NEURAL NETWORK BASED SPEED CONTROL OF INDUCTION MOTOR WITH IFOC TECHNIQUE

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ABSTRACT
This paper has been focus on developing the speed tracking control strategies in order to obtain an approach of modeling the IM drives system for vector control purposes focusing on indirect field oriented control (IFOC). Artificial intelligent (AI) controller which is Neural Network (NN) controller are implemented in the SVPWM that used to generate pulse width modulation (PWM) for switching three phase inverter to provide a suitable voltage for the motor to improve the overall performance of the IFOC of IM. The validity of proposed NN IFOC of IM is shown with experimental result carried out under different condition of speed variation. The theoretical principle and the performance results for NNIFOC of IM are analyzed. It shows that the proposed online NNIFOC of IM gives better performance rather than offline NNIFOC of IM in term of settling time.

Key words: Efficiency optimization · Adaptive Flux Control · Direct Torque Control · Motor Control ·

INTRODUCTION
Conversion from electrical energy to mechanical energy is an important process in modern industrial civilization [1]. A machine that can convert electrical energy to mechanical energy called as an electric motor [2], Electric motors are broadly classified into two categories which are direct current (DC) motor and alternating current (AC) motor. It can be able to run by supplying either AC or DC based on the type of the electric motor. The force within the motor will be generating by interaction between the winding current and the magnetic field of the motor to operate the electric motor [3]. Around half of the electrical energy generated in a developed country is ultimately consumed by electric motors, of which over 90% are induction motors (IM) [1]. The advantages of the IM includes high reliability, relatively simple, has rugged structure, low cost, robustness and require very less maintenance rather than DC motor [4].

A lot of researcher has been attracted to the field of electric drives by IM control over time. The IM control methods are dividing into scalar and vector control. The scalar control is usually used in low cost and low performances drives. Even though scalar control is easy to implement and offer a relatively steady state response, unfortunately the dynamics are sluggish. In order to obtain high precision and good dynamics, vector control (VC) approach is being employed with closed loop feedback control [5]. The translation of coordinate from the fixed references stator frame to the frame of rotating synchronous is implied by the VC [6]. IM variable speed ac drives with VC method expands in recent years to achieve better performances set by 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 (FOC) where it provides a suitable mathematical description of three phases IM [5]. In early 1970s, the decoupling technique makes the possibility of separated control for torque and flux in the complex dynamic for IM [7].

In the FOC technique, a control unit which is to develop flux controller signal is required. Conventionally, a proportional integral derivative (PID) control technique is employed; however the nonlinearity of the IM cause difficulty in determined the PID parameter. Besides that, by using PID controller, the performances of the FOC also could not be optimized. The performance of FOC PID also can be enhanced by adopting AI based method. NN has the advantages of parallel computation and simple hardware; hence it is superior to a DSP based in execution time and structure. A great attention has been made by 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 a noise environment [8].

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]. Either offline or online NN hold its own merit and demerits. The offline model have the ability to deal with large data as computation time that not desperate to their structure and robust to small variation, but when face to great changes, it lose to comply with 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.

The validity of proposed neural network indirect field oriented control (NNIFOC) in this paper is shown with experimental result by focusing on speed variation and load disturbance using digital signal processing (DSP) based
implementation. The results are obtained and the performance of NNIFOC of IM is analyzed.

CONTROL DESIGN

Dynamic model 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 [9].

Where the voltage equation is:

\[ V_{qr} = R_{iqr} + \frac{d\psi_{qr}}{dt} + \omega_s \psi_{ds} \]  
\[ V_{ds} = R_{idr} + \frac{d\psi_{dr}}{dt} + \omega_s \psi_{qr} \]  
\[ V_{qr} = R_{iqr} + \frac{d\psi_{qr}}{dt} + (\omega_s - \omega_r) \psi_{dr} \]  
\[ V_{dr} = R_{idr} + \frac{d\psi_{dr}}{dt} + (\omega_s - \omega_r) \psi_{qr} \]

Where, \( V_{qr}, V_{dr} = 0 \)

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

\[ T_e = \frac{3PL_m}{4L_r} (\psi_{dr}i_{qr} - \psi_{qr}i_{dr}) \]  
\[ T_e = \frac{3PL_m}{4L_r} (\psi_{dr}i_{qr}) \]

The parameters for the motor are given as Table 1.

<table>
<thead>
<tr>
<th>Motor Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency, ( f )</td>
<td>50 Hz</td>
</tr>
<tr>
<td>Pole, ( p )</td>
<td>4</td>
</tr>
<tr>
<td>Stator Resistance, ( R_s )</td>
<td>0.3Ω</td>
</tr>
<tr>
<td>Rotor Resistances, ( R_t )</td>
<td>0.25Ω</td>
</tr>
<tr>
<td>Stator Self Inductances, ( L_s )</td>
<td>0.0415H</td>
</tr>
<tr>
<td>Rotor Self Inductances, ( L_r )</td>
<td>0.0412H</td>
</tr>
<tr>
<td>Mutual inductances, ( L_m )</td>
<td>0.4867H</td>
</tr>
</tbody>
</table>

Speed Controller Design

The overall block diagram of SVPWM field oriented control of induction motor with indirect technique is shown in figure 1.

![Figure 1: Complete block diagram of SVPWM-FOC](image)

The reference flux, slip and the computed torque from NN controller that act as a speed controller in this system will be received by the FOC block to generates \( i_{abc} \). The flux is assumed to be constant; either the motor operates below the rated speed or beyond the rated speed.

