

IDENTIFICATION AND CONTROL OF AN ASYNCHRONOUS MACHINE USING NEURAL NETWORKS

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Abstract

In this work, we present the application of artificial neural networks to the identification and control of the asynchronous motor, which is a complex nonlinear system with variable internal dynamics. We show that neural networks can be applied to control the stator currents of the induction motor. The results of the different simulations are presented to evaluate the performance of the neural controller proposed.

Key words: Neural networks, nonlinear control systems, system identification, neuromorphic control, asynchronous machine.

Résumé

Ce travail présente l'application des réseaux de neurones artificiels à l'identification et au contrôle du moteur asynchrone, un système non linéaire complexe et aux dynamiques internes variables. Nous avons montré que les réseaux de neurones peuvent être utilisés pour la commande des courants statoriques du moteur à induction. Les résultats de différentes simulations sont présentés pour évaluer la performance du contrôleur neuronal proposé.

Mots clés: Réseaux de neurones, contrôle des systèmes non linéaires, identification des systèmes, contrôle neuromorphique, machine asynchrone.

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ملخص

هذا العمل يقدم تطبيق الشبكات العصبية الإسطناعية للتعيين و التحكم في المحرك الغير متزامن، الذي يعد نظاما لا خطي معقدا، ذا ديناميكيات داخلية متغيرة. لقد بينا أنه من الممكن إستعمال الشبكات العصبية من أجل التحكم في تيارات ساكن المحرك الحثي. نتائج مختلف الأمثلة التظاهريية قدمت لتقييم تأدية المتحكم العصبي المقترح.

الكلمات المفتاحية: الشبكات العصبية الإسطناعية، التحكم في الأنظمة اللاخطية، تعيين الأنظمة، التحكم العصبي، المحرك الغير متزامن.

The interest generated by artificial neural networks in recent years is justified by some of the fascinating properties that they have, such as adaptiveness, generalization, etc., which give a powerful tool to solve problems related to the control of nonlinear complex processes and to overcome the limitations of commonly used techniques [1].

Realizing an efficient command for nonlinear systems or whose dynamics are partially or totally unknown has always been an attempt to perform a less sophisticated linearization as the case of gain scheduling, adaptive control, self tuning, etc., [2], [3], [4]. Although giving results, we notice that the simplification of these systems in order to control them is not satisfactory. To alleviate the disadvantages of adaptive control, for example the sensitivity of the model, researchers have developed the notion of neurocontrol which consists of the instillation of the system's dynamic behavior to an ANN through the back propagation learning operation [5, 6, 7, 8, 9].

This scheme of intelligent control allows to decrease the chances of instability, linked to the variation of the process parameters, and thus, realize systems with intelligent self control [3].

With its size and its nonlinear nature worsened by irreducible changes in its internal characteristics in operational mode, the asynchronous machine constitutes a system of great complexity [4].

The elaboration of an advanced command for the induction motor has been the subject of multiple efforts. The solutions proposed such as the scalar control or the control by field orientation are not wholly satisfactory since they are subject to the variations of the system parameters in particular during abrupt load changes. In this work we propose a connectionist approach to the problem through a neuronal model of the asynchronous machine [10].

1. NEUROCONTROL

In order to produce complex systems, mainly nonlinear, capable of being autonomous in a hostile environment, researchers concentrated their attention to the development of intelligent control systems [3].

Recently, research efforts to apply ANN to the control of dynamic processes have led to the promising domain of neurocontrol, which can be seen as a connectionist branch of adaptive control theory [11]. ANN are sought to iron out the difficulties encountered with nonlinear systems or those having an unknown structure; noise rejection, fault tolerance and graceful degradation [12].

1.1 - Neuromorphic identification

In this context, the application of ANN in dynamic systems identification and control can be developed in a natural manner due to the adaptive nature of the networks learning process [13]. Virtually, all discrete and nonlinear systems can be represented by the *Nonlinear Autoregressive Moving Average with exogenous input model*, NARMAX [14], which is described by the following nonlinear discrete differences equation:

$$y_p(k+1) = f[y_p(k), \dots, y_p(k-n+1); u(k), \dots, u(k-m+1)] \quad (1)$$

an identification model would be to use the real inputs of the system for the training of the neural network emulator (NNE). Then, equation (1) becomes:

$$y_n = N[y_p(k), \dots, y_p(k-n+1); u(k), \dots, u(k-m+1)] \quad (2)$$

where y_n is the output of the NNE.

