Sensorless Control of Permanent Magnet Bearingless Synchronous Motors Using Online Parameter Identification

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Abstract. A novel rotor position estimation scheme using online parameter identification based on grey model is suggested in this paper, which will meet the need of sensorless control for permanent magnetism bearingless synchronous motor (PMBSM). The scheme is computationally simple and does not rely on the motor parameters. And then, the sensorless vector control system of PMBSM is set up based on this position estimation approach. The results of simulation and experiments show that the proposed method is capable of precisely estimating the rotor space position and is able to achieve stable suspension under the bigger disturbance.

1. Introduction
In recent years, permanent magnet synchronous motor (PMSM) drives have been widely used in many industrial applications. But, motor speed was limited because of mechanical contacts. In 1960s, the high-speed motors with active magnetic bearings (AMB) resolved this problem. The advantages of magnetic bearings are no mechanical contacts, no lubrication and no wear, etc. However, long shaft is required in these high-speed motors with magnetic bearings because magnetic bearings are arranged in the both ends of the motor. Therefore, the critical speeds are decreased, and increasing speed of the motor is limited to some extent.

The permanent magnet bearingless synchronous motor (PMBSM) is an integrated device machine that has the functions of the electric motor and an active magnetic bearing. PMBSM has some advantages over conventional high-speed motors with magnetic bearings as follows: a) the motor shaft length can be short, so the critical speed is high if the output power is equal. b) High power can be achieved if shaft lengths are the same. c) DC exciting current of conventional magnetic bearings is not needed [1].

The winding configurations of bearingless motors can be categorized into two groups: dual set of winding configurations and single set of winding configurations. Most bearingless motors belong to the former category. Its stator is composed of two separate sets of windings, and the difference of their pole-pair numbers is 1. The primary winding carries the “motor currents” which drive the motor, while the secondary winding carries the “levitation currents” which suspend the rotor [2]. However, the control performance of the PMBSM is greatly affected by the uncertainties of the plant which usually are mismatched motor parameters, external load disturbance, and nonlinear dynamics [3]. It can decouple the torque control and suspension force control that PMBSM uses the advanced control techniques, such as nonlinear control, air-gap field oriented control, rotor flux oriented control, stator flux oriented control.
In these advanced control techniques schemes, the speed or position signal is necessary for establishing the outer speed loop feedback and also in the flux and torque control algorithms.

From the viewpoints of reliability, robustness, and cost, several approaches have been proposed that address the elimination of the mechanical sensors. Some approaches are based on the motor equations in order to express rotor positions and speed as functions of terminal quantities. However, the sensitivity to motor parameters is a major drawback of this method. In other approach, sensorless control PMBSM drives have been developed on the basis of state observers. However, the overall stability may not be guaranteed in these schemes due to certain assumptions introduced, complicated.

In many sensor control schemes, the motor parameters are used to estimate the rotor position. Because of motor magnetic saturation and temperature change, the electrical parameters are distorted, so it will produce rotor position estimation error. An online parameter identification method can be realized to solve this problem. This method is used in a novel rotor position estimation scheme based on grey model. Computer simulations have been carried out in order to evaluate the effectiveness of the proposed scheme. The results have proved that the proposed controller can give better overall performance regarding to high estimation accuracy, quick recover from load disturbance, good tracking ability and simple implementation.

2. Mathematical Model of PMBSM

There is $L_{1d}=L_{1q}$ in the surface type PMBSM. For the convenience, the follows are assumed:

1. In this paper, use of $L_1$ to replace $L_{1d}$ and $L_{1q}$.
2. In this paper, subscripts “1” and “2” correspond to torque windings and suspension windings, respectively.

