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A Neural Network Left-Inversion Flux Estimation for Induction Motor Filed-Oriented Control

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Abstract—**This paper presents a new rotor flux estimation algorithm using neural network for induction motors, based on the left-inversion method. Using the fifth order model of the three-phase induction machines in a stationary two axes reference frame, a rotor flux "assumed inherent sensor" is constructed and its left-invertible is validated. The ANN left-inversion flux estimator is composed of two relatively independent parts - a static ANN used to approximate the complex nonlinear function and several differentiators used to represent its dynamic behaviors, so that the ANN left-inversion is a special kind of dynamic ANN in essence. The performance of the proposed algorithm is tested through simulation, proving the driven system has good behavior both in transient and steady-state operating conditions.**

I. Introduction

Artificial neural networks have been attracting a great attentions in the field of power electronics and motor drive system, in the last decades [1],[2]. This is due to their inherent parallelism which allows for high speed processing and permits implementation of real time control applications. ANNs also possess the ability to perform in noisy environments and are tolerant to faults and missing data**.** As a control method to tackle nonlinear system with uncertain factor, the ANNs have entitative advantage.

In [3], the authors utilized two NNs which approximate the nonlinear relations described by flux loop and rotor flux decoupled in field-oriented control (FOC), respectively, and pointed out that it can replace the traditional FOC. Because of the principle of FOC is invariable, although it is robust to parameters, the dynamic decoupling cannot be obtained. The [4] adapted NN to calculate the reference stator currents of two phases stationery components in indirect FOC, in essential, the slip frequency calculating and inverse transform loops were replaced with two NNs, the dynamic decoupling was not obtained yet. The implement of proposed structure was studied on the experiment setup based on DSP.

The "current model" (CM) and "voltage model" (VM) are traditional solutions to the flux estimation problem in the induction motor FOC and their benefits and drawbacks are well known [5]. Due to their different parameter sensitivities, they are useful at low and high speeds, respectively. On one hand, when using current model flux observers, flux estimation does not work well at high speed owing to its sensitivity to rotor resistance. On the other hand, when using current model flux observers, the voltage model flux observer can accurately estimate the stator flux when operating at high speed. However, at low speed this estimation is highly sensitive to the stator resistance variation. Generally, these algorithms require some calculations and integrations. Sequential integration routines are time consuming and limit the performance of real-time implementations

To avoid the drawbacks of the forenamed approaches, in this paper, a neural network is used to obtain a more accurate rotor flux estimate by mapping the nonlinear relationship between the rotor flux and other measurable motor variables based left-inversion measure method and "assumed inherent sensor" concepts [6].

II. IM Model and Left-Inverse Estimation Principle

The flux vector observer is usually based on a set of dynamical equations that describes the induction machine behavior. These equations can be expressed in different reference frames. In this section, the induction machine model is defined by the stator currents and rotor flux as state variables in the stationary reference frame α-β by the following equation:

$$\begin{pmatrix} \dfrac{di_{s\alpha}}{dt} \\ \dfrac{di_{s\beta}}{dt} \\ \dfrac{d\psi_{r\alpha}}{dt} \\ \dfrac{d\psi_{r\beta}}{dt} \\ \dfrac{d\omega_r}{dt} \end{pmatrix} = \begin{pmatrix} -(\dfrac{L_m^2 R_r}{\sigma L_s L_r^2}+\dfrac{R_s}{\sigma L_s})i_{s\alpha}+\dfrac{L_m R_r}{\sigma L_s L_r^2}\psi_{r\alpha}+\dfrac{n_p\omega_r L_m}{\sigma L_s L_r}\psi_{r\beta}+\dfrac{u_{s\alpha}}{\sigma L_s} \\ -(\dfrac{L_m^2 R_r}{\sigma L_s L_r^2}+\dfrac{R_s}{\sigma L_s})i_{s\beta}-\dfrac{n_p\omega_r L_m}{\sigma L_s L_r}\psi_{r\alpha}+\dfrac{L_m R_r}{\sigma L_s L_r^2}\psi_{r\beta}+\dfrac{u_{s\beta}}{\sigma L_s} \\ \dfrac{L_m R_r}{L_r}i_{s\alpha}-\dfrac{R_r\psi_{r\alpha}}{L_r}-n_p\omega_r\psi_{r\beta} \\ \dfrac{L_m R_r}{L_r}i_{s\beta}+n_p\omega_r\psi_{r\alpha}-\dfrac{R_r\psi_{r\beta}}{L_r} \\ \dfrac{n_p L_m}{J L_r}(i_{s\beta}\psi_{r\alpha}-i_{s\alpha}\psi_{r\beta})-\dfrac{T_L}{J} \end{pmatrix} \quad (1)$$