The preceding equation describes a series-parallel model [15], which is the most appropriate model in order to generate stable adaptation rules.

1.2 - Neuromorphic control

The desired closed loop performance of the system is specified by a stable model M, defined by the pairs of input-output $\{r(k), y_M(k)\}$ [8]. The controlled system attempts to follow the performance of the model, thus the control process becomes a tracking problem. In indirect adaptive control, we use a neuromodel of the system where the system's error is propagated first in the emulator then in the controller allowing the parameter adjustment of the neural network controller (NNC) [16].

2. THE ASYNCHRONOUS MACHINE

The induction motor is a highly nonlinear system; the study of its stability is difficult. Simulation becomes an advantageous choice for the stability and performance analysis of the control system. The application of modern control theory to the AC motor requires a discrete modeling of the induction motor in real time which must be fast, stable and accurate for the analysis and design of adequate

digital control [17]. Such system is a perfect candidate for the use of neural network for the implementation of a robust and efficient controller. We use an ANN for the identification of the motor stator currents and present a neural network controller for these currents [10].

2.1 - Identification

In order to identify the stator currents of the motor, the discrete representation of the induction machine in the stator referential $d-q$ is used [18].

$$\underline{i}^{dq}(k+1) = \Phi(k) \underline{i}^{dq}(k) + c_v \underline{v}^{dq}(k) \quad (3)$$

with:

$$\Phi = \begin{bmatrix} 1 - T/\tau_s & 0 & T\xi/\tau_r & T\xi\omega_r(k) \\ 0 & 1 - T/\tau_s & -T\xi\omega_r(k) & T\xi/\tau_r \\ TR_{22} & 0 & 1 - T/\tau_s & -T\omega_r(k) \\ 0 & TR_{22} & T\omega_r(k) & 1 - T/\tau_s \end{bmatrix}$$

$$\underline{i}^{dq} = [i_{ds} \ i_{qs} \ \phi_{dr} \ \phi_{qr}]^T, \ \xi = L_m / \sigma L_s L_r, \ R_{22} = L_m R_r / L_r,$$

$$c_v = T / \sigma L_s, \ \tau_r = L_r / R_r, \ \tau_s = 1 / \left(\frac{R_s}{\sigma L_s} + \frac{R_r L_m^2}{\sigma L_s L_r} \right)$$

where $\sigma = 1 - L_m^2 / L_s L_r$ is the leakage coefficient, i_{ds} , i_{qs} are the stator currents; ϕ_{dr} , ϕ_{qr} are the rotor fluxes; v_{ds} , v_{qs} are the stator voltages and ω_r is the motor's speed.

This model can not be used for identification since the flux vector is not observable; i.e. can not be measured. It is possible to modify these equations in two second order equations in terms of observable quantities $\underline{i}_s^{dq} = [i_{ds} \ i_{qs}]^T$ and $\underline{v}^{dq} = [v_{ds} \ v_{qs}]^T$. The deduction of this NARMAX model is given in the appendix of reference [18]:

$$\underline{i}_s^{dq}(k+1) = \underline{f}(\underline{i}_s^{dq}(k), \underline{i}_s^{dq}(k-1), \omega_r(k), \omega_r(k-1), \underline{v}^{dq}(k), \underline{v}^{dq}(k-1)) \quad (4)$$

where $\underline{f}(\cdot): \mathfrak{R}^{10} \rightarrow \mathfrak{R}^2$ is nonlinear.

An ANN $\mathfrak{N}_{10,21,2}^2$ is used for the estimation of $\underline{f}(\cdot)$, where $\mathfrak{N}_{10,21,2}^2$ stands for a network of 10 neurons in the input layer, 21 neurons in the hidden layer and 2 neurons in the output layer. The parameters of the learning algorithm can be found in [10]. Equation (4) requires the values of the stator voltages and currents in addition to the speed of the rotor. The identification model is given in [figure 1](#).

