Adaptive Nonlinear Control of Induction Motor Using Neural Networks

Nadir KABACHE And Boukhemis CHETATE
Laboratory of Research on Industrial Enterprises electrification
University of Boumèrdes
Tel/Fax: 213 24 81 70 50
Email: nadir_kabache@yahoo.fr

Abstract:

To avoid the various constraints related to the feedback linearisation control (FBLC), in this papers we propose a new control approach for the induction motor control based on artificial neural networks (ANN) trained on-line. The two ANN are used for the on-line reconstitution of the state feedback necessary for the FBLC. The training rules used result from a combination between the ANN properties, the adaptive nonlinear control propriety and the nonlinear adaptation rules. Via these three techniques a training rules were extracted, these last transform the tracking errors into a means to adjust the used ANN behavior so that they adapt with the various operation modes of induction motor.

1. Introduction

In reasons of the low cost, masses reduced, robustness and simple construction, the induction motor applications are diversified more and more. It proves to be useful to combine several techniques for, on the one hand, overcoming the problems arising from its dynamics (which is strongly non-linear with variable parameters) [1]-[2]-[3]. In addition, to find new controls allowing more control of its behavior.

The use of the classical control techniques such as the field oriented control [3]-[4] and the feedback linearisation control (FLC) [5]-[6]-[7]-[8]-[9] showed their insufficiency with the parameters variation and states uncertainties. In this case, the use of the classical adaptive rules [10]-[11]-[12]-[13] is limited by the difficulty of the on-line identification of parameters, the complexity of the control rules and its implementation.

To overcome this restrictions, the artificial neural network (ANN) proprieties (speed, capacity to approximate the nonlinear dynamic, the tolerance of certain uncertainty during operation, etc.) Offer an adequate solution.

In this paper, we try to develop a new control approach for the induction motor using the FLC techniques based on ANN. By principle, obtaining an input control by the FLC requires the precise and exact reconstitution of the necessary non-linear feedback state [15]-[16]. With the inaccuracy of the induction motor model, the uncertainty in state variables and the parameter variation, an exact reconstitution becomes difficult. To solve this problem, we propose an adaptive control scheme based on ANN trained on-line to reconstitute these feedback states. Indeed, the use of such ANN to control some nonlinear systems [17]-[18]-[19]-[20]-[21]-[22]-[23] permitted to obtain satisfactory performances. To do, a combination between the FLC technique, the non-linear adaptive control and the ANN properties permitted to extract non-linear adaptation rules allowing the ANN an autonomous training. To this end, the tracking errors (observed on rotor speed and rotor flux) are transformed via the proposed adaptation rules into a means to adjust, on-line, the ANN behaviors so that they can adapt with the various operation modes of the induction motor.

2. FLC of the induction motor.

Based on the results provided in [10], by choosing like outputs for the induction motor the variables:

$$\begin{cases} \zeta_1(X) = \Phi_r^2 = \Phi_{dr}^2 + \Phi_{qr}^2 \\ \zeta_1(X) = \Omega_r \end{cases} \quad (1)$$

By applying feedback linearisation principle [15] to the induction motor model following the chosen outputs, the induction motor dynamics is given by:

$$\begin{cases} \dot{z}_1 = z_2 \\ \dot{z}_2 = f_1(X) + G_{11}(X)V_{ds} + G_{12}(X)V_{qs} \\ \dot{z}_3 = z_4 \\ \dot{z}_4 = f_2(X) + G_{21}(X)V_{ds} + G_{22}(X)V_{qs} \end{cases} \quad (2)$$

Where $Z=[z_1 \; z_2 \; z_3 \; z_4]^T$ and $X=[I_{ds} \; I_{qs} \; \Theta_{dr} \; \Theta_{qr} \; \Omega_r]^T$ are the new and the initial states vector and:

$$\begin{cases} G_{11}(X) = \dfrac{2\alpha M}{\sigma L_s}\Phi_{dr} \\ G_{12}(X) = \dfrac{2\alpha M}{\sigma L_s}\Phi_{qr} \\ f_1(X) = \left(4\alpha^2 + 2\alpha^2\beta M\right)\left(\Phi_{dr}^2 + \Phi_{qr}^2\right) \\ \quad + 2\alpha M n p \Omega_r \left(\Phi_{dr} I_{qs} - \Phi_{qr} I_{ds}\right) \\ \quad - \left(6\alpha^2 M + 2\alpha\gamma M\right)\left(\Phi_{dr} I_{ds} + \Phi_{qr} I_{qs}\right) \\ \quad + 2\alpha^2 M^2 \left(I_{ds}^2 + I_{qs}^2\right) \end{cases} \quad (3)$$

$$
\begin{cases}
G_{21}(X) = -\dfrac{\mu}{\sigma L_s}\Phi_{qr} \\
G_{22}(X) = -\dfrac{\mu}{\sigma L_s}\Phi_{dr} \\
f_2(X) = -\mu\beta np\Omega_r\left(\Phi_{dr}^2+\Phi_{qr}^2\right) \\
\qquad -\mu(\alpha+\gamma)\left(\Phi_{dr}I_{qs}-\Phi_{qr}I_{ds}\right) \\
\qquad -\mu np\Omega_r\left(\Phi_{dr}I_{ds}+\Phi_{qr}I_{qs}\right)
\end{cases}
\tag{4}
$$

If Ω_{ref} and Φ_{ref}^2 are the tracked outputs for speed and flux respectively. Using a feedback state [15]-[16], the input control V_{ds} and Vqs are obtained by:

$$
\begin{bmatrix} Vds \\ Vqs \end{bmatrix} = \left[G(X)\right]^{-1}\begin{bmatrix} -f_1(X)+v_1 \\ -f_2(X)+v_2 \end{bmatrix}
\tag{5}
$$

With:

$$
G(X)=\begin{bmatrix} G_{11}(X) & G_{12}(X) \\ G_{21}(X) & G_{22}(X) \end{bmatrix}
\tag{6}
$$

$$
\begin{cases}
v_1 = \ddot{\Phi}_{ref} - \left[K_{f1}\left(\left|\Phi_r\right|^2-\Phi_{ref}^2\right)+K_{f2}\dfrac{d}{dt}\left(\left|\Phi_r\right|^2-\Phi_{ref}^2\right)\right] \\
v_2 = \ddot{\Omega}_{ref} - \left[K_{v1}\left(\Omega_r-\Omega_{ref}\right)+K_{v2}\dfrac{d}{dt}\left(\Omega_r-\Omega_{ref}\right)\right]
\end{cases}
\tag{7}
$$

The choice of the control parameters K_{fi} and K_{VI} is carried out by ensuring the asymptotic stability of the system (2).

3. FLC based on ANN of the induction motor

The evaluation of the previous control laws requires the exact reconstitution of the nonlinear term's f_1 and f_2. To do this, we propose to use two ANN trained on-line. Indeed, the use of such networks, to control some nonlinear systems [17]-[18]-[19]-[20]-[21]-[22]-[23] permitted to obtain satisfactory performances. In this paper, we try to formulate version of this technique for the control of induction motor.

To this end, to reconstitute the non-linear functions f_1 and f_2, we suppose two ANN, *Net1* and *Net2*, of three layers. If there exist an ideal parameters for these ANN such that they can exactly approximate the exact values of f_1 and f_2, these last are expressed by:

$$
\begin{aligned}
f_1(X_1) &= W_1^T f_{a1}(W_{c1}^T X_1) \\
f_2(X_2) &= W_2^T f_{a2}(W_{c2}^T X_2)
\end{aligned}
\tag{8}
$$

With W_i and W_{ci} are the ANN ideal weights matrix, f_{ai} is a sigmoid activation function for the hidden layer, X_i ($X_1 = [z_1 \quad z_2]$) and ($X_2 = [z_3 \quad z_4]$) are the input vectors for *Net1* and *Net2* respectively. Supposing also two matrix Θ_1 et Θ_2 such that:

$$
\begin{cases}
\Theta_1 = \begin{bmatrix} W_{c1} & 0 \\ 0 & W_1 \end{bmatrix} \\
\Theta_2 = \begin{bmatrix} W_{c2} & 0 \\ 0 & W_2 \end{bmatrix}
\end{cases}
\tag{9}
$$