Where ω_r, $\Psi_{r\alpha\beta}$, R_r and L_r are, rotor angular velocity, flux, resistance and inductance, respectively; $u_{r\alpha\beta}$, $i_{r\alpha\beta}$, R_s and L_s are,

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stator voltage, current, resistance and inductance, respectively; L_m is the mutual inductance; n_p is the number of pole pairs; σ is the leakage coefficient parameter; J is the total motor and load moment of inertia, and T_L is the external load torque.

As shown in (1), the induction motor is a nonlinear system: induced voltages are proportional to the product between magnetic flux and rotor speed, and the torque produced is proportional to the product between fluxes and currents. Defining the vector $\boldsymbol{x}$ of state variables, and the input vector $\boldsymbol{u}$ as:

$$x=[x_1,x_2,x_3,x_4,x_5]^T=[i_{s\alpha}\ i_{s\beta}\ \psi_{r\alpha}\ \psi_{r\beta}\ \omega_r]^T$$
$$u=[u_1,u_2]^T=[u_{s\alpha}\ u_{s\beta}]^T$$

To estimate rotor flux x_3, x_4, we assume that in the induction motor (1) exists a subsystem whose inputs just are the to-be-estimated x_3, x_4 while whose outputs are the measurable variables x_1, x_2, x_5. Such a subsystem would be viewed as an "assumed inherent sensor" (see Fig. 1), with the u_1~u_2 as parameter variables; under the condition that the left-inversion of the "assumed inherent sensor" exists, cascading the left-inversion with the "assumed inherent sensor" can lead to a composite identity system (see Fig. 2). Thus, the outputs of the left-inversion can completely reproduce the inputs to the "assumed inherent sensor" so that the problem of estimating the to-be-estimated variables x_3, x_4 can be solved.

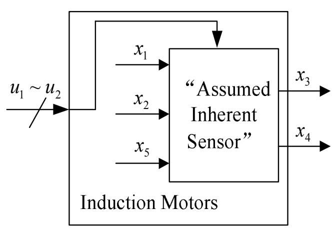

Fig. 1. The "assumed inherent sensor" in the induction motors.

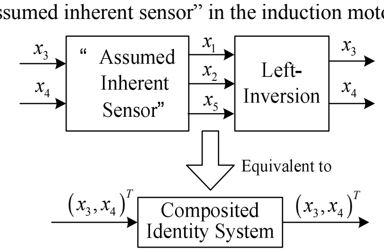

Fig. 2. Estimating principle based on left inversion of the "assumed inherent sensor".

The "assumed inherent sensor" can be achieved by coupling the first order derivative of x_1, x_2 as the first, second equations in (1):

$$\begin{pmatrix}\dot{x}_1\\ \dot{x}_2\end{pmatrix}=\begin{pmatrix}-(\dfrac{L_m^2R_r}{\sigma L_sL_r^2}+\dfrac{R_s}{\sigma L_s})x_1+\dfrac{L_mR_r}{\sigma L_sL_r^2}x_3+\dfrac{n_pL_m}{\sigma L_sL_r}x_4x_5+\dfrac{u_1}{\sigma L_s}\\ -(\dfrac{L_m^2R_r}{\sigma L_sL_r^2}+\dfrac{R_s}{\sigma L_s})x_2-\dfrac{n_pL_m}{\sigma L_sL_r}x_3x_5+\dfrac{L_mR_r}{\sigma L_sL_r^2}x_4+\dfrac{u_2}{\sigma L_s}\end{pmatrix} \quad (2)$$

