Speed-Sensorless Vector Control of a Bearingless Induction Motor With Artificial Neural Network Inverse Speed Observer

Xiaodong Sun, Long Chen, Zebin Yang, and Huangqiu Zhu

***Abstract*—To effectively reject the influence of speed detection on system stability and precision for a bearingless induction motor, this paper proposes a novel speed observation scheme using artificial neural network (ANN) inverse method. The inherent subsystem consisting of speed and torque winding currents is modeled, and then its inversion is implemented by the ANN. The speed is successfully observed via cascading the original subsystem with its inversion. The observed speed is fed back in the speed control loop, and thus, the speed-sensorless vector drive is realized. The effectiveness of this proposed strategy has been demonstrated by experimental results.**

***Index Terms*—Artificial neural network (ANN) inverse, bearingless induction motor (BIM), speed-sensorless, vector control.**

I. Introduction

In recent years, there is an increasing interest in bearingless motors around the world [1]–[3]. Due to the similarity of structure between electric motors [4], [5] and magnetic bearings [6], a bearingless motor combine the functions of a motor and a magnetic bearing together within the same stator frame. They can simultaneously produce the radial suspension force and torque on the rotor so that there is no mechanical contact between the stator and rotor. On the one hand, the magnetic suspension offers the advantages of no friction, no abrasion, no lubrication, high rotational speed, and high precision, in comparison to mechanical contact [7], [8]. On the other hand, a bearingless motor has incomparable advantages of small size, light weight, low cost as compared to a conventional tandem structure consisting of magnetic bearings and a motor. Therefore, bearingless motors are becoming more and more suitable for widespread applications, such as high-speed turbo machineries, machine tool spindles, vacuum pumps, blood pumps, computer disk drives, energy storage flywheels, etc [9]–[11]. Up to now, various types of bearingless motors have been proposed, such as bearingless reluctance motors, bearingless induction motors (BIMs), bearingless switched reluctance motors, bearingless permanent magnet synchronous motors, etc [12]–[16]. In these types of bearingless motors, the BIM has been paid much attention since its advent because its rotor construction is relatively simple and robust, and the torque ripples and cogging torque are less [12].

Since the BIM is a multivariable, nonlinear, and coupled system, the vector control is a reasonable choice to control its speed independently from the radial suspension forces. However, for all high-performance vector-controlled BIMs, it is necessary to gain the accurate rotational speed information. Normally, this information is achieved by using mechanical sensors such as incremental encoders, which are the most common positioning transducers used today in industrial applications. Nonetheless, using mechanical sensors will cause several disadvantages, such as increasing size, cost, maintenance, hardware complexity, electrical susceptibility, and reducing reliability and robustness of the drive system [17]–[20]. Especially, mechanical sensors are unsuitable for the inherent high-speed performance of BIMs due to the unavoidable mechanical contact. Therefore, the considerable speed-sensorless control strategies are badly needed for solving the problems, and the investigation of the speed-sensorless operation is essential for the further development of BIMs.

For the conventional induction motors, various techniques have been proposed to estimate speed for sensorless drives, such as the direct computing method [21], Luenberger observers method [22], [23], extended Kalman filter (EKF) method [24], [25], and model reference adaptive system (MRAS) method [26], [27]. The direct computing method is a simplest method based on the angular velocity of rotor flux vector and slip calculation using the induction motor model, but the estimated speed accuracy is not very satisfactory due to the great sensitivity to parameters variations and noise in the drive. The Luenberger observers method is a deterministic estimator which assumes a linearized time-invariant motor model. The EKF method can make the online estimation of states while identifying the motor parameters simultaneously in a relatively short time interval. The Luenberger observers and EKF methods are robust to motor parameters variations or identification errors, but they require a great number of real-time computations and are much more

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complicated in practical realization. In the MRAS method, an error vector is made up from the two models' outputs which are both dependent on different motor parameters. By adjusting the parameter that influences one of the models, the error is driven to zero. Compared with the Luenberger observers or EKF method, the MRAS method has the advantage in the simplicity of used models. But it is unstable in low speed or around zero speed running because the model-based estimation technique is dependent on rotor-induced voltages which is very small and even vanish at zero stator frequency.

In this paper, a novel method of speed-sensorless vector control for a BIM based on artificial neural network (ANN) inverse method is proposed. The basic principle of the method is to obtain the inverse model of the speed subsystem which consists of a static ANN and some differentiators, and then to establish the speed observer by cascading the original subsystem with the ANN inverse model. Based on this speed estimation method, the speed-sensorless vector control system of the BIM is set up. Finally, the proposed control strategy is confirmed on a dSPACE DS1104 DSP-based data acquisition and control (DAC) system.

