Simulation and identification of a field oriented controlled induction motor using artificial neural networks

Aldo Pardo García, PhD.
Universidad de Pamplona, Norte Santander, Colombia, apardo13@unipamplona.edu.co

Jorge Luis Díaz Rodriguez, Master of Sciencie
Universidad de Pamplona, Norte Santander, Colombia, jdiazcu@unipamplona.edu.co

Antonio Gan Acosta, Master of Science
Universidad de Pamplona, Norte de Santander,. Colombia, antoniogan@unipamplona.edu.co

***Abstract*—One of the main deficiencies of the conventional controllers of the electric drives is the inability of capturing the unknown characteristics of a load around a wide range of the operation point, that which hinders the selection and adjustment of the controller's parameters. In this work we intend the use of the Artificial Neural Networks (ANN) for the identification of an induction motor with field orientation control. The results of the training of the neural network and the simulation of the identification of the system are exposed in this paper.**

I. INTRODUCTION

In order to design a motion control system with a good tracking response it is necessary to device a complex adaptive control algorithm due, fundamentally, to the non-linear characteristic of both, the electromechanical converter and the driven mechanism. This is particularly true when an induction motor with field orientation control driven a non-linear mechanical load is being utilized.

In the past, a classical algorithm like a proportional integral one with variable parameters was employed. This choice brings about a complication of the software development. More recently another modern control techniques like the variable structure, the model reference adaptive control and the sliding mode control has been applied successfully. Nevertheless, these solutions are very complicated too.

Some years ago, Narendra and Parthasarathy, [3] demonstrated that the neural network parallel processing characteristic could be utilized to identify and control dynamic systems allowing to capture as a whole, the nonlinear properties of the electromechanical motion systems. Since then, some investigators have been engaged in the development of neural network control systems of direct current and alternating current electrical drives.

II. FIELD ORIENTED CONTROLLER

In this paper, the experiences of the authors concerning the SIMULINK® induction motor with field orientation simulation as a plant to be identified with neural networks are shown.

The indirect method of field orientation control was utilized. A three phase current controlled inverter with pulse width modulation and stationary control feeding an induction motor was simulated. This system is shown in figure 1.

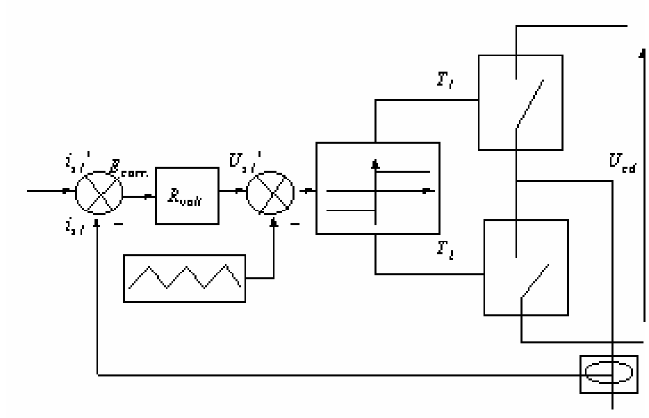

Fig. 1. Three phase current controlled inverter with pulse width modulation and stationary control

III. NEURAL NETWORK TOPOLOGY AND TRAINING

An open loop field orientation control like the one shown in figure 2 was simulated as the plant to be identified considering the torque producing current $i_{sq}(k)$ as input and the motor speed $w(k)$ as output.

The training pattern was obtained "exciting" the plant with a waveform very much alike to the corresponding to the motor starting. One composed by an initial increasing ramp and a final decreasing ramp was the choice.

The slopes and relative times of the two ramps were varied in order to generate different training patterns. The inputs to the Artificial Neural Network (*ANN*) were $w(k)$, $w(k\text{-}1)$ and $i_{sq}(k\text{-}2)$ and $i_{sq}(k\text{-}1)$ was the output.

A three layer back propagation neural network (351) with 0.2 as learning rate and 0.9 as the bias was selected. The maximum quadratic error was 0.3.

