

Neural Networks for controlled Speed Sensorless Direct Field Oriented Induction Motor Drives

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Abstract – The aim of this paper is to present a full digital implementation of a sensorless speed direct field oriented controlled induction motor drive. Thanks to its advantages, the neural network is used to simultaneously control and reconstruct the induction motor rotor speed.

Experimental results for a 1kw induction motor are presented and analyzed using a dSpace system with DS1104 controller board based on digital signal processors (DSP). Obtained results demonstrated that the proposed sensorless control scheme is able to obtain high performances.

Key Words: ANN, estimation, speed, control, DRFOC and induction motor.

I. Introduction

Thanks to the theory of the vector control, high performance speed and torque responses are achieved for a squirrel cage induction motors (SCIM) nowadays [8]. Driven by a vector control, a SCIM behaves similar to separately excited DC machine in which the torque and flux are controlled separately [9]. The most important drawbacks in using this theory is the need to mount the speed sensor in closed loop configuration which results to several economical and technical problems [3]. Controlled SCIM drives without mechanical sensor for speed control have the attraction of low cost and high reliability [3]. The estimation of rotor speed is based excessively on measured terminal voltages and currents [8] and [9]. So the performance of the controller is depended to the robustness of the speed estimation. In recent years, speed estimation based on the artificial intelligence technique such as fuzzy logic and neural network have been widely used [4], [11], [12] and [13]. Since these approaches doesn't require the knowledge of a mathematical machine model, the algorithm remains robust despite of parameter deviation and noise measurement [6].

In this paper, a neural network controller and observer are trained off line using the back propagation algorithm. The data for training are obtained when the motor is working in closed loop at various values of speeds and loads. The proposed sensorless control scheme is implemented for experimental validation.

This paper provides experimental results to demonstrate the effectiveness of the overall proposed control scheme.

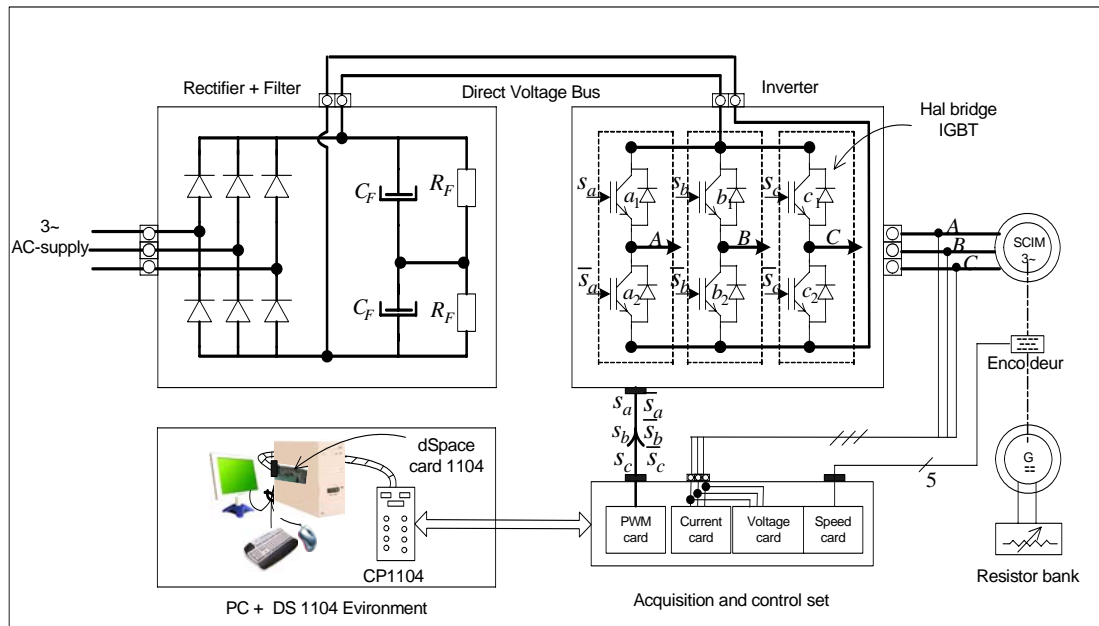


Fig. 1. The bloc diagram of the proposed induction motor drive system.

II. Induction motor model

Assuming linear magnetic circuits, equal mutual inductances and neglecting iron losses, the induction motor mathematical model in the stationary frame is formulated as [10]:

$$\begin{cases} v_{\alpha s} = r_s i_{\alpha s} + \frac{d\phi_{\alpha s}}{dt} \\ v_{\beta s} = r_s i_{\beta s} + \frac{d\phi_{\beta s}}{dt} \\ 0 = r_r i_{\alpha r} + \frac{d\phi_{\alpha r}}{dt} + \omega \phi_{\beta r} \\ 0 = r_r i_{\beta r} + \frac{d\phi_{\beta r}}{dt} - \omega \phi_{\alpha r} \end{cases} \quad (1)$$

