor signals, enabling online Hebb learning adaptation of PID weights to suppress vibration. Experimental validation on a 9.05 kg rotor system demonstrates the framework's efficacy. Key innovations include: (1) A Hebb learning rule with heuristic initialization for PD weight updates; (2) ANF-based synchronous disturbance extraction to decouple learning from broadband noise; (3) A hybrid offline-online tuning strategy eliminating model dependency. Results show up to 20% reduction in displacement vibration amplitude at 2000 rpm under steady state compared to conventional PID, confirming the method's superiority in stable regimes, while acceleration transients reveal ANF phase-delay limitations. This work establishes a practical, model-free pathway for autonomous AMB control, merging dynamic adaptability with operational safety.

Keywords : Active Magnetic Bearing, PID tuning, Hebb learning rule, adaptive notch filter, model-free control

1. Introduction

At present, rotating machinery is developing towards heavy load, high speed and high precision (K. N. V. Prasad and G. Narayanan, 2019). Due to the characteristics of no mechanical contact, high speed, low noise and high precision, the active magnetic bearings (AMBs) have received extensive attention and has been widely used in aerospace, energy storage and medical fields (G. Schweitzer and E. H. Maslen, 2009).

Since the AMB cannot be stable in open-loop, closed-loop control is necessary (M. Hutterer and M. Schroedl, 2022). Among controller, PID has simple structure and is widely used in AMB system (T. Huang et al., 2019). However, the AMB PID displacement controller requires experienced engineers to tune for a long time (M. Zhou et al., 2024). Nowadays, with the rapid development of artificial intelligence, intelligent algorithms are also applied to AMB control (S. Wang et al., 2020; Z. Xu and H. Xu, 2022). However, these methods often require an accurate AMB model. Some tuning methods require the system to be stable, which makes the optimization of the controller limited. Furthermore, many algorithms are too complex, occupying a large amount of data memory, and even affecting the stability of the system. the parameter adjustment process of many intelligent algorithms requires a large amount of experimental data for training. These trainings themselves are more complex, which actually increases the cost of debugging and reduces the benefits of the algorithm.

Hebb learning has the characteristics of simple structure and clear physical meaning (Y. -L. Xing et al., 2021). Based on these characteristics, Hebb learning provides a solution for model free online PID regulation of the system (H. Fang and X. Yu, 2011). In the experiment, the parameter adjustment of Hebb learning rules cannot guarantee the final stability of the system. Meanwhile, AMB operation is also affected by various types of noise from low to high frequencies, which further affects the adjustment results of PID (B. Widrow, 2018).

To optimize the tuning process, the proposed debugging procedure is divided into static and rotating conditions. During static levitation, offline tuning is employed, where the Hebb learning rule evaluates whether the PID parameters require increase or decrease. This process can significantly improve the heuristic algorithm. During rotation, online tuning is implemented. An adaptive notch filter (ANF) extracts the synchronous disturbance amplitude as the tuning reference, followed by parameter adjustment via the Hebb learning rule.

2. Modeling and controller design

The object of PID controller is rotor displacement. Thus, the models of other controllers, current loop, converter and sensor are simplified.

Under the condition of neglecting gyroscopic effects, the axes within the AMB system exhibit no coupling phenomenon. In this scenario, the linearized model for a single axis can be mathematically represented as

$$m\ddot{x}(t) = -k_x x(t) + k_i(i_{xc}(t) + i_{xG}) - mg + f = -k_x x(t) + k_i i_{xc}(t) + f \tag{1}$$

where m represents the rotor mass, $x(t)$ represents the shift displacement of the rotor relative to stable position, $\ddot{x}(t)$ represents the acceleration of the rotor, k_x represents the force/displacement stiffness (which is negative), k_i represents the force/current stiffness (which is positive), $i_{xc}(t) + i_{xG}$ represents the control current, g represents the gravitational acceleration and f represents the unbalanced force. i_{xG} is the gravitational compensation current, satisfying the steady-state equilibrium condition $k_i i_{xG} = mg$. As the dominant control variable, $i_{xc}(t)$ directly determines the transient motion characteristics of the rotor during active regulation.