The torque windings voltage model of the PMBSM can be described in the $d$-$q$ rotor frame as follows:

$$
\begin{align}
\frac{d}{dt}i_{1d} &= -\frac{R_1}{L_1}i_{1d} - \frac{\omega_1}{L_1}i_{1q} + \left[ \frac{1}{L_1} \right] v_{1d} + \left[ \frac{0}{L_1} \right] v_{1q} - \frac{\omega_1}{L_1} \psi_f
\end{align}
$$

The radial suspension force model of the PMBSM can be described in the $d$-$q$ rotor frame as follows:

$$
\begin{align}
\frac{d}{dt}i_{1u} &= \frac{R_2}{L_1}i_{1u} + \frac{1}{L_1} v_{1u} + \frac{\omega_1(t)}{L_1} \psi_f \sin \theta_1(t) \\
\frac{d}{dt}i_{1\beta} &= \frac{R_2}{L_1}i_{1\beta} + \frac{1}{L_1} v_{1\beta} + \frac{\omega_1(t)}{L_1} \psi_f \cos \theta_1(t)
\end{align}
$$

The radial suspension force model of the PMBSM can be described in the $d$-$q$ rotor frame as follows:

$$
\begin{align}
F_x &= \frac{\pi p_1 p_2 L_{a2}}{12 \mu_0 W_1 W_2} (i_{2d}\psi_{1d} + i_{2q}\psi_{1q}) \\
F_y &= \frac{\pi p_1 p_2 L_{a2}}{12 \mu_0 W_1 W_2} (i_{2q}\psi_{1d} - i_{2d}\psi_{1q})
\end{align}
$$

$$
\begin{align}
\psi_{1d} &= \psi_f + L_{1d}i_{1d} = \psi_f + L_1i_{1d} \\
\psi_{1q} &= L_{1q}i_{1q} = L_1i_{1q}
\end{align}
$$
Under the suspension force, rotor equation of radial displacement motion as

\[
\begin{align*}
\frac{d}{dt} \left( \frac{dx}{dt} \right) &= \frac{F_x}{m} \\
\frac{d}{dt} \left( \frac{dy}{dt} \right) &= \frac{F_y}{m}
\end{align*}
\]

(5)

Where \(i_{1d}, i_{1q}, v_{1d}\) and \(v_{1q}\) are torque windings stator current and voltage in \(d-q\) coordinate respectively; \(i_{1a}, i_{1b}, v_{1a}\) and \(v_{1b}\) are torque windings stator current and voltage in \(\alpha-\beta\) coordinate respectively; \(\omega_1\) is the electrical rotor angle velocity; \(\theta_1\) is the electrical rotor angle; \(R_s\) is stator resistance; \(\psi_f\) is permanent magnets flux linkages; \(l\) is the active length of the motor; \(r\) is rotor radius; \(\mu_0\) is the vacuum or air permeability; \(W_1\) and \(W_2\) are number of turns for the torque windings and suspension windings, respectively. \(p_1, p_2\) are number of pole pairs for the torque windings and suspension windings, respectively. \(i_{2d, i_{2q}}\) are suspension windings stator current in \(d-q\) coordinate; \(\psi_{1d}, \psi_{1q}\) is torque windings flux linkages in \(d-q\) coordinate; \(m\) is rotor mass; \(L_{m2}\) is mutual inductance of suspension windings.

3. Control Strategy

It can decouple the torque control and suspension force control that PMBSM uses the rotor flux oriented control \[2\]. The \(i_{1d}\) as

\[ i_{1d} = 0 \]

(6)

Substitution of equations (4) and (6) into equation (3), we can obtain radial suspension force equations as

\[
\begin{bmatrix}
    i_{2d} \\
    i_{2q}
\end{bmatrix} = \frac{k}{(\psi_f^2 + L_1^2 i_{1q}^2)} \begin{bmatrix}
    1 & -\frac{L_1 i_{1q}}{\psi_f} \\
    \frac{L_1 i_{1q}}{\psi_f} & 1
\end{bmatrix} \begin{bmatrix}
    F_x \\
    F_y
\end{bmatrix}
\]

(7)

Where \( k = \frac{12 br \mu_a W_1 W_2 \psi_f}{\pi p_1 p_2 L_{m2}} \) is constant.