The stator and rotor winding flux linkages are expressed as:

$$\begin{cases} \phi_{\alpha s} = L_s i_{\alpha s} + M i_{\alpha r} \\ \phi_{\beta s} = L_s i_{\beta s} + M i_{\beta r} \\ \phi_{\alpha r} = L_r i_{\alpha r} + M i_{\alpha s} \\ \phi_{\beta r} = L_r i_{\beta r} + M i_{\beta s} \end{cases} \quad (2)$$

$i_{\alpha s}$, $i_{\beta s}$, $v_{\alpha s}$ and $v_{\beta s}$ are respectively the stator currents and voltages components,

$\phi_{\alpha s}$, $\phi_{\beta s}$, $\phi_{\alpha r}$ and $\phi_{\beta r}$ are respectively the stator and rotor fluxes components.

r_s and r_r are respectively the stator and the rotor resistances, L_s , L_r and M are respectively the stator self, the rotor self and the mutual inductances. σ is the leakage coefficient and ω is the rotor speed. The electromagnetic torque developed by the motor is expressed in terms of rotor flux and stator currents as:

$$T_e = p \vec{\phi}_r \otimes \vec{i}_s, \quad (3)$$

While the load torque acts as a disturbance via the mechanical relation:

$$J \frac{d\omega}{dt} = T_e - T_L. \quad (4)$$

Where J is the moment of inertia of the rotor and T_L is the load torque.

III. Proposed scheme of the drive system

The bloc diagram of the proposed induction motor drive system is shown in Fig. 1. The closed loop control scheme consists of an inner currents control loops and an outer speed and flux control loops. The feedback signals for the outer control loops are estimated using an on line data of motor terminals in terms of stator voltages and currents. The stator's voltages and currents are sensed using Hall Effect voltage and current sensors. The signals corresponding to voltage and current of the stator are fed to the processor through the dSpace system with DS1104 controller board. Thereafter, the rotor speed and the rotor flux are estimated inside the processor using the sensed values of stator terminals (Fig. 2). The estimated speed $\omega_{ANN}(k)$ using the artificial neural network is used with the reference $\omega_{ref}(k)$ to compute the speed error, which is processed in an artificial neural network controller. The output of the speed controller which represents the target electromagnetic torque is used to compute the target reverse stator current i_{qsref} . The later is applied to a current limiter which sets a limit on this reference current. This limit on the target reverse current is desirable to operate the devices of the inverter circuit in their safe range of current. The current signals i_{qs} and i_{qsref} are processed in a PI controller to generate the reverse stator voltage v_{qs} .

The estimated rotor flux is used with the reference flux ϕ_{drref} to compute the flux error, which is processed in a PI controller. The output of the flux controller which represents the target direct stator current i_{dsref} is applied to a current limiter which sets a limit on this reference current. The two current signals i_{ds} and i_{dsref} are processed in a PI controller to generate the reverse stator voltage v_{ds} .

The estimated slip speed using the target rotor flux and the target reverse stator current is added to estimated rotor speed to get the synchronous one ω_s . The obtained v_{ds} , v_{qs} and ω_s are fed to the d_q to a_b_c bloc to get the reference target stator voltages v_{asref} , v_{bsref} and v_{csref} . The target stator voltages are processed in the PWM bloc to provide an appropriate switching pattern to the devices of the fed inverter.

III. 1. Direct rotor field oriented control (DRFOC)

For the DRFOC, the rotor flux vector is aligned with d axis and setting the rotor flux to be constant equal to the rated flux which means $\phi_{dr} = \phi_r$ and $\phi_{qr} = 0$. With respect to this condition, the estimated rotor flux and the slip speed are given as

$$\phi_{dre} = \frac{M}{1 + \tau_r s} i_{dsref} \quad (5)$$

$$\omega_{sl} = \frac{M i_{qsref}}{\tau_r \phi_{dre}} \quad (6)$$

With $\tau_r = \frac{L_r}{r_r}$ is the rotor time constant.

Fig. 2 shows the proposed DRFOC scheme of the SCIM.

