

Rotor Displacement Self-Sensing for Six-Pole Radial Active Magnetic Bearings Using a Physics-Enhanced LSTM Network

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ABSTRACT: To overcome the limitations of displacement sensors in six-pole radial active magnetic bearing (AMB) systems, such as large installation space and low reliability, this paper proposes a physics-enhanced long short-term memory (PhyLSTM) method for rotor displacement self-sensing. Firstly, a mathematical model is derived, and system feasibility is demonstrated. Then, the PhyLSTM network is developed to learn the dynamic mapping from three-phase control currents to rotor displacement. Multiple physical mechanisms, including rotor dynamics, gyroscopic coupling, and eddy-current effects, are incorporated into the loss function, thereby unifying data-driven learning with physical laws. As a result, high-accuracy prediction through the whole rotor motion process is achieved with reduced computational cost. Thirdly, a simulation system is established to evaluate the proposed method under startup, disturbance, and uncertain initial-position conditions, and the results verify the strong generalization capability of PhyLSTM. Finally, experiments of startup, steady-state suspension, acceleration, and anti-disturbance are conducted. Compared with the baseline method, PhyLSTM limits the maximum prediction error to 9 μm and reduces the error by 55.0%, demonstrating accurate rotor displacement prediction and enhanced robustness and reliability of the AMB system.

1. INTRODUCTION

Magnetic bearings support the rotor through controllable Maxwell forces. Benefiting from contactless, lubrication-free operation, long service life, and high-speed capability, they have been widely applied in flywheel energy storage systems [1], gas transportation [2], aerospace [3], high-speed spindles [4], and other fields. The six-pole radial active magnetic bearing (AMB) is derived from the theory of bearingless motors and driven via three-phase inverters. Therefore, displacement self-sensing methods developed for motor-drive systems can be extended to six-pole radial AMB.

Accurate rotor displacement detection is critical for maintaining stable suspension at equilibrium. Conventional displacement detection methods usually require additional sensors [5, 6] or auxiliary coils [7]. However, these methods have inherent limitations. Eddy current sensors are susceptible to electromagnetic interference, whereas other sensing schemes may suffer from rapid signal attenuation or increased structural complexity. Displacement self-sensing has therefore attracted increasing attention because it can reduce system complexity, cost, volume, and noise.

Existing displacement self-sensing methods for rotor displacement prediction fall into three categories: signal injection methods, model-state observation methods, and machine learning methods. Signal injection methods typically include high-frequency (HF) signal injection and pulse width modulation (PWM) carrier-signal injection. HF methods enable rotor displacement estimation under zero- and low-speed condi-

tions [8, 9] and can tolerate slow parameter variations to some extent. However, additional injection and filtering circuits increase system complexity, and the injected high-frequency signals introduce noise [10]. PWM methods are compatible with existing inverter control architectures and have low hardware cost [11], but their performance is highly sensitive to inverter parameters, switching frequency, and sampling accuracy.

Model state observation methods mainly include extended state observer (ESO) and Kalman filter (KF). In [12], a sinusoidal disturbance estimator is introduced to improve tracking of rapidly varying back electromotive force. Nevertheless, ESO methods remain strongly dependent on the adopted model structure and parameter tuning. In [13], a dual-model resonant Kalman filter is designed to reduce the inductance-parameter mismatch between the model and the actual motor. However, KF methods still depend strongly on model accuracy.

Machine-learning methods can be mainly divided into support vector machine (SVM) methods and neural networks. SVM can achieve displacement prediction without relying on an exact mathematical model of the measured system, and it has a compact structure with good generalization ability [14]. However, its performance is strongly affected by the choice of kernel functions and hyperparameters. Neural networks have been introduced for rotor displacement self-sensing because of their strong nonlinear mapping capability. In [15], a recurrent neural network (RNN) rotor displacement prediction method is proposed for DC AMB. However, RNN mainly relies on data-driven methods and lacks physical constraints, which increases the demand for training samples and may limit its generalization capability. In [16], a method combining multiscale feature

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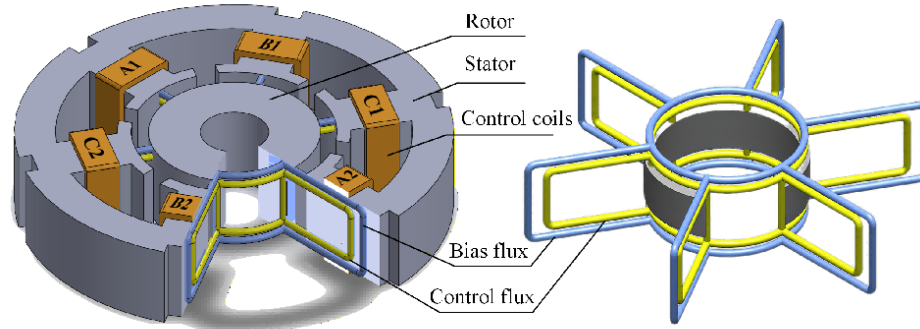


FIGURE 1. Configuration and flux distribution of the six-pole radial AMB.

extraction and long short-term memory (LSTM) is proposed, which shows LSTM's superiority in high-accuracy prediction tasks. In [17], an LSTM-physics fusion prediction method is proposed, in which the physical model is combined with the data-driven network. However, in practical operation, if the physical model is not sufficiently accurate, the LSTM may mainly compensate for model error, which increases computational burden and makes it difficult to learn the system's real operating state. Therefore, directly introducing physical laws into the loss function is an effective way to improve prediction accuracy and physical consistency. A physics-informed neural network (PINN) displacement self-sensing method is developed in [18], where boundary condition is used as physical priors in the training process. This enables the network to better learn the real rotor operating state and reduces the dependence on large-scale training data and computational resources. Similarly, a physics-based and data-driven framework for state estimation in AMB-supported rotors has been proposed in [19], providing a useful guideline for integrating physical models with data-driven learning. Therefore, integrating data-driven and physics-based approaches has become a promising direction for accurate, robust state estimation in active magnetic bearings, combining physical interpretability with data adaptability.

This paper proposes a physics-enhanced long short-term memory network (PhyLSTM) for rotor displacement self-sensing. The PhyLSTM network is used to characterize the complex time-varying nonlinear relationship between three-phase currents and rotor displacement by preserving historical input information. Meanwhile, the rotor dynamic equation and eddy-current equation are embedded into the loss function as physical constraints, so that parameter updating is guided by the underlying physical laws. Consequently, the proposed model integrates data-driven learning and physical laws to reduce computational cost and improve generalization capability.

The rest of this paper is arranged as follows. In Section 2, the mathematical model is derived, and the feasibility of displacement self-sensing is analyzed. In Section 3, the PhyLSTM displacement self-sensing model is developed. In Sections 4 and 5, the proposed method is evaluated through simulations and experiments. Section 6 presents conclusions.

2. OPERATION PRINCIPLE AND MATHEMATICAL MODEL

2.1. Structure and Working Principle

As illustrated in Fig. 1, a six-pole radial AMB is composed of a rotor and a six-pole stator. The magnetic poles are uniformly arranged around the rotor circumference. Each stator pole is equipped with a control coil, and the coils on each pair of opposite poles are connected in series to form one phase. The resulting three-phase windings are excited by a three-phase inverter.

The rotor is supported directly by the magnetic bearing, and the electromagnetic force is generated by the combined effect of bias and control fluxes. In Fig. 1, the blue lines indicate the bias flux, and the yellow lines indicate the control flux. By regulating the control current, the control-flux distribution is adjusted to produce a restoring force against the external disturbance, returning the rotor to equilibrium.