The equation (2) can be expressed as

\[
\begin{align*}
M &= \omega_1(t)\psi_f \sin \theta_1(t) = -v_{1a}(t) + R_s i_{1a}(t) + L_1 \frac{di_{1a}(t)}{dt} \\
N &= \omega_1(t)\psi_f \cos \theta_1(t) = v_{1\beta}(t) - R_s i_{1\beta}(t) - L_1 \frac{di_{1\beta}(t)}{dt}
\end{align*}
\]

(8)

From equation (8), one obtains

\[
M^2 + N^2 = (\omega_1(t)\psi_f)^2 = (-v_{1a}(t) + R_s i_{1a}(t) + L_1 \frac{di_{1a}(t)}{dt})^2 + (v_{1\beta}(t) - R_s i_{1\beta}(t) - L_1 \frac{di_{1\beta}(t)}{dt})^2
\]

Hence, we can obtain Speed estimates formula as

\[
\dot{\omega}_1(t) = \frac{1}{\psi_f} \sqrt{(-v_{1a}(t) + R_s i_{1a}(t) + L_1 \frac{di_{1a}(t)}{dt})^2 + (v_{1\beta}(t) - R_s i_{1\beta}(t) - L_1 \frac{di_{1\beta}(t)}{dt})^2}
\]

(9)
Because of M (or N) and sinθ₁(t) (or cosθ₁(t)) of the same sign. From equation (8), we can be obtain position estimates formula as

\[
\hat{\theta}_i(t) = \begin{cases} 
\bar{\theta}_i(t) & M > 0, N > 0 \\
2\pi - \bar{\theta}_i(t) & M < 0, N > 0 \\
\pi + \bar{\theta}_i(t) & M < 0, N < 0 \\
\pi - \bar{\theta}_i(t) & M > 0, N < 0 
\end{cases}
\]  

(10)

Where \( \bar{\theta}_i(t) \) can be expressed as

\[
\bar{\theta}_i(t) = \tan^{-1} \left[ \frac{M}{N} \right] = \tan^{-1} \left[ \frac{-v_{1a}(t) + R_s i_{1a}(t) + L_1 \frac{di_{1a}(t)}{dt}}{v_{1b}(t) - R_s i_{1b}(t) - L_1 \frac{di_{1b}(t)}{dt}} \right]
\]  

(11)

In the formulas (9), (10) and (11), Motor temperature, magnetic saturation, and other changes will affect parameter \( R_s \), \( L_1 \) and \( \psi_f \). To solve this problem, we can use the online parameter identification methods that will be discussed in Part 4. Traditionally, for \( \frac{di_{1a}}{dt} \) and \( \frac{di_{1b}}{dt} \) used \( \left( i_{1a}(n) - i_{1a}(n-1) \right) / \Delta T \) and \( \left( i_{1b}(n) - i_{1b}(n-1) \right) / \Delta T \), respectively, it lags than the actual differential coefficient of a sampling period. If we can predict \( \hat{i}_{1a}(n+1) \) and \( \hat{i}_{1b}(n+1) \), then expression \( \frac{i_{1a}(n+1) - i_{1a}(n)}{\Delta T} \) and \( \frac{i_{1b}(n+1) - i_{1b}(n)}{\Delta T} \) will more be close to actual differential coefficient. To obtain \( \hat{i}_{1a}(n+1) \) and \( \hat{i}_{1b}(n+1) \) can be using the grey forecasting methods that will be discussed in Part 5.