A sinusoidal current of variable magnitude and frequency used to represent the fundamental component of SVPWM. This will reduce the switching losses at high frequency and the stable output voltages can be provides.

Structure of NNIFOC

The design on the neuron at every layer will be the same to the amount of input and output signal through the system. While the intricacy and the necessary training accuracy of the system depends on the number of hidden layer and the total neuron. Depending on the type of the mission undertaking, the proposed structure of NNIFOC is as shown in figure 2.

![Figure 2: Structure of NNIFOC](image)
The output function of neuron at \( m^{th} \) layer is given by:

\[
a^m_i = f^m(p^m_i)
\]

(9)

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:

\[
f^m(p^m_i) = \frac{2}{1+e^{-2p^m_i}} - 1
\]

(10)

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

\[
w^m_j(k+1) = w^m_j(k) - \alpha \frac{\partial F(k)}{\partial w^m_{ij}}
\]

(11)

\[
b^m_i(k+1) = b^m_i(k) - \alpha \frac{\partial F(k)}{\partial b^m_i}
\]

(12)

where \( k \) is sampling time, \( \alpha \) 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.

**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:

\[
F(k) = \frac{1}{2} \sum e_i^2(k)
\]

(13)

\[
e_i(k) = t_i(k) - a_i(k)
\]

(14)

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:

\[
\frac{\partial F}{\partial w^m_{ij}} = \frac{\partial F}{\partial m_i} \frac{\partial m_i}{\partial w^m_{ij}}
\]

(15)

The sensitivity parameter of the network is defined as:

\[
s^m_i = \frac{\partial F}{\partial m_i}
\]

(16)

\[
s^m_i = \frac{\partial F}{\partial a^m_i} \frac{\partial a^m_i}{\partial m_i}
\]

(17)

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

\[
\frac{\partial m_i}{\partial w^m_{ij}} = a^{i-1}_m
\]

(18)

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

\[
w^{m-1}_j(k+1) = w^{m-1}_j(k) - \alpha s^m_j(k) a^{m-1}_i(k)
\]

(19)

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

\[
b^{m-1}_i(k+1) = b^{m-1}_i(k) - \alpha s^m_i(k)
\]

(20)

\[
\frac{\partial F}{\partial w^m_{ij}} = \frac{\partial F}{\partial m_i} \frac{\partial m_i}{\partial w^m_{ij}}
\]

(21)

The sensitivity parameter of the network is defined as:

\[
s^m_j = \frac{\partial F}{\partial n^m_j}
\]

(22)

\[
s^m_i = \frac{\partial F}{\partial a^m_i} \frac{\partial a^m_i}{\partial m_i}
\]

(23)

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

\[
\frac{\partial m_i}{\partial w^m_{ij}} = a^{i-1}_m
\]

(24)

From substitution equation (18) and (20) into (13) the updating connection parameter is given by:

\[
w^{m-1}_j(k+1) = w^{m-1}_j(k) - \alpha s^m_j(k) a^{m-1}_i(k)
\]

(25)

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

\[
b^{m-1}_i(k+1) = b^{m-1}_i(k) - \alpha s^m_i(k)
\]

(26)
RESULTS AND DISCUSSION

The proposed model has been simulating by using Matlab/Simulink software. To verify the simulation result in real time, the proposed control method has been applied to an experiment setup for real time testing. The experimental setup for the proposed speed tracking of IFOC of IM is shown in figure 3. The experimental setup consist of major component namely a DSP board, gate driver, inverter circuit, sensor and standard induction motor

The neural network model and indirect field oriented control is implementing in the DSP controller board. In this closed loop drive system prototype, the rotor mechanical speed is sensed by speed sensor and the current is sensed by current sensor to bring feedback to the proposed drive system

Figure 3: Hardware prototype of the proposed NNIFOC

In order to verify the validity of the proposed NNIFOC, both online and offline NN has been tested under speed variation condition.

With the same speed reference which is 1200rpm, both systems are run separately. The result of the motor speed versus with the time is shown in figure below.

Figure 4: Speed for online NNIFOC of IM during Start up response and constant speed

According to the figure above, it shows that online NNIFOC in figure 4, gives a better result compared to offline NNIFOC in figure 5 in term of settling time. Online NNIFOC achieve the settlement by 1.7s while offline NNIFOC takes 2.8s to follow the reference speed.

Figure 5: Speed for offline NNIFOC of IM during constant speed

Figure 6: Speed for online NNIFOC of IM during step-up response

Figure 7: Speed for offline NNIFOC of IM during step-up response

The speed is continuously tested under step-up condition by varying the speed from 500rpm to 1000rpm. From the result it shows that the settling time for online NNIFOC which is 5.7s in figure 6 is 0.5s faster than offline NNIFOC in figure 7 that settle at 6.2s.
Figure 8: Speed for online NNIFOC of IM during step-down response

Figure 9: Speed for offline NNIFOC of IM during Step-down response

Referring to the figure 8 and figure 9, the speed continuously tests by varying the speed from 1000rpm to 700 rpm under step down condition. Online NNIFOC still produced better performance rather than offline NNIFOC that settled at 10s while offline NNIFOC settle at 10.5s to achieve the desired output speed.

CONCLUSION.

The online and offline neural network based speed control of induction motor with IFOC technique has been presented in this paper. The validity of the proposed method is verified by the experimental setup. It conclude that the proposed online NNIFOC of IM gives better performance rather than offline NNIFOC of IM that carried out under start-up, step-up and step-down condition.

REFERENCE