2.2. Mathematical Model of the Six-Pole Radial AMB

Under stable suspension, the magnetic circuit is mainly governed by the air-gap reluctance, while the stator core generally operates in a near-linear magnetization region. Therefore, magnetic leakage and losses are neglected to simplify the six-pole radial AMB model.

Fig. 2 shows the magnetic-circuit representation. G_{ji} ($j = A, B, C$; $i = 1, 2$) represents the air-gap permeance; Φ_{ji} denotes the radial air-gap flux; N is the turn number of the radial coil; and i_j represents the control current.

When rotor offsets x and y occur in the two radial directions, the air-gap permeance can be expressed as:

$$\begin{cases} G_{A1} = \mu_0 S_0 / (\delta_0 + x) \\ G_{A2} = \mu_0 S_0 / (\delta_0 - x) \\ G_{B1} = \mu_0 S_0 / (\delta_0 + 1/2x - \sqrt{3}/2y) \\ G_{B2} = \mu_0 S_0 / (\delta_0 - 1/2x + \sqrt{3}/2y) \\ G_{C1} = \mu_0 S_0 / (\delta_0 - 1/2x - \sqrt{3}/2y) \\ G_{C2} = \mu_0 S_0 / (\delta_0 + 1/2x + \sqrt{3}/2y) \end{cases} \quad (1)$$

where μ_0 denotes the vacuum permeability; S_0 is the magnetic pole area; and δ_0 is the radial air-gap length at equilibrium.

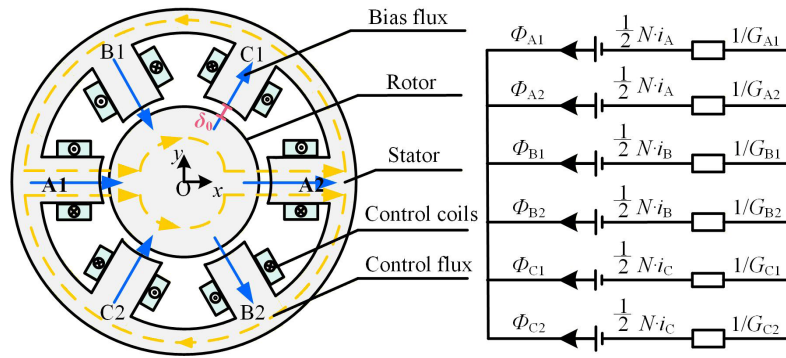


FIGURE 2. Magnetic-circuit representation of the six-pole radial AMB.

Using Kirchhoff's magnetic-circuit law, the air-gap flux is obtained as:

$$\Phi_{ji} = \frac{1}{2} N i_j G_{ji} \quad (2)$$

According to the Maxwell force relation, the radial suspension force generated by each phase is given by:

$$F_j = \frac{\Phi_{j1}^2 - \Phi_{j2}^2}{2\mu_0 S_0} \quad (3)$$

At equilibrium, the air-gap permeance G_{ji} is identical for all air gaps. After (3) is linearized by Taylor series expansion and the three-phase suspension forces are resolved along the x - and y -directions, the radial suspension force is derived as:

$$\begin{cases} F_x = \frac{\sqrt{3}}{\sqrt{2}} \cdot \frac{5S_0\mu_0 N^2 I}{24\delta_0^2} \cdot i_x + \frac{5S_0\mu_0 N^2 I^2}{24\delta_0^3} \cdot x \\ \quad = k_{i_x} \cdot i_x + k_x \cdot x \\ F_y = \frac{\sqrt{3}}{\sqrt{2}} \cdot \frac{5S_0\mu_0 N^2 I}{24\delta_0^2} \cdot i_y + \frac{5S_0\mu_0 N^2 I^2}{24\delta_0^3} \cdot y \\ \quad = k_{i_y} \cdot i_y + k_y \cdot y \end{cases} \quad (4)$$

where I is the amplitude of the single-phase current; k_{i_x} and k_{i_y} are current coefficients with units of N/A; and k_x, k_y are displacement coefficients with units of N/mm.

The three-phase currents i_A , i_B , and i_C are transformed to the x and y directions by the Clark transformation, and the equivalent control current is obtained as:

$$\begin{bmatrix} i_x \\ i_y \end{bmatrix} = \begin{bmatrix} 1 & -1/2 & -1/2 \\ 0 & -\sqrt{3}/2 & \sqrt{3}/2 \end{bmatrix} \begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix} \quad (5)$$

where i_x and i_y are the x - and y -direction control currents.

As shown in (5), near equilibrium, suspension forces in the x - and y -directions are approximately linear with corresponding displacements and control currents.

Based on rotor dynamics, motion equations of the six-pole radial AMB are written as:

$$\begin{cases} m\ddot{x} = F_x \\ m\ddot{y} = F_y - mg \\ J_x\ddot{\theta}_x = -l_a F_y - J_z \Omega \dot{\theta}_y \\ J_y\ddot{\theta}_y = l_a F_x + J_z \Omega \dot{\theta}_x \end{cases} \quad (6)$$

where m is the rotor mass; g is the gravitational acceleration; Ω is the mechanical angular velocity around the z direction; J denotes rotor moments of inertia about the coordinate directions, with equal values; l_a denotes the axial lever arm between the magnetic bearing force plane and the rotor center of mass; and θ denotes the rotor rotation angle about corresponding radial directions.

Accordingly, state-space equations of the six-pole radial AMB are formulated as:

$$\begin{cases} \ddot{x} = \frac{k_x}{m} \left(1 + \frac{ml_a^2}{J_d}\right) x + \frac{k_{i_x}}{m} \left(1 + \frac{ml_a^2}{J_d}\right) i_x - \frac{J_z \Omega}{J_d} \dot{y} \\ \ddot{y} = \frac{k_y}{m} \left(1 + \frac{ml_a^2}{J_d}\right) y + \frac{k_{i_y}}{m} \left(1 + \frac{ml_a^2}{J_d}\right) i_y + \frac{J_z \Omega}{J_d} \dot{x} - g \end{cases} \quad (7)$$

2.3. Feasibility Analysis of Displacement Self-Sensing

To assess whether rotor radial displacement can be estimated from control currents, the local invertibility of the six-pole radial AMB is examined. Near the operating point, the state, input, and output vectors are selected as:

$$\begin{aligned} \mathbf{x}(t) &= [x(t) \quad y(t) \quad \dot{x}(t) \quad \dot{y}(t)]^T \\ \mathbf{u}(t) &= [i_x(t) \quad i_y(t)]^T \\ \mathbf{s}(t) &= [x(t) \quad y(t)]^T \end{aligned} \quad (8)$$

The system can be expressed in the following linear state-space form:

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{d} \\ \mathbf{s}(t) &= \mathbf{C}\mathbf{x}(t) \end{aligned} \quad (9)$$

where

$$\mathbf{C} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix},$$

$$\mathbf{d} = [0 \ 0 \ 0 \ -g]^T$$

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ \frac{k_x}{m} \left(1 + \frac{ml_a^2}{J_d}\right) & 0 & 0 & -\frac{l_a J_z \Omega}{J_d(l_a + l_b)} \\ 0 & \frac{k_y}{m} \left(1 + \frac{ml_a^2}{J_d}\right) & \frac{l_a J_z \Omega}{J_d(l_a + l_b)} & 0 \end{bmatrix}$$