4. Online Parameter Identification

Equation (1) discrete form can be written as

\[
\begin{bmatrix}
i_{1d}(n+1) \\
i_{1q}(n+1)
\end{bmatrix} = A \begin{bmatrix}
i_{1d}(n) \\
i_{1q}(n)
\end{bmatrix} + B \begin{bmatrix}
v_{1d}(n) \\
v_{1q}(n)
\end{bmatrix} + C [1]
\]  

(12)

Where \( A = \begin{bmatrix}
a_{11} & a_{12} \\
a_{21} & a_{22}
\end{bmatrix} = \begin{bmatrix}
-\Delta T R_s / L_1 + 1 \\ -\Delta T \omega_1
\end{bmatrix} \); \( B = \begin{bmatrix}
b_{11} & b_{12} \\
b_{21} & b_{22}
\end{bmatrix} = \begin{bmatrix}
\Delta T / L_1 \\ 0
\end{bmatrix} \); \( C = \begin{bmatrix}
c_1 \\
c_2
\end{bmatrix} = \begin{bmatrix}
0 \\ -\omega_1 \Delta T \psi_f / L_1
\end{bmatrix} \).

When \( \Theta = [A \ B \ C] \), equation (12) can be written as

\[
y = \Theta z
\]  

(13)
Vector $y$ can be obtained using the grey forecasting methods that will be discussed in Part 5. Hence, the pending identification parameters matrix $\Theta$ can be identified from (14) and (15) used vector $y$ and $z$. This recursive least squares method can make the square error $(y - \hat{\Theta} z)^2$ minimum. [13]

$$\hat{\Theta} (k) = \hat{\Theta} (k - 1) + (y - \hat{\Theta} (k - 1) z) z^T P (k)$$

(14)

$$P (k) = \frac{1}{\lambda} \left\{ P (k - 1) - P (k - 1) z \times (\lambda + z^T P (k - 1) z)^{-1} z^T P (k - 1) \right\}$$

(15)

There $\lambda$ is the weighted coefficient.

From identification matrix $\hat{\Theta}$, order

$$a_o = 2 - (a_{11} + a_{22}) = \frac{2DT_{R_s}}{L_1}; \quad a_1 = a_{12} - a_{21} = 2DT\omega_s; \quad b_o = b_{11} + b_{22} = \frac{2DT}{L_1}$$

Then

$$\hat{R}_s = \frac{a_o}{b_o}; \quad \hat{L}_1 = \frac{2DT}{b_o}; \quad \hat{\psi}_f = -\frac{4DTc}{a_1b_o}.$$  

(16)

Evidently, $\hat{R}_s$, $\hat{L}_1$ and $\hat{\psi}_f$ be independent of the rotor position and speed.

5. Grey Forecast Method

Grey theory, originally developed by Deng [14], has become a very popular method of solving uncertainty problems under discrete data and incomplete information. The areas covered and applied by grey theory include systems analysis, data processing, modeling, prediction, decision-making and control. The traditional prediction methods usually require a large amount of historical data. In contrast, the grey model GM(1,1), which is the core of the grey forecasting theory, is that it does not need to make strict assumptions about the data set and it can be applied when the data set is as small as four. This simplifies data collections and allows for timely predictions to be made. Actually, the grey model is suitable for smaller amounts of data.

A group of original data with equal time interval is supposed

$$X^{(0)} = \{ x^{(0)} (1), x^{(0)} (2), \cdots , x^{(0)} (n) \}.$$  

The first-order accumulated generating operation (1-AGO) of $X^{(0)}$ is provided.

$$X^{(1)} = \{ x^{(1)} (1), x^{(1)} (2), \cdots , x^{(1)} (n) \}, \quad (x^{(1)} (k) = \sum_{i=1}^{k} x^{(0)} (i)).$$  

The sequence dynamics can be expressed as $W = B \Phi$, Where

$$W = \begin{bmatrix} x^{(0)} (2) \\ x^{(0)} (3) \\ \vdots \\ x^{(0)} (n) \end{bmatrix}, \quad B = \begin{bmatrix} -\frac{1}{2} (x^{(1)} (1) + x^{(1)} (2)) & 1 \\ -\frac{1}{2} (x^{(1)} (2) + x^{(1)} (3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2} (x^{(1)} (n - 1) + x^{(1)} (n)) & 1 \end{bmatrix}, \quad \Phi = [a \quad u]^T$$