Ignoring f, the single-axis bearing system is similar to the spring system. A second-order spring system can be expressed as

$$m\ddot{x}(t) = -kx(t) - d\dot{x}(t) \tag{2}$$

where the dynamic system can be characterized by $\dot{x}(t)$ denoting the rotor velocity, k and d correspond to the spring stiffness and damping coefficient respectively. This configuration demonstrates that an AMB is capable of emulating a second-order spring system when integrated with a PD displacement controller. As evidenced by equations (1) and (2), the PD displacement controller can be designed as

$$\begin{cases} i_{xc}(t) = P\big(-x(t)\big) + D(-\dot{x}(t)) \\ P = \dfrac{k - k_x}{k_i} \\ D = \dfrac{d}{k_i} \end{cases} \tag{3}$$

The PD controller affects the stability of $i_{xc}(t)$ controlled AMB system. The I controller will not directly affect the stability of the controller and is used to eliminate the static error.

The regulation of AMB systems necessitates discrete PID control implementation due to digital control requirements. Assuming that T_s represents the sampling cycle, ref represents the reference position ($ref = 0$) and P, I, D respectively represent PID controller parameters, the incremental discrete PID displacement control algorithm can be mathematically formulated as:

$$\begin{cases} \dot{x}(n) = \dfrac{x(n+1) - x(n)}{T_s} \\ \ddot{x}(n) = \dfrac{\dot{x}(n+1) - \dot{x}(n)}{T_s} \\ e(n) = ref - x(n) \\ \Delta i_{xc}(n) = P(e(n) - e(n-1)) + IT_s e(n) + \dfrac{D}{T_s}(e(n) - 2e(n-1) + e(n-2)) \\ i_{xc}(n) = \Delta i_{xc}(n) + i_{xc}(n-1) \end{cases} \tag{4}$$

According to (1), (2), the single-axis AMB with only variables x and i_{xc} can be represented as:

$$x(n) = (-\frac{k_x T_s^2}{m} + 2)x(n-1) - x(n-2) + \frac{k_i T_s^2}{m} i_{xc}(n-1) + \frac{T_s^2}{m} f \tag{5}$$

In conventional control systems, high-frequency noise is typically attenuated using low-pass filters and anti-aliasing filters. Given their high cutoff frequencies, these filters are often neglected in subsequent control loop analyses. For current loops and converters, they are commonly modeled as a cascade of a proportional element and a time-delay element. Due to their high bandwidth, they can be further simplified to a pure proportional gain. The sensor is modeled as an ideal proportional amplifier.

For typical PD controller regulation, the selection of k and d in (2) is often empirically determined. Additionally, factors such as non-ideal linearity in k_i, k_x, sensor dynamics, and controller limitations introduce further complexity. At higher speeds, the system is additionally influenced by structural mode vibrations and gyroscopic effects, necessitating adaptive PID tuning. These challenges collectively complicate the systematic optimization of PID parameters.

3 PID tuning based modified Hebb learning rule

3.1 Fundamentals of the Hebb learning rule

Considering the aforementioned reasons, the PID control of active magnetic bearing (AMB) systems presents significant tuning challenges. To address this issue, this study proposes a Hebbian learning-based approach for systematic parameter optimization. The basic idea of Hebb learning is that when two neurons are activated at the same time, the strength of the connection between them is proportional to their excitation product. Tuning PID based Hebb learning is actually aimed at adjusting weight value. In the adjustment process of AMB system, it is expected to adjust the displacement x to ref, so the expression can be obtained as follows:

$$\begin{cases} w_1(n) = w_1(n-1) + \Delta w_1(n) \\ w_2(n) = w_2(n-1) + \Delta w_2(n) \\ w_3(n) = w_3(n-1) + \Delta w_3(n) \\ \Delta w_1(n) = \eta_P e(n) i_{xc}(n) x_1(n) \\ \Delta w_2(n) = \eta_I e(n) i_{xc}(n) x_2(n) \\ \Delta w_3(n) = \eta_D e(n) i_{xc}(n) x_3(n) \\ i_{xc}(n) = i_{xc}(n-1) + K \sum_{j=1}^{3} w_j(n)\, x_j(n) \end{cases} \tag{6}$$