To characterize the dynamic relation from $\mathbf{u}(t)$ to $\mathbf{s}(t)$, the second-order input-output dynamic mapping $\mathbf{E}$ is defined as follows:

$$\mathbf{E} = \begin{bmatrix} \frac{k_x}{m} \left(1 + \frac{ml_a^2}{J_d}\right) x_1 + \frac{k_{ix}}{m} \left(1 + \frac{ml_a^2}{J_d}\right) u_1 - \frac{J_z \Omega}{J_d} x_4 \\ \frac{k_y}{m} \left(1 + \frac{ml_a^2}{J_d}\right) x_2 + \frac{k_{iy}}{m} \left(1 + \frac{ml_a^2}{J_d}\right) u_2 + \frac{J_z \Omega}{J_d} x_3 \end{bmatrix} \quad (10)$$

The Jacobi matrix is then obtained by differentiating $\mathbf{E}$ with respect to $\mathbf{u}(t)$:

$$\frac{\partial \mathbf{E}}{\partial \mathbf{u}} = \begin{bmatrix} \frac{k_{ix}}{m} \left(1 + \frac{ml_a^2}{J_d}\right) & 0 \\ 0 & \frac{k_{iy}}{m} \left(1 + \frac{ml_a^2}{J_d}\right) \end{bmatrix} \quad (11)$$

The Jacobi matrix has rank 2 and is full rank, indicating that it is nonsingular and has a left inverse. Therefore, the current-to-displacement dynamic mapping is locally invertible around the operating point, and radial displacement information can be extracted from measurable current signals.

According to Kalman observability theory, the observability matrix $\mathbf{H}$ is formulated as:

$$\mathbf{H} = [\mathbf{C} \ \mathbf{CA} \ \mathbf{CA}^2 \ \mathbf{CA}^3]^T \quad (12)$$

The rank of $\mathbf{H}$ is 4, identical to the order of the state vector. The six-pole radial AMB system is observable near the operating point. This result indicates that radial displacement information can be recovered from current-related system dynamics. Therefore, current-based rotor displacement prediction is theoretically supported, providing the foundation for the subsequent PhyLSTM self-sensing model.

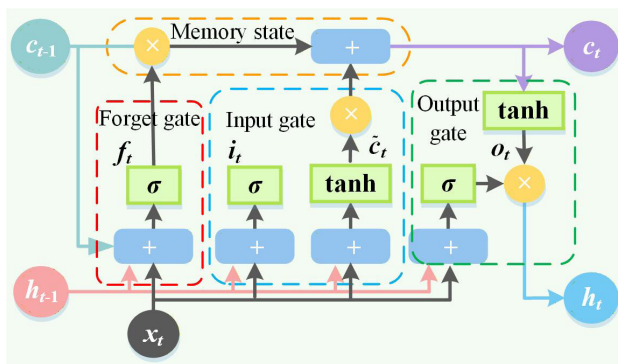


FIGURE 3. Schematic of the LSTM network.

3. DISPLACEMENT SELF-SENSING MODEL BASED ON PHYSICS-ENHANCED LSTM

3.1. Long Short-Term Memory Network

Figure 3 illustrates that the LSTM uses three gating units, namely the input, forget, and output gates, to manage information propagation and overcome the vanishing-gradient issue in conventional RNNs. For the input time-series sample $x(t)$, the gate states, cell state, candidate memory state, and hidden state are defined as:

$$\begin{aligned} i(t) &= \sigma(W_i[h(t-1), x(t)] + b_i) \\ f(t) &= \sigma(W_f[h(t-1), x(t)] + b_f) \\ o(t) &= \sigma(W_o[h(t-1), x(t)] + b_o) \\ h(t) &= o_t \odot \tanh(c(t)) \\ c(t) &= f(t) \odot c(t-1) + i(t) \odot \tilde{c}(t) \\ \tilde{c}(t) &= \tanh(W_c[h(t-1), x(t)] + b_c) \end{aligned} \quad (13)$$

where $x(t)$ is a time-series sample; W_i , W_f , W_o , and W_c are weight matrices for the input gate, forget gate, output gate, and candidate state, respectively; b_i , b_f , b_o , and b_c are corresponding bias matrices; and $\odot$ is the Hadamard product.

A sliding-window data-slicing strategy is adopted to construct historical current sequences. The measured three-phase currents and radial displacement signals are first normalized as:

$$[\mathbf{u}'(k) = [i'_A(k), i'_B(k), i'_C(k)]^T, \mathbf{s}'(k) = [x'(k), y'(k)]^T] \quad (14)$$

where $i'_A(k)$, $i'_B(k)$, and $i'_C(k)$ are normalized three-phase currents, and $x'(k)$ and $y'(k)$ are normalized radial displacements.

For the k -th training sample, a current sequence with a length of L sampling points is extracted by a sliding window:

$$\mathbf{X}_k = \begin{bmatrix} i'_A(k-L+1) & i'_B(k-L+1) & i'_C(k-L+1) \\ i'_A(k-L+2) & i'_B(k-L+2) & i'_C(k-L+2) \\ \vdots & \vdots & \vdots \\ i'_A(k) & i'_B(k) & i'_C(k) \end{bmatrix} \quad (15)$$

The corresponding output is the radial displacement vector at the current time step:

$$\mathbf{Y}_k = \mathbf{s}'(k) = [x'(k), y'(k)]^T \quad (16)$$

Therefore, the proposed model adopts a sequence-to-one prediction structure. After sliding-window slicing, the complete input and output datasets can be written as:

$$\begin{aligned} \mathbf{X} &= [\mathbf{X}_L \ \mathbf{X}_{L+1} \ \dots \ \mathbf{X}_{N_t}]^T, \\ \mathbf{Y} &= [\mathbf{Y}_L \ \mathbf{Y}_{L+1} \ \dots \ \mathbf{Y}_{N_t}]^T \end{aligned} \quad (17)$$

where N_t is the total number of sampling points.

In this paper, with $f_s = 10$ kHz and $L = 100$, each input sequence corresponds to a 10 ms historical window.

3.2. Construction of the Physics-Enhanced Loss Function

To improve physical consistency, a physics-enhanced loss function is constructed, in which the rotor state-space response variable is first defined. Then, the rotor motion equation together with the eddy-current dynamics is embedded into the training process. As a result, predicted results can satisfy both the mechanical motion law and electromagnetic dynamic characteristics.

LSTM₁ is used to establish the nonlinear mapping between the three-phase control currents and the rotor displacement state-space vector, generating the state-space response variable $\mathbf{Z}$:

$$\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \mathbf{z}_3]^T = [\mathbf{s}, \dot{\mathbf{s}}, \xi]^T \quad (18)$$

where $\mathbf{s}$, $\dot{\mathbf{s}}$, and ξ denote the displacement vector, velocity vector, and rotor's eddy-current parameter, respectively.

Based on the state-space response variable $\mathbf{Z}$, LSTM₁ extracts dynamic features across multiple time scales from the current excitation, i.e., $\mathbf{Z} = \text{LSTM}_1(\mathbf{u}, \theta_1)$.

To ensure that the network output satisfies fundamental dynamic relationships, a Savitzky-Golay differential filter is employed to smooth and differentiate variable $\mathbf{Z}$:

$$\dot{\mathbf{Z}} = [\dot{\mathbf{z}}_1, \dot{\mathbf{z}}_2, \dot{\mathbf{z}}_3]^T \quad (19)$$

Ideally, state variables should satisfy the relationships shown in Fig. 4. Thus, the data loss function is expressed as:

$$L_d(\theta_1) = \sum_{i=1}^N (\|\mathbf{z}_1(\theta_1) - \mathbf{s}\|_2^2 + \|\mathbf{z}_2(\theta_1) - \dot{\mathbf{s}}\|_2^2) \quad (20)$$

where θ_1 represents the trainable weights of LSTM₁.

