A novel iterative learning control method and control system design for active magnetic bearing rotor imbalance of primary helium circulator in high-temperature gas-cooled reactor

Yangbo Zheng¹,²,³, Xingnan Liu¹,²,³, Jingjing Zhao¹,²,³, Ni Mo¹,²,³ and Zhengang Shi¹,²,³

Abstract
As one of the key technologies of high-temperature gas-cooled reactor, primary helium circulator–equipped active magnetic bearing provides driving force for primary helium cooling system. However, repetitive periodic vibration produced by rotor imbalance may introduce risks to primary helium circulator (even for high-temperature gas-cooled reactors). First, this article analyzes a periodic component extraction algorithm which is widely used in active magnetic bearing rotor unbalance control methods and points out the problem that the periodic component extraction algorithm occupies numerous computing resources which cannot satisfy the real-time request of active magnetic bearing control system. Then, a novel iterative learning control algorithm based on the iteration before last iteration of system information (iterative learning control-2) and a plug-in parallel control mechanism based on the existing control system are put forward, meanwhile, an integrated independent distributed active magnetic bearing control system is designed to solve the problem. Finally, both the simulation and experiment are carried out, respectively. The corresponding results show that the control method and control system proposed in this article have significant suppression effect on the repetitive periodic vibration of the active magnetic bearing system without degrading the real-time requirement and can provide important technical support for the safe and stable operation of the primary helium circulator in high-temperature gas-cooled reactor.

Keywords
High-temperature gas-cooled reactor, primary helium circulator, active magnetic bearing, rotor imbalance, iterative learning control, the iteration before last iteration

Introduction
As a typical mechatronics system, active magnetic bearing(AMB) rotor system (AMBRS) of the primary helium circulator (PHC) provides technical conditions for the high clean helium circulation system in the primary loop of the high-temperature gas-cooled reactor (HTR).¹ However, the AMBRS has some problems such as mass imbalance, sensor runout, asymmetrical circuit, misalignment of geometric centers between the rotor and the stator,²–⁵ which would result in asymmetric magnetic forces produced by the AMB or the motor, and eventually lead to characteristic repetitive periodic rotor vibrations. Fortunately, the active control characteristics of AMB can provide favorable technical means for rotor vibration suppression of the PHC.⁶,⁷ However, the closed-loop feedback control system (CFCS), based on proportional-integral–
derivative (PID) algorithm, cannot effectively control repetitive periodic vibration (RPV).

Until now, there are lots of research results on the AMB rotor unbalance control. From the literature research works, AMB rotor unbalance control methods were divided into unbalance compensation and automatic balance. The unbalance compensation is a method that can control the rotor spins around its geometric axis via compensating periodic signal, and the automatic balance is a method that can control the rotor spins around its inertia axis via ignoring periodic signal. The former is suitable for high-precision applications and the latter is suitable for high-speed applications.

However, RPV is not only caused by the problems stated above, but also a large number of non-periodic disturbances existing in the operational process of AMB system. Therefore, most of unbalance control methods need to extract periodic components from the rotor displacement signal directly or indirectly. As mentioned in previous studies, the process of the periodic component extraction algorithm (PCEA) is basically divided into two steps: the first step is to calculate the coefficients of the frequencies to be extracted using the Fourier transform theory and the second step is to synthesize the periodic signals with respect to the frequencies using the inverse Fourier transform theory. This seems to be a very simple process but it takes numerous digital signal processing (DSP) computing resources in the AMB digital control system due to calling of the sine and cosine functions repeatedly. Obviously, this is a huge challenge to the real-time requirement of the control system. Therefore, if these algorithms are not processed in an efficient mode, PCEA based on Fourier transform theory is difficult to apply to the actual rotor unbalance control. Fortunately, iterative learning control (ILC) algorithm can deal with repetitive problems using the previous system information. If ILC is applied to the AMB rotor unbalance control, then the control system may have sufficient time to complete the extraction of the rotor displacement periodic components through some ingenious mechanisms.

Actually, ILC has been widely and successfully applied in industrial fields with repetitive characteristics. Recently, lots of research works have been performed in the theory and application of ILC. From these research results, the structure of ILC algorithm is flexible, which provides convenience for selecting different previous system information according to different application needs.

