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ROTOR FLUX ESTIMATION OF INDUCTION MOTOR USING ARTIFICIAL NEURAL NETWORKS

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Abstract: -

Rotor flux measurement is needed for the control of induction motor by methods like field-oriented control. But it is difficult to measure rotor flux in induction motors. Hence rotor flux is estimated by using neural networks in this paper. Rotor flux is simulated using model equations of induction motor and is compared with output of neural network.

Keywords: Induction Motor, Field Oriented Control, Artificial Neural Network, Error Back Propagation

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I. INTRODUCTION

Induction motors are very rugged and cheap and mostly used in industries. Industries require the control of induction motor like constant and variable speeds. For this control methods information of rotor flux is necessary. In squirrel cage induction motor, it is difficult to measure the flux inside the rotor bars. Hence for control purposes the flux has to be estimated by different methods. One of such method is artificial neural networks. Neural networks have the function approximation capabilities. Using this capability, the functional relationship between input and output can be established. By using this property, the rotor flux can be estimated using neural networks. For this purpose, multilayer neural networks with feed forward network are used. Error back propagation algorithm is used for training this network. First true value of rotor flux is obtained from the model of the induction motor and these values are compared with those estimated by neural network.

II. Induction Motor Modeling

In this paper the α - β or dynamic equivalent circuit of the induction motor represented in the rotating reference frame shown in the below equations [1]. It should be noted that all quantities in equations have been referred to the stator [2]. For the interested reader, a paper that includes the steady-state T-type equivalent circuit model of the induction motor can be found in [3][4]. The differential equations produced from analysis of the circuits are shown below.

$$v_{\alpha z} = R_z i_{z\alpha} + \frac{d}{dt} \phi_{z\alpha} - \omega_z \phi_{z\beta}$$
(1)

$$v_{\beta z} = R_z i_{z\beta} + \frac{d}{dt} \phi_{z\beta} - \omega_z \phi_{z\alpha}$$
⁽²⁾

$$0 = R_r i_{r\alpha} + \frac{d}{dt} \phi_{r\alpha} - [\omega_z - \omega_r] \phi_{r\beta}$$
⁽³⁾

$$0 = R_r i_{r\beta} + \frac{d}{dt} \phi_{r\beta} - [\omega_s - \omega_r] \phi_{r\alpha}$$
⁽⁴⁾

where α is the direct axis, β is the quadrature axis, $v_{\alpha s}$ is the α -axis stator voltage, $v_{\beta s}$ is the β -axis stator voltage, $v_{\alpha r}$ is β -axis rotor voltage, $v_{\beta r}$ is β -axis rotor voltage, *ias* is the α -axis stator current, *i* βs is the β -axis stator current, *iar* is α -axis rotor current, *i* βr is β -axis rotor current, *Rs* is the stator resistance, *Rr* is the rotor resistance, ωs is the angular velocity of the reference frame, ωr is the angular velocity of the rotor, and $\varphi \alpha s$, $\varphi \beta s$, $\varphi \alpha r$, and $\varphi \beta r$ are flux linkages. It is assumed that the induction motor analyzed is a squirrel cage machine, leading to the rotor voltage in and being zero[5]. The flux linkages shown below

$$\phi_{\alpha s} = L_s i_{\alpha s} + M i_{\alpha r} \tag{5}$$

$$\phi_{\beta s} = L_s i_{\beta s} + M i_{\beta r} \tag{6}$$

$$\phi_{\alpha r} = L_r i_{\alpha r} + M i_{\alpha s} \tag{7}$$

$$\phi_{\beta r} = L_r i_{\beta r} + M i_{\beta r} \tag{8}$$

Where Lr is the rotor self-inductance, Ls is the stator self-inductance, M is the magnetizing inductance, Llr is the rotor leakage inductance, and Lls is the stator leakage inductance.

$$L_{S} = M + L_{lS} \tag{9}$$

$$L_{r} = M + L_{lr} \tag{10}$$

The electromagnetic torque of the machine is

$$T_e = \frac{3}{2} \frac{p}{2} M(i_{\alpha s} i_{\alpha r} - i_{\beta s} i_{\beta r})$$
(11)

Where *P* is the number of poles and *Te* is the electromagnetic torque. The torque and rotor speed are related by

$$\frac{\mathrm{d}w_{\mathrm{r}}}{\mathrm{d}t} = \frac{\mathrm{p}}{2\mathrm{j}} \left(\mathrm{T}_{\mathrm{e}} - \mathrm{T}_{\mathrm{l}} \right) \tag{12}$$

Where *Tl* is the load torque and *j* is the inertia of the rotor and connected load.

By substituting the current equations in above we get differential equations [7]. The differential equations as follows

$$x(t) = Ax + g(x, u, t)$$
(13)

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 $x = \begin{bmatrix} i_{s\alpha} & i_{s\beta} & \emptyset_{r\alpha} & \emptyset_{r\beta} & \omega \end{bmatrix}^{T}$ is state vector consist of stator current $i_{s\alpha}$, $i_{s\beta}$ rotor flux $\emptyset_{r\alpha}$, $\emptyset_{r\beta}$ and speed ω . $u = \begin{bmatrix} V_{s\alpha} & V_{s\beta} \end{bmatrix} T$ control vector consist of stator voltage $V_{s\alpha}$, $V_{s\beta}$.