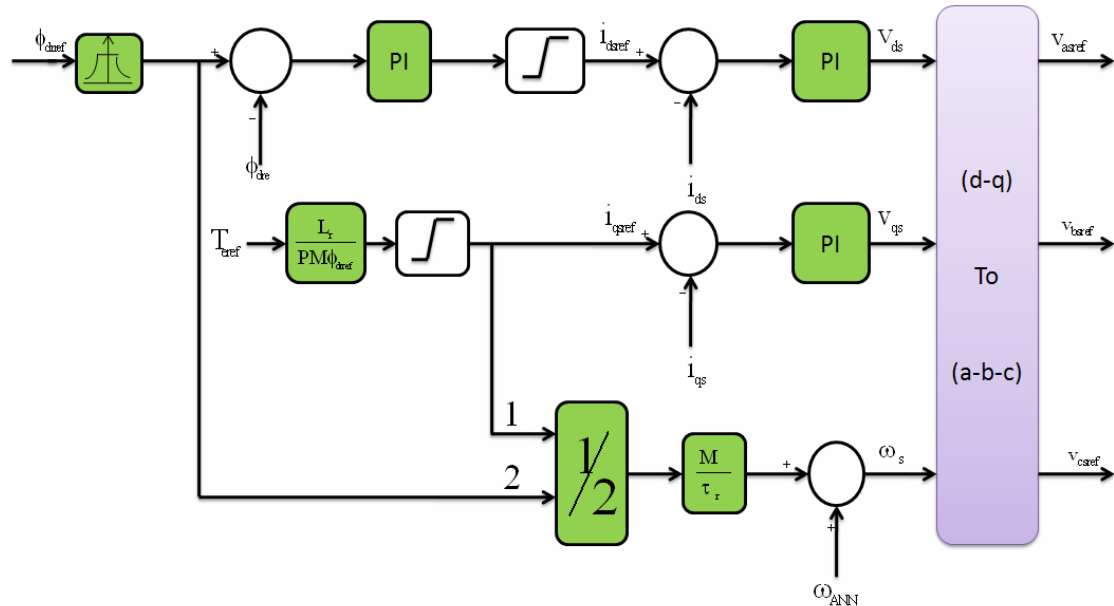


Fig. 2. DRFOC scheme of induction motor.

III. 2. Neural NETWORK: BASIC PRINCIPLE

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. It's an information processing system that is non-algorithmic, non-digital,

and intensely parallel. It consists of a number of very simple and highly interconnected processors called neurons, or like their biological pattern, neural cells in the brain, neurons. The neurons are Connected by a large number of weighted links, over which signal can pass [1]. Real neurons have a finite dynamic range from nil response to the full firing rate, which is modeled by a non-linear, leveling off at 0 and 1. The additional bias term that determines the spontaneous activity of the neuron in the absence of inputs is modeled by a threshold value [2]. The transfer function of a neuron would consist of two steps. First, the neuron computes the weighted input receiving along its input connection. The second step consists of converting the net input to an activation level. Artificial neural network technique is based on a learning process. It is defined as changing the synaptic weights of each interconnection in the network to update it until the target error is reached. Generally, the back propagation method is used for adjusting the neural network weights during the training phase. The basic back-propagation algorithm consists of three steps. The input pattern is presented to the input layer of the network. These inputs are propagated through the network until they reach the output units. This forward pass produces the actual or predicted output pattern. As back-propagation is a supervised learning algorithm the desired outputs are given as part of the training vector. The actual network outputs are subtracted from the desired outputs and an error signal is produced. This error signal is then the basis for the back-propagation step, whereby the errors are passed back through the neural network by computing the contribution of each hidden processing unit and deriving the corresponding adjustment needed to produce the correct output. The connection weights are then adjusted and the neural network has just learned from an experience. The use of a neural network in control or modeling consists of an association of some inputs with some outputs. In this case, for each set of inputs, there is a set of outputs. To accomplish this operation, the net will have to be trained in a first phase. It is not necessary to carry out this phase in real time and give the net all possible inputs - outputs combinations since it has the capacity to generalize results starting from a limited set of inputs outputs. The most significant points to keep in mind when defining the structure and operation of neural nets is mainly the choice of the inputs and outputs. Some inputs should be chosen that determine completely the target output and must be easily measured so that the used hardware will be simplified. To train the neural network, the calculation of the synaptic weights should be done.

The training algorithm of the neural network is as follows:

- 1st step: initially randomize the weights from -0.5 to 0.5,
- 2nd step: obtain the input data of the neural network,
- 3rd step: calculate the error between real and observed outputs,
- 4th step: adjust the weights of the neural network,
- 5th step: calculate the output of the neural network,
- 6th step: repeat 2nd step until the stipulated error is reached.

III. 2. a. Neural Network speed observer

By replacing stator flux with its expression and eliminating the rotor current in (1), we obtain:

$$\begin{cases} v_{as} = [r_s + L_s \sigma s] i_{as} + \frac{M}{L_r} \frac{d\phi_{ar}}{dt} \\ v_{bs} = [r_s + L_s \sigma s] i_{bs} + \frac{M}{L_r} \frac{d\phi_{br}}{dt} \\ 0 = \frac{1}{\tau_r} \phi_{ar} - \frac{M}{\tau_r} i_{as} + \frac{d\phi_{ar}}{dt} + \omega \phi_{br} \\ 0 = \frac{1}{\tau_r} \phi_{br} - \frac{M}{\tau_r} i_{bs} + \frac{d\phi_{br}}{dt} - \omega \phi_{ar} \end{cases} \quad (7)$$

Based on these equations, we defined twos models: voltage model (VM) and current model (CM). The equality between the rotor fluxes deduced from the two models, we obtain:

$$\begin{cases} \frac{L_r}{M} [v_{as} - [r_s + L_s \sigma s] i_{as}] = \frac{M}{\tau_r} i_{as} - \frac{1}{\tau_r} \phi_{ar} - \omega \phi_{br} \\ \frac{L_r}{M} [v_{bs} - [r_s + L_s \sigma s] i_{bs}] = \frac{M}{\tau_r} i_{bs} - \frac{1}{\tau_r} \phi_{br} + \omega \phi_{ar} \end{cases} \quad (8)$$