In this article, the periodic vibration caused by the AMB rotor unbalance of the PHC is combined with ILC algorithm with the advantages in the aspect of repetitive periodic problems via using the previous system information. Iterative learning control-2 (ILC-2) is proposed for the AMB rotor unbalance control of the PHC. Furthermore, an integrated distributed parallel digital control system is designed for an AMB experiment system to verify the unbalance control method.

A novel ILC algorithm for the AMB rotor unbalance control

Problem formulation

Most research results on the AMB rotor unbalance control need to extract the periodic components of the signal, but unfortunately most of them only described the algorithm theory and did not analyze the existing problems from the perspective of digital control system. However, we found PCEA based on Fourier transform theory would occupy numerous computing resources, which ultimately cannot meet the real-time requirement of the control system.

Since the periodic vibrations of AMBRS have the same frequency or multi-frequency relationship with the period of rotor rotation $(T)$. In other words, the frequencies of the periodic vibrations are integral multiples of the rotor rotational frequency. Clearly, the main component of the periodic vibrations is the synchronous vibration. Therefore, PCEA of displacement information is usually carried out based on $T$. Here, we assume that active magnetic bearing control system (AMBCS) can acquire $N$ displacement signals within $T$, which is shown as

$$ T = \frac{N}{f_s} \tag{1} $$

where $f_s$ is the sampling frequency of the control system. Visibly, a displacement error sequence of length $N (\varepsilon_k[i]_{i=0}^{N-1})$ can be obtained within $T$. Here, we take the synchronous vibration extraction achieved by the principle of discrete Fourier transform theory used in our work as an example. First, the coefficients calculation of the synchronous vibration component are performed according to equation (2), and then the periodic displacement error sequence of length $N (\varepsilon_k[i]_{i=0}^{N-1})$ can be obtained according to equations (3)-(5). Obviously, this method can not only obtain a strict periodic sequence, but also has an absolute filtering effect on non-periodic vibration, which can guarantee ILC control effect on repetitive problems.

\[
\begin{align*}
    a_1 &= \sum_{i=0}^{N-1} \varepsilon_k[i] \cos \left( \frac{2\pi i}{N} \right) \\
    b_1 &= \sum_{i=0}^{N-1} \varepsilon_k[i] \sin \left( \frac{2\pi i}{N} \right) \\
    \varepsilon_k[N-1] &= \frac{2}{N} \left( a_1 \cos \left( \frac{2\pi}{N} \right) + b_1 \sin \left( \frac{2\pi}{N} \right) \right) \\
    \varepsilon_k[N-1] &= A_1 \cos \left( \frac{2\pi}{N} \theta \right) \\
    A_1 &= \frac{1}{2} \sqrt{a_1^2 + b_1^2} \\
    \tan \theta &= \frac{b_1}{a_1}
\end{align*}
\]

Unfortunately, the PCEA widely used in the AMB rotor unbalance control is performed at the end of the each rotation and cannot be performed in real-time. In addition, from the description of the algorithm as...
described in equations (2)–(5), a large number of sine and cosine functions need to be called in the process of solving the discrete Fourier transform. Although only a few low-frequency periodic components are needed to be extracted, this process would occupy numerous computing resources of DSP embedded system, resulting in the failure to meet the real-time requirement of the control system. This is an important reason why many unbalance control algorithms cannot be effectively applied in the actual AMB system.

In the early stage of our research, the data loss rate of the control system was very serious, reaching about 20%, as the problem regarding PCEA that occupies numerous computing resources was not considered, which brought huge risks to the stable operation of the PHC. Therefore, how to solve the above problems is the key to the AMB rotor unbalance control.

Algorithm mechanism

ILC is a learning control method based on previous system information. It can effectively solve two problems in the AMB rotor unbalance control. One is that the learning mechanism can be used to suppress RPV disturbance produced by the rotor imbalance and the other one is that the control system can be given sufficient time to extract the periodic components using some ingenious mechanisms.