Gaussian samples in the input voltage current $\underline{v}^{dq}(k)$ are used to excite the electromagnetic dynamics of the induction motor in order to ensure the generality during training. The

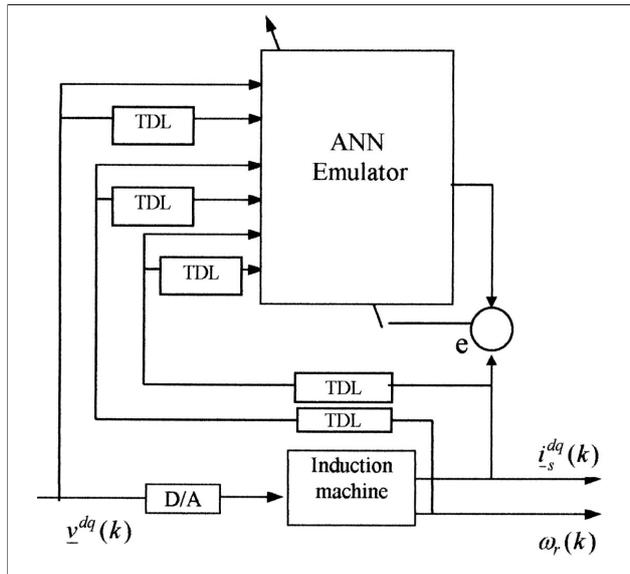


Figure 1: Current identification of the induction machine.

voltage vector $\underline{v}^{dq}(k)$, the stator current vector $\underline{i}_s^{dq}(k)$ and the speed $\omega_r(k)$ are sampled, delayed then propagated in the ANN. We proposed an off-line training scheme of the ANN in order to reproduce existing stator current controller. The training required 526×10^3 presentations of the 850 training vectors. After the network convergence, the emulator is then tested with respect to the motor's output. The performances of the NNE have an acceptable accuracy. The results of the identification are obtained for the quadrature and direct currents and are presented in figures 2 and 3.

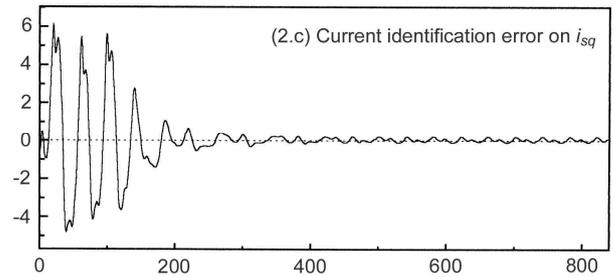


Figure 2: Quadrature current identification

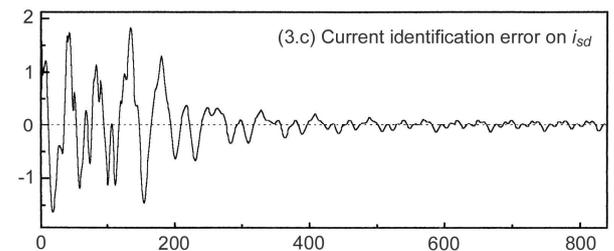
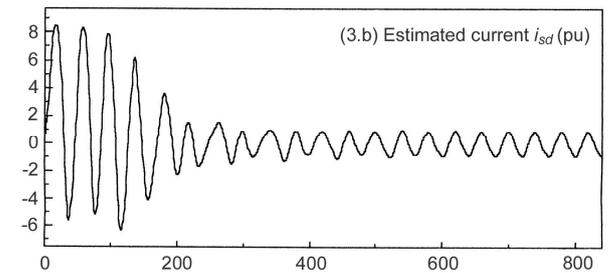
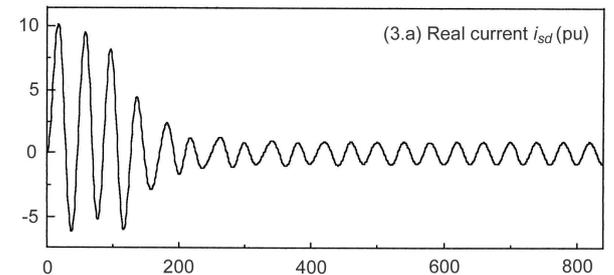
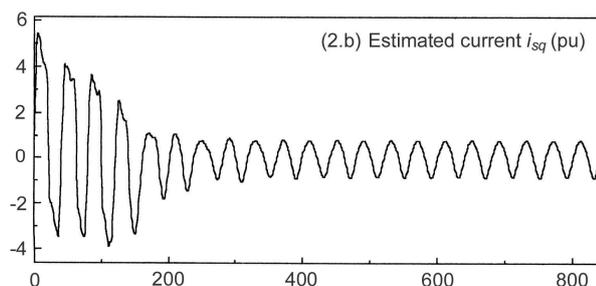
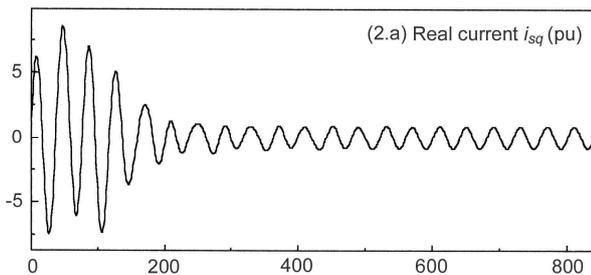


