Speed Estimator in Closed-Loop Scalar Control Using Neural Networks

T. H. Santos, A. Goedtel, S. A. O. Silva, M. Suetake

Abstract – **This work proposes an artificial neural network approach to estimate the induction motor speed applied in a closed-loop scalar control. The induction motor speed is the important quantity in an industrial process. Thus, when the load coupled to the axis needs speed control, some of the drive and control strategies are based on the estimated axis speed of the motor. This paper proposes an alternative methodology for estimating the speed of a three phase induction motor driven by a voltage source inverter, using space vector modulation under the scalar control strategy and based on artificial neural networks. Experimental results are presented to validate the performance of the proposed method under motor load torque and speed reference set point variations.**

Index Terms—**Induction Motors, Neural Networks, Scalar Control, Speed Estimation.**

I. Introduction

Three-Phase Induction Motors (TIM) are used in many industrial sectors as leading element to convert electrical into mechanical energy. TIM applications can be divided into two groups: motors which are directly coupled to the grid without a control element and motors where scalar, vector or other control methodologies are applied. Knowledge of the machine shaft speed, whether measured directly or estimated, is required for both groups in several industrial sector applications.

Commonly the motor speed is measured by eletromechanical devices, with electromagnetic resolvers, optical encoders or brushless dc tachogenerators. However, the use of these devices present some limitation, such as the increasing driver cost, reduced mechanical robustness, low noise immunity and the requirement of a special attention with respect to applications in hostile environments [1-3].

Sensorless technique is mainly found in high performance applications, such as vector-controlled and direct torque controlled drivers. The main sensorless control strategies use open-loop estimators with stator current and voltage monitoring, state observers, reference systems with adaptive models and estimators based on intelligent systems which come primarily from artificial neural networks (ANN) and fuzzy logic [1,4].

Most speed estimators are obtained from the mathematical model of induction motor, where a precise knowledge of motor parameters is required [5]. Speed estimators based on State Observers (SO) need the exact values of the machine parameters for the correct operation in low-speed regions [6]. This method also requires a considerable computer effort, since the estimator algorithm demands differential equations solving. Accuracy is also affected as modeling does not take into account the electromagnetic saturation, skin effect or parametric variations due to temperature effects [7-9].

Recently, several methods for TIM speed estimation have been investigated [10]-[13]. In [10] a neural speed and rotor resistance estimator of a TIM using an Adaline network is presented. In this proposal, the stator current and voltage are measured in the three-phase stationary reference frame (*abc*-axes). After the transformation from *abc*-axes to two-phase stationary frame ($\alpha\beta 0$-axes), the stator current and voltage are used to estimate the rotor current, rotor flux and derivative of the rotor flux, which are the inputs quantity of the ANN. To validate this neural speed estimator, it is applied various TIM control strategies, such as scalar and vector control.

A TIM speed estimator based on Multilayer Perceptron Neural Network (MPNN) is also presented in [11]. The inputs are the current and voltage on synchronous reference frame. In steady state, the training and validation data set of the neural speed estimator are acquired with the machine operating at 500 to 1000 revolutions per minute (rpm).

In [12], an adaptive reference model for TIM speed estimation is used. The tuning of the reference model is accomplished by adjusting the parameters of the adaptive model aiming to cancel the error between the instantaneous reactive magnetizing power in the rotor and the estimated by the adaptive model

A ANN applied to estimate the rotor magnetic flux of an induction motor is presented in [13]. In this paper, the ANN is trained to operate with a rotor magnetic flux observer, which is used as reference for adjust of a Model Reference Adaptive System (MRAS). The error between the estimated rotor flux and MRAS is the input of a Proportional Integral (PI) controller, thereby obtaining the estimated speed. This estimated speed is used as adaptation parameter of MRAS.