With

$$
\begin{cases}
\left\|\Theta_1\right\| \le \Theta_{max\,1} \\
\left\|\Theta_2\right\| \le \Theta_{max\,2}
\end{cases}
\tag{10}
$$

If $\hat{f}_1$ and $\hat{f}_2$ are the estimates of the function f_1 and f_2 by the two ANN where:

$$
\begin{aligned}
\hat{f}_1(X_1) &= \hat{W}_1^T f_{a1}(\hat{W}_{c1}^T X_1) \\
\hat{f}_2(X_2) &= \hat{W}_2^T f_{a2}(\hat{W}_{c2}^T X_2)
\end{aligned}
\tag{11}
$$

Where: $\hat{W}_1$, $\hat{W}_{c1}$, $\hat{W}_2$ and $\hat{W}_{c2}$ are the estimated parameters for the two ANN.

Considering the tracking error victors e_{p1} and e_{p2} and the filtered error victors e_{r1} and e_{r2} for the two supposed outputs which are given bay:

$$
\begin{bmatrix} e_{p1} \\ e_{p2} \end{bmatrix} = \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix} = \begin{bmatrix} z_1 - \Phi_{ref}^2 & z_2 - \dot{\Phi}_{ref}^2 \\ z_3 - \Omega_{ref} & z_4 - \dot{\Omega}_{ref} \end{bmatrix}
\tag{12}
$$

And

$$
\begin{aligned}
e_{r1} &= \Lambda_1^T e_{p1} \\
e_{r2} &= \Lambda_2^T e_{p2}
\end{aligned}
\tag{13}
$$

With: $\ddot{\mathrm{E}}_1 = [K_{f1} \quad K_{f2}]$ and $\ddot{\mathrm{E}}_2 = [K_{v1} \quad K_{v2}]$, where K_{fi} and K_{vi} are chose so that the system (12) is Hurwitz [15]-[16]. The filtered error dynamics are expressed (using (4)) as:

$$
\begin{aligned}
\dot{e}_{r1} &= f_1(X) + G_{11}(X)Vds + G_{12}(X)Vqs - \ddot{\Phi}_{ref} + K_{f1}e_{12} \\
\dot{e}_{r2} &= f_2(X) + G_{21}(X)Vds + G_{22}(X)Vqs - \ddot{\Omega}_{ref} + K_{v1}e_{22}
\end{aligned}
\tag{14}
$$

Considering the filtered error dynamics (14), and the estimate values $\hat{f}_1$ and $\hat{f}_2$, the control laws (5) become:

$$\begin{bmatrix} V_{ds} \\ V_{qs} \end{bmatrix} = [G(X)]^{-1} \begin{bmatrix} -\hat{f}_1(X) + \ddot{\Phi}^2_{ref} - v_{r1} \\ -\hat{f}_2(X) + \dot{\Omega}_{ref} - v_{r2} \end{bmatrix} \quad (15)$$

With:

$$\begin{aligned} v_{r1} &= K_F e_{r1} - \dot{\Phi}_r + K_{f1} e_{12} \\ v_{r2} &= K_V e_{r2} - \dot{\Omega}_r + K_{v1} e_{22} \end{aligned} \quad (16)$$

Where K_F and K_V are positive constants represent the new control parameters which are selected ensuring the asymptotic stability of the filtered error dynamics (14)

If we add and subtract v_{r1} and v_{r2} in (14), while using (5) and (15) we obtain:

$$\begin{aligned} \dot{e}_{r1} &= -K_F e_{r1} + \left(f_1 - \hat{f}_1 \right) \\ \dot{e}_{r2} &= -K_V e_{r2} + \left(f_2 - \hat{f}_2 \right) \end{aligned} \quad (17)$$

The estimation error for the two ANN *Nte1* and *Nte1* are given by:

$$\begin{aligned} \tilde{f}_1 &= \hat{f}_1 - f_1 = \hat{W}_1^T f_{a1}(\hat{W}_{c1}^T X_1) - W_1^T f_{a1}(W_{c1}^T X_1) \\ \tilde{f}_2 &= \hat{f}_2 - f_2 = \hat{W}_2^T f_{a2}(\hat{W}_{c2}^T X_2) - W_2^T f_{a2}(W_{c2}^T X_2) \end{aligned}$$