Figure 3: Direct current identification.



2.2 - Control

The induction motor is a nonlinear system, in addition, many parameters change with time and functioning conditions. The induction motor system is structurally a multivariable control system. The voltage and the frequency are the control inputs and the outputs can be any of the following: speed, position, torque, air-gap flux, stator current or any of their combination [7].

Many control methods such as the vectorial control or the direct self control attempt to reduce the complex dynamic structure to a linear structure in order to apply techniques of linear design [17]. However, the changes in the motor parameters can deteriorate the performances of the motor and lead eventually to instability, but the problem can be solved by using adaptive techniques [7].

The neuronal model obtained in section 3.1 contains all the internal dynamics of the motor and by this fact it is robust against any changes in internal parameters of the induction machine. Our controller controls the stator currents of the induction motor. Once, it is sufficiently trained, it will replace the controller, which results in high execution speed and fault tolerance [18]. The NNE of section 3 is used for training the neuronal controller as shown by figure 4. The purpose of the control is to force \tilde{i}_s^{dq} to follow the desired stator vector \tilde{i}_s^{dq} . Thus, the controller synthesizes the elements of the vector \underline{v}^{dq} of relation (5).

$$\underline{v}^{dq} = RNA(\tilde{i}_s^{dq}(k), \tilde{i}_s^{dq}(k-1), \omega_r(k), \omega_r(k-1), \underline{v}^{dq}(k), \underline{v}^{dq}(k-1))$$

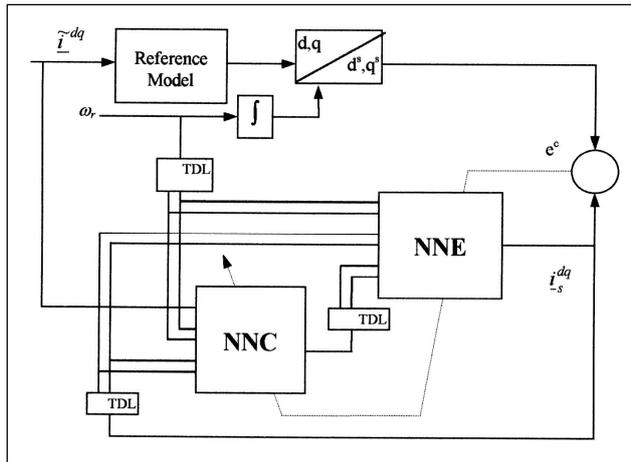


Figure 4: Neurocontroller training.

A network type $\mathfrak{N}_{10,21,2}^2$ is trained with random samples. The convergence of the network is obtained after 85×10^4 presentations of the 601 training vectors.

The NNC is applied to the asynchronous motor with no load. Then, the controller is tested with 70% change in the motor's rotor resistance. The simulation results are shown in figures 5, 6, 7 and 8. We see that the stator currents stabilize quickly around the reference values in amplitude, phase and frequency. In addition, the test with the change in rotor resistance shows the adaptive nature of the controller. The latter reaches and remains at the reference values in less than 0.13 seconds.