The purpose of this work is the development of a neural speed estimator applied to a TIM using scalar control. Voltage and current in the *dq* axis are obtained through a phase locked loop (PLL) circuit. The training data are generated via computer simulation of mathematical models of the TIM and its drive, which is performed by a three-phase voltage inverter with space vector pulse width modulation (SVPWM) applied to the scalar control. The training procedure is offline. In order to validate the proposed methodology, experimental results are presented and compared with the direct speed measurement. This paper is organized as follows: Section II presents the modeling aspects of a three-phase induction motor and

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drive system; Section III discusses the principles involved with the ANN; Section IV presents the experimental results which validate the proposed work, while Section V the conclusions are presented.

II. MODELING AND TIM DRIVER

An equation, or set of equations, comprising a mathematical model is an approximation of the actual physical system. This requires a mathematical modeling of the element under consideration: the three-phase induction motor. These equations provide a computing environment implementation of the physical system, namely, the electrical machine and its drive system.

One of the main steps involved in the training of an artificial neural network is to obtain the set of input and output patterns in order to adjust the internal parameters of the network. This procedure is known as the training process and should ensure that the neural structure is exposed to sequences of patterns that satisfactorily describe the behavior of the analyzed system.

A. *Aspects of the TIM Model*

To generate the training data set of induction motor, several simulations are executed using Matlab/Simulink software at different speed operating points. Fig. 1 shows the block diagram which describes the input and output of the proposed model. The TIM is driven by a VSI with vector pulse width modulation (SVPWM). The adopted control strategy is based on voltage/frequency (*V/f*) ratio scalar control.

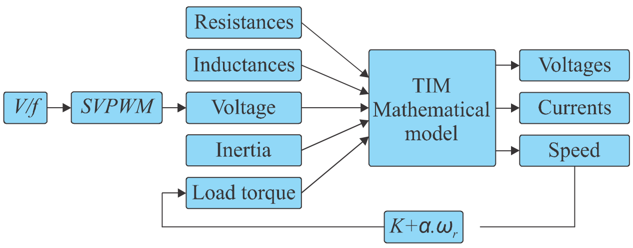

Fig. 1. Block diagram of system model.

The induction motor model used in the simulations was developed in [14] and [15] and the machine parameters are obtained from a WEG manufacturing induction motor with 4-pole, 220/380V, IP55. Table 1 shows the parameters used in TIM simulations.

TABLE I
TIM PARAMETERS

Standard Line – IV Pole – 60Hz – 220/380V	
Power	1 cv
Nominal current	3.02 A
Stator resistance	7.32 Ω
Rotor resistance	2.78 Ω
Stator inductance	8.95 mH
Rotor inductance	5.44 mH
Mutual inductance	0.141 H
Moment of Inertia	$2.71.10^{-3}$ kg.m²
Synchronous speed	188.49 rad/s
Slip	3.8%
Nominal torque	4.1 Nm

The voltage, current and rotor speed are the quantities used in the ANN training process. In this study, a linear load, which are mainly found in fans, rolling mills, piston pumps and wood saw applications, was coupled on the rotor axis to evaluate the proposed method.

B. *Driver SVPWM*

The SVPWM has been widely applied in VSI. This technique has some advantages over the sinusoidal modulation, such as reducing the number of switching, reducing the harmonic content and higher modulation index [16]. In this work, the studied SVPWM is based on the model described in [17].

C. *TIM Scalar Control*

Due to its simplicity, scalar control is one of the most commonly used methods in industry machine drives. However, its dynamic performance is limited, even in closed loop, particularly when operating in regions of low speed [6]. Recent studies have used the strategy to scale the verification of new proposals for control and sensorless techniques [18]. The essence of the control is to maintain a constant scalar voltage/frequency ratio (V/f), in order to maintain the magnetic flux in the air-gap constant maximum value. If the voltage does not have a proper relationship with the frequency, the machine can operate in the saturation or field weakening region [18]. The electromagnetic flux produced can be calculated by using the relationship between the voltage and frequency, expressed as:

$$\Phi_m \cong \frac{V_p}{f} \cong K_v \tag{1}$$

where Φ_m is the maximum air-gap flux (Weber), K_v is the TIM magnetizing condition in scalar control. The constant K_v calculation does not take into account the ripple of DC bus voltage and copper losses in the stator. However, in low speed operation, these losses have a significant effect on the control performance, reducing the electromagnetic torque of the machine [19,20]. To minimize the voltage drop in the stator resistance, a voltage is added to the *V/f* ratio, called *Vboost*. In this control method, the slip speed and the reference voltage *Vboost* represent the variable speed, which is calculated based on the characteristics of the TIM and the desired operating point.