Obviously, we can get:

$$det\left(\frac{\partial(\dot{x}_1,\dot{x}_2)^T}{\partial(x_3,x_4)}\right)=\begin{bmatrix}\dfrac{R_rL_m}{\sigma L_sL_r^2} & \dfrac{n_pL_m}{\sigma L_sL_r}x_5\\ -\dfrac{n_pL_m}{\sigma L_sL_r}x_5 & \dfrac{R_rL_m}{\sigma L_sL_r^2}\end{bmatrix}=\frac{R_r{}^2L_m^2}{\sigma^2L_s^2L_r^4}+\frac{n_p^2L_m^2}{\sigma^2L_s^2L_r^2}x_5{}^2\neq 0$$

If $det\left(\partial(\dot{x}_1,\dot{x}_2)^T/\partial(x_3,x_4)\right)\neq 0$ according to the inversion theory [7], [8], the "assumed inherent sensor" (2) will be left-invertible and its left-inversion can be expressed by the following inverse function:

$$[x_3,x_4]^T=\boldsymbol{\varphi}(x_1,x_2,\dot{x}_1,\dot{x}_2,x_5,\boldsymbol{u}) \quad (3)$$

Obviously, it is hard to implement directly the left-inversion (3) by analytic means due to high inaccuracy and nonlinearity of the induction motors. To overcome this problem, a static ANN is adopted to approximate the static nonlinear function $\varphi(\bullet)$ appearing in (3) by taking advantage of ANN's strong potential to approximate the nonlinear function, thus resulting in an ANN left-inversion.

The static ANN adopts Back Propagation (BP) network with a three-layers structure of 7-25-2 using "tan sigmoid" transfer function on the nodes of hidden layers, and "linear" transfer function on the output layer. Besides the static ANN, the ANN left-inversion flux observer also feathers a set of differentiators that describing its dynamic behaviors (see Fig. 3) so that it is a kind of dynamic ANN in essence.

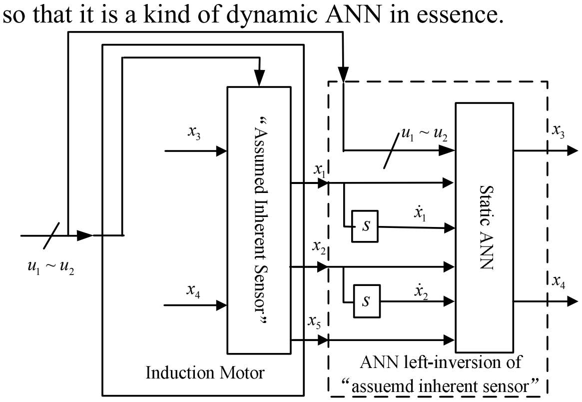

Fig. 3. ANN left-inversion of the "assumed inherent sensor" (s denotes a differentiator).

Replacing the traditional "current model" (CM) or "voltage model" (VM) flux observer with the ANN left-inversion flux observer, the block diagram of proposed induction motor field-oriented control is showed in Fig.4.

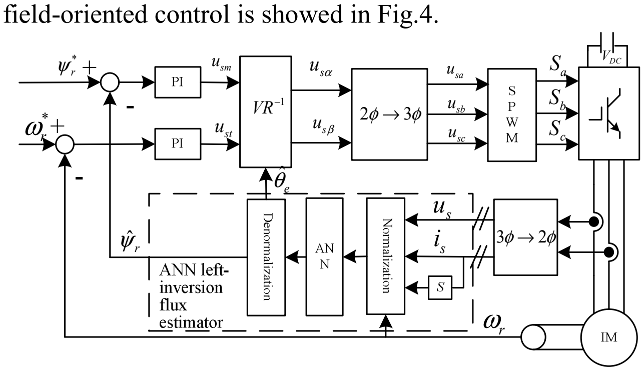

Fig. 4. Block diagram of proposed FOC with NN left-inversion flux observer.

III. OFF-LINE TRAINING OF THE NEURAL NETWORKS

The complete drive system including the motor, the controllers and the observer was simulated in the computer using Matlab/Simulink. A 1.1-kW three-phase induction machine has been used whose parameters are summarized in Table I.

