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A Sensorless Neural Network Speed Control of Induction Motor Drive

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Abstract: Development trends in industrial electrical drives indicate that the next generation of electrical drives will include some type of sensorless control. Controlled induction motor (IM) drives without speed sensors have the attractions of low cost and high reliability due to the absence of the mechanical component and its sensor cable. Speed estimation schemes that allow high dynamic performances are based on IM vector control. However, volt per Hertz (V/f) IM drives law produces satisfactory precision in speed sensorless control and is adequate for low dynamics applications. The proposed speed control scheme presented in this study using a simple low cost IM scalar control consists of a neural network controller (NNC) and a neural network speed estimator (NNSE). The NNC is used to produce a control force so that the motor speed can accurately tracks the reference command. The NNSE is trained off line by using the error back-propagation algorithm. The estimated speed is then fed back in the speed control loop and the speed-sensorless is then realized. A back-propagation algorithm is used as the learning algorithm to automatically adjust the weights of the NNC and NNSE in order to minimize the performance functions. The proposed sensorless control scheme has shown good performance in the transient and steady states and also at either variable-speed operations and load torque disturbances. Both computer simulations and experimental results demonstrate that the proposed control scheme is able to obtain robust speed sensorless IM control.

Key words: Scalar control, Neural Network Controller (NNC), Neural Network Speed Estimator (NNSE), Back-propagation algorithm, induction motor drive

INTRODUCTION

Many years ago, thanks to the development of fast calculators (real time), IM were widely used in industry because of their reliability, ruggedness and relatively low cost. In contrast to DC motors, they could be used in aggressive environments since there were no problem with spark and corrosion (Bensalem and Sbita, 2006). In fact, the IM belongs to the class of the highly coupled systems. The practical task is to solve the IM control problem dynamic performance, energy efficiency, robustness and simple implementation (Bensalem *et al*., 2007; Ben Hamed and Sbita, 2006). Because of the advances in power electronics and microprocessors, the IM drive used in variable speed control has become more attractive (Abbondanti, 1977). In fact, the IM is a highly coupled, nonlinear dynamic plant and its parameters vary with time and the operating conditions. Therefore, it is very difficult to obtain good performance for an entire range of speed and transient states using classical methods (conventional PI controller). A high-performance servo system must have good dynamic speed command tracking and load regulating responses.

In this study, the operation of IM is made using the so-called constant volts per hertz (V/f) mode which has been known for last decades and its principle is well understood (Bose, 1996; Tsuji *et al*. 2006). With the introduction of solid state inverters, the constant V/f control became popular and the great majority of variable-speed drives in operation today are of this type (Kioskeredis and Margaris, 1996; Garcia *et al*., 1998). In fact, scalar control means that the variables are controlled only in magnitude and the feedback and command signals are proportional to dc quantities (Bose, 1996). A scalar control method can only drive the stator frequency using a voltage or a current as a command. Among the scalar method known to control an IM, one assumes that by varying the stator voltages in proportion with frequency,

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the torque is kept constant. The advantages of this control technique are its simplicity, its easiness and quickness to program which requiring only few calculation capabilities (Rajashekara *et al*., 1996).

Nowadays, the need for sensorless IM speed control has become widely recognized because of the cost and fragility of a mechanical speed sensor and because of the difficulty of installing the sensor in many applications (Sbita *et al*., 2006). For these reasons many attempts were made in the past to extract the IM speed signal (Toliyat and Campbell, 2004; Hurst *et al*., 1998; Vas, 1998).