From the perspective of the ILC algorithm mechanism,16–24 the kth control input of the iterative learning controller can be described as

$$u_k(t) = F(u_0(t), \ldots, u_{k-1}(t), e_0(t), \ldots, e_{k-1}(t), e_k(t))$$

(6)

where $e_{k-1}(t)$ and $u_{k-1}(t)$ are the control error and the control input of the $(k-1)$th iteration, respectively. From equation (6), the current control input $u_k(t)$ is a combination of the previous control inputs, the previous control errors, and the current control error. Furthermore, this combination can be linear or non-linear, and it is a typical intelligent control method by learning from the previous system information. In recent years, ILC has been successfully applied in robot control,25,26 hard disk drive,27 linear motor,28 chemical engineering,29 and so on. Considering the rigid rotor characteristics of the PHC and the requirement of the periodic component extraction in the AMB rotor unbalance control, an open-loop differential ILC-2 with variable forgetting factor and variable learning gain is proposed and expressed as shown in equation (7)

$$u_k(t) = (1 - \xi_f(k - 2))u_{k-2}(t) + \xi_f(k - 2)u_0(t) + L_{k-2}(k - 2, t)(\hat{e}_{k-2}(t + 1) - \hat{e}_{k-2}(t))$$

(7)

where $\xi_f(k - 2)$ is the variable forgetting factor and $L_{k-2}(k - 2, t)$ is the variable learning gain. Corresponding mechanism of the algorithm can be described as shown in Figure 1.

In Figure 1, $k = \{0, 1, \ldots\}$ is the direction indicator of the iteration domain, which represents the kth learning process, $t = \{0, 1, \ldots, N - 1\}$ is the direction indicator of the time domain, namely, the iterative learning time step. Here, the period of rotor rotation ($T$) is set as iterative learning period in AMB rotor unbalance control. Therefore, it is necessary to perform PCEA on the control error collected in previous iteration at the end of each iteration (always described as the $(k - 1)$th iteration), and this process is shown as $e_{k-1}(t) \rightarrow \hat{e}_{k-1}(t)$ in Figure 1. According to the previous analysis, the signal extraction process would occupy numerous system computing resources, and if it continues to be processed in the current controller, it would affect the real-time requirement of the kth ILC process. Therefore, to avoid this problem, the signal extraction can be performed on another process or processor in parallel with this controller. That is to say, the iteration before last iteration of system information ($u_{k-2}(t)$ and $\hat{e}_{k-2}(t)$) is used in the kth ILC process since the last iteration of system information ($e_{k-1}(t) \rightarrow \hat{e}_{k-1}(t)$) is being processed, which is the main reason for ILC-2. Furthermore, ILC-2 has powerful filtering function because it retains only synchronous vibration component.

Figure 1. Mechanism diagram of ILC-2.
Algorithm analysis

Stability analysis. Here, the AMBRS with single degree of freedom (DOF) is taken as an example to analyze the convergence of the algorithm. The system model can be described as

\[
x_k(t + 1) = A(t)x_k(t) + B(t)u_k(t)
\]

\[
y_k(t) = C(t)x_k(t)
\]  

(8)

where \( u_k(t) \in R, y_k(t) \in R, \) and \( x_k(t) \in R^n \) are the input, output, and state matrices, and the system control objective is expressed as

\[
\lim_{t \to \infty} e_k(t) = \lim_{t \to \infty} [y_d(t) - y_k(t)] = 0
\]  

(9)

\[
\begin{align*}
\hat{e}_k(t + 1) & = \hat{e}_k(t + 1) - \xi_f(k - 2) - \sum_{l = 0}^{t} C(t + 1)\Phi(t + 1, t + 1)B(l)(u_0(t + 1) - u_k(l)) - C(t + 1)B(l)k_{-2}(k - 2, t)\hat{e}_k_{-2}(t + 1) - C(t + 1)\Phi(t + 1, t + 1)B(l)k_{-2}(k - 2, t)\hat{e}_k_{-2}(t + 1) + \sum_{l = 0}^{t} C(t + 1)\Phi(t + 1, t + 1)B(l)k_{-2}(k - 2, t)\hat{e}_k_{-2}(t + 1)\end{align*}
\]  

(12)

Now, we need to assume that the system is reachable, that is, there exists a unique target control input sequence \( u_d(t) \) for the target output sequence \( y_d(t) \). Thus, the goal of ILC is to find the target control input sequence \( u_d(t) \) through repetitive iterations until \( y_d(t) \) can track \( y_k(t) \).

