NEURAL FLUX ESTIMATION APPLIED TO THE VECTOR SPEED CONTROL FOR INDUCTION MACHINES

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Abstract – **This paper presents the vector speed control system using a neural rotor flux observer for a triphasic induction machine of 1.1 kW. The neural flux observer is composed of two multilayer neural networks of the feedfoward type which estimate the angular rotor flux speed and the magnetizing current magnitude. The neural networks were projected to substitute the observer based on the induction machine vector model, which has non-linearities and parametric dependences in its equations. These characteristics can generate errors in the flux estimation. The control system was implemented in a 32-bit Digital Signal Processor (DSP) operating at 150 MHz. The results proved that the system operates with smaller energy consumption and higher performance when oriented by the neural flux observer.**

Index Terms – **Induction machine, DSP, flux estimation, neural network, vector control.**

I. INTRODUCTION

The researches in control and drive strategies for electric machines developed in recent years firmed up the induction machine as one of the most applied in the industry due to its low cost and high performance.

To control the induction machine, the vector control techniques were developed. The main objective of the vectorial controllers is making the induction machine to operate in high performance in the steady state and in the transitory state. The vector controller approaches the induction machine mathematical model to the direct-current machine model [1][2]. This approach allows the independent operation of the flux and torque controllers.

In the vector control techniques, it is necessary to choose one of three fluxes present in the machine to be used as field reference. The three possible fluxes are, respectively, the rotor flux, the stator flux and the airgap flux[3]. The choice of one of these references must take into consideration the desired exactness in the angular estimation and the computational demand required from the digital microprocessor.

Amongst the three cited referentials, the rotor flux has a reduced model and also supplies a good exactness during the estimation, since the stator currents and the rotational speed are known.

The main requirement of the vector techniques is the exact knowledge of the machine parameters. However, the difficulty on obtaining accurate measurements of these parameters may compromise the flux estimation and the global control system performance.

Other problems presented in the use of observers based on models with fixed parameters are the nonlinearities present in the induction machine's mathematical model and the possibility of these parameters to change by the action of external agents such as the temperature and/or by internal agents such as the rotor flux saturation[4]. These factors prejudice the decoupling between the flux and torque vectors.

To solve these problems with the observers based in the inverse models with fixed parameters, many types of robust observers have been proposed. One of the most studied observer nowadays are the observers based in the neural networks[5]. The neural observers use the neural network characteristics of learning, non-linear function approximation, generalization, fault tolerance, adaptability and robustness [6][7].

Due to these characteristics, the neural networks come being widely applied to estimate the electric machines feedback signals [8][9].

Following this trend, this paper presents the implementation in DSP of a vector speed control system for three-phase induction machines using a neural rotor flux observer and studies its energy consumption to the reference speed variations and load changes.

This study compares the machine behavior under orientation of the neural flux observer with the same essays applied to the machine oriented by the conventional flux observer.

Thus, the implemented system unites the advantages offered by the vector control techniques based on the rotor flux referential and the neural networks characteristics applied to the rotor flux estimation[10].

The control program was developed in ANSI C standard language operating at fixed point. Additionally to the vector speed control was implemented current control.

II. INDUCTION MACHINE MODEL ORIENTED BY ROTOR FLUX VECTOR

The vector induction machine models allow the angular position control and the rotational speed control in a similar way to the direct-current machine control [1][2].

Each model is based on a different referential. The possible referentials are the rotor flux, the stator flux or still the airgap flux. The adopted referential must consider the relation between the desired exactness and the computational effort applied to the digital system processor.

Amongst the three cited referentials, the flux rotor referential despite of losing a little of exactness, it does not compromise the global performance of the system. The stator and the airgap referentials are more accurate, but its respective models need decoupling equations. This fact increases the computational demand to the digital processor [3].

For these reasons, the rotor flux referential was chosen to be used in the estimation of the variables related to the rotor. This choice simplifies significantly the digital system implementation.