To overcome problems related to the use of a shaft mechanical speed transducers, an IM neural network speed estimator using a multilayer artificial neural network (ANN) with 2 hidden layers is proposed in this study. ANN has been applied for a few cases mainly in the control of converters and drives, but its application in estimation, particularly with time-varying input signals, is practically new (Boldea and Nasar, 2005; Haghgoeian *et al*., 2005; Shao and Li, 2000). Here, the feed forward neural network technique is explored for feedback signals estimation of a scalar-controlled IM drive. Neural networks have been one of the most interesting topics in the control community because they have the ability to treat many problems that cannot be handled by traditional analytic approaches (Seong *et al*., 2001). In general, a feed forward multilayer neural network is the most prevalent neural network architecture for identification and control applications (Kuchar *et al*., 2004; Tsai-Juin and Tien-Chien, 2006; Abboud, 2008). A widely used training method for feed forward multilayer neural networks is the back propagation algorithm developed (Ku and Lee, 1995). ANN can be classified as feed forward networks and recurrent neural networks. Feed forward neural networks can approximate a continuous function to an arbitrary degree of accuracy. However, feed forward neural network is a static mapping, which can not represent a dynamic mapping well. Although this problem can be solved by using tapped delays, it requires a large number of neurons to represent dynamical responses in the time domain. In addition, adaptive neural networks are able to represent dynamic mapping very well and store the internal information for updating weight later (Grellet and Clerc, 1999). ANN have been recently attracting a great attention in the field of power electronics. This is due to their inherent parallelism which allows high speed processing and permits implementation of real time control applications. They also possess the ability to perform in noisy environments and are tolerant to faults and to missing data (Liang and Wang, 2000; Michael and Harely, 1995).

In this research, a speed control scheme with a neural network controller and a neural network speed estimator is designed and applied to a fully digital controlled IM. A widely used back-propagation algorithm is adapted as the learning algorithm, in order to automatically adjust the parameters of the NNC and NNSE. The overall proposed control scheme is tested by an extensive simulation and experimental works and obtained results demonstrate the effectiveness of the proposed sensorless control scheme.

INDUCTION MOTOR AND SCALAR STRATEGY DRIVES

Scalar control as the name indicates, is due to magnitude variation of the control variables only and disregards the coupling effect in the machine. Scalar-controlled drives have been widely used in industry the fact that they are easy to implement (Bose, 1996; Ba-razzouk *et al*., 1997; Hurst *et al*., 1998). As shown in Fig. 1, the proposed strategy is based on simplified V/f control scheme with stator frequency regulation. For adjustable speed applications, voltage is required to be proportional to frequency so that the flux remains constant ($\phi_s = V_s/\omega_e$), neglecting the stator resistance voltage drop. The block diagram of the used speed control method is shown in Fig. 1.

The principal control objectives are that the drive should follow the desired command as closely as possible and any type of external disturbances should be rejected. With a voltage-fed PWM inverter, both voltage and frequency can be controlled to control the machine flux at a constant value. As clearly illustrated in Fig. 1, the closed-loop speed control adds some performances improvement to the open-loop scalar control: the motor speed is compared with the command speed and the error generates the synchronous angular speed ω_s command through a PI compensator and a limiter. The generated signal is then used to obtain the frequency and voltage commands.

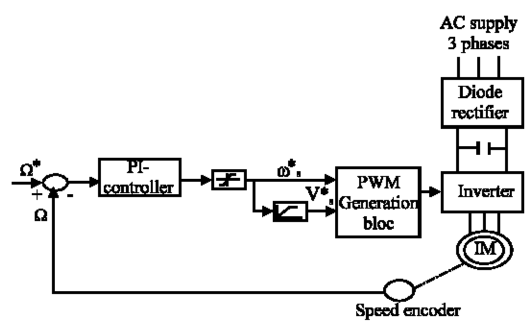

Fig. 1: Scalar control scheme

Scalar control strategy is based on the steady state operation using the mathematical equations governing electrical dynamic of an IM in a synchronous rotating frame in the steady state, we obtain (Zidani *et al.*, 2002; Ben *et al.*, 2007):