TABLE I
PARAMETERS OF THE INDUCTION MOTOR

Motor type		Squirrel-cage Y90s-4- X2/W	
Rated power（kW）	1.1	Stator resistance（Ω）	5.9
Rated voltage（V）	220/380	Rotor resistance（Ω）	5.6
Rated speed（rpm）	1400	Stator inductance（H）	0.57
Rated current（A）	2.7	Rotor inductance (H)	0.58
Number of pole pairs	2	Mutual inductance(H)	0.55

To train the neural network, an induction motor drive system with conventional direct field-oriented control is firstly implemented in the Matllab/Simulink [9]. The training data are produced by applying different speed step inputs and rotor flux step inputs to the simulation system.The input and output training data of neural network are obtained from the response of the system. The training input data $[x_1, x_2, x_5, u_1, u_2]^T$and output data $[x_3, x_4]^T$ are obtained from the simulation results. One set of sampled speed and flux datas is showed in Fig.5.and Fig.6.The training input data $[\dot{x}_1, \dot{x}_2]^T$ is obtained by using 5-point derivative method that can guarantee high accuracy. Thus, we obtain the ultimate ANN training data sets (about 8000 sampled sets).

It should be noted that the sampled flux data is estimated using the current model flux observer or the voltage model flux observer in low or high speed range, corresponding. So, using the better estimated flux to train NN in all speed range is guaranteed.

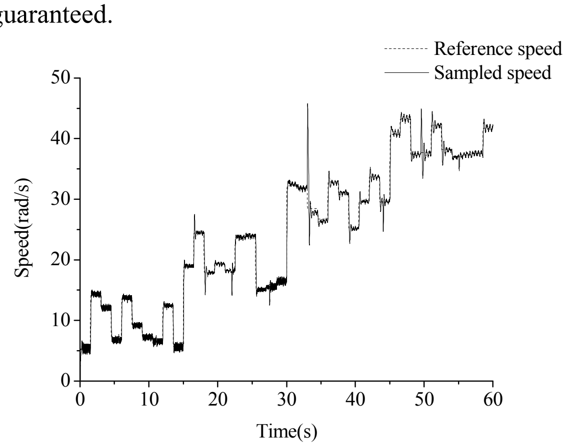

Fig. 5. The sampled speed data from the simulation system.

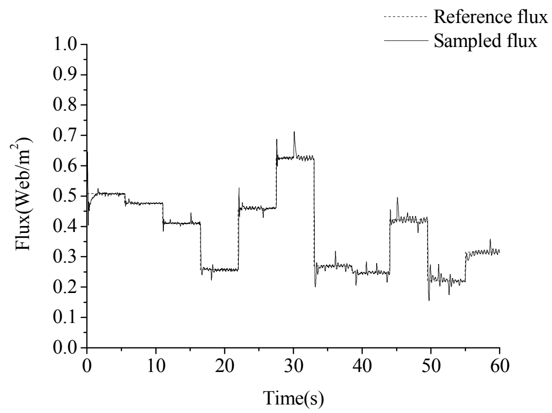

Fig. 6. The sampled flux data from the simulation system.

The ANN was trained with Levenberg-Marquardt training algorithm due to its faster convergence than common BP algorithms and trained after 500 iterations (requiring about 15 minutes on a Pentium 2.8GHz computer). The sum-squared error goal 1.42×10^{-4} is reached (see Fig. 7). In addition, the trained ANN left-inversion was tested with the data not used for training. The test results showed that the generalization of the ANN left-inversion is appropriate for actual application.

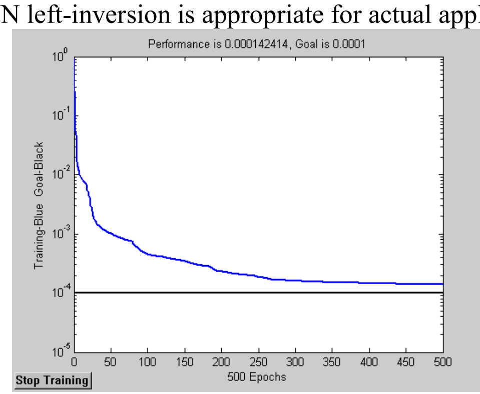

Fig. 7. The sum-squared error goal varying with the training epochs.

IV. SIMULATION RESULT

In both of classical FOC control and FOC control using proposed ANN left-inversion estimator, the command inputs are the speed reference step from 100rad/s to 80rad/s at 2 seconds, and the rotor reference step 0.8Wb to 1.0Wb at 4 seconds.