Using the Taylor development of the terms $f_{a1}(W_{c1}^T X_1)$ and $f_{a2}(W_{c2}^T X_2)$ around $\hat{W}_{c1}^T X_1$ and $\hat{W}_{c2}^T X_2$, the filtered error dynamic becomes:

$$\begin{aligned} \dot{e}_{r1} &= -K_F e_{r1} + \tilde{W}_1^T \left\{ \hat{f}_{a1} - \hat{F}'_{a1} \hat{W}_{c1}^T X_1 \right\} + \hat{W}_1^T \hat{F}'_{a1} \tilde{W}_{c1}^T X_1 + d_1 \\ \dot{e}_{r2} &= -K_V e_{r2} + \tilde{W}_2^T \left\{ \hat{f}_{a2} - \hat{F}'_{a2} \hat{W}_{c2}^T X_2 \right\} + \hat{W}_2^T \hat{F}'_{a2} \tilde{W}_{c2}^T X_2 + d_2 \end{aligned} \quad (18)$$

With:

$$\begin{aligned} d_1 &= \tilde{W}_1 \hat{F}'_{a1} W_{c1}^T X + O(\hat{W}_{c1}^T X_1)^2 \le \|W_{c1}\| \cdot \|X_1 \hat{W}_1^T \hat{F}'_{a1}\| + \|W_{c1}\| \cdot \|X_1 \hat{W}_1^T \hat{F}'_{a1}\| + |W_1| \\ d_2 &= \tilde{W}_2 \hat{F}'_{a2} W_{c2}^T X + O(\hat{W}_{c2}^T X_2)^2 \le \|W_{c2}\| \cdot \|X_2 \hat{W}_2^T \hat{F}'_{a2}\| + \|W_{c2}\| \cdot \|X_2 \hat{W}_2^T \hat{F}'_{a2}\| + |W_2| \\ \hat{F}'_{a1} &= diag\{ f'_{a1,1} \; \cdots \; f'_{a1,N_{c1}} \} \\ \hat{F}'_{a2} &= diag\{ f'_{a2,1} \; \cdots \; f'_{a2,N_{c2}} \} \end{aligned}$$

Where N_{c1} and N_{c2} are the numbers of neurons in hidden layers of Net1 and *Net2* respectively. The derivative between brackets are given by:

$$f'_{aj,i} = \frac{df_{ai}(P_{j,i})}{dP_{j,i}}$$

With $P_{j,i}$ represents the i neuron input of the hidden layer for the *Netj* network

According to the filtered error dynamics, the tracking error became depending of the deviation in the used ANN parameters. The approximation problem becomes, therefore, a problem of parameter adjustment to guarantee the asymptotic stability of the filtered error. To this end, the application of the " *e1-modification* " rule developed by K.S.Narendra and A.M.Annaswamy [24] makes it possible to obtain the following adaptation rules:

For *Net1*:

$$\begin{aligned} \frac{d\tilde{W}_1}{dt} &= -\Gamma_{w1} \left\{ (\hat{f}_{a1} - \hat{F}'_{a1} \hat{W}_{c1}^T X_1) e_{r1} + \delta_f |e_{r1}| \hat{W}_1 \right\} \\ \frac{d\tilde{W}_{c1}}{dt} &= -\Gamma_{wc1} \left\{ X_1 \hat{W}_1^T \hat{F}'_{a1} e_{r1} + \delta_f |e_{r1}| \hat{W}_{c1} \right\} \end{aligned} \quad (19)$$

For *Net2*:

$$\begin{aligned} \frac{d\tilde{W}_2}{dt} &= -\Gamma_{w2} \left\{ (\hat{f}_{a2} - \hat{F}'_{a2} \hat{W}_{c2}^T X_2) e_{r2} + \delta_v |e_{r2}| \hat{W}_2 \right\} \\ \frac{d\tilde{W}_{c2}}{dt} &= -\Gamma_{wc2} \left\{ X_2 \hat{W}_2^T \hat{F}'_{a2} e_{r2} + \delta_v |e_{r2}| \hat{W}_{c2} \right\} \end{aligned} \quad (20)$$

With:

Γ_i and Γ_{ci} : Are positive definite symmetrical matrices.
δ_f and δ_v : Are positive constants use to improve the adaptation rules convergence.