$$V_{ds} = R_s\, i_{ds} - \omega_s \phi_{qs} \tag{1}$$

$$V_{qs} = R_s\, i_{qs} + \omega_s \phi_{ds} \tag{2}$$

$$V_{dr} = R_s\, i_{dr} - \omega_{sl}\, \phi_{qr} \tag{3}$$

$$V_{qr} = R_r\, i_{qr} + \omega_{sl}\, \phi_{dr} \tag{4}$$

Where,

ω_s and ω_{sl} : The electrical synchronous and slip speeds.
i_{ds} and $_{IQs}$: The d, q axis voltages.
i_{ds} and $_{IQs}$: The d, q stator axis currents.
i_{dr} and i_{qr} : The d, q rotor currents.
ϕ_{ds} and ϕ_{qs} : The d, q stator fluxes.
ϕ_{dr} and ϕ_{qr} : The d, q rotor fluxes.
R_s and R_r : The stator and the rotor resistances.

The d and q axis can be referred in a space vector if they are, respectively placed as real and imaginary axis, hence:

$$V_s = V_{ds} + jV_{qs} \tag{5}$$

$$i_s = i_{ds} + ji_{qs} \tag{6}$$

$$i_r = i_{dr} + ji_{qr} \tag{7}$$

Here, the well known transformation to the stator equivalent single phase model is used where the magnetic leakages are totalized in the rotor side and designed by $N_e\omega_s$ (Toliyat and Campbell, 2004, Ben Hamed and Sbita, 2007). Figure 2 shows this model.

Where, R'_r and N_e represent, respectively the equivalent rotor resistance and the total leakage inductance located in the rotor side, L_m is the mutual inductance. The magnetizing current can be expressed by the following equation:

$$I_m = \frac{\nu'_s}{L_m \omega_s} = \frac{\nu'_s}{f_s}\frac{1}{2\pi L_m} \tag{8}$$

Where,

$$\nu'_s = \nu_s - R_s i_s$$

$$i_m = \frac{\nu_s - R_s i_s}{L_m \omega_s} \tag{9}$$

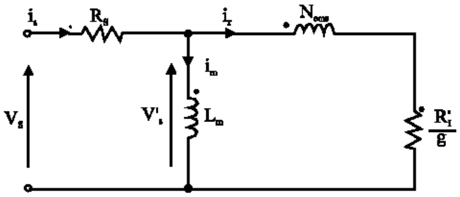

Fig. 2: Single phase equivalent circuit of induction motor

If we neglect the resistance voltage drop $R_s i_s$, we obtain:

$$I_m = \frac{\nu_s}{L_m \omega_s} = \frac{\nu_s}{f_s}\frac{1}{2\pi L_m} \tag{10}$$

Hence, the module of i_m can be maintained constant if the ratio V_s/f_s remains constant. If we note I_r the actif current, then this current can represent the active power and it generates the electromagnetic torque, its expression is:

$$I_r = \frac{\nu_s - R_s i_s}{\frac{R'_r}{g} + jL_m\omega_s} \tag{11}$$

where the slip coefficient is:

$$g = \frac{\omega_s - \omega}{\omega_s}$$

We can obtain the Eq. 12 when neglecting the voltage drop $R_s i_s$:

$$I_r^2 = \frac{\nu_s^2}{\left(\frac{R'_r}{g}\right)^2 + (L_m\omega_s)^2} \tag{12}$$

By replacing g with its expression, the Eq. 12 can be written as:

$$I_r^2 = \frac{\nu_s^2}{\left(\frac{R'_r}{\frac{\omega_s - \omega_r}{\omega_s}}\right)^2 + (L_m\omega_s)^2} \tag{13}$$

The stator current can be written as:

$$\vec{I}_s = \vec{I}_m + \vec{I}_r$$

Where ,

$\vec{I}_m$: Constant so the current

$\vec{I}_r$: An be represented by $\vec{I}$.