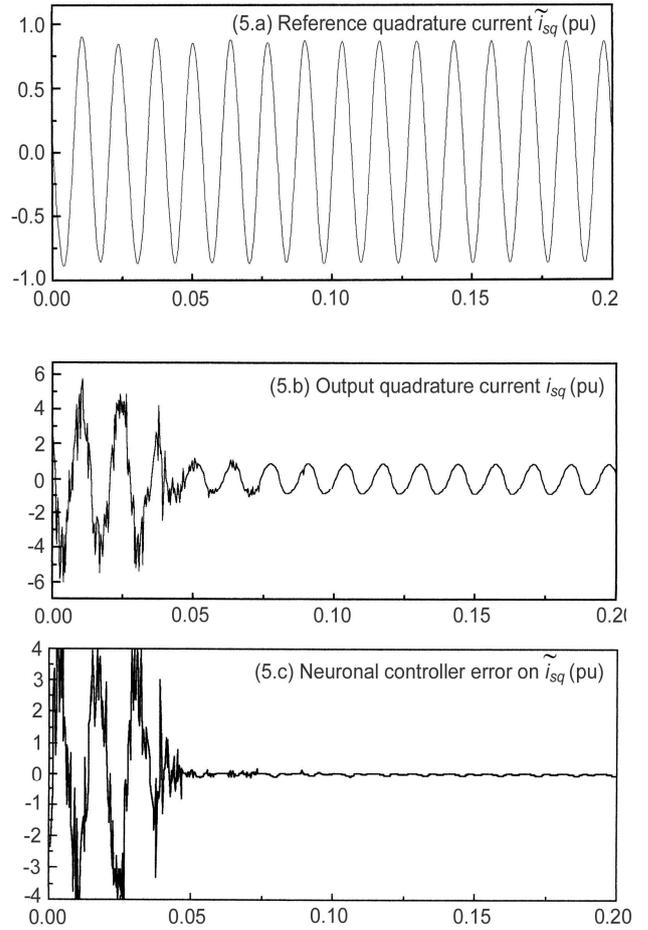
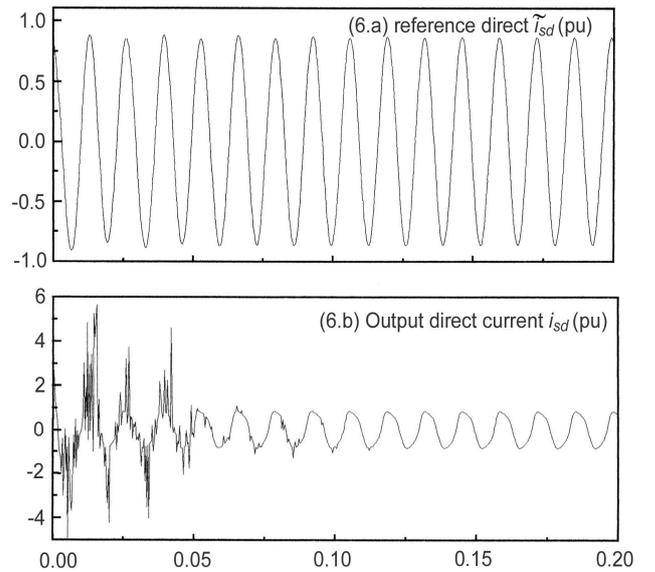


Figure 5: Quadrature current control



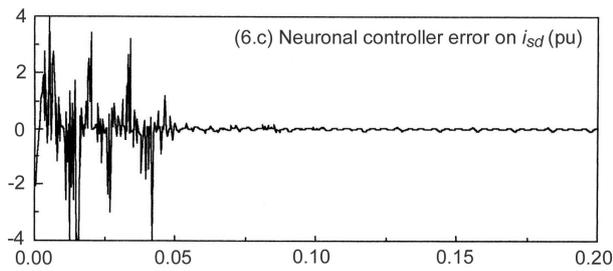


Figure 6: Direct current control.