Multiplying the first equation by $\phi_{\beta r}$ and the second one by $\phi_{\alpha r}$, we establish:

$$\omega = \frac{\frac{L_r}{M} \left[v_{\beta s} \phi_{\alpha r} - [r_s + L_s \sigma s] i_{\beta s} \phi_{\alpha r} - [v_{\alpha s} \phi_{\beta r} - [r_s + L_s \sigma s] \phi_{\beta r} i_{\alpha s}] - \frac{M}{\tau_r} (\phi_{\alpha r} i_{\beta s} - \phi_{\beta r} i_{\alpha s}) \right]}{|\phi_r|^2} \quad (9)$$

With the vector control, $\phi_{\alpha r}$ and $\phi_{\beta r}$ are constants. Therefore, ω varies with respect to $v_{\alpha s}$, $v_{\beta s}$, $i_{\alpha s}$ and $i_{\beta s}$. Hence, the significant inputs which determine completely the rotor speed are $v_{\alpha s}$, $v_{\beta s}$, $i_{\alpha s}$ and $i_{\beta s}$.

It is better to obtain a neural network speeds observer which observes the whole range of speeds (from negative to positive values). By looking at extent training data, we find them very huge and the neural network observer finds many training problems because of the amount of information to be learnt by the neural network. Many solutions are proposed [5] and [7]. For example, we can increase the number of layers and neurons. However, this creates a problem of computation time and memory capacity. A simple and easy solution is to learn only the range of the positive speed. It is known that the relation between positive and negative speeds is a minus mark in the command issue. How to detect the negative speeds? If the reference speed becomes negative, the speed becomes also negative and vis versa. To make the neural network available in negative speeds, an absolute value is added to the bipolar inputs of the neural network and a sign function is implemented. Using this technique, we save time, memory capacity and we observe the speed in the whole range (from positive to negative). The final structure of the neural network used is a multilayer net with the three layers. The first one formed with four neuron inputs ($v_{\alpha s}$, $v_{\beta s}$, $i_{\alpha s}$ and $i_{\beta s}$), the second one formed by two hidden layers and the third one by one neuron to give observed speed. This final structure is chosen by trial and error method. The sigmoid function has an output signal varying between 0 and 1. Therefore, we adopt the signals by dividing the output by its nominal value. The way of training the neural network consists of taking the training data corresponding to the positive speed and presenting these pieces of information to the back propagation algorithm. The training algorithm of the neural network speed observer is as follows:

- 1st step: initially randomize the weights from -0.5 to 0.5,
- 2nd step: obtain the stator currents and voltages,
- 3rd step: calculate the error between real and observed speeds,
- 4th step: adjust the weights of the neural network,
- 5th step: calculate the output of the neural network,
- 6th step: repeat 2nd step until the stipulated error is reached.

The internal structure of the neural network speed observer is shown in Fig. 3.

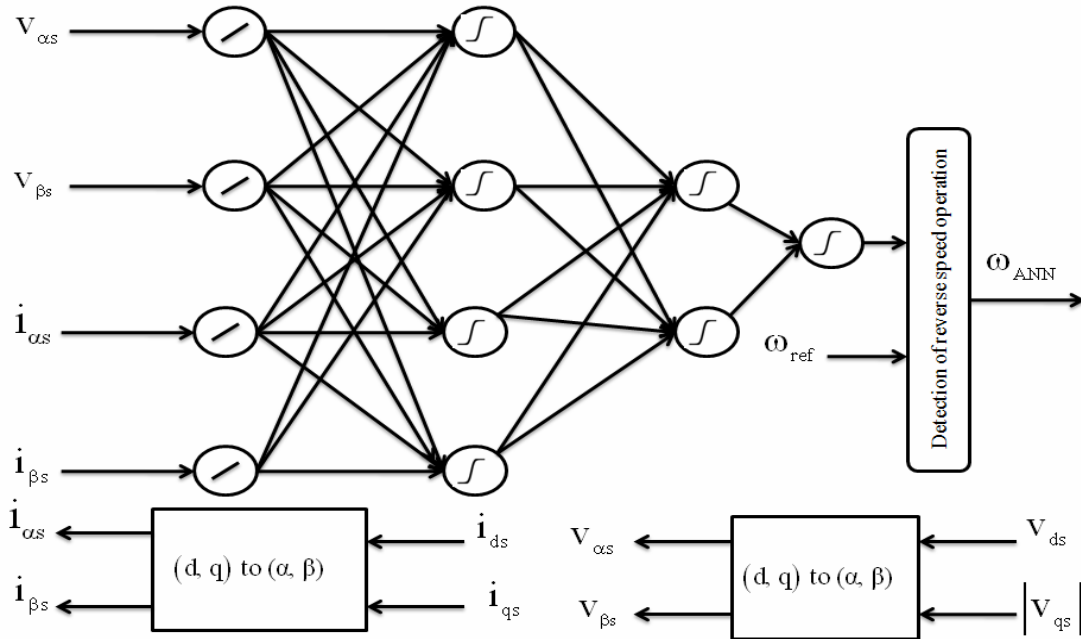


Fig. 3. The internal structure of the neural network speed observer.