In Fig. 4, under normal operating conditions, the state space satisfies the variable equality condition. Therefore, the state consistency loss function is formulated as:

$$L_s(\theta_1) = \sum_{i=1}^N \|\dot{\mathbf{z}}_1(\theta_1) - \mathbf{z}_2(\theta_1)\|_2^2 \quad (21)$$

LSTM₂ is used to learn the nonlinear dynamic mapping during rotor motion. Considering the gyroscopic coupling between the two radial directions, a coupling operator $\mathbf{S}$ is introduced to describe the displacement dynamics in a unified manner, and (7) is rewritten as:

$$\mathbf{M}\ddot{\mathbf{s}} - \mathbf{K}\mathbf{S}\dot{\mathbf{s}} - \mathbf{Q}\mathbf{s} - \mathbf{B}\mathbf{i} - \mathbf{g} = 0 \quad (22)$$

where $M = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $K = \begin{bmatrix} \frac{J_z \Omega}{J_d} & 0 \\ 0 & \frac{J_z \Omega}{J_d} \end{bmatrix}$, $S = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$, $Q = \begin{bmatrix} \frac{k_x}{m} \left(1 + \frac{ml_a^2}{J_d}\right) & 0 \\ 0 & \frac{k_y}{m} \left(1 + \frac{ml_a^2}{J_d}\right) \end{bmatrix}$, $B = \begin{bmatrix} \frac{k_{ix}}{m} \left(1 + \frac{ml_a^2}{J_d}\right) & 0 \\ 0 & \frac{k_{iy}}{m} \left(1 + \frac{ml_a^2}{J_d}\right) \end{bmatrix}$.

Therefore, the dynamic loss function is constructed as:

$$L_{dy} = \sum_{i=1}^N \|M\dot{\mathbf{z}}_2(\theta_2) - \mathbf{K}\mathbf{S}\mathbf{z}_2(\theta_2) - \mathbf{Q}\mathbf{z}_1(\theta_2) - \mathbf{B}\mathbf{i} - \mathbf{g}\|_2^2 \quad (23)$$

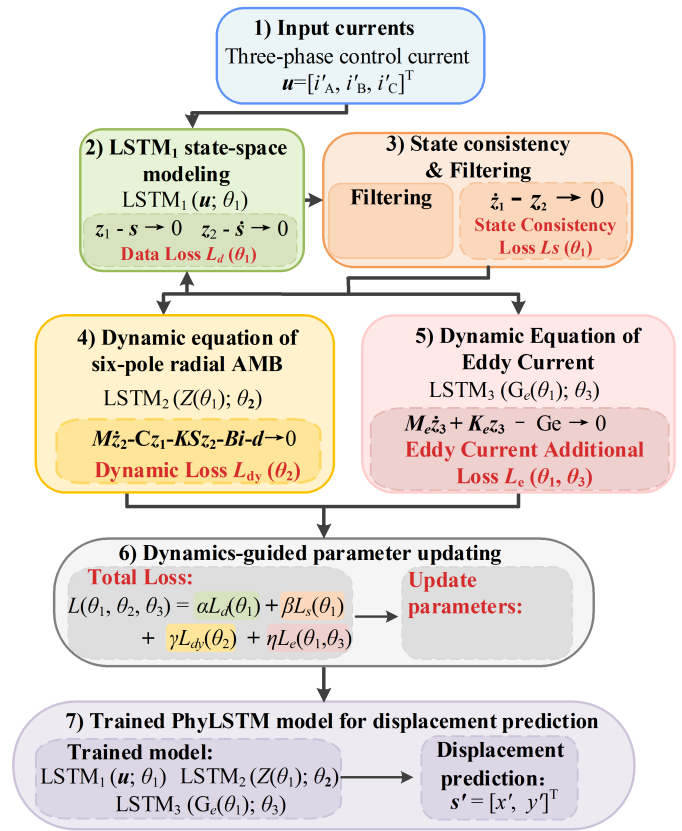


FIGURE 4. Architecture of the PhyLSTM displacement self-sensing model with physics-enhanced parameter updating.

where θ_2 represents the trainable weights of LSTM₂.

The rotor core of the six-pole radial AMB is made of 0.35 mm laminated silicon steel sheets to suppress eddy currents induced by the time-varying air-gap magnetic field. However, under high-speed operation, the increased magnetic-field variation frequency may still induce non-negligible eddy currents in the core, leading to changes in the air-gap flux distribution and electromagnetic force. To account for this high-speed effect in displacement prediction, eddy-current dynamics are further embedded into the physical constraints of the proposed model.

According to electromagnetic diffusion theory, the magnetic diffusion equation of the eddy-current field in the iron core is spatially discretized, yielding the following electromagnetic dynamic equation:

$$\mathbf{M}_e \dot{\xi} + \mathbf{K}_e \xi - G_e(\mathbf{s}, \mathbf{u}) = 0 \quad (24)$$

where ξ is the internal state characterizing the eddy-current effect; G_e is the eddy-current function; $\mathbf{M}_e = \int_{\Omega_c} \sigma \mathbf{N}^T \mathbf{N} d\Omega$,

$$\mathbf{K}_e = \int_{\Omega_c} (\nabla \times \mathbf{N})^T \nu (\nabla \times \mathbf{N}) d\Omega.$$

Thus, the eddy-current loss function is constructed as:

$$L_e(\theta_3) = \sum_{i=1}^N \|\mathbf{M}_e \dot{\mathbf{z}}_3(\theta_3) + \mathbf{K}_e \mathbf{z}_3(\theta_3) - G_e(\theta_1, \theta_3)\|_2^2 \quad (25)$$

where θ_3 stands for the trainable weights of LSTM₃.

To further characterize additional dynamics induced by eddy currents under high-speed operating conditions, LSTM₃ is in-

roduced to learn the temporal evolution of the eddy-current internal state ξ .

The total loss function of the PhyLSTM model is composed of (20), (21), (23), and (25):

$$L(\theta_1, \theta_2, \theta_3) = \alpha L_d(\theta_1) + \beta L_s(\theta_1) + \gamma L_{dy}(\theta_2) + \eta L_e(\theta_3) \quad (26)$$

where L_d , L_s , L_{dy} , and L_e correspond to the data fitting loss, state consistency loss, dynamics loss, and eddy-current loss, respectively, and α , β , γ , and η are weighting coefficients.

Weighting coefficients are determined by validation-set sensitivity analysis. The data fitting loss is assigned the dominant weight, while the state consistency, dynamic, and eddy-current losses are used as auxiliary constraints. Accordingly, $\alpha = 1$, $\beta = 0.1$, $\gamma = 0.05$, and $\eta = 0.05$ are selected to balance prediction accuracy and physical consistency.

This multi-constraint joint training mechanism enables network parameters to be optimized under the guidance of both observed data and physical laws. The former ensures prediction accuracy, whereas the latter ensures physically reasonable state evolution. Because hidden-state evolution is constrained not only by data errors but also by dynamic equations, the model can more stably learn long-term dependencies in time-series data and mitigate drift and error accumulation under uncertain operating conditions.