The equations of the rotor flux states are the following:

$$\frac{di_{mR}(t)}{dt} = \frac{i_{sd}(t)}{T_R} - \frac{i_{mR}(t)}{T_R} \tag{1}$$

$$\frac{d\rho(t)}{dt} = n_p.\omega_{mec}(t) + \frac{i_{sq}(t)}{T_R i_{mR}(t)} \tag{2}$$

$$m_M(t) = k.i_{mR}(t) i_{sq}(t) \tag{3}$$

$$T_R = \frac{L_R}{R_R} \tag{4}$$

$$k = \frac{2}{3}(1-\sigma)L_S \tag{5}$$

where:

$i_{mR}(t)$	- Magnetizing current.
$i_{Sd}(t)$	- Field Current.
$i_{Sq}(t)$	- Torque Current.
$\rho(t)$	- Rotor flux position.
$m_M(t)$	- Electric torque.
n_p	- Par poles number.
$\omega_{mec}(t)$	- Rotor mechanical speed.
T_R	- Rotor time constant.
R_R	- Rotor Resistance.
L_R	- Rotor inductance.
L_s.	- Stator inductance.
σ	- Leakage factor.

Although the rotor flux shows a reduced model, this type of observer has nonlinear characteristics and depends directly of the machine parameters. This dependence generates some performance limitations, mainly when these parameters are not so well known or they change by the influence of external agents as, for example, the temperature or the flux saturation[4]. Thus, if some parametric variation occurs, the rotor flux estimation will present an error that can influence the global system performance.

To compensate the limitations imposed by the observers based on the models with fixed parameters, this work proposes a flux neural observer composed of two multilayers feedfoward neural networks. These neural networks execute, simultaneously, the rotor flux speed estimation and the magnetization current estimation which defines, respectively, the rotor flux position (after the integration of the flux speed) and the rotor flux magnitude.

III. NEURAL ROTOR FLUX ESTIMATION

The Artificial Neural Networks(ANNs) had been spread out as estimation strategy in control systems for its capacities of learning, approaching of nonlinear functions, generalization and parallel processing[7][8]. Another important characteristic of the ANNs is its robustness to the errors in the measurements and variations in the systems parameters.

The learning in the ANNs is obtained from the interconnection of elements called neurons. Each neuron executes the activation function whose inputs are combination of weights calculated by the learning algorithm.

Amongst the several learning algorithms, the most known is the "backpropagation" algorithm whose objective is to minimize error $e(t)$ between the desired model output $y(t)$ to be followed and the neural estimated output $\hat{y}(t)$. For the learning process the model and the neural network must be submitted to the same control law $u(t)$, as shows Figure 1

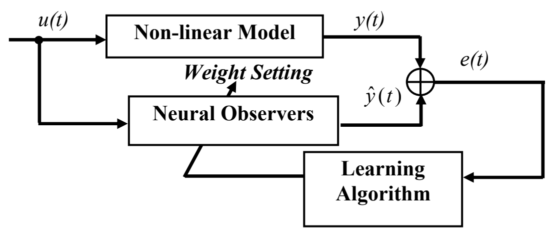

Fig. 1. Training block diagram

The application of the artificial neural networks to estimate the induction machine variables allows an adaptation to the parametric variations. Analyzing the presented vector model in section II, it is observed a strong dependence of the parameter T_R in the attainment of the values of $\frac{d\rho(t)}{dt}$ and $i_{mR}(t)$.

Thus, using the learning capacity to estimate the rotor flux speed and the magnetization current, the control system desires to compensate the dependence of the model in relationship to the rotor time constant T_R .

To implement the neural rotor flux observer, two feedfoward multilayers networks were projected, and they were used in the $\frac{d\rho(t)}{dt}$ and $i_{mR}(t)$ estimation, respectively.

To simplify the system implementation in DSP, linear activation functions were chosen for both networks. These functions were used in all networks layers.

The two networks implemented are based in the topology showed in the Figure 2.

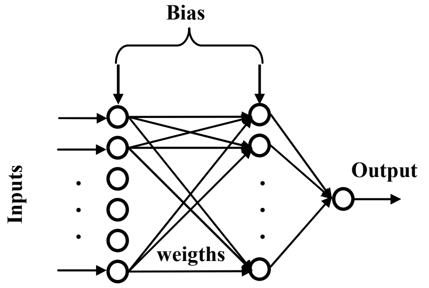

Fig. 2. General model of the neural observers implemented.