The solution of the state equation of the discrete system is expressed in equation (8) and is described as

\[
x_k(t) = \Phi(t, 0)x_k(0) + \sum_{l = 0}^{t - 1} \Phi(t, l + 1)B(l)u_k(l),
\]  

(0 \leq t \leq T)

(10)

where \( x_k(0) \) is the initial states of the system.

In this article, we analyze the convergence of the algorithm using the periodic component of the system control error. The analysis process is described as follows

\[
\hat{e}_k(t + 1) = y_d(t + 1) - y_k(t + 1) = y_d(t + 1) - y_k(t + 1) - (y_k(t + 1) - y_k(t + 1)) = \hat{e}_k_{-2}(t + 1) - C(t + 1)x_k(t + 1) - C(t + 1)x_k(t + 1) - \sum_{l = 0}^{t} C(t + 1)\Phi(t + 1, t + 1)B(l)u_k(l) + \sum_{l = 0}^{t} C(t + 1)\Phi(t + 1, t + 1)B(l)u_k(l)
\]

\[
\sum_{l = 0}^{t} C(t + 1)\Phi(t + 1, t + 1)B(l)u_k(l)
\]  

\[
B(l)u_k_{-2}(l)
\]

where \( \hat{e}_k(t + 1) = y_d(t + 1) - y_k(t + 1) \) is an approximate representation because ILC-2 only conducts the periodic component of the system control error. And now, equation (7) is substituted into equation (11), and then we get the following

\[
\begin{align*}
\|\hat{e}_k(t + 1)\| & \leq \|1 - \xi_f(k - 2) - C(t + 1)B(l)k_{-2}(k - 2, t)\|\|\hat{e}_k_{-2}(t + 1)\| + \sum_{l = 0}^{t - 1} \|C(t + 1)\Phi(t + 1, t + 1)B(l)k_{-2}(k - 2, t)\|\|\hat{e}_k_{-2}(t + 1)\|
\end{align*}
\]

(13)

where we define

\[
\begin{align*}
\rho & = 1 - \xi_f(k - 2) - C(t + 1)B(l)k_{-2}(k - 2, t) \\
a_1 & = \sup_{0 \leq t \leq T, 0 \leq \xi \leq \lambda} C(t + 1)\Phi(t, t + 1)B(l)k_{-2}(k - 2, t)
\end{align*}
\]  

(14)

Multiplying both sides of equation (13) by \( \lambda' \) (0 < \( \lambda' < 1 \)), and then we get the following
\[
\lambda^{t+1}||\hat{e}_k(t+1)|| \leq \rho \lambda^{t+1}||\hat{e}_{k-2}(t+1)|| + 2a_1
\]

\[
\sum_{t=0}^{T-1} \frac{\lambda^{t+1}||e_{k-2}(l+1)||}{1 - \lambda} \leq \rho \lambda^{t+1}||\hat{e}_{k-2}(t+1)|| + 2a_1 \sup_{0 \leq l \leq T} \{ \lambda^{t+1}||e_{k-2}(l+1)|| \}
\]

The supremum of equation (15) can be written as

\[
\sup_{0 \leq l \leq T} \{ \lambda^{t+1}||\hat{e}_k(t+1)|| \} \leq \bar{\rho} \sup_{0 \leq l \leq T} \{ \lambda^{t+1}||e_{k-2}(l+1)|| \}, \quad (0 \leq t \leq T)
\]

(16)

where

\[
\bar{\rho} = \rho + 2a_1 \frac{\lambda(1 - \lambda^T)}{1 - \lambda}
\]

(17)

When the determined parameters are selected to meet \( \rho < 1 \), there must exist a \( \lambda \) to ensure \( \bar{\rho} < 1 \), that is

\[
\lim_{k \to \infty} \sup_{0 \leq l \leq T} \{ \lambda^{t+1}||\hat{e}_k(t+1)|| \} = 0
\]