3.3. Development of the PhyLSTM Rotor Displacement Prediction Model for the Six-Pole Radial AMB

Figure 5 depicts the proposed PhyLSTM model for rotor displacement self-sensing in the six-pole radial AMB. The model contains an input layer, three stacked LSTM layers, two fully connected (FC) layers, and an output layer. The hidden units of the three LSTM layers are set to 128, 64, and 32, respectively. To reduce overfitting, a dropout operation with a rate of 0.2 is placed after the second LSTM layer.

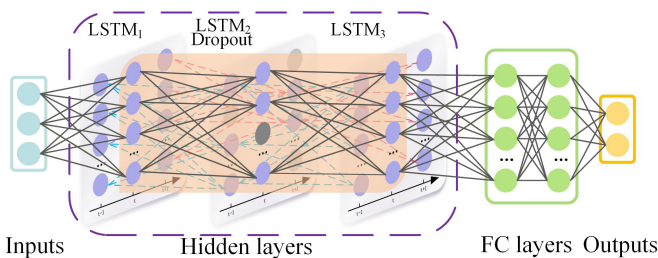


FIGURE 5. Schematic of the proposed PhyLSTM displacement self-sensing model.

A total of 8,000 time-series input-output samples are collected and normalized. To avoid temporal information leakage, the dataset is divided in chronological order. The dataset is chronologically partitioned: the first 70% form the training set; the following 20% constitute the test set; and the last 10% of training samples are retained as an internal validation subset for model selection. The Adam optimizer is used with a learning rate of 10^{-3} , and $L(\theta_1, \theta_2, \theta_3)$ are adopted as the loss function. Early stopping is applied during training. Once the validation loss shows no decrease for five successive epochs, training is stopped, and the model checkpoint with the mini-

um validation loss is retained. This reduces overfitting and ensures consistent model comparison.

4. ANALYSIS OF SIMULATION RESULTS

4.1. Acquisition and Preprocessing of Samples

Fig. 6 shows the control scheme of the six-pole radial AMB with PhyLSTM self-sensing. Three-phase control currents $\{i_A, i_B, i_C\}$ are taken as the inputs of the PhyLSTM module, from which the rotor displacements $\{x, y\}$ are predicted. The prediction errors relative to $\{x^*, y^*\}$ are regulated by a proportional integral differential (PID) controller to generate suspension control forces. After current transformation and power amplification, the generated phase currents excite the six-pole radial AMB. The predicted displacements are returned to the controller, thereby realizing closed-loop displacement self-sensing control for stable rotor suspension.

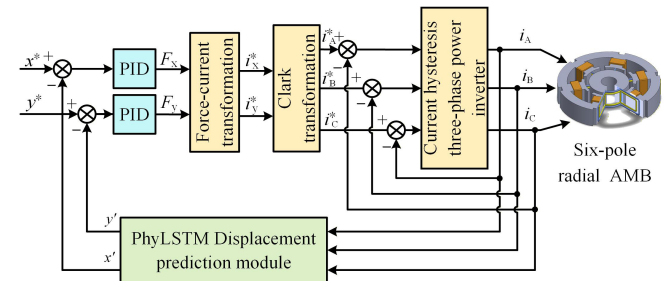


FIGURE 6. Control scheme of the six-pole radial AMB with PhyLSTM self-sensing.

A MATLAB simulation platform for the six-pole radial AMB is built, and PID closed-loop control is adopted to achieve stable rotor suspension. To obtain effective input-output samples, data are collected over a rotational-speed range of 0–10000 r/min, covering typical operating conditions such as no-load operation, static suspension, and dynamic disturbance. A sinusoidal signal with $f = 50$ Hz and $A = 0.3$ mm is used as the external excitation in the simulation. Raw sample data are preprocessed by eliminating outliers generated during sampling.

4.2. Real-Time Prediction Results of the PhyLSTM Displacement Self-Sensing Model

Considering auxiliary bearings in the actual operation, the rotor is initialized at $x = 0 \mu\text{m}$ and $y = -200 \mu\text{m}$. Simulated displacement responses predicted by LSTM and PhyLSTM are compared with the actual values in Fig. 7. During rotor startup, PhyLSTM model achieves better prediction accuracy than LSTM model, reducing the error rate from 19.27% to 5.36% and the maximum error from $31 \mu\text{m}$ to $14 \mu\text{m}$. After 133 ms, the rotor reaches stable suspension, and the PhyLSTM prediction remains consistent with the measured displacement.

Disturbance adaptability is further evaluated by applying the same disturbance successively in the x - and y -directions with a 200 ms interval. Fig. 8 presents the corresponding prediction results. After the first disturbance, the rotor settles back to equilibrium within 70 ms in the x -direction and 92 ms in

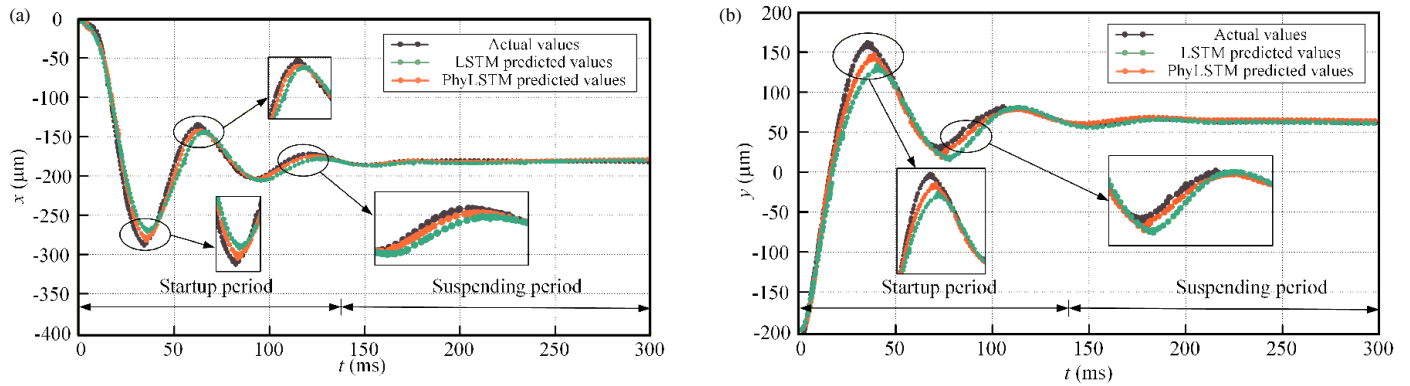


FIGURE 7. Comparison of real-time rotor displacement prediction results from startup to stable suspension. (a) x direction and (b) y direction.