So, one can write that ω_r = f (I_s, ω_s) where f is a nonlinear function. To estimate the rotor speed using ANN, the function f should be identified. Therefore, the current I_s and the command ω_s will be used as inputs to the speed neural network estimator. The current magnitude is obtained from the instantaneous values of the current per phase i_{sa}, i_{sb} and i_{sc} (Sbita *et al*., 2007; Zidani *et al*., 2002). The current expression used in this case is given by the Eq. 14 as:

$$I_s = \sqrt{i_{sa}^2 + \frac{1}{3}(2i_{sb} + i_{sc})^2} \quad (14)$$

NEURAL NETWORK CONTROLLER DESIGN

The NNC is a neural network which calculates the input u (or the signal control), using the input-outputs values. The standard model which can be represented by the various nonlinear discrete systems is the NARMA model (Nonlinear Autoregression-Moving Average) which is used to approximate the input/output IM model:

$$\begin{aligned} y(k) = N[&y(k), y(k-1),\ldots, y(k-n+1),\\ &u(k), u(k-1),\ldots, u(k-m+1)] \end{aligned} \quad (15)$$

where

u (k) = ω_s (k) : Is the input.

y (k) = ω_r (k) : Is the output.

If the objective is that the output of the plant can track the reference command that:

y (k) = y_r (k), it is necessary to develop the nonlinear controller as:

$$\begin{aligned} \omega_s(k) = G[&\omega_r(k), \omega_r(k-1),\ldots, \omega_r(k-n+1),\\ &\omega_s(k-1),\ldots,\omega_s(k-m+1)] \end{aligned} \quad (16)$$

where, G is an unknown linear or nonlinear function which will be identified, ω_r and ω_s are, respectively the output and the input of the IM and n and m are, respectively the order of ω_r and ω_s. The purpose of this neural network is to provide, at every sampling time, the variation of the input $\Delta\omega_s = \omega_s(k) - \omega_s(k-1)$ using the future variation output $\Delta\omega_r$ (k+1), so this neural network structure can represent a predictive control with integration. The ANN used for the NNC is a feed forward multilayer network with one hidden layer activated by tanh (hyperbolic tangent) function and output layer activated by linear function. In order to have a good training, the data must contain sufficient information about the system dynamics. The network weights and biases updating are performed only after the entire training set has been applied.

The feed forward neural network is usually trained by a back-propagation training algorithm. The distributed weights in the network contribute to the distributed intelligence or "associative memory" property of the network. With the network initially untrained, i.e., with the weights selected at random, the output signal will totally mismatch the desired output for a given input pattern. The actual output is compared with the desired output and the weights are adjusted by the supervised back-propagation training algorithm until the pattern matching occurs, i.e., the errors become acceptably small. For this structure, the input vector as shown in Fig. 3 is [$d\omega_r$ (k+1), $d\omega_r$ (k), ω_r (k), ω_s (k-1), $d\omega_s$ (k-2)] and the neural network output is the command variation $\Delta\omega_{snet}$. The training diagram of this architecture is given on Fig. 4.

Training procedure: A learning procedure of a neural network with M layers and n inputs using a back propagation algorithm is defined. In this description, the index i corresponds to a neuron in the output layer, the index j to a hidden layer. During the learning procedure, we search to minimize the couple (input, desired output) by modifying the weights ω_{mij}:

- Initialize all the network weights to small random numbers.
- Propagate the input forward through the network:

$$x_i^m(t) = f\left[E_i^m(t)\right] \quad (17)$$

$$E_i^m(t) = \sum_j w_{ij}^m(t) x_j^{m-1}(t) \quad (18)$$

Where,

x_{mi} : Output of the neuron i and the layer m,

x_{mj} : Output of the neuron j of the layer m (m: 1, ..., M),

w_{mij} : Weights relating the neuron j of the layer (m-1) to the neuron i of the layer m.