III. NEURAL SENSORLESS CONTROL

The identification system using artificial neural networks has shown promising results in the power systems area. More specifically, the use of ANN has provided alternative approaches to the treatment of problems related to electrical machines [20-22]. In this paper the ANN is used to estimate the speed on the axis of at three-phase induction motor driven by a voltage source inverter with SVPWM modulation, based on measured current and voltage supply of the machine. This methodology is based on the sensorless technique. The use of sensorless control techniques in electric machines is commonly found in industrial applications of commercial drives. These techniques considerably reduce the implementation cost of the control strategy, as accurate and satisfactory noise-free speed sensors have a high cost. Some studies using the TIM voltage and/or current as input variable estimators are presented in [10,11], which uses these variables in synchronous and stationary coordinate axes, respectively, in their applications estimators.

A. Data processing

In applications where variable speed control is needed, the TIM is usually driven by a VSI. The estimated machine speed through primary quantity, such as current and voltage, as the papers shown in Section 1, leads to the increasing cost of drivers with their transducers. However, this cost is lower compared to the direct speed measurement through sensors such as optical and tachogenerator.

Following the quantities acquisition, there is a need for a signals processing, in order to extract information that can be used to mapping the rotor speed as a TIM voltage and current function.

The voltage supplied by the inverter has a switching characteristic, which passes through the low-pass filter (LPF) with 600 Hz cut off frequency before being processed in the Phase Locked Loop (PLL) system. Although the electric current are naturally filtered, due to the inductive characteristic of the machine, the same LPF is used, in order to obtain high frequency noise attenuation and provide the similar phase displacement compared with voltage signal.

In order to obtain the input patterns of the rotor speed function, stator voltage and current on synchronous reference frame *dq0* were used. Since the machine is considered a balanced load to the VSI, its currents are also balanced. Thus, by currents measurement of phase *a* and *b*, the phase *c* current can be directly calculated. Likewise, the line voltages v_{ab}, v_{bc} and v_{ca} are obtained. Fig. 2 presents the block diagram of the voltages and currents treatment system.

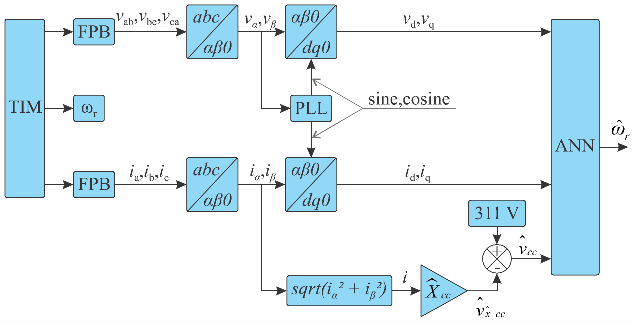

Fig. 2. Block diagram of the data processing.

In order to improve the performance of the speed estimator, given the relevance of DC bus voltage behavior, this paper proposes a new strategy for the neural estimator. The DC bus voltage can begin to compose a set of input variables of ANN. However, the use of this new variable would increase the cost of implementation since another signal conditioning sensor would be required. To overcome this problem, this work proposes to estimate the DC bus voltage from the ideal bus voltage (311 V) by subtracting a portion of the voltage drop across DC bus impedance, as a function of the drawn current. This would allow the interference of the bus voltage variation to be estimated with those variables which are already measured.