The network for estimating of the flux rotor speed has six neurons in the input layer, six neurons in the hidden layer and one neuron in the output layer. Its inputs are the currents $i_{Sd}(t)$ and $i_{Sq}(t)$ and the mechanical speed $\omega_{mec}(t)$, together with its respective previous values in $(t\text{-}h)$, where h is the sample period.

The network to calculate the magnetizing current has a similar structure to the network shown previously, and its inputs are the $i_{Sd}(t)$, $i_{Sd}\,(t\text{-}h)$ and $i_{mR}(t\text{-}h)$ currents.

With these two networks operating in a sycronized way, the conventional induction machine model can be substituted without performance losses.

III.1. TRAINING PROCESS

The networks training process was made in off-line mode using the neural network toolbox of the **MATLAB®** platform.

During this process, the vectors generated by the simulations with the vector rotor flux model and the nominal induction machine parameters were used.

The machine parameters were measured in laboratory, and its values are, respectively: the nominal speed ω_{nom} = $1800rpm$, the nominal voltage $V_{nom}=220V$, the nominal current $I_{nom}=1A$, the stator resistance $R_S=4.5853\Omega$, the rotor resistance $R_R=32{,}0894\Omega$, the stator and rotor inductance $L_S=L_R=459{,}6mH$, the magnetizing inductance $L_M=278.6mH$, the par pole number $n_p=2$, the inertia moment $J=6.06.10^{-3}$ $Kg.m^2$ and the leakage factor $\sigma=0.1$. Thus, the nominal value of the rotor time constant T_R is 0,0143s^{-1}.

To provide an adaptation of the networks for different operating conditions, variations in the following variables were applied: Mechanical reference speed, load torque and mainly in the T_R parameter.

The values applied to the T_R parameter were varied from 0 percent to 50 percent of the nominal value during a time interval of 10 seconds. As the T_R parameter influences directly in the machine's transitory state, the variations applied during the training coincided with the variations applied to the reference speed and with the load torque.

After the training stage, the projected flux neural observer behavior was compared to the same conventional observer variables, both submitted to the same variations.

The Figure 3 shows the speed behaviors generated by the model for the training, which is equivalent to the conventional observer, and the mechanical speed generated by the neural rotor flux observer. In this figure, a good approach between the respective behaviors is observed. However, the speed response generated by the conventional observer is prejudiced by the parameter and load variation, while the speed response generated by the neural observer is only sensible to the load variation, because the machine was simulated without speed control.

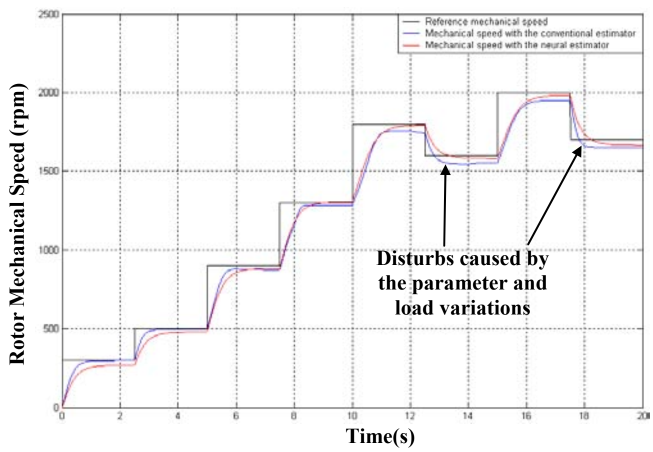

Fig. 3. Rotational speeds generated, respectively, by the conventional model and by the neural networks of $\dfrac{d\hat{\rho}(t)}{dt}$ and $\hat{i}_{mR}(t)$.

The Figure 4 shows the rotor flux angular speed $\dfrac{d\hat{\rho}(t)}{dt}$ generated by the neural and conventional observers, respectively. In this figure it is observed that both observers follow the reference angular speed. However, the neural observer is more robust and less oscillatory to the parameter variation than the conventional observer. This characteristic facilitates the parameter adjustment of the vector speed controller.