- For each network output unit i, calculate the error term of the output layer:

$$\delta_i^M(t) = f'\left[E_i^M(t)\right]\left[\Delta\omega_{si}(t) - \Delta\omega_{inet}^M(t)\right] \quad (19)$$

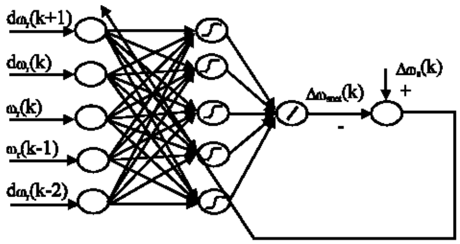

Fig. 3: The internal structure of NNC

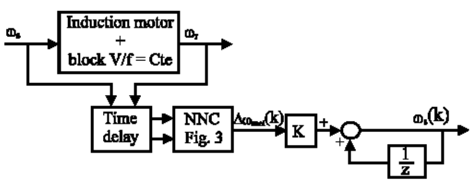

Fig. 4: The block diagram of the NNC architecture

where, d_i (t) the desired output of the neuron i of the output layer.

- For each hidden unit h, calculate the error term by propagating the error:

$$x_i^{m-1}(t) = f'\left[E_i^{m-1}(t)\right]\sum_j w_{ji}^m(t)\delta_j^m(t);\quad m = M, M-1, ..., 2 \tag{20}$$

- Update the network weights W_{ij}:

$$(w_{ij}^m)_{new} = (w_{ij}^m)_{old} + \Delta w_{ij}^m \tag{21}$$

with

$$\Delta w_{ij}^m = \eta\, \delta_i^m\, x_j^{m-1}$$

η is the learning rate of the back propagation algorithm These steps are repeated so that to minimize the function J:

$$J = \frac{1}{2}\sum_t \sum_i \left[\Delta\omega_{si}(t) - \Delta\omega_{\sin et}^M(t)\right]^2 \tag{22}$$

where, t is the pattern number.

Simulation results: We present in this study the simulation results of the NNC. The tests carried out confirm the robustness of this control scheme. The speed responses are observed under different operating conditions such as a change in the speed command and a change in load torque "T_l" (t = 19 s, T_l = 5N m, t = 45 s, T_l = 8 Nm, t = 55 s, T_l = 5 Nm). For the results presented in Fig. 5, it is shown that the speed tracks the reference values well.

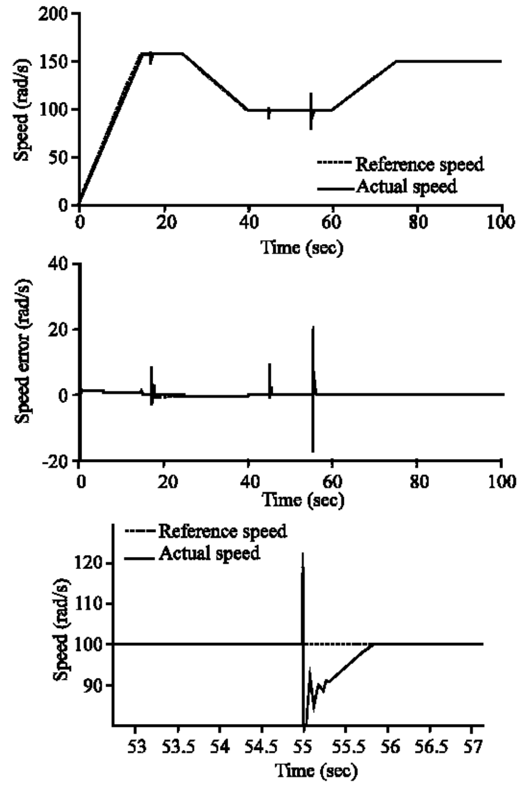

Fig. 5: Simulation results of the scalar controlled IM speed responses with the NNC

In Fig. 5, we can show that the speed error which is obtained as the difference between the desired input signal ω_{ref} and the signal ω_r that represents the actual system output is null thanks to the presence of integration. The application of the load torque creates a disturbance on the output of the model. This disturbance is rejected quickly but with an overshoot. The overshoot amplitude depends on the gain K, the sampling step and the value of the load torque applied.