The PLL system used in this paper is based on the single phase p-PLL algorithm described in [23]. Based on the three-phase instantaneous active power theory, the p-PLL system is developed in the two-phase stationary reference coordinate system (*αβ* coordinates). The three-phase instantaneous active power can be represented into two forms, such as two-phase or three-phase, both in the stationary reference frame, as follow:

$$\begin{aligned} p &= v_a \cdot i_a + v_b \cdot i_b + v_c \cdot i_c = v_\alpha \cdot i_\alpha + v_\beta \cdot i_\beta \\ &= \bar{p} + \tilde{p} \end{aligned} \tag{6}$$

where the dc and ac components of the real power p are represented by $\bar{p}$ and $\tilde{p}$, respectively.

The three-phase p-PLL implemented is showed in Fig. 3. The PLL structure operates to cancel the component $\bar{p}$ of the fictitious instantaneous power p'. Thus, when the average value of the portion p' is zero, the output signal is locked with the fundamental component of input signal. The dynamics behavior of the PLL is defined by PI controller output, which provides the reference angular frequency ($\omega = 2\pi f$), where f is the frequency of the input signal fundamental component. The angle $\theta = \omega . t$ is obtained by integrating the angular frequency ω. Therefore, θ is used to calculate the fictitious current i'_α and i'_β. To cancel the *dc* component of the p' the fictitious current i'_α and i'_β must be orthogonal to the voltages V_α and V_β respectively [23].

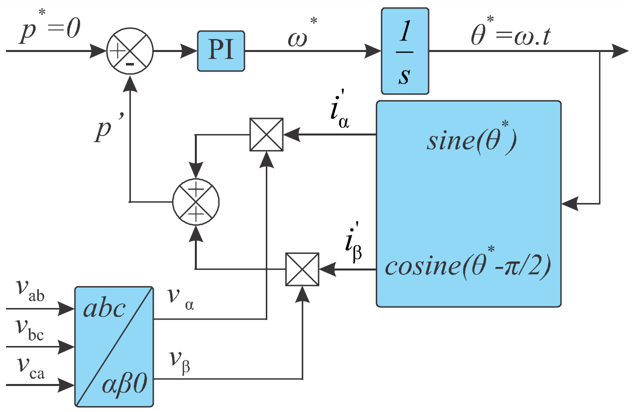

Fig. 3. Three-phase p-PLL system control.

B. Structure of the Neural Speed Estimation

Artificial neural networks have proven to be effective in solving several engineering applications problems. In this study a neural structure is applied to estimate the speed of a three-phase induction motor when it is driven by a frequency inverter with scalar control.

To compose the training data set, several simulations are performed with the TIM mathematical model implemented in Matlab/Simulink, operating in the 1–60 Hz range [26]. For every frequency operating point of the scalar control, five values of resistant load torque are used, ranging from 0.1 Nm to 4.1 Nm with an increment of 1 Nm for each simulation. Load torque disturbances are also applied after the TIM reach steady state, so that the training set characterizing the dynamics of the machine with this variation approaches the operating conditions found in industrial environments.

This work involves testing various ANN configurations, namely the multilayer perceptron (MLP) and the time delay neural network (TDNN). This type of network, called TDNN, is known as concentrated, since it indicates that memory is only in the input layer. TDNN replaces the input neurons of a MLP for a delay line. This network can be trained with the static back-propagation algorithm since the desired signal is available at every moment. The best dynamics response is presented by the TDNN network with an order 4 delay. Fig. 4 presents a voltage source inverter together with scalar control, plus data processing and neural speed estimator.

Unlike other ANN inputs, only the estimated bus voltage is used. It is not necessary to use the samples delayed due to the low frequency DC bus voltage ripple. To save processing time and memory space, only the current sample variable is used.

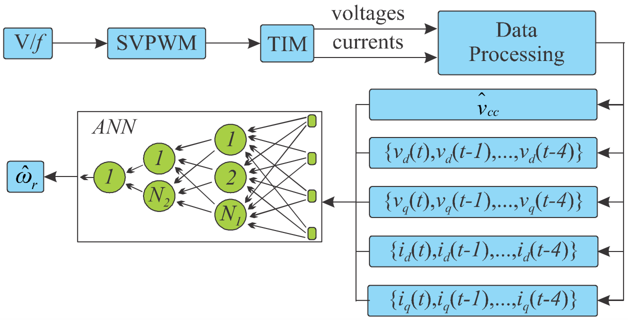

Fig. 4. Estimator structure of training and testing.