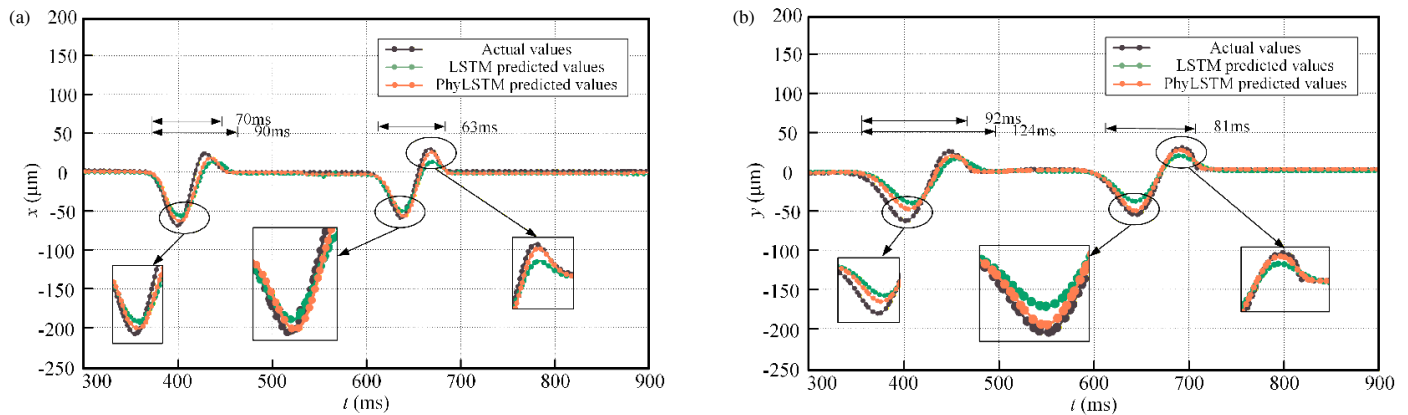


FIGURE 8. Comparison of real-time rotor displacement prediction results after two identical disturbances. (a) x direction and (b) y direction.

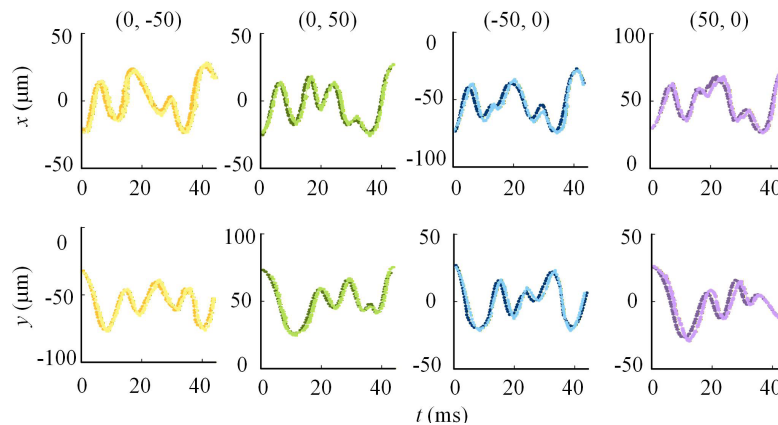


FIGURE 9. Displacement prediction performance under random disturbances at four different initial rotor positions.

the y -direction, while the PhyLSTM prediction error decreases to 3.93%. After the second disturbance, the recovery time is shortened to 63 ms and 81 ms, and the fitting accuracy reaches 97.4%. These results indicate that the proposed PhyLSTM model effectively learns intrinsic rotor dynamics during operation, which enables it to respond more quickly to repeated disturbance patterns and maintain high prediction accuracy under startup, suspension, and disturbance conditions.

The generalization of the PhyLSTM model is tested under four different rotor initial positions with random perturbations. As presented in Fig. 9, the predicted displacements closely follow the measured values. The average prediction accuracy reaches 95.37%, and the maximum error is kept below $9 \mu\text{m}$, demonstrating strong generalization and prediction performance of the PhyLSTM model.

4.3. Evaluation and Comparative Analysis of Model Predictive Performance

The prediction performance of the proposed PhyLSTM model is evaluated by comparing it with KF, Least Squares Support Vector Machine (LSSVM), and RNN methods in the six-pole radial AMB system. KF is mainly a physical model, while LSSVM and RNN are data-driven methods. Since the RNN does not explicitly consider rotor dynamic laws, its prediction results may lack physical consistency.

As shown in Fig. 10, the time required for the three models to reach steady suspension corresponds to 137.59%, 125.56%, and 112.78% of the actual value, respectively. In general, machine-learning methods show better prediction performance than model methods. In addition, the RNN captures inherent patterns in sequential data by leveraging temporal dependencies, thereby outperforming the LSSVM in prediction accuracy.

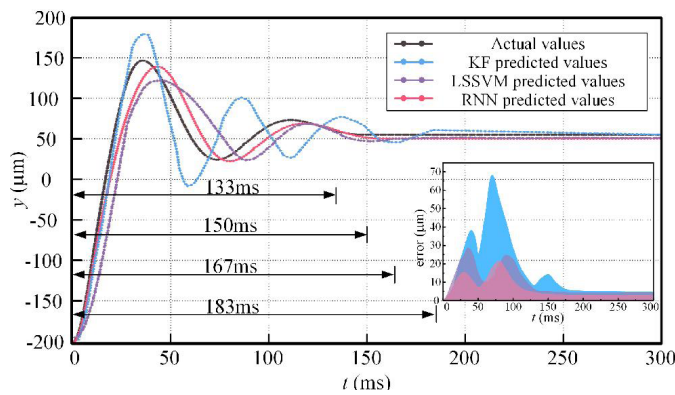


FIGURE 10. Real-time prediction results of KF, LSSVM, and RNN models in the y -direction.

The four models are quantitatively compared using the root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). Table 1 lists the corresponding results.

TABLE 1. Comparison of prediction ability among four models.

Models	RMSE (μm)	MAE (μm)	R^2
KF	25.77	17.58	0.81
LSSVM	18.22	11.26	0.90
RNN	13.72	9.10	0.94
PhyLSTM	6.73	4.00	0.98

5. EXPERIMENTAL ANALYSIS

Table 2 lists specifications of the six-pole radial AMB investigated in this paper.

To verify the simulation results and evaluate the PhyLSTM method experimentally, a test platform for the six-pole radial AMB is built, as illustrated in Fig. 11. The platform includes a six-pole radial AMB prototype, OD-900803 eddy-current displacement sensors, signal-conditioning circuits, a DSP digital controller, isolated gate drivers, IGBT-based power modules, an oscilloscope, and a host computer. OD-900803 sensors provide 0.5-class measurement accuracy, micrometer-level reso-

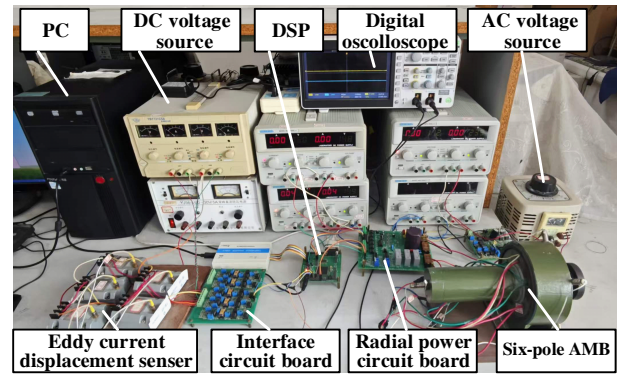


FIGURE 11. Test setup of the six-pole radial AMB system.

TABLE 2. Specifications of the six-pole radial AMB prototype.

PARAMETERS	Values
Radial air gap length δ_0	0.5 mm
Saturation flux density B_s	0.8 T
Effective pole-face area S_0	393 mm ²
Maximum radial-coil magnetomotive force	160 At
Rotor outer diameter	32 mm
Rotor inner diameter	16 mm
Axial length of rotor	28 mm
Nominal current of inverter	5 A
DC link voltage of inverter	311 V

lution, and a wide response range from DC to 20 MHz, making them suitable for acquiring both low-frequency and fast transient rotor displacement signals. In operation, the sensors measure the rotor radial displacement, and the output signals are conditioned by the signal-conditioning circuits before being sampled by the DSP. Meanwhile, the DSP also samples three-phase control currents. The DSP runs the PhyLSTM model to estimate the rotor displacement from the current sequences. The estimated displacement is compared with the reference displacement, and the resulting error is fed to the PID controller. The controller generates the force commands, which are transformed into three-phase current references. The power inverter tracks these current references and supplies the output currents to the three-phase control coils, thereby regulating the radial rotor position and maintaining stable levitation. Based on this platform, startup, steady-suspension, acceleration, and disturbance experiments are performed to verify the PhyLSTM model.