NEURAL NETWORK SPEED ESTIMATION DESIGN

The aim of using ANN to model a nonlinear system is to build a mathematical model which can be used in nonlinear predictor design. By giving some prior knowledge about the system and information on inputs and outputs, the ANN can accurately describe the nonlinear behavior of the machine without requiring the knowledge of machine parameters (Zilkova *et al*., 2006).

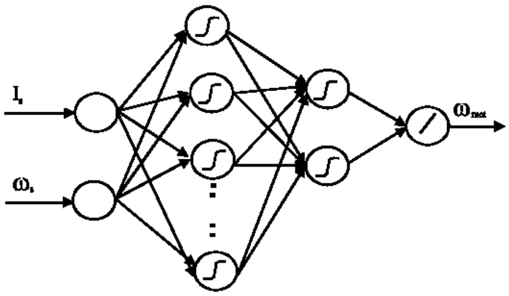

Fig. 6: The internal structure of the NNSE

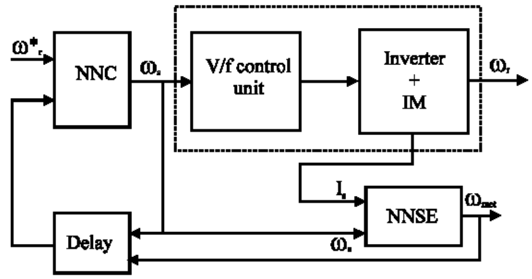

Fig. 7: Block diagram of the speed sensorless IM control scheme

Neural networks have the ability to learn, so it has become an attractive tool for variables identification (Shao and Li, 2000, Hiyama *et al.*, 2000). In this study, an alternative estimation of ω_r is attempted with an ANN. The four-layered neural network based on back-propagation technique is used to estimate the rotor speed.

The first stage is to take the various value measurements for the training procedure. The motor is triggered by an instruction which covers all the operation conditions to obtain the (I_s, ω_s, ω_r) training vectors. For each measures vector, the error between the two outputs (real and desired speed) is calculated. It is used to correct the weights and the biases of the various layers. Measurements are bounded before using them in the learning procedure because the used activation functions are limited.

In the training stage, input values (I_s, ω_s) are applied to the neural network and there is a known output which is the rotor speed (which corresponds to the used input values). If the inputs are time-varying signals, then their sampled values at the first sampling instant are applied to the NNSE and the weights and biases are randomly initialized (Fig. 6). The output signal of the NNSE is then computed by using the back-propagation technique (the input signals are propagated through the network to obtain the output signal). This output is then compared to the known output and the error is determined. If the error is zero, then obviously the correct weights and biases have been chosen. If not, the error is back-propagated from the output layer and the weights and biases are modified in such a way that the sum of the squares of the errors (global error) is minimized.

IM SPEED SENSORLESS AND CONTROL SCHEMES

Figure 7 depicts the bloc diagram of the proposed closed-loop control scheme with a neural network controller (NNC) and a neural network estimator (NNSE). The NNC was used to produce a control force so that the motor speed could accurately track the target one. A widely used back-propagation algorithm was adapted as the learning algorithm, in order to adjust the parameters of the NNC and NNSE. The system consists of a speed controller, an ANN speed estimator and a scalar controlled IM.

Simulation results: In this study, the simulation results are presented to evaluate the effectiveness of the proposed speed sensorless IM control scheme. The package language MATLAB/Simulink was used for the simulations. The number of hidden layer nodes in the NNC and NNSE were set to 5. This nodes number was sufficed to control the IM. Figure 8 presents the speed responses of the proposed control scheme. Figure 8a presents the real and the command speed with the speed error of the proposed control scheme. Figure 8b reveals the estimated speed responses of the drive system using neural network estimator with a variable reference speed. It is evident from Fig 8 that the proposed controller can follow the command speed without any overshoot neither a steady-state error. Thus, the NNC is not affected by the sudden change of the speed command and a good tracking has been achieved for this control scheme. For these simulation results a load torque is applied (at t = 40s, T_l = 5 Nm and at t = 50s, T_l = 2 Nm) and omitted at t = 140s. The IM and the DC generator parameters are, respectively presented in Table 1 and 2.