$$g = \begin{bmatrix} \beta \omega \phi_{r\beta} + \gamma V_{s\alpha} \\ -\beta \omega \phi_{r\alpha} + \gamma V_{s\alpha} \\ \omega \phi_{r\beta} \\ -\omega \phi_{r\alpha} \\ -\mu \phi_{r\beta} I_{s\alpha} + \mu \phi_{r\alpha} I_{s\beta} - \frac{p}{j} C_r \end{bmatrix}$$
$$A = \begin{bmatrix} -\Lambda & \omega_s & \beta \alpha_r & 0 & 0 \\ -\omega_s & -\Lambda & 0 & \beta \alpha_r & 0 \\ M\alpha_r & 0 & -\alpha_r & 0 & 0 \\ 0 & M\alpha_r & 0 & -\alpha_r & 0 \\ 0 & X = \begin{bmatrix} I_{s\alpha} & q_{s\beta} & \phi_{s\alpha} & \phi_{s\beta}^{-\alpha} m \\ 0 & g_{s\beta} & \phi_{s\alpha} & \phi_{s\beta}^{-\alpha} m \\ 0 & g_{s\beta} & \phi_{s\alpha} & \phi_{s\beta}^{-\alpha} m \\ 0 & g_{s\beta} & \phi_{s\alpha} & \phi_{s\beta}^{-\alpha} m \\ \end{bmatrix}$$

The parameters, characterizing the induction motor shown below.

$$\alpha_r = \frac{R_r}{L_r} \qquad \alpha_m = \frac{f}{j} \qquad \alpha_s = \frac{R_s}{L_s} \qquad \beta = \frac{M}{\sigma L_s L_r} \qquad \eta = \frac{1}{\sigma}$$
$$\mu = \frac{PM}{JL_r} \qquad \gamma = \frac{1}{\sigma L_s} \qquad \xi = \frac{P}{J} \qquad \Lambda = \frac{L_r^2 R_s + R_r M^2}{L_r (L_s - M^2)}$$

Where Lr and Ls are the rotor and stator inductance, M is the mutual inductance, Rr and Rs are the rotor and stator resistances, p is the pair pole number, f is the viscous friction, J is the rotor inertia moment.

Parameter of IM	Values
R _r	1 Ω
Rs	1.1Ω
Lr	156.8 Mh
L_S	155.4 Mh
Р	2
J	0.013
	Kgm2
М	150Mh

Table: 1 induction motor numerical parameters

III.Artificial Neural Network Architecture

The architecture of a neural network is determined by its structure, i.e., the overall connectivity and transfer function of each node in the network [8]. A typical three-layer feed forward neural network is given in Fig1. It consists of an input layer, hidden layer and output layer [10]. Each input is connected via a weight to each node in the hidden layer [10][11]. Each hidden node is, in turn, connected via a weight to each node in the output layer.



Figure:1 Multi-layer feed forward Artificial neural network

The output of hidden node j is given by

With

$$o_m = \sigma(z_m) \tag{14}$$

$$z_{m} = \sum_{i} w_{i} m x_{i} + w_{m} n \qquad (15)$$

Where

 w_{lm} the weight between the *ith* input and the mth hidden node. x₁ represents the input. μ_n is a threshold of node m.

 σ depicts the activation function of the hidden nodes that is considered as a sigmoid function. Indeed, we can find many forms of this function. But we propose this form to simplify the development concerning the stability study.

$$\sigma(z_m) = \frac{1}{1 + e^{-z_m}} \tag{16}$$

The output of output node m is a sum of its weighted inputs, that is

$$y_n = \sum m \, w_n m o_n \tag{17}$$

where w nm is the weight between the mth hidden and the nth output node.

IV. State Estimation by Neural Network:

State estimation of induction motor using artificial neural network in this a multi-layer feed forward Artificial Neural Network is using for rotor flux estimation[12]. Our proposed ANN contains 7 neurons in input layer, 15 neurons in output layer and 2 neurons in output layer. From the induction motor modeling we are taking 500 samples in that 500 samples we train artificial neural network with first 200 samples and test remaining 300 samples. The ANN block is shown below Fig: 2



Figure:2 Artificial Neural Network Training block

Results:

Induction motor is simulated in mat lab take 500 samples in 0.5 sec time period current, flux and speed wave forms are shown below. Fig: 3 shows stator current waveform of induction motor at alpha axis. Fig: 4 show stator current waveform of induction motor at alpha axis, Fig: 6 shows rotor flux of induction motor at beta axis, Fig 7 shows speed wave form of induction motor.



Figure:3 Waveform of stator current in alpha axis



Figure:4 Waveform of stator current at beta axis



Figure:5 Waveform of Rotor flux at alpha axis



Figure:6 Waveform of Rotor flux at beta axis



Figure:7 Speed wave form of induction motor

Training waveforms of artificial neural network with 200 samples shown in below figures. To train ANN initialize the weights if hidden layer randomly taken. Fig:8 represents ANN Training wave form of rotor flux at alpha axis for 200 samples. Fig:9 Represents ANN Training wave form of rotor flux at beta axis for 200samples. Fig:10 ANN estimated wave form rotor flux at alpha axis for 300 untrained inputs. Fig:11 ANN estimated wave form rotor flux at alpha axis for 300 untrained inputs. From Fig 10 and Fig 11 It can be that ANN accurately estimates rotor flux.





Figure:10 ANN estimated wave form rotor flux at alpha axis for 300 untrained input



Figure:11 ANN estimated wave form rotor flux at alpha axis for 300 untrained input

Conclusion:

In this paper, we have estimated the behavior of induction motor using artificial neural network. It is a three-layer feed forward artificial neural network, trained with the modified error back propagation learning algorithm. Moreover, the efficiency of the proposed recurrent observer is due to the parallel architecture. Hence from the above training and tested samples ANN is more accurately estimates the rotor flux of induction motor.

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