Where $x_1(n) = e(n) - e(n-1)$; $x_2(n) = e(n)$; $x_3(n) = e(n) - 2e(n-1) + e(n-2)$. η_P, η_I, η_D respectively represent learning rates of proportion, differentiation and integration. K represents neural ratio coefficient. w_i represent weight value.

η_P, η_I, η_D determine the learning rate of PID respectively. For AMB system, P and D have the greatest impact on system stability and response rate. The selection of K is very important for the regulation process. When the value of K is large, the system response is fast, but the overshoot will increase, and when the value of K is too large, the stability of the system will be affected. When K value is small, the system stability is good, but the stability time increases. Therefore, taking the response time and the magnitude of vibration as the measurement standard, the heuristic algorithm is used to adjust the PID learning factor and K value.

3.2 Offline tuning during static levitation

According to Hebb theory, learning processes are particularly sensitive to features that are susceptible to noise interference. Under non-steady-state conditions, the direct application of Hebb learning algorithms for online parameter adaptation may lead to system instability due to excessive modulation. Furthermore, inappropriate initialization of parameters could result in disproportionately large PD gains. To address these challenges in static suspension systems, it is recommended to first employ offline optimization methods to calibrate the P and D parameters, using the Δw_1 and Δw_3 values in (6) as reference indicators for parameter tuning. This approach ensures system stability before implementing online adaptive control strategies. The I has a relatively minor impact on stability compared to the PD. Therefore, selecting an appropriate I-value through empirical tuning during the adjustment process is generally sufficient.

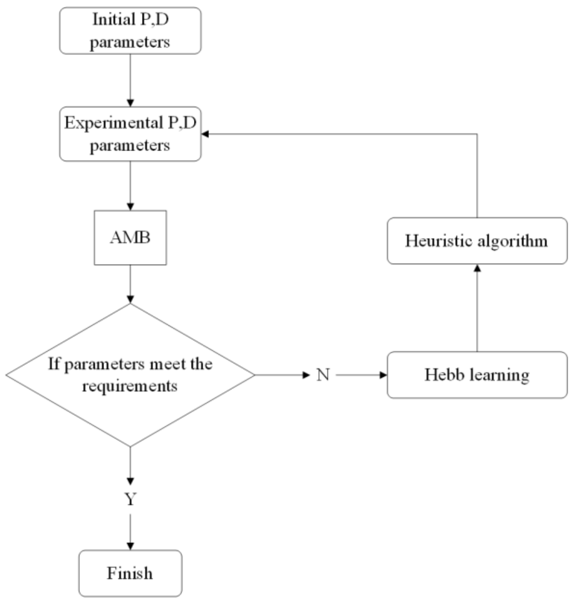


Fig.1 Offline tuning algorithm

The offline algorithm, illustrated in the Fig.1, incorporates Hebb learning to simplify the analysis of P and D parameter effects on magnetic bearings, unlike traditional heuristic algorithm. If coefficients $\Delta w_1(n)$ and $\Delta w_3(n)$ are positive, P and D values are increased; if negative, they are decreased. To ensure robustness, amplitude and collision count remain critical validation metrics. The algorithm's completion is determined by the vibration magnitude. When the measured vibration falls below a predefined threshold, the system is considered stable, enabling the transition to online rotational adjustment.

3.3 Online tuning during rotation

The offline adjustment yields a set of suboptimal but stabilizing PID parameters for rotor suspension, representing a coarse-tuned solution. However, as rotational speed increases, the system encounters dynamic disturbances that compromise stability, necessitating further refinement.