Figure (1) shows the proposed control scheme.

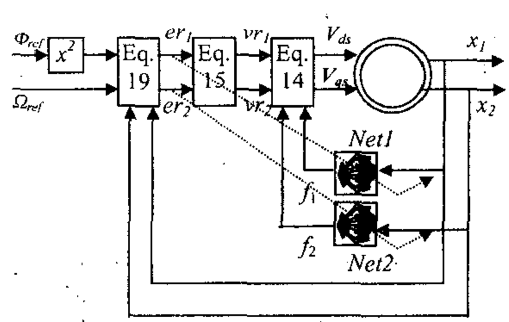

Figure 1: the ANN proposed scheme for the induction motor control.

To check the stability of these rules, the Lyapunov theories [25]-[26] provide a powerful tool. Considering, therefore, the two Lyapunov functions which correspond to *Net1* and *Net2* respectively :

$$V_1 = \frac{1}{2}\left\{ e_{r1}^2 + \tilde{W}_1^T \Gamma_1^{-1} \tilde{W}_1 + tr\left(\tilde{W}_{c1}^T \Gamma_{wc1}^{-1} \tilde{W}_{c1} \right) \right\} \quad (21)$$

$$V_2 = \frac{1}{2}\left\{e_{r2}^2 + \tilde{W}_2^T \Gamma_2^{-1} \tilde{W}_2 + tr\left(\tilde{W}_{c2}^T \Gamma_{wc2}^{-1} \tilde{W}_{c2}\right)\right\} \quad (22)$$

The evaluation of its derivatives makes it possible to obtain :

$$\dot{V}_1 \leq -\left(C_F \cdot e_{r1}^2 - \frac{1}{2} d_1^2\right) - \delta_1 e_{r1}^2 \left(\tilde{\Theta}_1 - \frac{\Theta_{Max1}}{2}\right)^2 \quad (23)$$

With:

$$C_F = \frac{4K_F - \delta_1 \Theta_{Max1}^2 - 2}{4}$$

$$\dot{V}_2 \leq -\left(C_V e_{r2}^2 - \frac{1}{2} d_2^2\right) - \delta_2 e_{r2}^2 \left(\tilde{\Theta}_2 - \frac{\Theta_{Max2}}{2}\right)^2 \quad (24)$$

With:

$$C_V = \frac{4K_V - \delta_2 \Theta_{Max2}^2 - 2}{4}$$

If the choice of K_F and K_V are such that :

$$K_F \leq \frac{\delta_1 \Theta_{Max1}^2 + 2}{4} \quad (25)$$

$$K_V \leq \frac{\delta_2 \Theta_{Max2}^2 + 2}{4}. \quad (26)$$

We will thus have:

$$C_F \leq 0$$
$$C_V \leq 0 \quad (27)$$

Therefore:

$$\dot{V}_1 \leq 0 \Rightarrow e_{r1}^2 \leq \frac{d_1^2}{2C_F}$$

$$\dot{V}_2 \leq 0 \Rightarrow e_{r2}^2 \leq \frac{d_2^2}{2C_V} \quad (28)$$

If D_1 and D_2 are two subsets defined as :

$$D_1 = \left\{ e_{r1} : \left|e_{r1}\right| \leq \frac{d_1}{\sqrt{2C_F}} \right\}$$

$$D_2 = \left\{ e_{r2} : \left|e_{r2}\right| \leq \frac{d_2}{\sqrt{2C_V}} \right\} \quad (29)$$

For both V_1 and V2, we deduce, according to the Krasovskii-LaSalle theorem that the dynamic (18), (19) and (20) are uniformly asymptotically stable [25]-[26].

4. Analyze and interpretation of the results :

The results represented on the figures (2,3,4,5) show that the variation of rotor and stator resistances, with load, causes some reduction in speed and torque. However, the block control, while acting on input control, allowed a fast compensation of these reduction. The figures (6,7) show the *Net1* and *Net2* parameters evolution. We notes clearly the capacity of the adaptation rules which allow the ANNs to adapt quickly and on-line with the rotor and stator resistance variations. In addition, the rotor flux dynamic is not affected by these variations. For the parameters of the used induction motor, see [10].