Experimental results: The scalar control IM drives of the proposed scheme in Fig. 7 is implemented using DSPACE 1104 as shown in Fig. 9 which is a control board with a digital signal processors, thereby to check the validity of the previous computer simulations and to show the merits of the proposed control scheme. The sampling time is 0.1 ms. The DC link and PWM inverter were implemented using a power diodes rectifier and a power inverter based on IGBT transistors, respectively. The current signals at the input of the NNSE were filtered and adapted before being applied to the speed estimator.

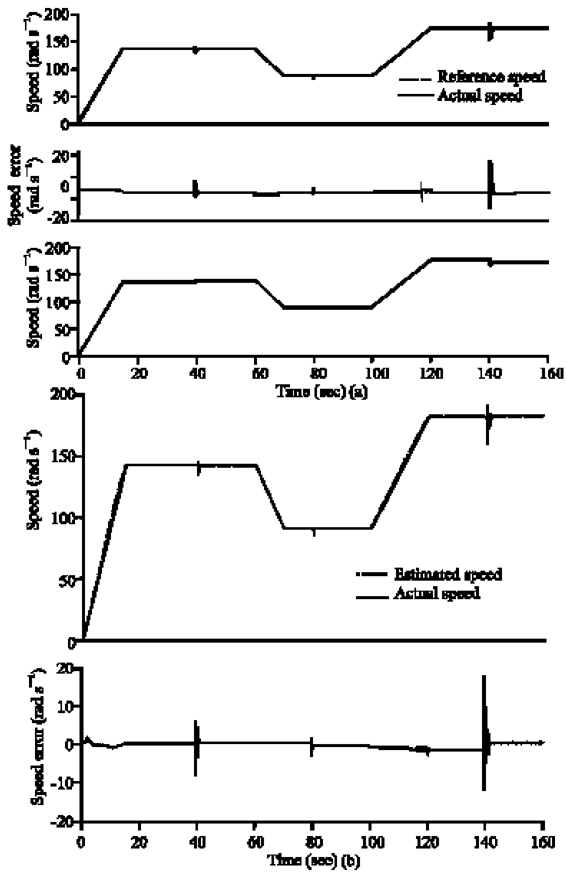

Fig. 8: The speed responses for a change of the speed command: (a): actual and reference speed responses, (b): estimated and reference speed response

Table 1: The induction motor parameters

Sizes (terms)	Values	Units
Rated power	1	kWatts
Rated voltage (Δ/Y)	230/4000	Volts
Rated frequency	50	Hz
Rated speed	1410	rpm
Rated current (Δ/Y)	4.6A/2.65A	ohms
Rated power factor	0.83	

Table 2: DC generator parameters

Sizes (terms)	Values	Units
Rated power	1	kWatts
Rated armature voltage	220	Volts
Rated armature current	6.2	Amper
Rated field voltage	200	Volts
Rated field current	0.24	Amper
Rated speed	2100	rpm

Figure 10 and 11 show the experimental results of the estimated speed using the NNSE in an open loop. The Fig. 11 illustrated the results taken for a variable load torque.

Figure 10 shows the variable-speed control sperformance at ±1500 rpm reference speed with no load applied. The result shows that it has stable and good variable-speed control performances. Figure 11 shows the speed-sensorless control performance where the load was