During rotor rotation, imbalance-induced disturbances occur at the rotational frequency (J. Li et al., 2022). To eliminate low/high-frequency interference in Hebbian learning estimation, the system's output displacement is filtered to extract synchronous-frequency components as the learning reference. Employ an adaptive notch filter (ANF) to isolate synchronous disturbances for Hebb learning based PD parameter adaptation. The ANF expression is derived as (7). Where ω_c represents the cutoff angular frequency and Ω represents the rotor speed (rpm). Q represents the quality factor of ANF. A higher Q results in a narrower filter bandwidth, enhancing frequency selectivity for targeted signal extraction.

$$\begin{cases} y_o = \dfrac{\omega_c^2}{s^2 + \dfrac{\omega_c}{Q}s + \omega_c^2} \\ \omega_c = 2\pi\dfrac{\Omega}{60} \end{cases} \tag{7}$$

The complete control architecture is illustrated in Fig.2. The sensor-acquired displacement signal is initially processed through ANF to attenuate synchronous-frequency disturbances. By subtracting the ANF-filtered signal from the original displacement, a residual signal containing exclusively the synchronous disturbance component is obtained, effectively isolating the rotational-frequency response while suppressing both high and low frequency noise components. This purified disturbance signal is subsequently utilized as the input to the Hebb learning algorithm, which adaptively modifies the PD control parameters, thereby facilitating real-time optimization of the controller's performance. This approach enables dynamic self-tuning of the control system during operation.

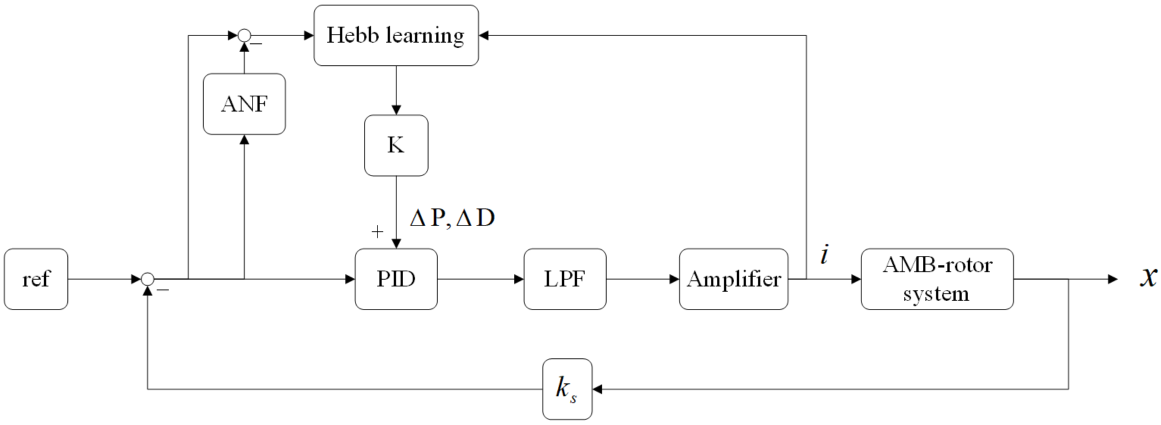


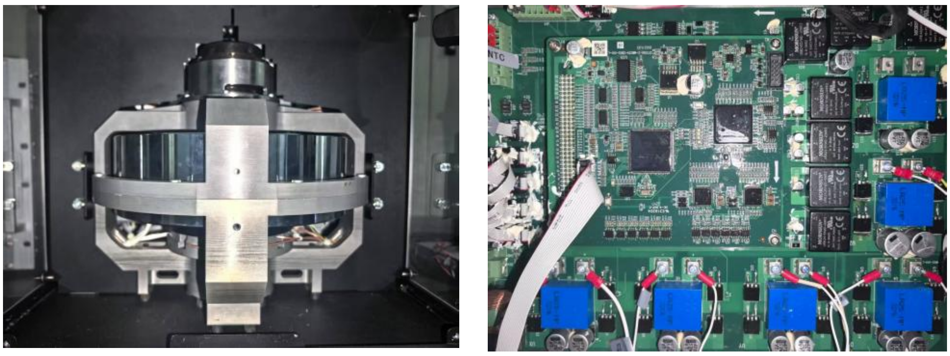
Fig.2 Online tuning algorithm

The ANF requires rotor speed as its input, but fails to extract meaningful frequency components at extremely low speeds. Consequently, Hebb learning tuning is disabled in this regime, and offline-learned PD values are applied instead.