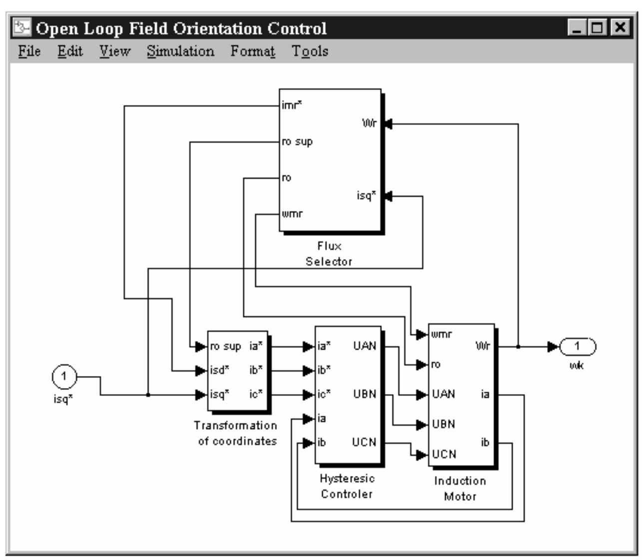

Fig. 2. Open loop field orientation control simulation

In figure 3 the simulation implemented in order to training the neural network is shown and the simulation of the identification of the induction motor using the trained ANN is shown in figure 4.

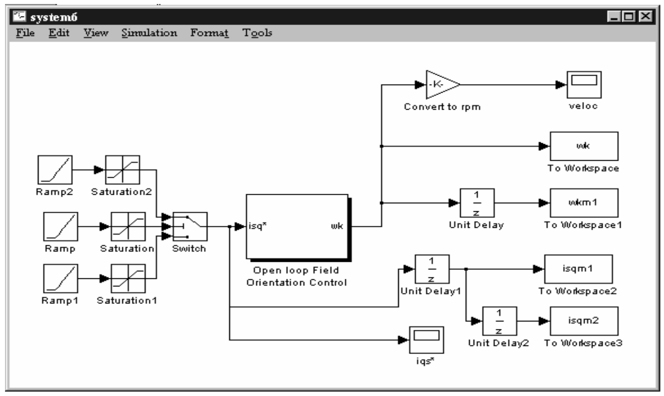

Fig. 3. Simulation scheme for neural network training

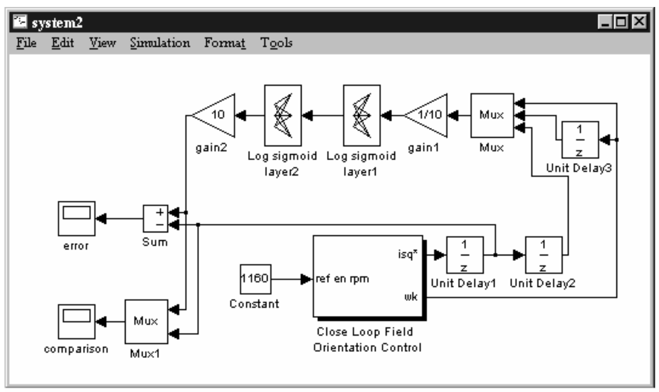

Fig. 4. Identification process using Artificial Neural Network

As a training final result was obtained that the identification error of the closed loop system, like it can be observed in the figure 5, it is below the preset level and in steady state it ends up being very small, in the order of 0.04, which demonstrates that a successful network training was carried out, and the training patterns emulate the real system dynamics.

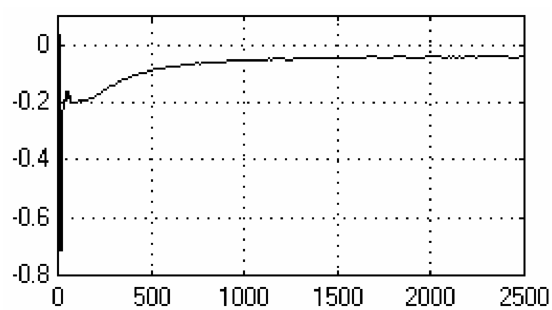

Fig. 5. Identification error (step reference change)

Comparison between the torque producing current i^*_{sq} obtained by closed loop system simulation and the one obtained using ANN is shown in figure 6. The error is shown in figure 6. Its value was never grater than 0.1.