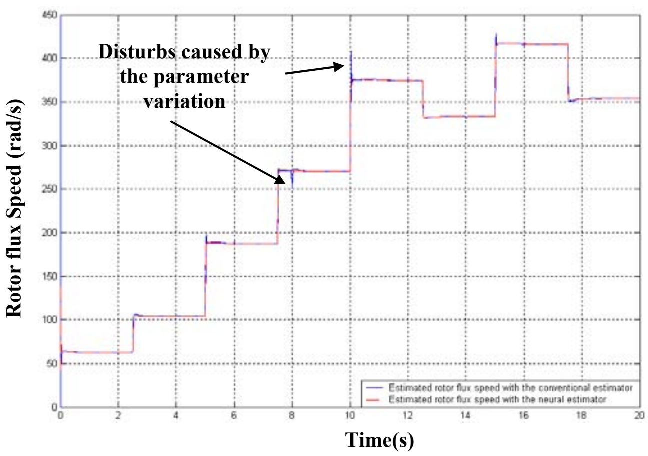

Fig. 4. Flux angular speeds generated, respectively, by the conventional model and by the neural networks of $\dfrac{d\hat{\rho}(t)}{dt}$ and $\hat{i}_{mR}(t)$.

The Figure 5 shows respectively the currents $i_{Sd}(t)$, $i_{mR}(t)$ and $i_{Sq}(t)$ generated by the neural and conventional observers.

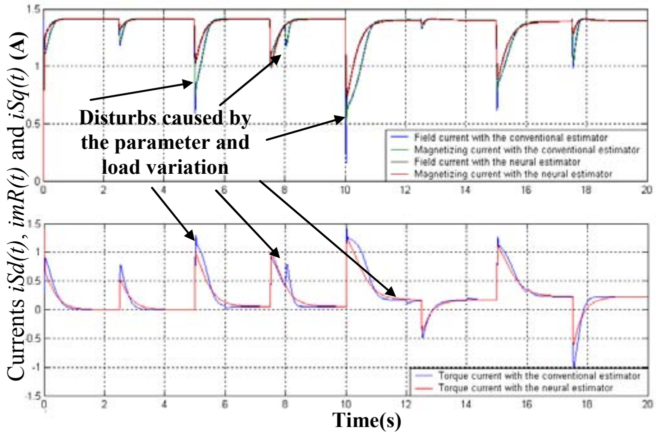

Fig. 5. Vector currents $i_{Sd}(t)$, $i_{Sq}(t)$ and $i_{mR}(t)$ generated, respectively, by the conventional model and by the neural networks of $\frac{d\hat{\rho}(t)}{dt}$ and $\hat{i}_{mR}(t)$.

In this figure, the disturbs caused by the parameter and load variations are more evident to the conventional observer.

For these reasons, it was possible to apply directly the projected neural observers in the speed vector control system to substitute the observer based on the inverse induction machine model.

IV. SYSTEM DESCRIPTION

The vector speed control system using neural flux estimation was developed to operate connected to the current controllers.

For the vector speed control implementation, the chosen referential is the rotor flux because it presents a reduced model and, consequently, the computational effort applied to the DSP is minimized[9]. This choice allows the execution of other auxiliary tasks such as serial communication with a supervisory system hosted in a PC.

The general speed control system diagram is shown in the Figure 6. In this figure is possible to observe that most of the system components were implemented into the DSP.

The system inputs are the phase currents and the rotational speed and its outputs are the triphasic reference currents, which are applied to the PWM inverter.

The vector speed control is executed through the following PI (Proportional-Integrative) controllers: the speed controller, which generates the torque reference m_{Mref}, the torque controller, which supplies the torque component i_{Sqref} and the flux controller, which supplies the field component i_{Sdref}.

Although this system was developed to a neural network application, it allows the implementation of the other observers. This modular system characteristic made possible a direct comparison with the rotor flux observer based on the model presented in section II.

The used DSP has a 32-bit data bus, clock of 150 MHz and allows the communication with a PC computer through the parallel and serial RS-232 interfaces. Several ports resources are available as 12 Analog/Digital channels and 12 PWM channels, which drive the inverter that feed the induction machine.

The control program was developed in ANSI C language with fixed point arithmetic and its programming was executed through the parallel PC interface.

