Improved FOC of Induction Motor with Online Neural Network

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Abstract: - This paper proposed improvement performance from offline towards online neural network scheme for speed control of induction motor field oriented control based on load disturbance and parameter variation. The neural network is design as 1-3-1 network structure by feedforward architecture to maintain the speed trajectory specified by reference model. Both offline and online networks were trained by backpropagation algorithm and the updating of weight and bias will be done in the online model. Simulation model were developed for both networks by using MATLAB/Simulink software and the results shows that the performance of online NNIFOC improved rather than offline NNIFOC and robust to load disturbance and parameter variation.

Key-Words: - Neural Network, Induction Motor, Field Oriented Control

1 Introduction

A three phase induction motor (IM) is designed to operate from a three phase source of alternating voltage and it is a one of asynchronous alternating current (AC) motor. The advantages of the IM includes high reliability, relatively simple, has rugged structure, low cost, robustness and high efficiencies. These advantages make the IM advance in all aspects like speed change, speed reversal, starting and braking. The overall system performance depends on the IM dynamic operation. Due to the swift development in microprocessor and power electronic, the advanced control methods have IM possible for high performance applications.

A lot of researcher has been attracted to the field of electric drives by IM control over time. IM with variable speed ac drives and employed the field oriented control (FOC) method expands in recent years to achieve better performances set by direct current (DC) drives. In order to provide good steady-state performance in fast dynamic response, decoupling between the torque and flux is highly recommends. High dynamic performance in IM can be achieved by means of field oriented control where it provides a suitable mathematical description of three phases IM.

The translation of coordinate from the fixed references stator frame to the frame of rotating synchronous is implied by the vector control [1]. In early 1970s, the decoupling technique makes the possibility of separated control for torque and flux in the complex dynamic for IM [2].

By applying the control techniques such as adaptive control [3] a good performance can be achieve with parameter sensitive property. A great attention has been made by neural network (NN) due to its natural parallelism in the field of power electronic, thus allow and permit the high speed processing. The NN have capability for tolerance, to miss data, to fault, and to carry out in noise environment [4].

To identify and control nonlinear dynamic systems and nonlinear parameter estimation, the use of NN has been proposed [5][6]. An estimation of the stator flux and trained to map the nonlinear behavior of a rotor flux is performed on the proposed NN [7]. High performance control has been the objectives of [8], which presents robust neural controller and against variation of parameter. The NN are excellent estimators in non-linear system because it does not use the mathematical model of the system [9].

In the past decade, NN have been used in some power electronic applications such as inverter [10], energy saving [11], dc motor control [12-13], flux estimation [14], and estimation of feedback signal [15]. Online and offline neural models have their own advantages and disadvantages. Even an offline model can handle large data as computation time that not critical to their structure, it only robust to small variation, but fail to adapt to larger changes in the system. While, the online model quickly adapts to variation in the non-linear behavior of the system [16].

The use of an offline training of NN to emulate the function of FOC has been proposed in [17-19]. It shows that NN presents new solution to simplify the implementation of FOC. The input and output signal for training the NN are extracted from FOC of IM. The NN has been trained using a several condition to update their weight because of their limitation to larger changes of the system so that it can follow the speed trajectory specified by reference model.

2 Modeling of Induction Motor

The IM model has been derived in a number of different reference frames. This makes it easier to fix the reference frame to a particular motor quantity and adjust the model accordingly. Most of induction motors are the rotary type with basically a stationary stator and a rotating rotor. The dynamic model of the induction motor is derived by transforming the three phase quantities into two phase direct and quadrature axes quantities. The mathematical model in compact form can be given in the stationary reference frame as follows [20].