This paper is organized as follows. In Section II, we describe the principle of radial suspension force generation in BIMs. Then, we analyze the inherent subsystem, gain its inverse model, and obtain the speed observer using the inverse system method in Section III. In Section IV, an ANN inverse speed observer is constructed. In Section V, the speed-sensorless vector control system of the BIM is set up. In Section VI, experiments are carried out, and the performance of the BIM drive system is analyzed and discussed. Finally, some conclusions are given in Section VII.

II. Principle of Radial Suspension Force Generation

Suppose the pole-pair number of torque windings is p_1, and that of suspension force windings is p_2. When the rotating magnetic field produced by the two sets of windings satisfy the following three conditions: 1) $p_2 = p_1 \pm 1$, 2) the two magnetic fields have the same rotation direction, and 3) the currents in two sets of windings have the same frequency, then the interactive magnetic fields will produce radial suspension forces in the constant direction.

According to the electromagnetic field theory, there are two kinds of magnetic force, namely, Lorentz force and Maxwell force in the BIM. Besides the electromagnetic torque produced by Lorentz force just as it works in an induction motor, it also can generate radial suspension force. Compared with Lorentz force, Maxwell force, also named magnetic resistance force, is the main source of the radial suspension force in the BIM. Fig. 1 shows the principle of radial suspension force generation. The four-pole flux ψ_4 and two-pole flux ψ_2 are generated by the torque winding currents i_1 and suspension force winding currents i_2 in the N_4 and N_2 turns of stator windings, respectively. Under no-load balanced conditions, if a positive radial suspension force along the x-axis is needed, the torque winding current i_1 and suspension force winding currents i_2 are electrified as shown in Fig. 1. The flux density in the airgap 1 is increased, because both fluxes ψ_4 and ψ_2 are in the same direction. On the other hand, the flux density in the airgap 2 is decreased because fluxes ψ_4 and ψ_2 are in the opposite direction. Therefore, a positive suspension force F_x is produced in the x-axis direction only. If the direction of suspension force winding currents is reversed, the radial suspension force in negative x-axis direction will be generated. Suspension force F_y in the y-axis direction can be produced using electrically perpendicular two-pole suspension force winding currents distribution. So, the rotor can be suspended steadily in the central equilibrium position by adjusting the magnitude and direction of the suspension force winding currents.

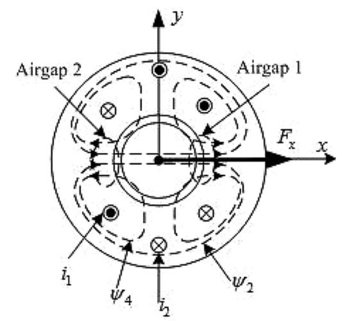

Fig. 1. Principle of radial suspension force generation.

III. Design of the Speed Observer

A. Left Inverse System

From the viewpoint of functional analysis, the dynamic model of a general system can be described as an operator mapping the inputs into the outputs. We consider a continuous system $\sum$ (linear or nonlinear) with a p-dimensional input vector $\boldsymbol{u}(t) = [u_1, u_2, \ldots, u_p]$, a q-dimensional output vector $\boldsymbol{y}(t) = [y_1, y_2, \ldots, y_q]$, and an initial state vector $\boldsymbol{x}(t_0) = \boldsymbol{x}_0$. Let $\theta : \boldsymbol{u} \to \boldsymbol{y}$ be the operator describing the aforementioned mapping relation, i.e., [28]

$$\boldsymbol{y}(\bullet) = \theta[\boldsymbol{x}_0, \boldsymbol{u}(\bullet)] \quad \text{or} \quad \boldsymbol{y} = \theta\boldsymbol{u}. \tag{1}$$

A system which can realize an inverse mapping from the output $\boldsymbol{y}$ to the input $\boldsymbol{u}$ can be defined as an inverse system or an inversion equivalently. In general, according to the difference of the function or purpose, the inverse systems can be divided into two classes, e.g., right inverse systems and left inverse systems. A right inverse system often serves as an output controller to make the output $\boldsymbol{y}$ of the original system to follow a given output, while the left inverse system serves as an input observer. Since what we are considered in this paper is studying effective observer approaches, all inverse systems refer to the left inverse systems hereafter if no special statement is given.

Definition 1: Consider a system $\sum$ expressed by (1). Assume Π to be another system with $\boldsymbol{y}(t)$ as input and $\boldsymbol{u}(t)$ as output, and it can be described by an operator $\bar{\theta} : \boldsymbol{y} \to \boldsymbol{u}$. If the operator $\bar{\theta}$ satisfies

$$\bar{\theta}\theta\boldsymbol{u} = \bar{\theta}\boldsymbol{y} = \boldsymbol{u} \tag{2}$$

the system Π is called the inverse system or inversion of the original system $\sum$, and the original system $\sum$ is invertible [29].