The purpose of the proposed estimator is to become general with respect to the induction motor drive. Accordingly, the normalization procedure with maximum values of all input and output variables is adopted so the estimator provides satisfactory performance, even for a machine whose parameters are different from those used in the simulations. Table II presents the structural parameters of ANN, where the convergence of the training process occurs with 312 training epochs.

TABLE II
ANNs Parameters

Network architecture	TDNN Perceptron multilayer
Type of training	Supervised
Number of layer	3
Neurons of the 1st hidden layer	6
Neurons of the 2nd hidden layer	21
Training algorithm	Levenberg-Marquardt backpropagation
Learning rate	5.10^{-2}
Epochs	3000
Square error goal	1.10^{-2}
Hidden layer activation function	Hyperbolic tangent
Output layer activation function	Linear

C. *Training and Validation Methodology*

The method proposed in this work appears in Fig. 5, where the block diagram presents the structure resulting from the modeling and experimentation conducted in steps 1 to 9. The first phase is modeling the TIM, as described in Section 2 (step 1), followed by TIM simulation with the drive method in order to generate the database used in training and test the proposed neural structure (steps 2, 3 and 4). The next step is the ANN training, followed by an evaluation of the data acquired via simulation, and which is stored in steps 3 and 4. This cross-validation process is performed in steps 6 and 7 with speed and load conditions which are different from those used in training process.

After validating the simulation data with the ANN, these data are loaded into a digital signal processor (DSP) embedded system. Tests are then performed with ANN using experimental data consistent with steps 8 and 9. The results obtained using the neural estimator are compared with the measured speed in order to validate the ANN (step 10). This process of validating a trained ANN using simulation data followed by experimental data is called double cross-validation [24, 25].

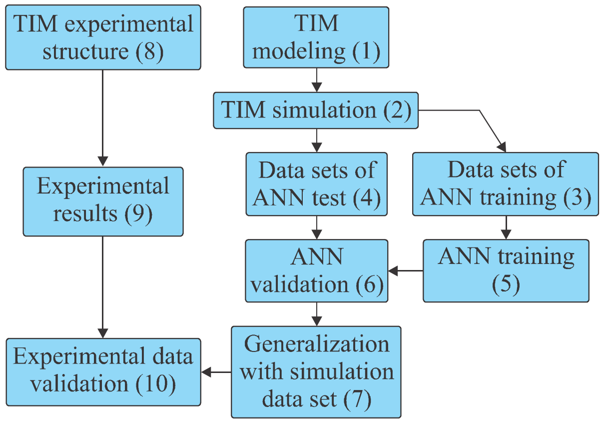

Fig. 5. Block diagram of the proposed methodology.

To optimize the neural network training, a learning reinforcement process was applied in low speed regions. Therefore, data set which represents various aspects of the system dynamic in all operating domain is presented.

The test bench is composed primarily of the direct current machine (DCM) with a tachogenerator, which is coupled to the TIM by a rotating torque sensor. Fig. 6 presents the picture of the test bench, including the following signal conditioning sets: (i) current and voltage of the DC machine; (ii) the torquemeter signal conditioning, and (iii) data acquisition board. The DCM is configured to operate as a direct current generator (DCG), whose goal is to have the impose load torque on TIM. The voltage generated in the armature of the DCG is applied to the resistive load. This allows varying the resistive torque imposed by the TIM with the DCG acting on the field coil voltage supply via a DC power source. The test bench structure is shown in Fig. 6.

Power switches command pulses are generated by the frequency module inverter. This consists of current and voltage signal conditioning boards which receive signals from the respective Hall sensors, while the signal amplitude is adapted to A/D inputs. Due to the tachogenerator output voltage level, a signal conditioning device for the acquisition board and A/D conversion in the digital signal processor (DSP) device is required.