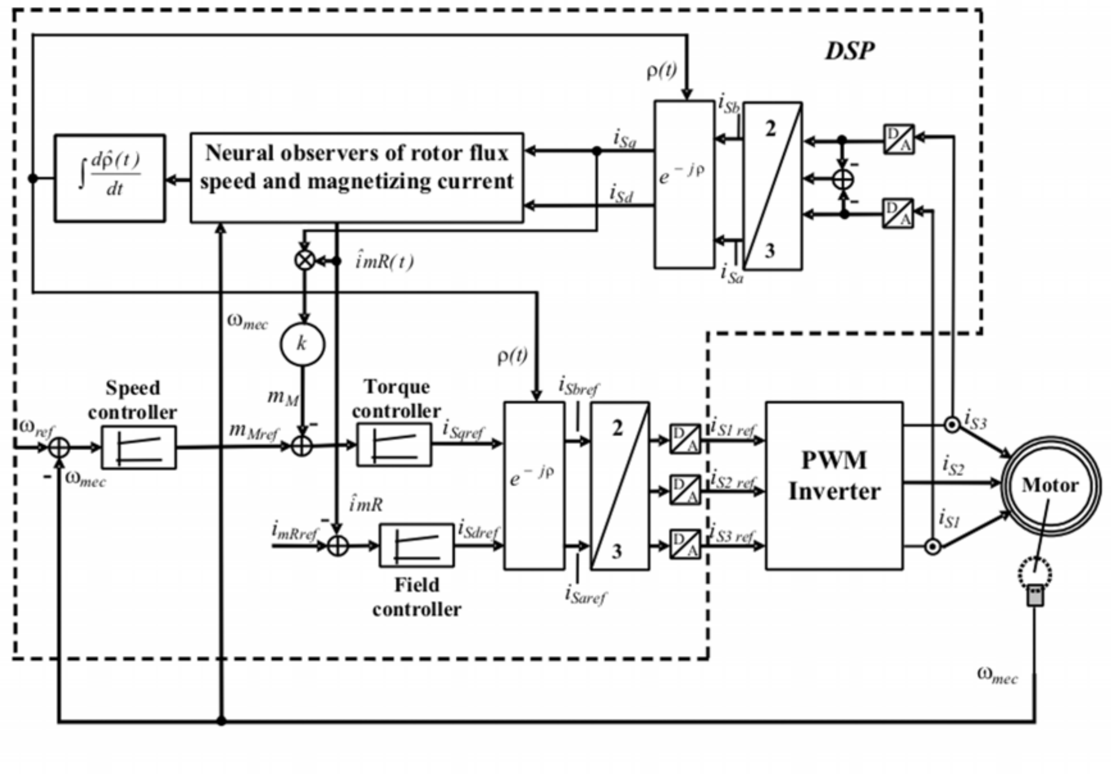

Fig. 6. Diagram of the vector Speed Control System.

V. EXPERIMENTAL RESULTS

After the general system implementation comparisons were made between the system respective performance to the conventional flux observer and the neural flux observer. These observers execute the rotor flux speed $\frac{d\rho(t)}{dt}$ and the magnetizing current $i_{mR}(t)$.

The Figure 7 shows the machine mechanical speed responses for the system operating with the conventional and neural rotor flux observers submitted to different step speed references.

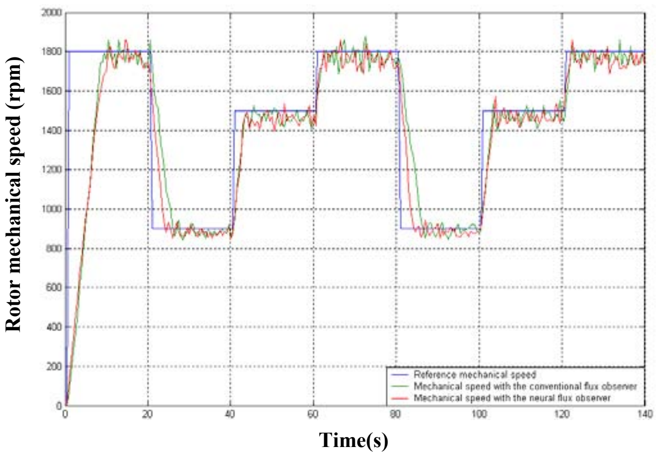

Fig. 7. Comparison between the induction machine mechanical speed behaviour using the conventional flux observer and the neural flux observer for periodic steps references of 1800 rpm, 900 rpm and 1500 rpm.