(18)

Since the process of ILC-2 is to successively search the target input sequence \( u_d(t) \), equation (7) can be rewritten as the parameters selected should meet the convergence requirement stated above

\[
\lim_{k \to \infty} u_k(t) = \lim_{k \to \infty} u_{k-2}(t)
\]

(19)

To sum up, the convergence conditions for a single input single output (SISO) plant with the control algorithm expressed in equation (7), such as the AMB system with single DOF in PHC, can be summarized as follows

\[
\begin{cases}
1 - \xi_B(k) - \mathbf{L}(k, t)\mathbf{C}(t+1)\mathbf{B}(t) < 1
\end{cases}
\]

(20)

According to the above analysis process, consistent convergence conditions shown in equation (20) can be obtained as the ILC based on the last iteration of system information (ILC-1) with the same algorithm expressed in equation (7). And, our previous work has proved this conclusion.

Convergence rate analysis. From the above analysis, it can be known that the convergence conditions of ILC-1 and ILC-2 are consistent, but intuitively, the convergence speed of ILC-2 is slower than that of ILC-1. Obviously, a control algorithm with a very slow convergence rate has almost no application value in engineering. Therefore, the stability analysis is the essential requirement of the ILC algorithm, but the convergence rate analysis is also very important. Here, the spectral radius and iterations are introduced to evaluate the convergence rate of the ILC-1 and ILC-2 based on the contracting mapping principle used in the above stability analysis.

1. Evaluation of convergence rate based on spectral radius

According to equation (16), the relationship of the system control errors based on ILC-2 of two successive iterations can be expressed as

\[
\|\hat{e}_k(t + 1)\|_A \leq \bar{\rho} \|\hat{e}_{k-2}(t + 1)\|_A, (\bar{\rho} < 1)
\]

(21)

Similarly, the relationships of the system control errors based on ILC-1 of two successive iterations can be expressed as

\[
\|\hat{e}_k(t + 1)\|_A \leq \bar{\rho}_1 \|\hat{e}_{k-1}(t + 1)\|_A, (\bar{\rho}_1 < 1)
\]

(22)

\[
\|\hat{e}_{k-1}(t + 1)\|_A \leq \bar{\rho}_1 \|\hat{e}_{k-2}(t + 1)\|_A, (\bar{\rho}_1 < 1)
\]

(23)

By comparing equations (21) and (24), it can be concluded that under the completely identical conditions that include the parameters and the initial state of the system, the convergence rate based on ILC-1 is faster than ILC-2.

2. Evaluation of convergence rate based on iterations

Practically, a threshold control strategy is generally adopted in the AMB rotor unbalance control, which means that the unbalance control is active only when the vibration amplitude exceeds a certain range. Therefore, it can be assumed that when the system has the same initial control error, which would converge within the threshold (\( \hat{e}_{in} \)) as the ILC is active, and the iterations can be used as evaluation index of the convergence rate, here we define

\[
v = \frac{1}{k}
\]

(25)

Furthermore, according to equation (21), the following recurrence relations can be obtained (\( k \) is assumed to be an even number)

\[
\|\hat{e}_k(t + 1)\|_A \leq \bar{\rho} \|\hat{e}_{k-2}(t + 1)\|_A
\]

\[
\|\hat{e}_{k-2}(t + 1)\|_A \leq \bar{\rho} \|\hat{e}_{k-4}(t + 1)\|_A
\]

\[
\vdots
\]

\[
\|\hat{e}_2(t + 1)\|_A \leq \bar{\rho} \|\hat{e}_0(t + 1)\|_A
\]