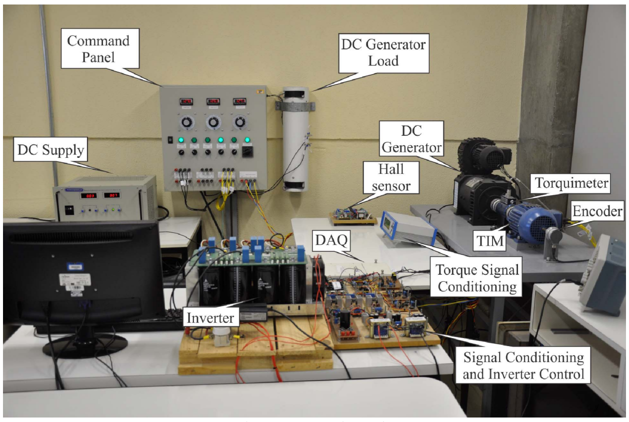

Fig. 6. Test bench.

The signal processor used in this work was a Texas Instruments DSP (TMS320F28335), as well as a Spectrum Digital development kit (TMS320F28335 eZdsp). The data acquisition board is a National Instruments NI USB-6221, which acquires the signals from the tachogenerator, the Hall current and voltage sensors signal, the DSP estimated speed as output, plus the torque and mechanical speed reference. The acquired data are formatted for graphical and estimator performance by calculating and operating under the TIM speed control. After these operating elements are arranged in the laboratory, the testing process begins for the experimental validation of the methodology proposed in this paper.

IV. EXPERIMENTAL TEST BENCH

The experimental validation of systems which are primarily evaluated via computer simulation is a constant theme in current electrical machine research projects [24]. Accordingly, this section describes the main components of laboratory tests involved in the acquisition of experimental data.

Tests are conducted on two ways, first the ANN performance is demonstrated was speed observer, and in second, the speed estimated is used in closed-loop control. The tests configurations are presented in Table III.

TABLE III
TIM OPERATION POINT

Test	Operating Point (Hz)			Load torque (Nm)		
	O.P.1	O.P.2	O.P.3	O.P.1	O.P.2	O.P.3
1	29.71			2.409	4.33	2.416
2	5.81	45.2	22.1	0.718	4.404	2.315
3	29.4			0.521	3.050	0.526
4	6.55			0.428	1.237	0.666

Figs. 7 and 8 show the response of the neural speed estimator when the TIM is driven through a closed-loop measured speed. Tests are conducted by varying the reference speed and load torque. Test 1 (Table III) demonstrates that for a variation of load torque when the speed reference is 29.71 Hz, the control is stable, as presented in Fig. 7. Fig. 8 presents the performance of the system using three different operating frequencies and load torque (Test 2 – Table III).

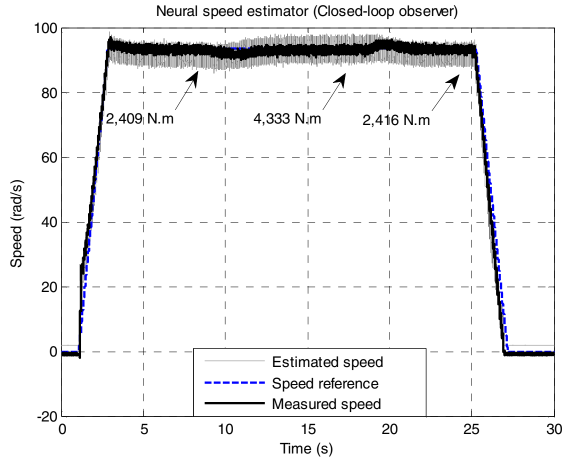

Fig. 7. Speed estimator as observer for Test 1 – Table III.

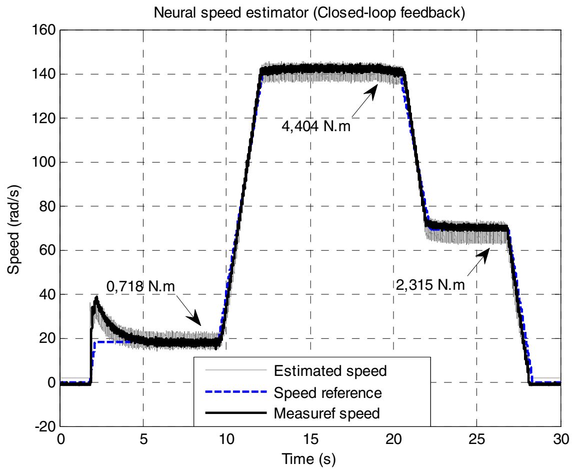

Fig. 8. Speed estimator as observer for Test 2 – Table III.