III. 2. b. Neural Network speed controller

The following section describes the design procedure for the neural network speed controller (NNC). The objective of this NNC is to develop a back propagation algorithm such that the output of the neural network speed observer can track the target one. Fig. 4 depicts the network structure of the NNC, which indicates that the neural network has three layered network structure. The first is formed with five neurons inputs ($\Delta\omega_{\text{MRF}}(k+1)$, $\Delta\omega_{\text{MRF}}(k)$, $\omega_{\text{MRF}}(k)$, $i_{\text{qref}}(k-1)$ and $\Delta i_{\text{qref}}(k-2)$). The second layer consists of five neurons. The lasted one contains one neuron to give the command variation $\Delta i_{\text{qref}}(k)$. The aim of the proposed NNC is to compute the command variation based on the future output variation $\Delta\omega_{\text{MRF}}(k+1)$. Hence, with this structure, we realize a predictive control with integrator. At time k , the neural network computes the command variation based on the output at time $(k+1)$, while the later isn't defined at this time. In this case, we suppose that $\omega_{\text{MRF}}(k+1) \cong \omega_{\text{MRF}}(k)$. The control law is deduced using the recurrent equation (10):

$$i_{\text{qref}}(k) = i_{\text{qref}}(k-1) + G \Delta i_{\text{qref}}(k) \quad (10)$$

The proposed NNC was trained with the procedure illustrated in Fig. 5.

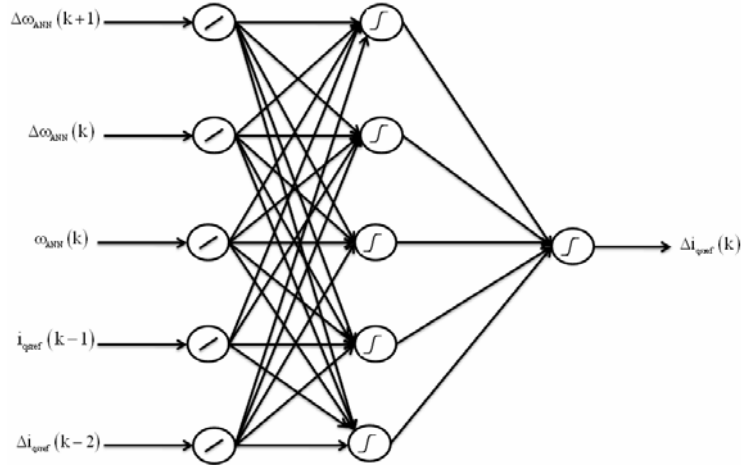


Fig. 4. Neural network speed controller.

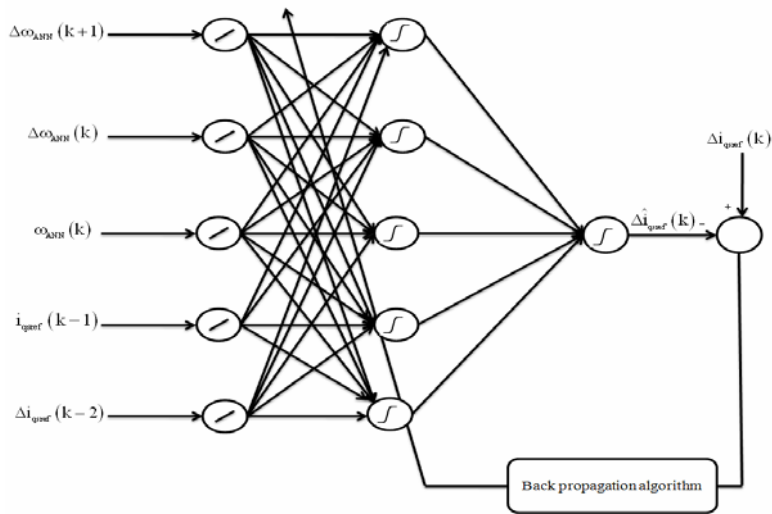


Fig. 5. Training of the neural network speed controller.

IV. Implementation of the drive system

We have tested the neural network for controlled speed sensorless direct field oriented control of induction motor drive at different speed values under no load and with load applied. Fig. 7 shows the experimental set up drive system of the used configuration. It consists of an appropriate hardware and its software.

The major parts of the drive system are:

- (a) Neural network speed observer,
- (b) Neural network speed controller,
- (c) Current controller,
- (d) Rotor flux estimator,
- (e) Rotor flux controller,
- (f) Gate drivers,
- (g) Voltage source inverter based on IGBT transistors,
- (h) Direct current voltage supply,
- (i) DSpace controller board DS1104 and its connector panel,
- (j) Voltage, current and speed sensors.