(17)

From equation (17) and equation-least squares method, coefficient $\Phi$ becomes

$$\Phi = [\hat{a} \quad \hat{u}]^T = (B^T B)^{-1} B^T W$$

(18)
The sequence predictive value can be expressed as

\[
\hat{x}^{(0)}(n + p) = (1 - e^{\hat{a}})\left[ x^{(1)}(1) - \frac{\hat{u}}{\hat{a}} \right]e^{-\hat{a}(n + p - 1)}, \quad p = 1, 2, \ldots
\]  

(19)

The GM(1,1) model sequence as a non-negative requirements, if \( x_{\min}^{(0)} < 0 \) (where \( x_{\min}^{(0)} = \min X^{(0)} \)) then all the elements of sequence plus \( x_{\min}^{(0)} \) When actual use. After completion forecast all the elements of the sequence \( X^{(0)} \) minus \( x_{\min}^{(0)} \).

Figure 1 shows \( \hat{i}_{1\alpha}(n + 1), \hat{i}_{1\beta}(n + 1), \hat{i}_{1\delta}(n + 1) \) and \( \hat{i}_{1\gamma}(n + 1) \) forecast schematics.
6. Simulation And Experiment Results

![Control Block Diagram of PMBSM Sensorless Control](image)

Figure 2. A control block diagram of PMBSM sensorless control

System control principle in fig. 2. In order to verify the control algorithm proposed in this paper, and to offer the consulting basis for the control system hardware debugging, the control system is simulated based on Matlab/Simulink. The prototype parameters are as follows:

- Mass of rotor $m = 0.85 \, kg$;
- Inertia moment $J = 0.0012 \, kg \cdot m^2$;
- Pole pairs $p_1 = 1$, $p_2 = 2$;
- Stator resistance $R_s = 1.8 \, \Omega$;
- Stator self-inductance $L_1 = 8.5 \, mH$;
- Mutual inductance $L_{m2} = 4.5 \, mH$;
- The active length of the motor $l = 70 \, mm$;
- Rotor radius $r = 58 \, mm$;
- Permanent magnets flux linkages $\psi_f = 0.175 \, Wb$. 


Figure 3. Simulation results of proposed algorithm

The speed at the starting are given by 5500 r/min. Fig. 3(a) (b) Shows the actual speed curve and the rotor actual position curve, respectively. Fig. 3(c) (d) shows the speed estimation curve and the Rotor position estimation curve, respectively. Fig. 3(e), (f) shows the rotor position and speed estimation error, respectively. Fig. 4(a) (b) Shows the rotor actual position curve and the Rotor position estimation curve, respectively. Fig. 4(d) shows the rotor position estimation error. From Fig.3 and Fig.4, there is the maximal speed estimation error in the process of start-up (less than 32rpm). At steady state speed estimation error is extremely small. There is the maximal speed estimation error in the process of start-up (less than 7.8degree).
For further verify the control method, the DSP TMS320LF2407A was used to design the experimental control system. The rated speed at the starting is given by 5500 r/min. Fig. 5 shows the experiment result of start-up process at 0-5500 rpm speed with no-load. Fig. 5(a) shows the actual speed curve, Fig. 5(b) actual rotor position, it is measured using optical encoder. Fig. 5(c), (d) shows Rotor actual radial displacement curve, it uses eddy current sensor measurement. Starting in the foreseeable rotor stability suspended soon after entering the state. There is a certain process of starting overshoot but soon reaching a given value, and maintaining good steady-state performance.
7. Conclusion
This paper presents a technique to calculate the rotor position using GM (1, 1). The online parameter identification method was realized in surface type PMBSM. This method can be solving the problem of parameters with temperature and magnetic saturation changes. The proposed sensorless control method improved control system parameters robustness. The results of simulation and experiments show that the proposed method is capable of precisely estimating the rotor space position and is able to achieve stable suspension under the bigger disturbance. The study of technology is continuing.

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