(26)
Then, we get
\[
\|\tilde{e}_k(t+1)\|_A = \tilde{\rho}^{k/2}\|\tilde{e}_0(t+1)\|_A < \tilde{e}_h \tag{27}
\]
\[
\tilde{\rho}^{k/2} < \frac{\tilde{e}_h}{\|\tilde{e}_0(t+1)\|_A} = e \tag{28}
\]
where \(e\) is a very small positive number. By solving the natural logarithm of both sides of equation (28) and combining equation (25), it can be obtained that the iterations or the convergence rate of ILC-2 needs to meet
\[
k > 2\frac{\ln e}{\ln \tilde{\rho}} \quad \text{or} \quad e < \frac{\ln \tilde{\rho}}{2\ln e} \quad (29)
\]
Similarly, the iterations or the convergence rate of ILC-1 needs to meet
\[
k > \frac{\ln e}{\ln \tilde{\rho}_1} \quad \text{or} \quad e < \frac{\ln \tilde{\rho}_1}{\ln e} \quad (30)
\]
From equations (29) and (30), we can get a conclusion that the evaluation of convergence rate based on iterations is consistent with spectral radius, which also fully conforms that the dependence of ILC algorithm on previous system information is gradually decreasing. Of course, this conclusion is also consistent with the ILC algorithm described in equation (7) and the convergence conditions described in equation (20).

**Algorithm synthesis**

To improve the convergence rate, ILC-2 expressed in equation (7) specifically adopts the setting methods with variable forgetting factor and variable learning gain. Here, we get
\[
u_0(t) = 0 \quad (31)
\]
\[
\xi_{j\beta}(k) = \frac{1}{k} \quad (32)
\]
\[
L_k(k, t) = k_{BC} \frac{1}{k} \tilde{e}_k \tag{33}
\]
Here, \(k_{BC}\) is determined by the convergence conditions described in equation (20). \(L_k(k, t)\) is used to improve the convergence rate at the beginning of ILC-2, and \(\xi_{j\beta}(k)\) is mainly used to improve the stability condition with too fast convergence rate producing by variable gain learning. It is also a kind of robust design method to solve the problem that the identical initial conditions cannot be satisfied completely in each iteration.

Furthermore, the variable forgetting factor and variable learning gain satisfy
\[
\lim_{k \to \infty} (1 - \xi_{j\beta}(k)) = 1 \quad (34)
\]
\[
\lim_{k \to \infty} \frac{1}{k} \tilde{e}_k = 0 \quad (35)
\]
This means that the system control input satisfy
\[
\lim_{k \to \infty} u_k(t) = \lim_{k \to \infty} u_{k-2}(t) = u_d(t) \quad (36)
\]
The conclusion obtained above shows that the target control input sequence \(u_d(t)\) can be eventually solved through repetitive iterative learning, which can ensure that
\[
\lim_{k \to \infty} e_k(t) = 0 \quad (37)
\]

**ILC control system design for AMB rotor imbalance**

**AMB CFCS with single DOF**

Although there exists a certain coupling in four radial DOFs of the mechanical rotor system, the AMBRS of the PHC is a typical rigid rotor with weak coupling. So, it can always be ignored in the actual control system design, which means that an independent distributed control strategy is adopted in four radial DOFs. Therefore, the AMB CFCS with single DOF is only needed to be discussed here, the block diagram is shown in Figure 2.

In Figure 2, \(K_P\) and \(K_D\) are the power amplifier coefficient and displacement sensor coefficient, respectively, \(k_p\) and \(k_c\) are the current coefficient and displacement coefficient, respectively. Therefore, the transfer function of the AMB plant with single DOF can be expressed as
\[
G_{AMB}(s) = \frac{k_p}{ms^2 - k_c} \quad (38)
\]
Obviously, AMB is an unstable system, meanwhile, ILC-2 is an open loop control method that has no stabilizing effect on the system. Thus, the closed-loop feedback loop scheme must be used to achieve the system stability control. At present, PID control algorithms are always used in actual AMB system\(^6\) and the PID control algorithm is described as follows
\[
G_{PID}(s) = k_p \left(1 + \frac{1}{\tau_i s} + \tau_ds \right) \quad (39)
\]
where \(k_p\), \(\tau_i\), and \(\tau_d\) are the proportional coefficient, integral time, and differential time. Substituting equation (39) into Figure 2, the transfer function of the AMB CFCS with single DOF can be described as
\[
K_P k_p \left(\tau_i s + \tau_ds + 1 \right) + K_P K_D k_p \left(\tau_i s + \tau_ds \right) + \tau_d \left(K_P K_D k_p - k_c \right) s + K_P K_D K c_k p
\]
\[
k_p, \tau_i, \text{ and } \tau_d \text{ are set according to system stability conditions and system control requirements.}
Parallel ILC mechanism based on CFCS