5.1. Startup Experiment

Figure 12 presents the rotor transition from the static state to stable suspension. Before suspension, the rotor shifts toward the negative y -direction under gravity. The eddy-current sensor measures displacements of 37 μm and 56 μm in the x - and y -directions, respectively. The PhyLSTM displacement self-sensing method gives close estimates of 40 μm and 62 μm , indicating that the rotor suspension process can be accurately predicted. In contrast, the LSTM method shows larger deviations, with corresponding displacements of 54 μm and 65 μm .

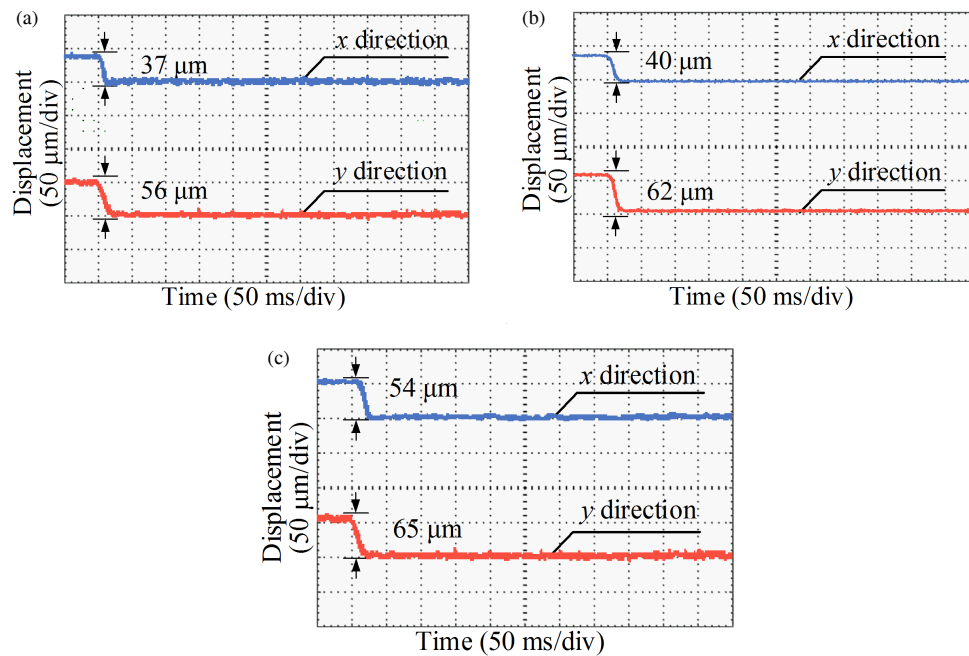


FIGURE 12. Startup response of rotor radial displacement. (a) Eddy current displacement sensor, (b) PhyLSTM displacement self-sensing, and (c) LSTM displacement self-sensing.

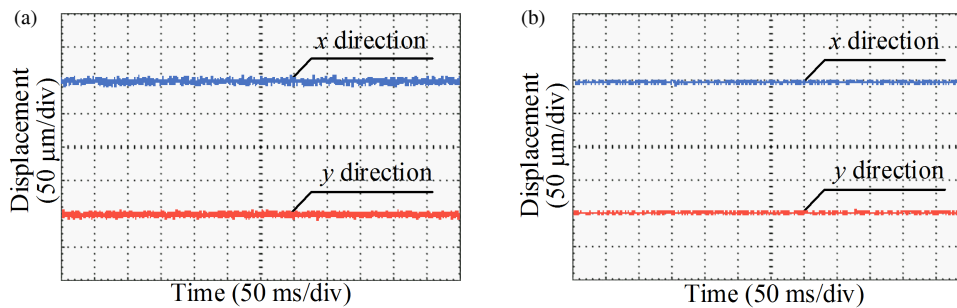


FIGURE 13. Radial displacement response during steady rotor suspension. (a) Eddy current displacement sensor and (b) PhyLSTM displacement self-sensing.

5.2. Steady-State Suspension Experiment

Fig. 13 shows steady-suspension responses. Although the stator poles limit the maximum rotor displacement to 0.5 mm, the actual vibration amplitude is far below this limit. The proposed method shows negligible differences from the sensor results. Benefiting from the memory capability of PhyLSTM, the predicted displacement shows smaller fluctuations during stable suspension, demonstrating high prediction accuracy and reliable support for stable rotor suspension.

5.3. Acceleration Experiment

Figure 14 presents the speed-up response and corresponding radial displacement variation. During acceleration from 3000 r/min to 5000 r/min, the enhanced unbalance-induced vibration makes displacement prediction more challenging. The sensor measurement gives a speed-up duration of 97 ms and displacement amplitudes of 64 μm and 78 μm in the x - and y -directions, respectively. For the proposed PhyLSTM, the estimated speed-up duration is 91 ms, corresponding to 93.8% of

the measured value, while the predicted displacement amplitudes reach 89.1% and 88.5% of the sensor results. In contrast, the LSTM shows a longer speed-up duration of 103 ms, equivalent to 106.2% of the measured value and overestimates displacement amplitudes to 104.7% and 106.4% of the sensor results. These comparisons indicate that the proposed PhyLSTM provides better dynamic tracking and limits prediction-error amplification under variable-speed operation.

5.4. Anti-Interference Experiment

As shown in Figs. 15 and 16, external disturbance tests are carried out in the x - and y -directions, respectively. In the experiment, a 5-kg weight is connected to the rotor shaft through an auxiliary bearing and a rope. The weight is initially supported by an auxiliary device to avoid affecting the motor's normal operation. After the rotor reaches stable suspension, the auxiliary support is released, thereby applying an external disturbance force of approximately 50 N in the specified radial direction. Due to the coupling effect between the x - and

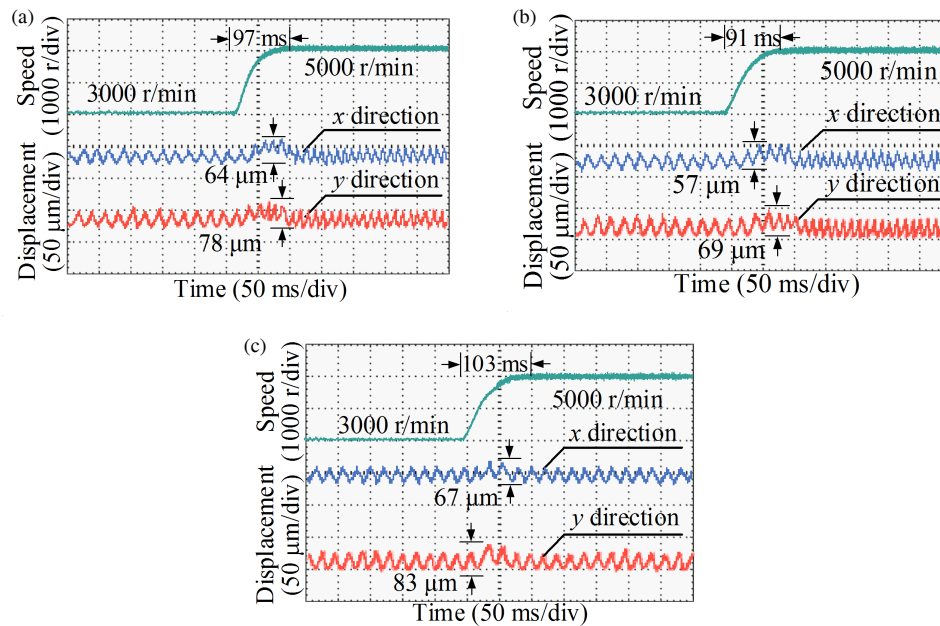


FIGURE 14. Speed-up response from 3000 r/min to 5000 r/min and corresponding radial displacement. (a) Eddy current displacement sensor, (b) PhyLSTM displacement self-sensing, and (c) LSTM displacement self-sensing.