4 Experimental results

4.1 Setups

To validate the reliability of the proposed scheme, experimental verification was conducted using the setup illustrated in Fig.3.



(a) (b)

Fig.3 (a) the rotor and AMB (b) DSP

The digital control system for AMB was implemented on a TMS320F28335 digital signal processor (DSP), with the detailed system parameters provided in the Table 1. The displacement data output by the sensor is collected by the logic analyzer (Kingst Logic Analyzer LA5016).

Table 1 Major parameters of the rotor system

Parameter	Symbol	Value
Rotor mass	m	9.05 kg
Radial protecting bearing half air gap	g_0	200 μm
Radial force/current stiffness	k_i	62.3 N/A
Radial displacement/current stiffness	k_x	-4.08×10^5 N/m
PWM switching frequency	f_s	20 kHz
Sampling frequency	f_{sam}	3.33 kHz

Set the initial value of parameter adjustment. P is set to $(2 \times |k_x| - |k_x|)/ki$, which represents k is the natural stiffness, and then set $D = 0.1\sqrt{m(k_i P + |k_x|)}/k_i$. The stability judgement value of offline tuning is set to $g_s = 0.25g_0$. The initial parameters of the algorithm show in Table 2. To analyze the impact of the PD controller, normalizing the displacement by multiplying $1/k_s$ on the control system. It is mathematically equivalent to setting the k_s to unity. To optimize filtering performance, $Q > 0.707$ is selected to improve ANF selectivity.

Table 2 Algorithm initialization parameters

Parameter	Symbol	Value
Radial base parameter P	P_0	6.549×10^3 A/m
Radial base parameter D	D_0	4.362 A · s/m
Offline tuning stability judgement	g_s	50 μm
Learning rate of P	η_P	6×10^8
Learning rate of D	η_D	3×10^7
Neural ratio coefficient	K	1.2
Quality factor of ANF	Q	2

4.2 Tuning process and results

In the static levitation experiment, stabilizing the PD parameters is essential. Experimental observations indicate a positive ΔP and negative ΔD, suggesting that the initial proportional gain P_0 is insufficient while the derivative gain D_0 is excessive. However, the Hebb learning tuning exhibits limited efficacy under unstable conditions due to contamination by mixed-frequency noise, rendering it ineffective for parameter tuning. Consequently, manual offline calibration was employed to optimize system stability, yielding refined PD values of $P = 3.5 \times 10^4$ A/m and $D = 100$ A · s/m.

To enable a fair comparison between conventional PID and Hebb learning PID during online adjustment, the experiment employed manually optimized PD parameters for conventional PID ($P = 5 \times 10^4$ A/m and $D = 90$ A · s/m.), while initializing Hebb learning PID with the PD values obtained from static levitation. The system acceleration results are presented in Figure 4. Below 100 rpm, the system operates without Hebbian adaptation, resulting in smaller displacement vibrations with conventional PID control. Above this threshold, Hebb-PID implementation reduces vibration amplitude. However, increasing rotational speed introduces disturbances from unbalanced electromagnetic forces and gyroscopic coupling, leading to an overall vibration increase, though Hebb-PID maintains superior performance.

At higher speeds, ANF-induced phase delays cause a discrepancy between the filtered frequency components and actual rotor dynamics. This temporal mismatch degrades Hebb-PID effectiveness, eventually rendering its performance comparable to conventional PID, with occasional amplitude increases. The acceleration profile concludes at this stage (Fig.5). Under steady-state conditions, Hebbian adaptation demonstrates consistent stability improvements over traditional PID.