5. Conclusion

The obtained results permitted to conclude that the use of the proposed ANN for the induction motor control guarantees an adaptive and robust control. The adaptation rules offer to the two ANN the capacity of adapting with the various induction motor operation modes. In addition, these rules allow a fast compensation of the rotor and stator resistances without using any identification. tool

References

[1] P.C.Krause " Analysis of Electric Machinery ", Edition McGraw-Hill, New York, 1986.

[2] W.Leonhard " Control of Electrical Drives ", Edition Springer-Verlag, 1996

[3] J.P.Caron And J.P.Hautier " Modélisation et Commande de la Machine Asynchrone ", Edition Technip–Paris, 1995.

[4] F.Blaschke " The Principle of Field Orientation as Applied to the New Trans-vector Closed-Loop Control System for Rotating-Field Machines. ", Siemens Review, XXXIX, No. 5, 1972.

[5] A.De-Luca And G.Ulivi " Full Linearization of Induction Motors Via Nonlinear State-Feedback ", in Proc. 26th Conf. Decision and Control, Los Angeles, CA, December 1987.

[6] A.De-Luca And G.Ulivi " Design of an Exact Nonlinear Controller for Induction Motors", IEEE Trans. On Automatic Control, Vol. 34, No. 12, December 1989.

[7] A.De-Luca And G.Ulivi " The Design Linearizing Output for Induction Motors ", In Proc. 1st IFAC Symp. Nonlinear Control Systems Design (NOLCOS'89), Capri, Italy 1989.

[8] J.Chaisson " Dynamic Feedback Linearization of Induction Motors ", IEEE Trans. On Automatic Control, Vol. 38, No. 10, October 1993.

[9] J.Chaisson " A New Approach to Dynamic Feedback Linearization Control of Induction Motors ", IEEE Trans. On Automatic Control, Vol. 43, No. 3, March 1993.

[10] R.Marino, S.Peresada And P.Valigi " Adaptive Input-Output Linearizing Control of Induction Motors ", IEEE Trans. On Automatic Control, Vol. 38, No. 2, February 1993.

[11] R.Marino, S.Peresada And P.Tomei " Adaptive Output Feedback Control of Current-Fed Induction

Motors With Uncertain Rotor Resistance and Load Torque ", Automatica, Vol. 34, No. 5, 1998.
[12] R.Marino, S.Peresada And P.Tomei " Global Adaptive Output Feedback Control of Induction Motors With Uncertain Rotor Resistance ", IEEE Trans. On Automatic Control, Vol. 44, No. 5, May 1999.
[13] S.Peresada, A.Tonielli And R.Morici " high-performance Indirect Field-Oriented Output-Feedback Control of Induction Motors ", Automatica Vol. 35, 1999.
[14] B.Chetate And N.Kabache " Commande vectorielle d'un moteur asynchrone par application de la technique des réseaux de neurones artificiels ", Proceeding of International Symposium on Hydrocarbons and Chemistry, Boumerdes, Algeria, 2000;
[15] A.Isidori " Nonlinear Control Systems " 2nd ed. Springer-Verlag, New York 1989
[16] R.Marino And P.Tomei " Global Adaptive Output-Feedback Control of Nonlinear Systems, Part I: Linear Parameterization ", IEEE Trans. On Automatic Control, Vol. 38, No. 1, January 1993.
[17] F.C.Chen And C.C.Liu " Adaptively Controlling Nonlinear Continuous-Time Systems Using Multi-layer Neural Networks ", IEEE Trans. On Automatic Control, Vol. 39, No. 6, June 1994.
[18] A.Yasildirek And F.L.Lewis " Feedback Linearization Using Neural Networks ", Automatica, Vol. 31, No. 11, 1995.
[19] T.Zhang, S.S.Ge And C.C.Hang " Design and Performance Analysis of a Direct Adaptive Controller for Nonlinear Systems ", Automatica, Vol. 35, 1999.
[20] S.Jagannathan And F.L.Lewis " Discrete-Time Neural Net Controller for a Class of Nonlinear Dynamical Systems ", IEEE Trans. On Automatic Control, Vol. 41, No. 11, November 1996.
[21] F.C.Chen And H.Khalil " Adaptive Control of a Class of Nonlinear Discrete-Time Systems Using Neural Networks ", IEEE Trans. On Automatic Control, Vol. 40, No. 5, 1995.
[22] S.Jagannathan " Adaptive Fuzzy Logic Control of Feedback Linearizale Discrete-Time Dynamical Systems Under Persistence of Excitation ", Automatica, Vol. 34, No. 11, 1998.
[23] K.S.Narendra And K.Parthasarathy " Identification and Control of Dynamical Systems Using Neural Network ", IEEE Trans. On Neural Network, Vol. 1, No. 1, 1990.
[24] K.S.Narendra And A.M.Annaswamy " A New Adaptive Law for Robust Adaptation Without Persistent Excitation ", IEEE Trans. On Automatic Control, Vol. AC-32, No. 2, February 1987.
[25] M.Coriess And G.Leitmann " Deterministic Control of Uncertain Systems: A Lyapunov Theory Approach ", Deterministic Control of Uncertain Systems, Edited by A.S.I.Zinoer, 1990.
[26] M.Vidyasagar " Nonlinear Systems Analysis ", Ed. Prentice-Hall, 1978.