Where the voltage equation is:

$$V_{qs} = R_s i_{qs} + \frac{d\psi_{qs}}{dt} + \omega_e \psi_{ds} \tag{1}$$

$$V_{ds} = R_s i_{ds} + \frac{d\psi_{ds}}{dt} + \omega_e \psi_{qs} \tag{2}$$

$$V_{qr} = R_r i_{qr} + \frac{d\psi_{qr}}{dt} + (\omega_e - \omega_r)\psi_{dr} \tag{3}$$

$$V_{dr} = R_r i_{dr} + \frac{d\psi_{dr}}{dt} + (\omega_e - \omega_r)\psi_{qr} \tag{4}$$

Where, $V_{qr}, V_{dr} = 0$

The electromagnetic torque of the machine can be presented as follow:

$$T_e = \frac{3PL_m}{4L_r}(\psi_{dr} i_{qs-} \psi_{qr} i_{ds}) \tag{5}$$

Where P, denote the pole number of the motor. If the vector control is fulfilled, the q component of the rotor field ψ_{qr} would be zero. Then the electromagnetic torque is controlled only by q-axis stator current and becomes:

$$T_e = \frac{3PL_m}{4L_r}(\psi_{dr} i_{qs}) \tag{6}$$

3 NNIFOC Control System Description

Neural network indirect field oriented control (NNIFOC) in Fig.1 is a control procedure for operating the induction motor that results in fast dynamic response and energy efficient operation at all speeds. It commutates the motor by calculating voltage and current vectors based on motor current feedback. It maintains high efficiency over a wide operating range and allows for precise dynamic control of speed and torque.

The NNIFOC controls the stator currents represented by a space vector. It transforms three-phase stator currents (A, B, C) into a two-phase time variant system (α,β). In this structure, the motor flux generating part is d (direct) and a toque generating part is q (quadrature).

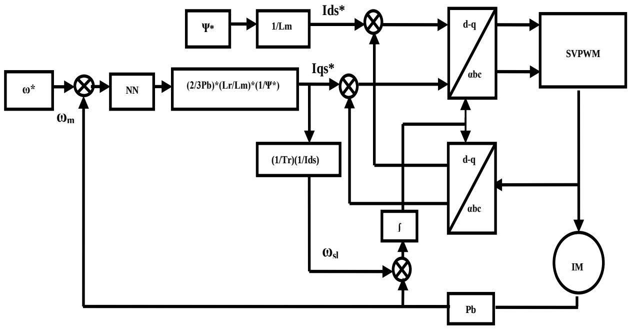

Fig.1 Proposed NNIFOC System

The flux references, $\psi*$ indicates the rotor flux references for every speed references within the nominal value. The d-axis current, id can be calculated by using this equation,

$$i_{ds}* = \frac{\psi_{dr}}{L_m} \tag{7}$$

The rotor speed ω_m is compared to rotor speed references ω_m* and the resulting error is process in the NN controller. The NN controller produces changes of torque, $\Delta\tau_c$ to generates the q-axis references current by using equation below,

$$i_{qs}* = \frac{2L_r \Delta\tau_c}{3PL_m \psi*} \tag{8}$$

The references current in d-axis and q-axis is compared to feedback from the motor current through Clark and Park Transformation. From the respective error, the voltage references signal is generated and converted into three phase voltage and fed to SVPWM.

4 Structure of NNIFOC

To design the neural network control some information about the plant is required. Basically, the numbers of input and output neuron at each layer are equal to the number of input and output signals of the system respectively. Further the number of hidden layers and the total neurons is depended on the complexity of the system and the required training accuracy. Based on the type of the task to be performed, the structure of the proposed NNIFOC is as shown in Fig.2.

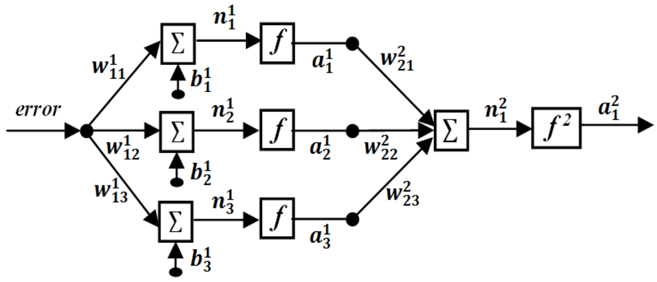

Fig.2 Structure of NNIFOC

The controller consists of input layer, hidden layer and output layer. Based on number of the neuron in the layers, the NNFOC is defined as a 1-3-1 network structure. The first neuron of the output layer is used as a torque reference signal ($a^2_1=m_f$). The connections weight parameter between j^{th} and i^{th} neuron at m^{th} layer is given by w^m_{ij}, while bias parameter of this layer at i^{th} neuron is given by b^m_i. Transfer function of the network at i^{th} neuron in m^{th} layer is defined by:

$$n_i^m = \sum_{j=1}^{s^{n-1}} w_{ij}^m a_j^{m-1} + b_i^m \tag{9}$$

$$\psi_{ds} = \int (V_{ds} - R_s i_{ds}) dt \tag{10}$$

The output function of neuron at m^{th} layer is given by:

$$a_i^m = f^m(n_i^m) \tag{11}$$

Where f is the activation function of the neuron. In this design the activation function of the output layer is unity and for the hidden layer is a tangent hyperbolic function given by:

$$f^m(n_i^m) = \frac{2}{1+e^{-2n_i^m}} - 1 \tag{12}$$

Updating of the connection weight and bias parameters are given by:

$$w_{ij}^m(k+1) = w_{ij}^m(k) - \alpha \frac{\partial F(k)}{\partial w_{ij}^m} \tag{13}$$

$$b_i^m(k+1) = b_i^m(k) - \alpha \frac{\partial F(k)}{\partial b_i^m} \tag{14}$$

where k is sampling time, α is learning rate, and F performance index function of the network. The next section will be explaining the details of offline and online learning NN that used for the simulation testing.

4.1 Updating Parameter of NNIFOC

After the neural network architecture is modeled, the next stage defines the learning model to update network parameters. By this learning capability, it makes the NN suitable to be implemented for the system with motor parameters which are difficult to define and vary against with environment. The training process minimizes the error output of the network through an optimization method. Generally, in learning mode of the neural network controller a sufficient training data input-output mapping data of a plant is required.

The weight can be updated in two primary ways which is offline and online. The offline learning is occurs when the updating weight is compute after summing over all of the training examples. While online learning will update the weights after each training example. The backpropagation algorithm is used for updating the weight and bias by finding the minimum error between the references and actual output for all given training pattern. The error at the output propagated backward through the network to the hidden layer.

Based on the first order optimization scheme, updating of the network parameters are determined. The performance index sum of square error is given by:

$$F(k) = \frac{1}{2} \sum_i e_i^2(k) \tag{15}$$

$$e_i(k) = t_i(k) - a_i(k) \tag{16}$$

where t_i is target signal and a_i output signal on last layer.

The gradient descent of the performance index against to the connection weight is given by:

$$\frac{\partial F}{\partial w_{ij}^m} = \frac{\partial F}{\partial n_i^m}\frac{\partial n_i^m}{\partial w_{ij}^m} \quad (17)$$

The sensitivity parameter of the network is defined as:

$$s_i^m = \frac{\partial F}{\partial n_i^m} \quad (18)$$

$$s_i^m = \frac{\partial F}{\partial a_i^m}\frac{\partial a_i^m}{\partial n_i^m} \quad (19)$$

Gradient the transfer function again to the connection weight parameter is given by:

$$\frac{\partial n_i^m}{\partial w_{ij}^m} = a_i^{m-1} \quad (20)$$

From substitution equation (9) and (11) into (4) the updating connection parameter is given by:

$$w_{ij}^{m-1}(k+1) = w_i^{m-i}(k) - \alpha s_i^m(k) a_i^{m-1}(k) \quad (21)$$

With the same technique the updating bias parameter is given by:

$$b_i^{m-1}(k+1) = b_i^{m-i}(k) - \alpha s_i^m(k) \quad (22)$$

5 Simulation Results

A simulation was constructed for the entire system with the implementation of online and offline NN based IFOC scheme for the three-phase IM using Borland C++, and then embedded as S-function in Matlab/Simulink software. Both online and offline NN system will be tested simultaneously. The effect of the parameter variation towards the system will be tested on both systems.