Figs. 9 and 10 present the response of the neural speed estimator when the TIM is driven through a closed-loop speed estimated by ANN, which is found in Test 3 and Test 4 of Table III, respectively. Following the same procedures conducted in Tests 1 and 2, new tests are performed to validate the proposed approach.

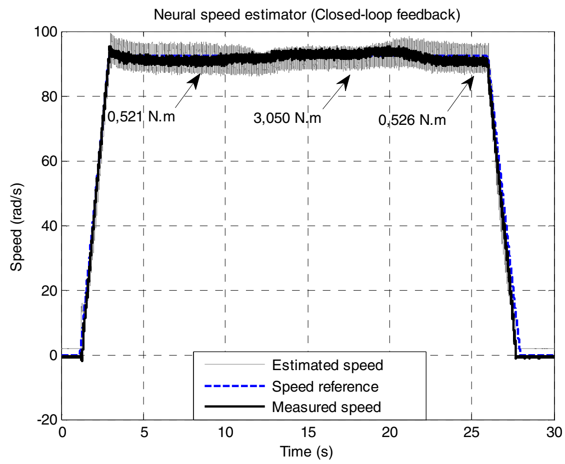

Fig. 9. Estimator speed feedback control in a closed-loop for Test 3 – Table III.

Table IV presents the steady state speed control RME.

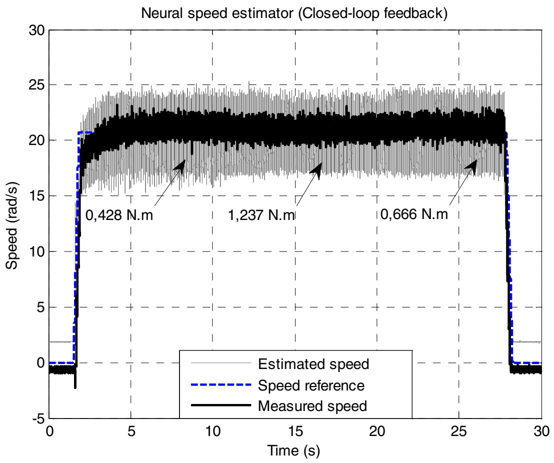

Fig. 10. Estimator speed feedback control in a closed-loop for Test 4 – Table III.

TABLE IV
STEADY STATE SPEED CONTROL RELATIVE MEAN ERROR

Test number	Steady State Slip Control RME (%)		
	O.P.1	**O.P.2**	**O.P.3**
1	0.313	0.374	0.340
2	0.268	0.509	0.759
3	1.608	0.505	1.857
4	2.326	1.401	2.197

Experimental results demonstrate the ability of the ANNs to estimate the TIM speed in the transitory and steady state by scalar control even in low speed region.

V. CONCLUSIONS

This paper proposed an alternative methodology to estimate the speed of an induction motor driven by a voltage inverter with scalar control, using a closed-loop SVPWM modulation based on a TDNN with supervised and offline training. The proposed method estimates the speed from the transient to steady state, comprising the entire operating range of the scalar control.

The experimental essay was achieved in which the induction motor started at ambient temperature (about 25◦C) and left for a long time under mechanical axis overload condition. In this case, the resulting over heat causes parameter variations such as stator and rotor resistance.

The neural speed estimator is evaluated using the traditional control method: speed feedback with a tachogenerator and the neural speed estimator. Thus, when the estimator acts in a feedback loop, the speed error with respect to the axis set point varies from 0.505% to 2.326%. These results are show that methodology can applied in a low cost systems control.

VI. ACKNOWLEDGMENT

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