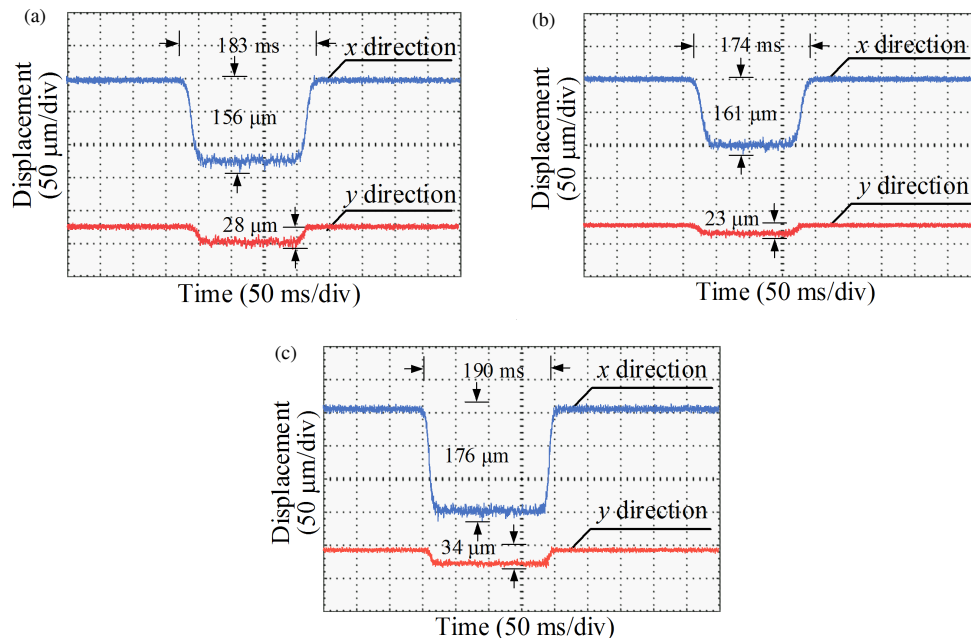


FIGURE 15. Radial displacement response subjected to x -direction disturbance. (a) Eddy current displacement sensor, (b) PhyLSTM displacement self-sensing, and (c) LSTM displacement self-sensing.

y -direction suspension force control currents, the disturbance causes displacement fluctuations in both radial directions. Benefiting from its ability to learn the coupling relationship between the two directions, the proposed PhyLSTM provides predictions closer to the eddy-current sensor measurements than the LSTM method. For example, under x -direction disturbance, the sensor-measured displacement variation is 156 μm with a recovery time of 183 ms, while the PhyLSTM prediction is 161 μm and 174 ms, corresponding to a displacement ratio of 103.2% and a recovery-time ratio of 95.1% relative to

the sensor measurements. The comparisons verify the superior dynamic tracking and disturbance prediction capability of the PhyLSTM method.

Overall, experiments confirm accurate rotor radial displacement estimation under startup, steady suspension, acceleration, and disturbance conditions. During acceleration, the predicted speed-up time is 93.8% of the sensor-measured value, and the displacement amplitudes remain close to the measured results. Under external disturbances, the predicted displacement variation and recovery time are also consistent with eddy-

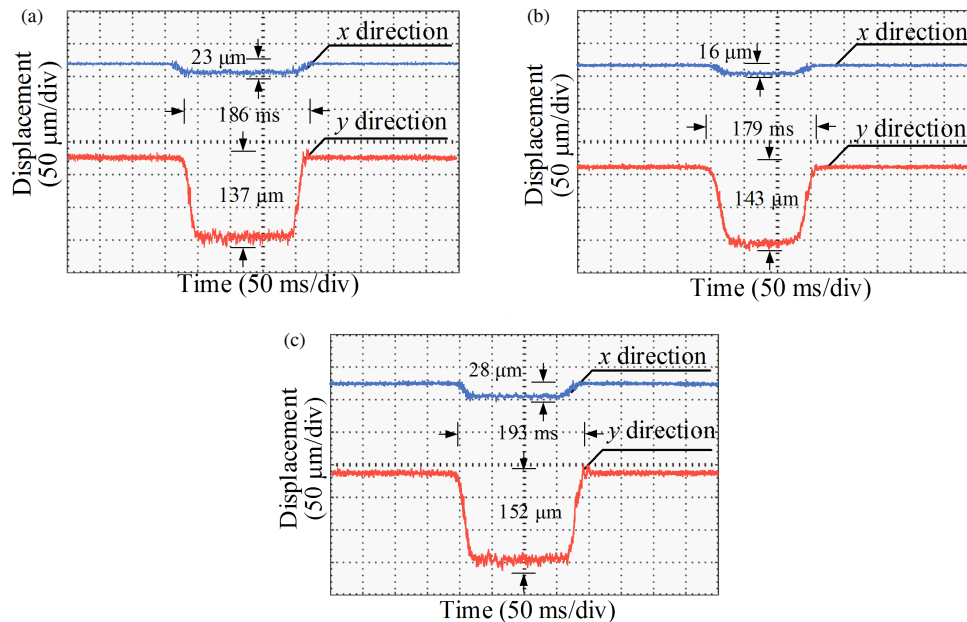


FIGURE 16. Radial displacement response subjected to y -direction disturbance. (a) Eddy current displacement sensor, (b) PhyLSTM displacement self-sensing, and (c) LSTM displacement self-sensing.

current sensor measurements, indicating good dynamic tracking and disturbance response capability. Across all experiments, the maximum displacement prediction error of the proposed method is limited to $9\text{ }\mu\text{m}$, whereas that of the LSTM method reaches $20\text{ }\mu\text{m}$. These results verify that the proposed method provides higher prediction accuracy, better physical consistency, and stronger generalization under different operating conditions.

6. CONCLUSION

To address the drawbacks of displacement sensors in AMB systems, including large installation space, high cost, and limited reliability, a PhyLSTM-based rotor displacement self-sensing method is proposed for the six-pole radial AMB. The main conclusions are given as follows:

- 1) The PhyLSTM network is adopted as the basic prediction framework, which effectively learns the hidden temporal dependencies during rotor motion. Therefore, the nonlinear mapping between control currents and rotor displacement can be accurately established.
- 2) Physical laws are incorporated into the loss function to guide the training process of the neural network. In this way, the proposed model better conforms to the physical characteristics of rotor motion and improves the physical consistency of the displacement prediction results.
- 3) The comparison results show that the proposed method outperforms conventional model-based and data-driven methods in both prediction accuracy and dynamic robustness. Considering the application of AMB systems in high-speed rotating equipment, future research will be directed toward ultra-high-speed operation and multi-degree-of-freedom AMB systems.

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