Some of them are implemented through software and they are mainly speed observer, speed controller, current controller, rotor flux estimator and rotor flux controller. The experimentation has been achieved with the help of Matlab/Simulink package and dSpace system with DS1104 controller board based on digital processors (DSP). The voltage source inverter utilizes a diode rectifier with dc bus voltage feeding the IGBTs. The power circuit part is composed of intelligent power modules with rated 75A, 1200A to drive the induction motor. Intelligent power modules are conducted with gate bipolar transistor working at a frequency up to 20KHZ with a dead fixed time of $3.25\mu\text{s}$ as it is shown in Fig. 6. (b). The pulse width modulation (PWM) signals to control the power modules are generated by dSpace system. An optical isolation and an amplification of the switching signals are provided through on optocoupler PC900V. After that the obtained signals are updated using three drivers SKH122A (Fig. 6. (a)). The sampling period of 1ms is selected since the computation time of the algorithm is about 0.1ms. We measure two stator current using Hall type sensors LM LA 100 – P through 16bits analogical – digital converter. An incremental encoder position sensor delivering 1024 pulses per revolution is mounted on the rotor shaft only for comparison of the observed and real speed of the induction motor. A 1kw Direct Current Generator (DCG) supplying a variable resistor bank is used as variable load for 1kw induction motor. The control and observation algorithms are implemented in a Matlab/Simulink package, compiled to machine language and downloaded on a Real Time Interface dSpace DS1104 (Fig. 7).

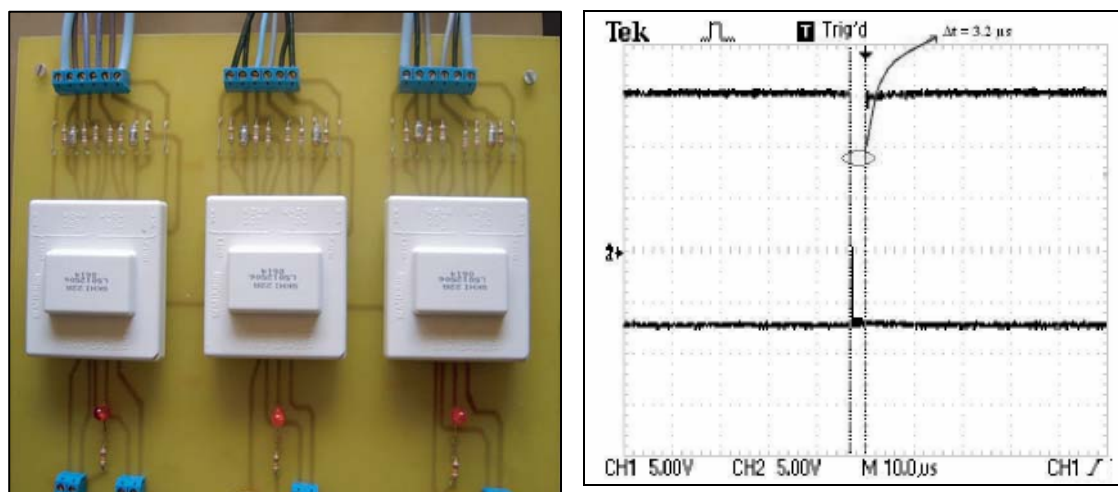


Fig. 6. (a) Switching signals drivers circuit of the inverter - (b) switching signals of half bridge with dead time of 3.25s.



Fig. 8. A photo of the experimental set up.

Results without load

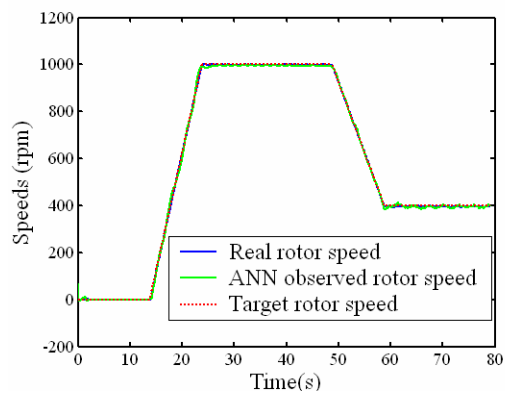


Fig. 9. Measured, ANN's observed speeds at variable target speeds under no load in experimentation.

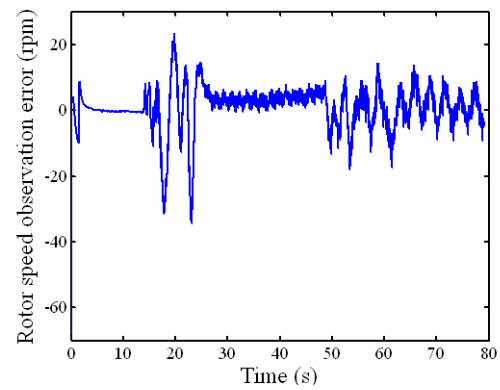


Fig. 10. Speed observation error at variable target speeds under no load in experimentation.