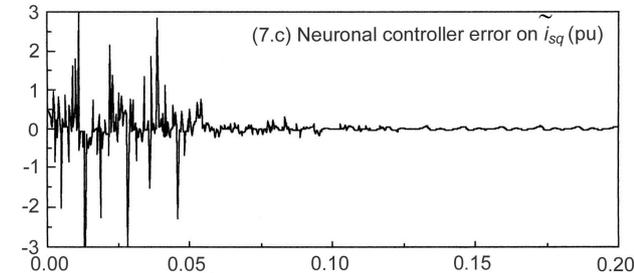
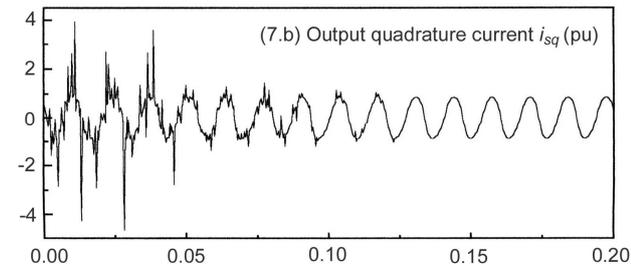
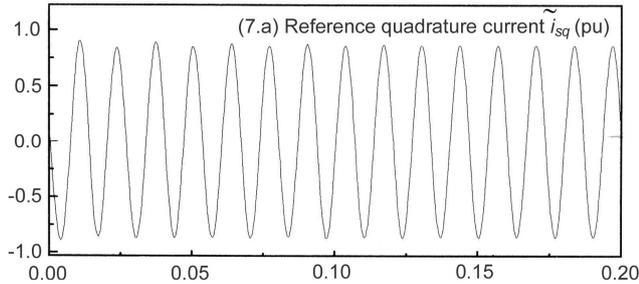


Figure 7: Quadrature current control with a charge in R_r .

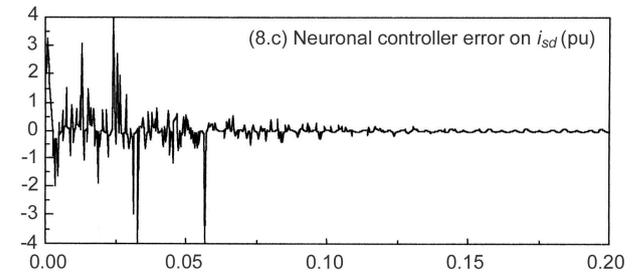
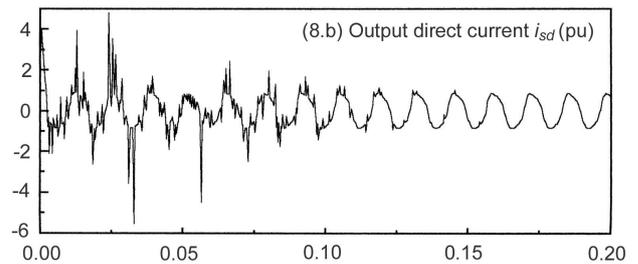
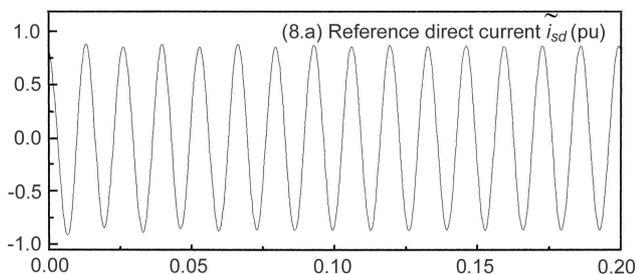


Figure 8: Direct current control with a charge in R_r .

CONCLUSION

According to the results obtained, it seems clear that the control with neural networks of the asynchronous machine is robust and efficient. The use of ANN for the synthesis of the control of stator currents of an asynchronous machine, in addition to its simplicity with respect to its implementation, has enabled to make the tracking of a reference model that is quick and insensitive to the motor's internal parameter changes unlike other control schemes which are robust only if the characteristics of the system are stable. Thus, neural networks represent an attractive and pertinent solution to the adaptive control. Unfortunately, the main handicap of the application of ANN is the huge training time as well as the delicate choice of the different network parameters.

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