There are not only rotor imbalance, but also lots of reasons, such as circumstance noise, measurement error, which can produce vibration disturbances. To avoid the deterioration of ILC-2 performance by the non-periodic signals, it is also necessary to extract the periodic components according to equations (2)–(5). Therefore, a parallel ILC mechanism shown in Figure 3 is adopted to realize ILC-2 expressed in equation (7). Certainly, there are other combinations.

From Figure 3, the iterative learning controller (ILC-2) described in equations (7), (31), (32), and (33) for AMB rotor unbalance control is applied in parallel with PID controller. There are many advantages using this parallel control mechanism, such as the existing CFCS can be used to stabilize the AMB system and suppress the non-periodic vibration disturbances, which can make up for the deficiency of ILC-2. In addition, this parallel structure design does not need to change the original CFCS, which can reduce the cost of controller redesign and has practical engineering application significance in the optimization of AMB system.

Furthermore, the operating mechanism shown in Figure 3 can be described as:

First, the PID controller should continue to execute the PID algorithm in the time domain as before.

Second, the control system must calculate the control error $e_k(t)$ by sampling the rotor displacement information $y_k(t)$. And at the end of each iteration (here means the rotor rotated one round), a complete period control error sequence $e_k[t]$, $t = \{0, \ldots, N - 1\}$ with length $N$ can be obtained, and this process is shown in Figure 3(iii).

Third, when $e_k[t]$, $t = \{0, \ldots, N - 1\}$ is obtained, the system can start to extract the periodic components as described in equations (2)–(5). And it can be known that this process would occupy numerous computing resources of the control system. Without affecting the real-time requirement, the rotor displacement information acquisition, periodic component extraction, and ILC-2 algorithm operation are being performed synchronously. More specifically, when $e_k(t)$ is being acquired, $e_{k-1}[t]$ is being extracted to $\tilde{e}_{k-1}[t]$ and ILC-2 is being executed, and these processes are shown in Figure 3(ii) and (iii).

In short, there are two reasons for the adoption of ILC-2. One reason is the real-time requirement of the ILC loop, which can avoid the problem of occupying the system computing resources due to the periodic component extraction. The other reason is that ILC-2 can ensure the convergence requirement with directly available system information ($u_{k-2}[t]$ and $\tilde{e}_{k-2}[t]$) according to the analysis previous.
Rotor unbalance control system based on a parallel iterative learning mechanism

To keep consistent with the closed-loop feedback control strategy of the AMBRS in the PHC, this article adopts an integrated independent distributed parallel mechanism for four radial directions when designing the rotor unbalance control scheme. And the parallel control system is shown in Figure 4.

Therefore, it is necessary to upgrade the control system of the AMB test bench. The upgraded AMB test bench is shown in Figure 5, and is used to experimentally verify the control method proposed in this article.

The speed sensor in Figure 5 is used to detect the speed and phase of rotor rotation in real-time, and the real-time phase information is used to trigger each iteration. The AMB test bench adopts the self-developed digital control system, of which, ILC-2 controller and PID controller are all developed based on TMS320F28335. Meanwhile, control algorithms are developed on the Code Composer Studio 8.1.0 environment and flash_debug mode is adopted to observe parameters. In addition, NI USB 6215 with the frequency of 10 kHz is used to acquire the displacement signal of each control channel for real-time monitoring.

Experimental research on ILC method for rotor imbalance

In this article, experimental research works on the AMB rotor unbalance control method are divided into simulation and experiment. As the foundation of experiment research, simulation research can provide the basis for experiment directly. Therefore, this article adopts the real design parameters of the AMB test bench shown in Figure 5 to carry out the simulation research. Because the four radial directions are symmetric, this article just shows and analyzes simulation results for the AMB test bench with single DOF. The control parameters designed are shown in Table 1.