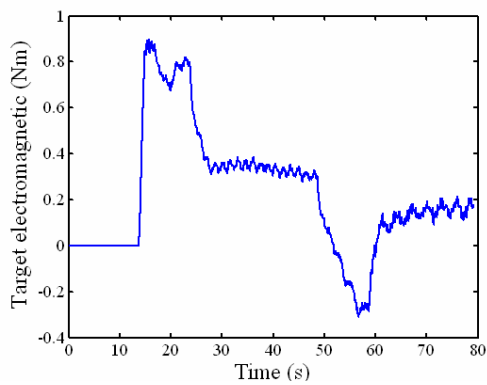


Fig. 11. Target electromagnetic torque at variable target speeds under no load in experimentation.

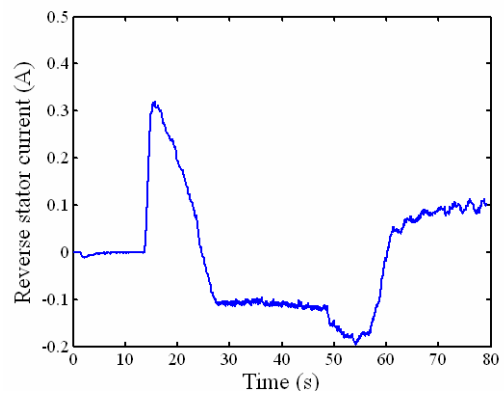


Fig. 12. Reverse stator current at variable target speeds under no load in experimentation.

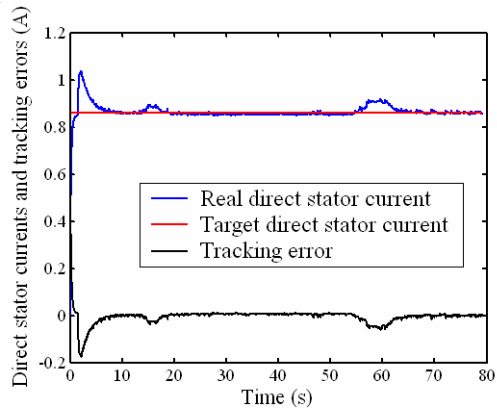


Fig. 13. Real and target direct stator currents and tracking error at variable target speeds under no load in experimentation.

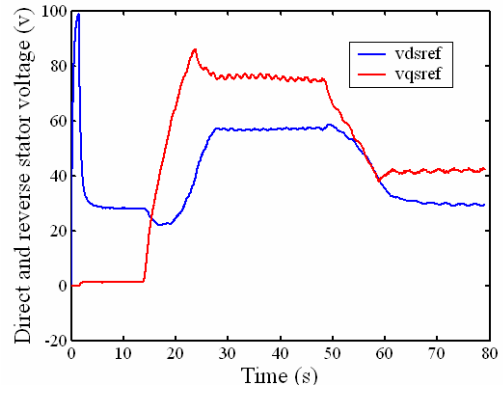


Fig. 14. Direct and reverse stator voltage at variable target speeds under no load in experimentation.

Results with load applied

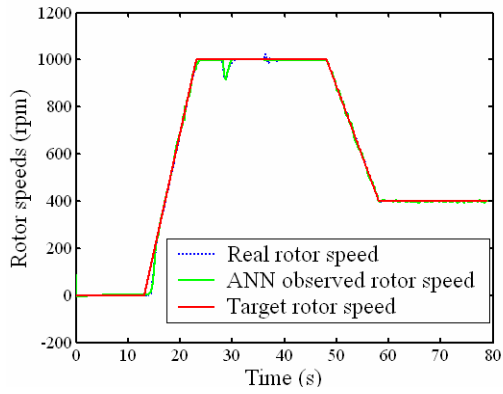


Fig. 15. Measured, ANN's observed speeds at variable target speeds under load torque appliance in experimentation.

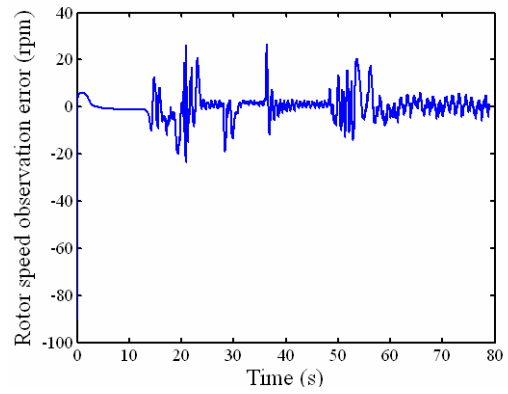


Fig. 16. Speed observation error at variable target speeds under load torque appliance in experimentation.

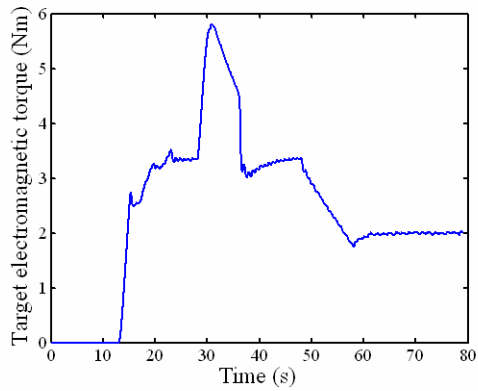


Fig. 17. Target electromagnetic torque at variable target speeds under load torque appliance in experimentation.