It is possible to observe in this figure that the system presents fast and near responses operating with the conventional flux observer and with the neural flux observer. However, in the descending speed references the machine reaches its goal more quickly operating with the neural flux observer.

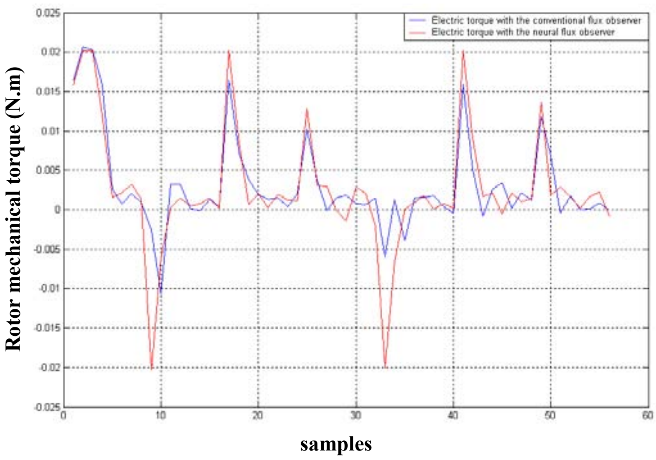

Fig. 8. Electric torques samples operating with the conventional and the neural flux observers for periodic steps references of 1800 rpm, 2200 rpm and 800 rpm.

The electric torque samples presented in the Figure 8 shows that the electric torque generated by the system operating with the neural flux observer is more efficient than the electric torque generated by the system operating with the conventional flux observer.

Using the torque and speed responses, it was possible to estimate the energy system demand to both observers. Their respective response is showed in the Figure 9.

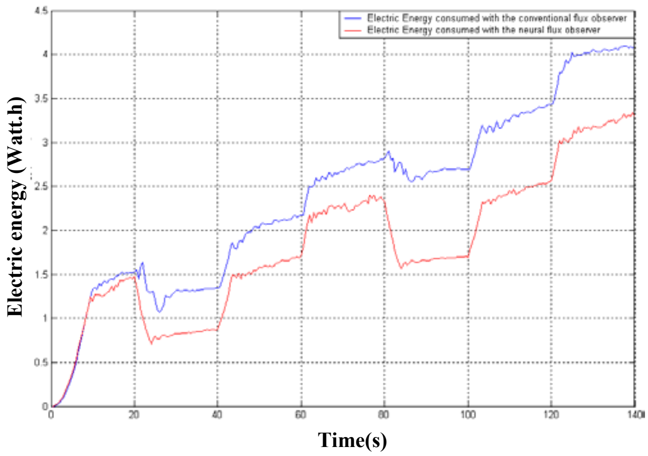

Fig. 9. Electric energy system demand operating with the conventional and the neural flux observers for periodic steps references of 1800 rpm, 900 rpm and 1500 rpm.

These graphs present a smaller energy consumption to the system operating with the neural observer. Hence, it can be concluded that the neural observer provides a larger efficiency for abrupt reference speeds variations.

The Figures 10 to 12 present the system behavior submitted to the mechanical load. In these trials, the mechanical load applied to the system oriented by the neural flux observer is larger than the load applied to the same system guided by the conventional flux observer.

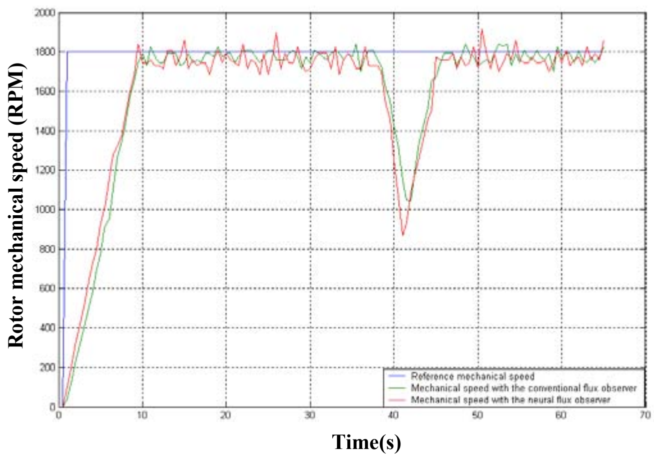

Fig. 10. Comparison between the induction machine speed behaviour using the conventional flux observer and the neural flux observer for load application.