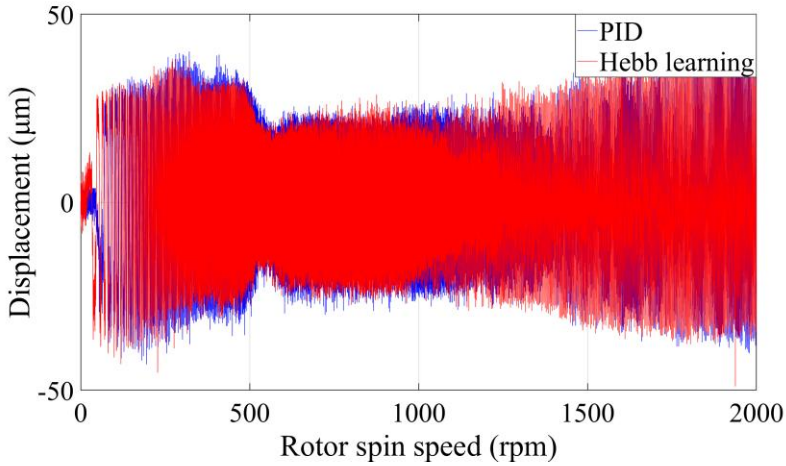


Fig.4 Comparison of PID and Hebb learning control effects under acceleration conditions

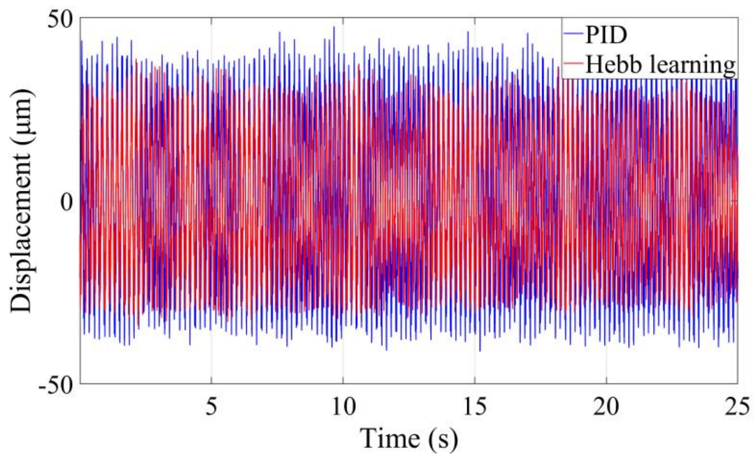


Fig.5 Comparison of PID and Hebb learning control effect at 2000rpm

5 Conclusion

This study presents a systematic framework for PID tuning in AMB systems using enhanced Hebbian adaptation, overcoming limitations of model dependency and manual calibration. During offline tuning, the Hebb rule dynamically adjusts P and D gains through error-current correlation analysis to stabilize static levitation. The online stage employs ANF for synchronous disturbance extraction, enabling real-time PD adaptation during rotation.

Experimental results demonstrate that:

1. The Hebb method effectively guides static levitation tuning;

2. The enhanced Hebb learning achieves superior performance with equivalent PID parameters, particularly at constant speeds (20% displacement vibration reduction versus conventional PID);

3. Acceleration conditions diminish this advantage due to ANF phase errors.

The proposed hybrid approach—combining offline heuristic initialization with online adaptive learning—offers a robust, model-free solution for AMB control. Key contributions include: (1) a noise-resilient Hebb learning update rule for PID weights, (2) ANF-based disturbance isolation for rotational tuning, and (3) empirical validation of stability and performance metrics. The existing approach remains suboptimal due to offline learning's inability to adjust data size dynamically and online learning's excessive dependence on stable processing rates. Optimizations are necessary to achieve faster and more intelligent regulation.

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