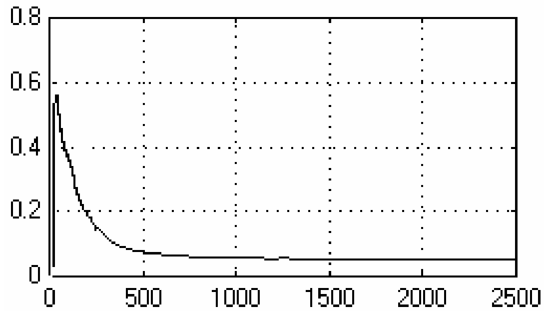

Fig. 6. Motor current and network output
(step reference change)

The network behavior before random sudden reference variations can be examine in figures 7 and 8 where can observe that the network and the system outputs are very similar each other and that the actual error between these signals is below the allow maximum error

Some instantaneous picks can be occurred due to that the network has one input that comes from the output signal, unit delayed, then, the network take a time instant to give the right answer.

This time instant is similar to the one used as integration interval and very inferior to the smallest time constant of the system, that is way; the identification behaviour is not affected at all.

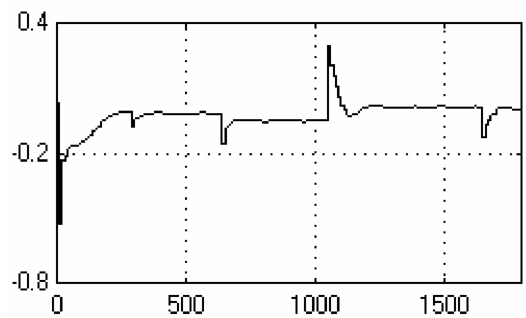

Fig. 7. Identification error (random reference change)

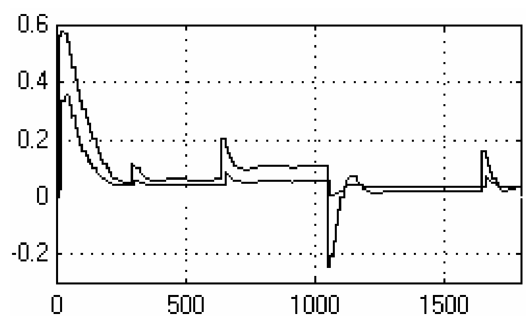

Fig. 8. Motor current and network output
(random reference change)

IV. CONCLUSIONS

The training patterns selection is very important in order to obtain successful neural network learning. The better selection of the neurones number of each layer is a matter of experience.

The training patterns selection also influences the successful learning of the network in a decisive way when the dynamic processes of the system are considered. It could also be established that the learning process accelerates during the training if the network output signal is feedback.

With the simulation results is demonstrated that the trained network identified the system in open and closed loop with errors inferior to 0.1, when the system was stimulated with random input reference signals.

Finally, we can also conclude, that this neural network representing the non-linear system can be use in the future as the control algorithm of the speed loop of the field orientation system.

REFERENCES

[1] El–Sharkawi, M. and Niebur, D. IEEE Power Engineering Society. A Tutorial course on Artificial Neural Networks with applications to Power Systems. 1996.

[2] Haykin, S. *Neural Networks*. A Comprehensive Foundation. 1994.

[3] Narendra, K. S. y Parthasarathy, K. Identification and Control of Dynamical Systems using Neural Networks. IEEE Transaction on Neural Networks. Vol. I No. 1 1990.

[4] Wassarman, Philip D. *Neural computing theory and practice*. 1989.

[5] Weerasooriya, S. and El-Sharkawi, M. Identification and control of DC motor using back propagation neural networks. IEEE Transaction on Energy Conversion. No. 6. 1991.

[6] Weerasooriya, S. and El-Sharkawi, M. Laboratory Implementation of a Neural Network Trajectory Controller for a DC Motor. IEEE Transaction on Energy Conversion. Vol. 8 No. 1 1993.

[7] Yang, Hong-Tzer; Huang, Kven-Yen and Huang, Ching-Lien. An Artificial Neural Network based identification and control approach for the field-oriented induction motors. Electric Power System Research 30. 1994.

Authorization and disclaimer

If you have any questions, please contact:

Prof. Aldo Pardo García
Universidad de Pamplona, Norte de Santander, Colombia.
apardo13@unipamplona.edu.co
57 75 685303 ext 156.