The parameters for the motor are given by:

- Frequency and pole are 50Hz and 4
- Stator and rotor resistances, R_s=8Ω and R_r=5.8Ω
- Stator and rotor self inductances are 0.215H and 0.215H
- Mutual inductances is 0.198H

To verify the performance of online and offline NN for the speed control of induction motor based field oriented control, the simulation result for both system are compared based on load disturbance applied to the system. With the same speed reference which is 1200rpm, both systems are run simultaneously. The result of the motor speed with the time is shown in figure below.

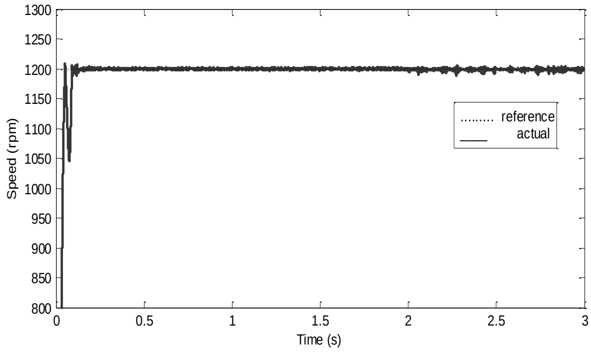

Fig.3 Speed for online NNIFOC during load disturbance applied

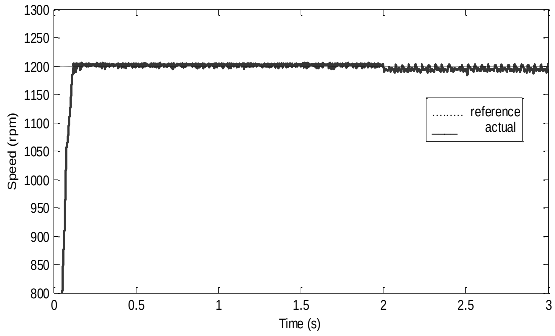

Fig.4 Speed for offline NNIFOC during load disturbance applied

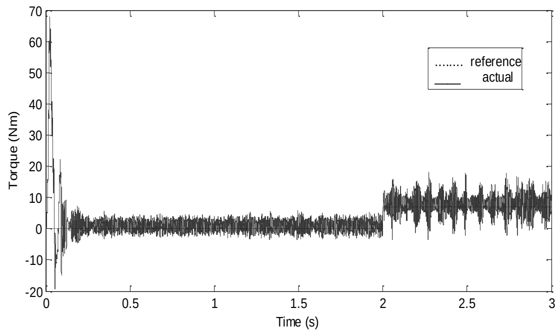

Fig.5 Load disturbance for online NNIFOC

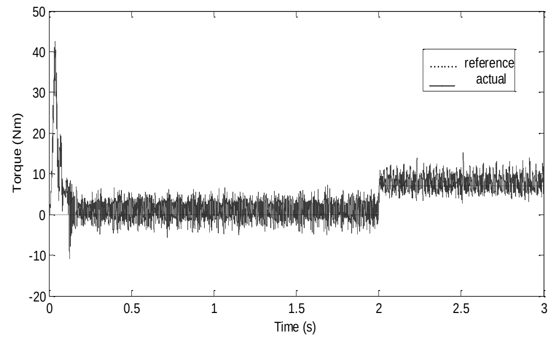

Fig.6 Load disturbance for offline NNIFOC

The online NNIFOC is implemented in Fig.3 while the offline NNIFOC is illustrated in Fig.4. For both systems, load disturbance applied on the time of 2s as shown in Fig.5 and Fig.6. At the initial, both systems are run under no load condition then, at the time of 2s, the 6Nm load is applied.

From the results shown in the figure, both systems manage to follow the speed reference at the initial before the load disturbance is applied. While the load disturbance is applied it is obviously that the online NNIFOC not effects by the load disturbance. On the other hand, offline NNIFOC show a slightly drop on the speed and not manages to follow the speed reference after load applied. In addition, the setting time also improve from 0.2 s to 0.1 second by using the online NNIFOC.