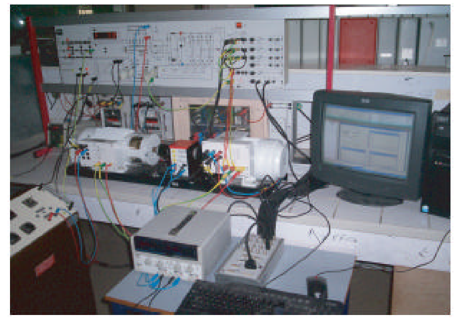

Fig. 9: A photo of the experimental Setup

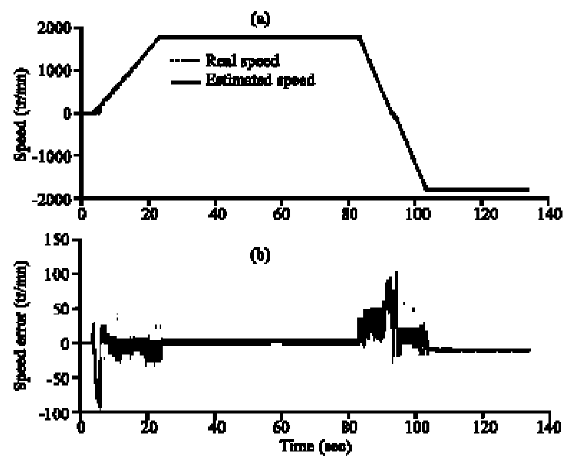

Fig. 10: Experimental speed responses for a change speed command: (a) The actual and the estimated speed, (b) The estimation error of the NNSE

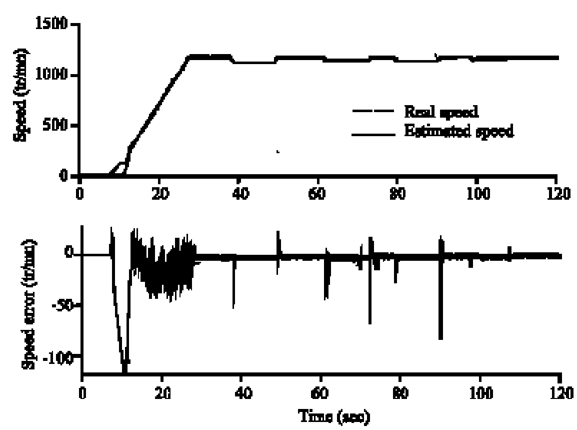

Fig. 11: Experimental speed sensorless control with variable load application

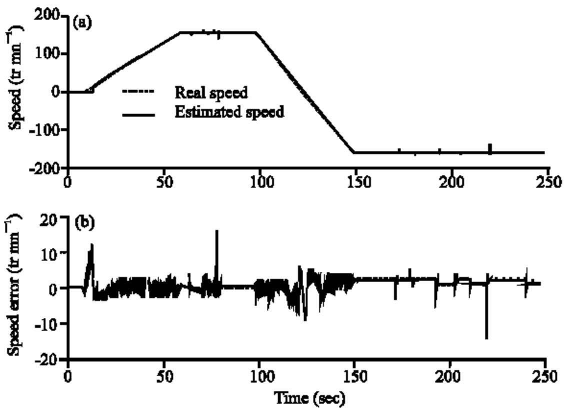

Fig. 12: Experimental speed responses of the proposed control scheme: (a) Actual and estimated speed, (b) Speed error

applied and omitted. The estimated speed coincides exactly with the real speed even at the load torque application instant. From these results, it is shown that the proposed speed-sensorless control algorithm has good performances from low speed to entire speed range.

The Fig. 12 shows the experimental results of NNC with estimate speed by neural network NNSE.

CONCLUSION

In this study, a sensorless IM neural network speed control is realized which is composed of two control architectures: a neural network control and the neural network speed estimator structure. The study successfully demonstrates the application of neural network in the estimation of feedback signals for a scalar-controlled IM drive system. The speed estimation is used to increase the speed-sensorless drive performance so a four-layer feed forward neural network of the structure is used to estimate the IM speed and the performance of the estimator was found to be excellent in the wide torque and speed regions. From the simulation and experimental results, it is shown that the proposed speed control scheme has a good performance over the entire speed range from low to full speed. Also, it has a robust speed estimation performance even at load variation or variable-speed operation.

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