The Figure 10 shows that system speed oriented by the neural flux observer provides a speed recovery as fast as the system running with the conventional observer. However, this fast speed recovery generates an increase in the electric torque oscillations, as showed in the Figure 11.

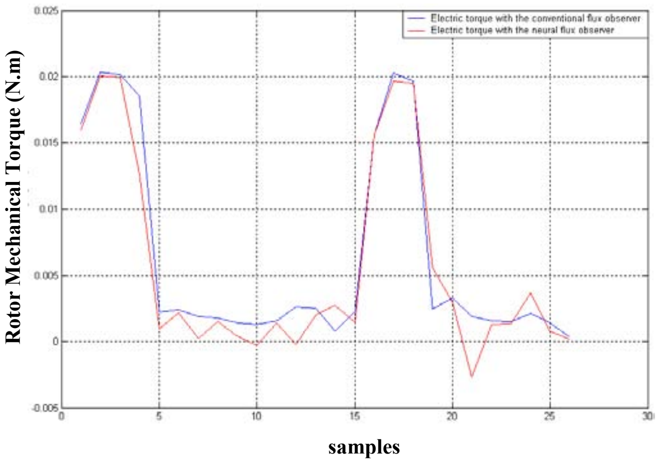

Fig. 11. Electric torque behavior with the conventional and the neural flux observers during the load application.

Figure 12 proves that, in spite of the oscillations in the electric torque with the system oriented by the neural flux observer increase, the energy consumption is still lesser than the demand required by the system operating with the conventional flux observer, for the same time interval.

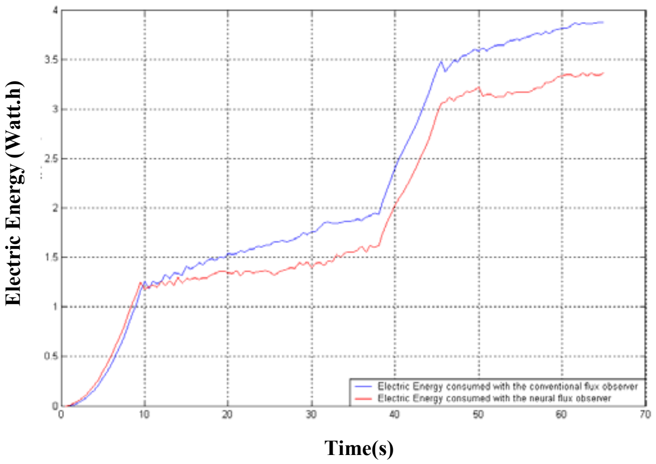

Fig. 12. Electrical energy system demand operating with the conventional and the neural flux observers for load application.

These results demonstrate that the system operating with the neural flux observer substitutes efficiently the conventional observer based on the inverse model, mainly when the applied variations to the machine are abrupt.

VI. CONCLUSIONS

The speed vector control system using neural flux estimation presented in this work is one more successful application of the vector techniques for induction machines.

In agreement with the vector techniques, it is necessary to choose a flux referential for the system orientation. To simplify the digital system implemetation in DSP, it was chosen the rotor flux referential.

After the system implementation in DSP oriented by the neural rotor flux observer, it was observed that the system presents similar behaviors in the acceleration commands for the conventional and neural flux orientation. However, for abrupts reductions of the reference speed, the system running with the neural observer always presented faster responses.

Finally, the main result to be observed in all the trials was the less consumption of energy for the system operation with the neural rotor flux.

All these results justify the substitution of the conventional flux observer, whose main limitations are its non linearity and its dependence related to the machine parameters.

ACKNOWLEDGEMENT

The authors would to thanks CAPES and CNPq for the financial support.

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