The results of simulation

In the simulation, a sinusoidal signal and a random white noise signal are superimposed in the control loop, in which the sinusoidal signal is used to simulate the periodic vibration disturbance caused by the rotor.
imbalance, and the random white noise signal is used to simulate the random vibration disturbance. Then, three groups of simulation as shown in Table 2 are carried out for comparative analysis. The ILC parameters are set according to equations (31), (32), and (33), and $k = 50$ to distinctly observe the ILC process. The simulation results are shown in Figures 6 and 7.

It can be seen from Figure 6 that the AMB CFCS based on PID alone cannot effectively suppress the repetitive periodic disturbance. This is because the PID algorithm is only based on the current system information and without learning from the previous system information, so it has little control effect on the repetitive periodic disturbance. Conversely, if the ILC loop is incorporated into the control system as shown in Figure 3, the repetitive periodic disturbance can be well suppressed, which indicates that ILC with the previous system information has a good control effect on repetitive disturbance. In addition, it can be further seen from Figure 7 that the control error converges to target value at the 9th iteration via ILC-1, while at the 18th iteration via ILC-2. Obviously, the relationship of iterations between ILC-1 and ILC-2 satisfies the theoretical calculation results of equations (29) and (30). Although the former is faster than the latter, the suppression effect of the two methods on repetitive periodic disturbance is consistent in the end.

### Table 2. The groups of simulations.

| Simulations | System configuration |
|-------------|----------------------|
| Group 1     | Only PID             |
| Group 2     | PID and ILC-1        |
| Group 3     | PID and ILC-2        |

PID: proportional–integral–derivative; ILC: iterative learning control.

According to the results of simulation shown above, ILC-2 can satisfy the RPV of the AMB rotor. Although the convergence rate is slower, it is allowed in the AMB rotor unbalance control. Furthermore, the key is that
ILC-2 can meet the real-time requirement of the control system, which is crucial to the system stable operation. To further verify the effectiveness of the control method proposed in this article, the experimental verification is carried out in the AMB test bench as shown in Figure 5. Considering that the PHC usually is operating at rated speed, thus the rotor unbalance control experimental researches are carried out at fixed speed at 4000 r/min (f = 66.7 Hz) with the same configuration and parameters of group 3 in the simulation. The experimental results are shown in Figure 8.

From the experimental results shown in Figure 8, the AMBRs have serious RPV disturbances in four radial directions only under the PID, which means that the PID controller has little control effect on the RPV disturbances. When the control method proposed in this article is adopted, the RPV disturbances are suppressed effectively, and the random disturbances are left finally which can conform to the feature that the ILC has no control effect on non-periodic disturbances. The axis loci shown in Figure 8 are circles or ellipses that indicates the rotor has obvious RPV distortions. If the loci are too large, it may cause the collision between the rotor surface and the auxiliary bearing, which is not allowed in the AMB system. Therefore, the axis loci of the AMBRs need to be monitored in real-time when the PHC is operating. Certainly, the axis loci can be convergent to the safest range via ILC-2, which can provide basic guarantee for the safe and stable operation of the PHC in HTR.

**Conclusion and discussion**

Although ILC-2 proposed in this article is relatively slow in convergence rate, the results of the simulation and experiment show that it can effectively suppress the RPV disturbance produced by the AMB rotor imbalance. In addition, compared with ILC-1, ILC-2 can meet the real-time control requirement of the control system and provide a safety guarantee for the safe and stable operation of the AMB system. Meanwhile, compared with other unbalance control methods, ILC-2 does not need to detect the complex rotor imbalance as ILC can learn from previous system information. Obviously ILC-2 solves the problem that other AMB rotor unbalance control methods cannot meet the real-time requirement.

That is to say, the unbalance control problem of the AMB rotor imbalance in PHC is solved through the novel learning mechanism proposed in this article. Furthermore, the research results of this article can provide the theoretical and experimental basis for the safety and stability of the PHC and the HTR. Of course, it can be further extended to the other AMB application fields.

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**ORCID iD**

Yangbo Zheng https://orcid.org/0000-0002-5086-8436

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