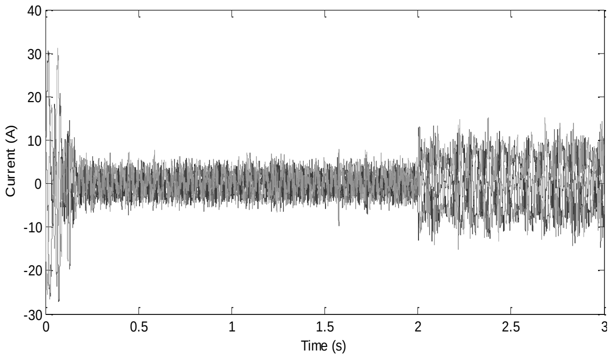

Fig.7 Current for online NNIFOC during load disturbance applied

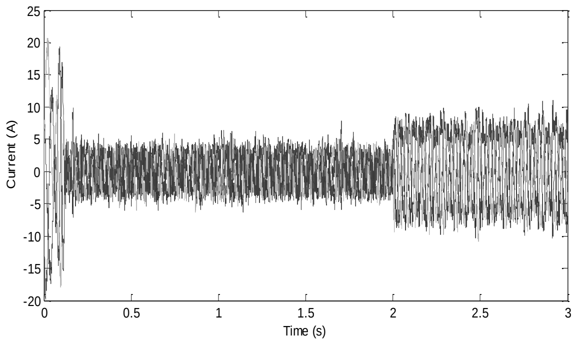

Fig.8 Current for offline NNIFOC during load disturbance applied

The three phase current for online NNIFOC and offline NNIFOC is show in Fig.7 and Fig.8 respectively. The current is clearly increased when the load applied. It can be said that the current is proportional to the load applied to the system. When the load increased, the current also will increase. When the load is applied to the system, more current will be draw to maintain the speed in order to follow the speed command.

The testing is continuing by examining the parameter variation. The parameter for stator and rotor resistance will be change according to the change of temperature from the reference temperature towards the maximum temperature. The resistance at maximum temperature for the induction motor is calculated based on the formula below.

$$R_T = R_o(1+\alpha(\Delta T)) \qquad (23)$$

Where R_o is the value of initial resistance, while α is temperature coefficient ($\alpha = 0.004041$) for copper material and Δ_T is changes of reference temperature usually $20°c$ towards maximum temperature in $°_C$.

The testing is start by the initial temperature assume as $20°c$ and change to the maximum temperature at the time on 2s. The maximum temperature for induction motor is assumed to be $155°c$. The rotor and stator resistance at maximum temperature is 8.566Ω and 11.8147Ω.