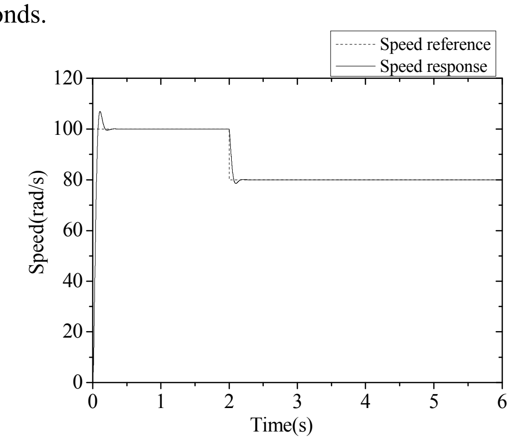

Fig. 8. The speed response with conventional FOC.

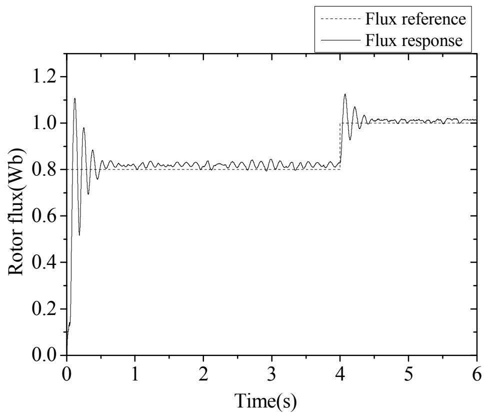

Fig. 9. The flux response with conventional FOC.

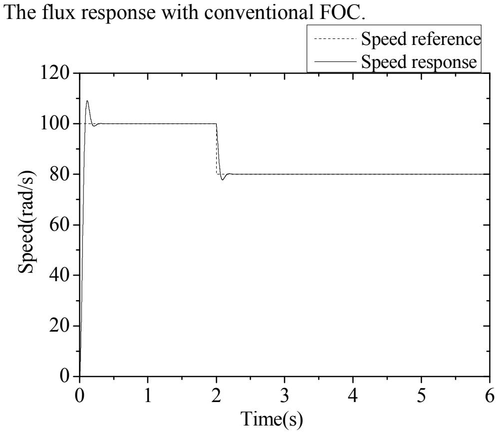

Fig. 10. The speed response with proposed NN left-inversion FOC.

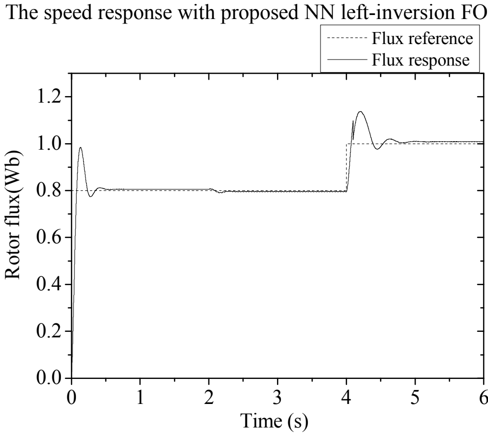

Fig. 11. The flux response with proposed NN left-inversion FOC.

The results in Fig. 8 and Fig. 9 represent the speed response and rotor flux response in the classical FOC. The results using the proposed NN left-inversion estimator are shown in Fig. 10 and Fig. 11. Though both methods produce same speed response, flux response by the proposed method is more stable than conventional FOC. Fig. 9 shows that the flux has the typical "saw-tooth" waveform by conventional FOC. Fig. 11 shows the "saw-tooth" waveform in the flux is completely vanished by proposed NN left-inversion FOC.

V. Conclusion

A new approach for flux estimation based on the "assumed inherent sensor" Left-inverse method of induction motors using ANN has been presented. The ANN was trained to estimate the rotor flux for direct control and map the nonlinear behavior of the rotor flux. Some important advantages of the proposed method are summarized as follows:

1) The ANN improves the time response since no time-consuming routines are required.
2) The effect of motor parameters is reduced since the training of the ANN can be held with experimental measured quantities (voltages, currents, and speed).
3) Improvement of drive robustness can also be achieved with ANNs since they are fault tolerant and can extract useful information from noisy signals.

Finally, the simulation results revealed some interesting features and showed that this method can be used in real-time induction motor control.

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