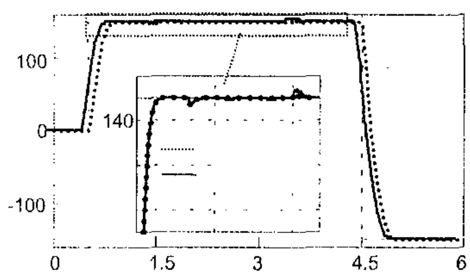

Figure 2: Evolution of rotor speed with variation of rotor resistance.

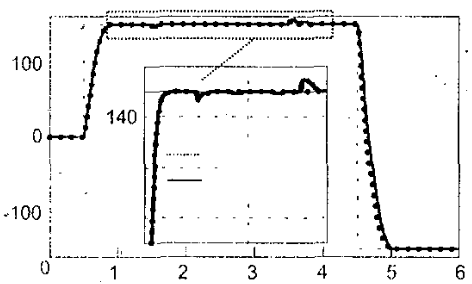

Figure 3: Evolution of rotor speed with variation of stator resistance.

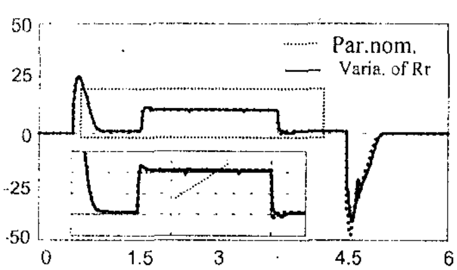

Figure 4: Evolution of torque with variation of rotor resistance.

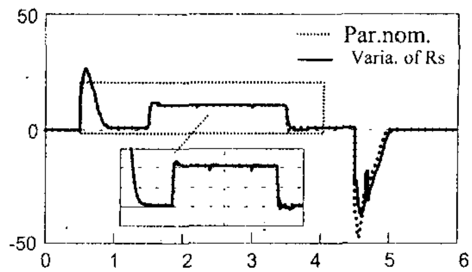

Figure 5: Evolution of torque with variation of stator resistance.

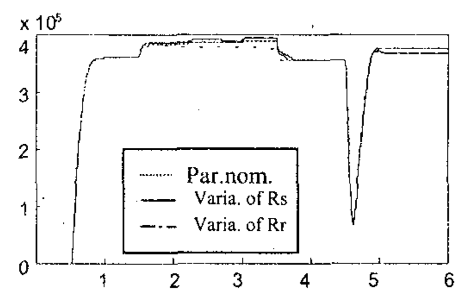

Figure 6: Evolution of $|\Theta_1|$ with variation of rotor resistance.

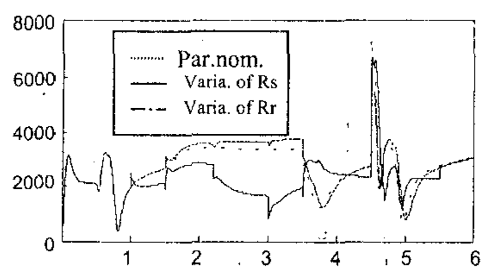

Figure 7: Evolution of $|\Theta_2|$ with variation of stator resistance