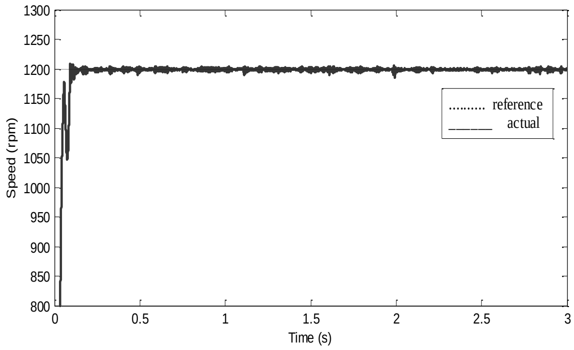

Fig.9 Speed for online NNIFOC during parameter variation applied

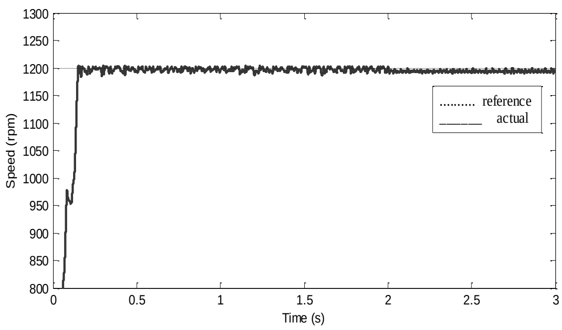

Fig.10 Speed for offline NNIFOC during parameter variation applied

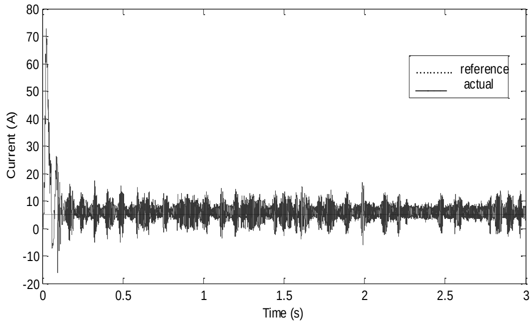

Fig.11 Constant Load applied for online NNIFOC during parameter variation

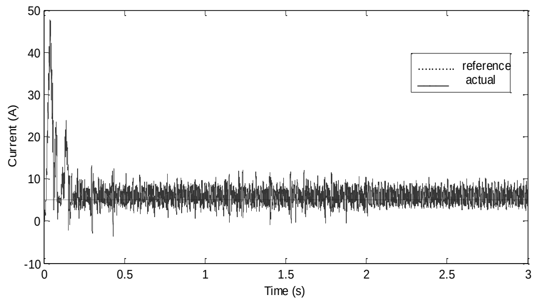

Fig.12 Constant Load applied for offline NNIFOC during parameter variation

The speed achievement as illustrate in Fig.9 and Fig. 10 show a difference at the time of 2s between offline and online NNIFOC with constant load of 5Nm applied as show in Fig. 11 and Fig.12 when the parameter is varies. Both of the system shows no overshoot for the speed response however the online NNIFOC show the advantages of maintain the speed even the parameter is varies while the offline NNIFOC shows speed is merely drop at the time of 2s.

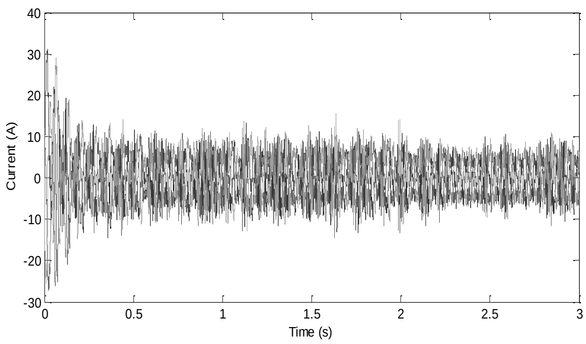

Fig.13 Current for online NNIFOC during parameter variation

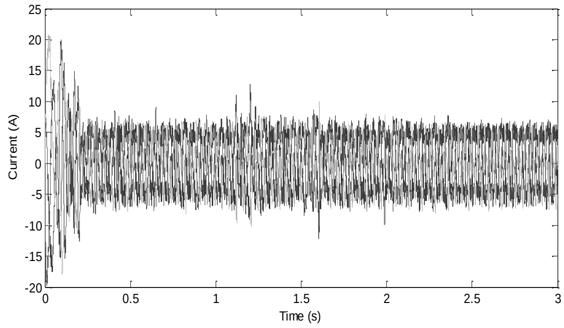

Fig.14 Current for offline NNIFOC during parameter variation

The three phase current for online NNIFOC and offline NNIFOC is show in Fig.13 and Fig.14 respectively. The current is decreased when parameter variation applied. It can be said that the current is inversely proportional to the parameter variation to the system. When the resistance increased, the current will be decreased. When the parameter variation is applied to the system, less current will be draw to maintain the speed in order to follow the speed command.

4 Conclusion

The comparison performance of online and offline NNIFOC of induction motor has been presented in this paper. Both structures were trained by backpropagation algorithm and the updating of weight and bias has been done in the online NNIFOC model. The controller does not require data of motor parameter. The simulation model were developed for both networks by using MATLAB/Simulink software and the results shows that the performance of online NNIFOC improved rather than offline NNIFOC and robust to load disturbance and parameter variation.

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