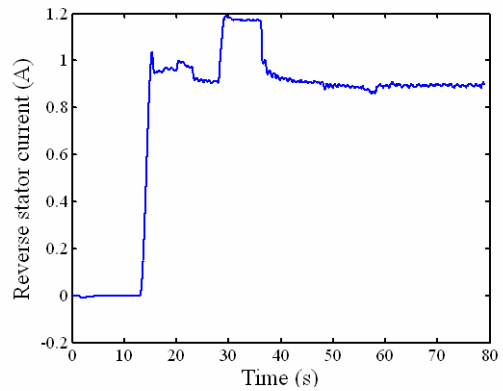


Fig. 18. Reverse stator current at variable target speeds under load torque appliance in experimentation.

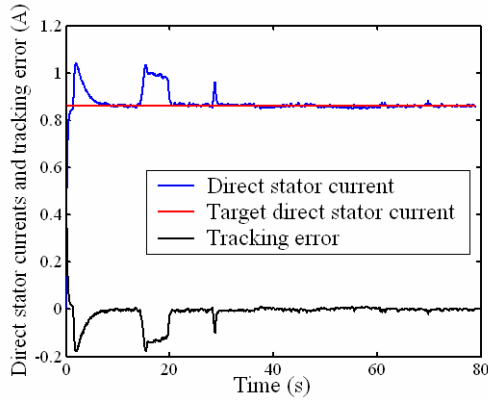


Fig. 19. Real and target direct stator currents and tracking error at variable target speeds under load torque appliance in experimentation.

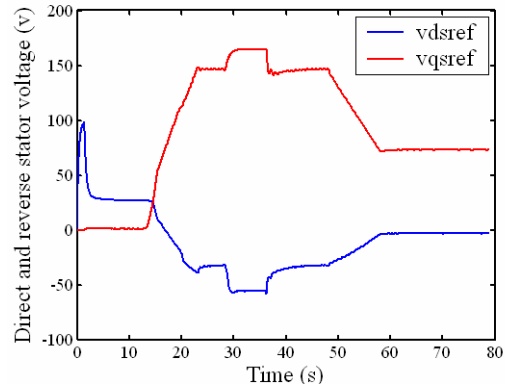


Fig. 20. Direct and reverse stator voltage at variable target speeds under load torque appliance in experimentation.

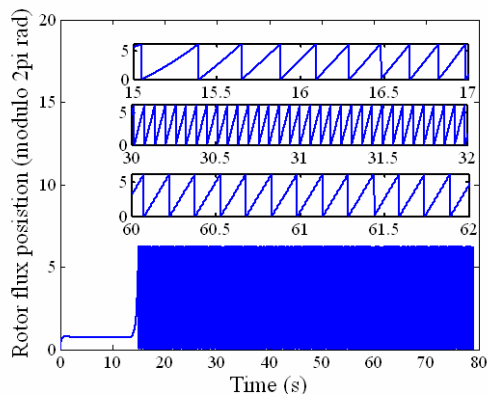


Fig. 21. Rotor flux position at variable target speeds under load torque appliance in experimentation.

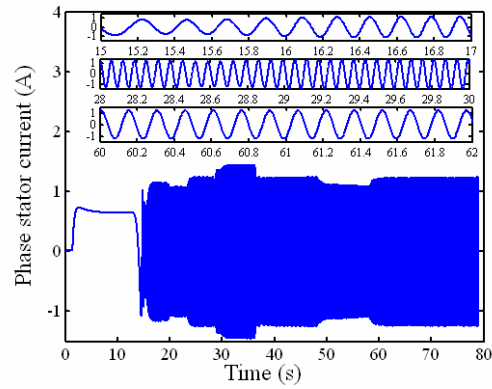


Fig. 22. One phase stator current at variable target speeds under load torque appliance in experimentation.

IV. Conclusion

In this paper, a neural network speed observer and controller algorithms of a SCIM to increase the speed-sensorless drive performance were proposed. From the experimental results made on a 1kw induction motor using a dSpace system with DS1104 controller board system based on digital signal processors, it is shown that the proposed algorithms observe and correct respectively the speed over the entire speed range. Also, it has robust speed observation and tracking performances even at load variation or variable-speed operation. Finally, it is confirmed that the proposed speed sensorless vector control algorithm has good dynamic performances and stability.

The most interesting conclusion of all the tests carried out is that the motor response and the one estimated by the net are quite similar, and there is nearly no error in the steady state. That shows the capacity that the model has to generalize and to adapt itself to situations not contemplated in the training phase. The main advantages of controlling an induction motor with ANNs are the following: 1) more accurate models without having to use approximations; 2) the neural network learns the real motor behavior, more accurately than the approximate one; and 3) once the learning is accomplished, in the operation phase it is only necessary to make sums and multiplications to estimate the speed, and they can be made in real time way.

In this paper, we are limited to the neural network speed observer and controller. A neural network flux observer and controller may be a significant prospect for this work.

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