

Neural Network Observer for Nonlinear Systems Application to Induction Motors

A. N. Lakhal, A. S. Tlili, and N. Benhadj Braiek

*Laboratoire d'Etude et Commande Automatique de Processus (LECAP)
Ecole Polytechnique de Tunisie, B.P. 743, 2078, La Marsa, Tunisie
Asma.Lakhal@fsb.rnu.tn ; ali.tlili@ept.rnu.tn ; naceur.benhadj@ept.rnu.tn*

Abstract

In this paper, we investigate the problem of Neural Network (NN) observer for nonlinear systems. Therefore, it can be applied to systems with higher degree of nonlinearity with any a priori knowledge about system dynamics.

The proposed neuro-observer is a three-layer feedforward neural network, which is trained extensively with the error backpropagation learning algorithm including a correction term to guarantee good tracking as well as bounded NN weights. Furthermore, the Lyapunov's direct method is used in order to ensuring the stability of the proposed non-conventional observer and of the NN weight errors.

The effectiveness of the proposed state observer scheme is demonstrated through numerical simulation to reconstruct the unavailable state variables of an induction motor (IM) and especially the rotor flux despite the effect of the arisen parameters such as the load torque which is also reconstructed using the NN observer.

Keywords: Artificial neural network, Nonlinear observer, Backpropagation algorithm, Stability analysis, Lyapunov method, Induction motor.

1. Introduction

The state observation problem has been widely developed in the literature, and used in numerous applications. However in most cases, the state variables are rarely available for direct online measurements. Furthermore, there is a substantial requirement for reliable reconstruction of the state variables, especially when they are required in the synthesis of control and observation laws or for process monitoring purposes [1], [2], [3].

However, in most realistic cases merely input and output of the system are measurable. Therefore, estimating the state variables by observers plays a crucial role in the control of processes to achieve better performances [4], [5].

On the other hand, several conventional nonlinear observers have been suggested during the past decades, such as high-gain observers, sliding mode observers and others [6], [7], [8], however these conventional methods are relatively complex and are applicable to systems with knowledge of model structure. Whereas the use of non conventional techniques as neural networks in many scientific disciplines mainly in identification and control of dynamical systems has been widespread [9], [10], [11]. However, the application of the neural networks in the state observation remained an over problem.

Moreover, neural network techniques have showing a good promise as competitive methods for signal processing, power systems and other applications [12], [13], [14]. Indeed, these

performances are due to their capacity for approximating a wide range of nonlinear functions [15], [16].

It is noted that most practical systems are nonlinear and it is difficult to design a performant controller or observer. So far, the linearisation techniques can be used to overcome these problems. However, this linearisation can limit enormously the performances of such approaches of control and observation. In this case, the use of neural networks permits to approximate suitably the nonlinear functions and then to bypass the linearisation problem.

In order to guarantee stability, robustness and good performances, several schemes based on the Lyapunov stability theory have been proposed in the literature. In [17], a neural net controller is derived using a filtered error passivity approach leading to new NN passivity properties. Via the Lyapunov theory, the stability of the neural net controller is guaranteed by using a tuning algorithm including a correction term to backpropagation. This correction term is used to relaxing the persistence of excitation (PE) condition, which is required to guarantee boundedness of the weight estimates. In [18], specific bounds are determined, and the tracking error bound can be made arbitrarily small by increasing a certain feedback gain. The correction terms involve a second-order forward-propagated wave in the backpropagation network. In order to tackle more general nonlinear systems, [19] extend the previous result. Indeed, two linearly parameterised neural networks are used to capture the unknown dynamic of the system, where their weights are adjusted via robust adaptation laws in order to guarantee the stability of the overall scheme. In [14], a neural network multimodel identification using radial basis function is presented. It is considered one tuneable layer neural network. To provide the convergence of the parameters of the identifier to the ideal parameters, persistency of excitation condition is developed. In [17], it is proposed a stable neural network based observer for general multivariable nonlinear systems using a backpropagation algorithm with a modification term.

In our paper, we present the development of a multi-layer feedforward neural network observer for nonlinear systems. The NN, adopting a sigmoid activation function, is used to parameterize the nonlinearities of the system. This NN observer is trained with the error backpropagation algorithm.

To guarantee the stability of the designed NN observer, several forms of weight tuning equations have been considered in the literature. In this paper, we succeed to obtain less complex conditions of the NN observer stability by selecting suitable weight tuning equations. Furthermore, a good choice of a sigmoidal activation function has been carried out. Notice that there are many different activation functions used in literature, see for instance [15], [16] and the issue of selecting of these functions is a current topic of research.

The proposed neural network state observer is applied to the rotor flux reconstruction of an inductor motor. In fact, the induction motor is a nonlinear and complex system, which makes difficult the design and implementation of efficient control and observation laws [3], [20]. Moreover, the state variable is not always available and especially the rotor flux [20], [21]. Therefore, the control of induction motors, requiring high dynamic performance, is based on the accurate knowledge of rotor flux.

An outline of this paper is as follows. The architecture of the feedforward neural network is presented in section 2. The section 3 is devoted to developing the neural network observer. The stability of the proposed non conventional observer is studied in section 4. Then, section 5 is concerned with the application of the proposed neural network observer to the rotor flux reconstruction of an induction motor. Finally, some conclusions are provided in section 6.

2. Artificial neural network architecture

The architecture of a NN is determined by its topological structure, i.e., the overall connectivity and transfer function of each node in the network.

A typical three layer feedforward NN is given in figure 1. It consists of an input layer, hidden layer and output layer. Each input is connected via a weight to each node in the hidden layer. Each hidden node is, in turn, connected via a weight to each node in the output layer.

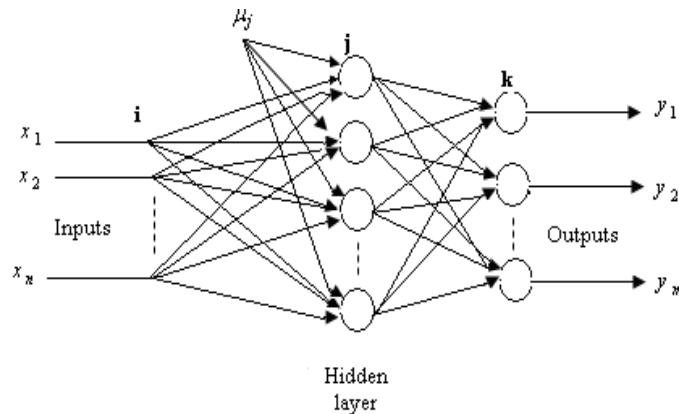


Figure 1. A three layer feedforward ANN

The output of hidden node j is given by

$$a_j = \sigma(z_j)$$

with

$$z_j = \sum_i v_{ji} x_i + \mu_j$$

where

v_{ji} is the weight between the i^{th} input and the j^{th} hidden node;

x_i represents the input of the ANN;

μ_j is a threshold of node j ;

$\sigma(\cdot)$ depicts the activation function of the hidden nodes that is considered as a sigmoidal function. Indeed, we can find many forms of this function. But, for us we propose this form to simplify the development concerning the stability study.

$$\sigma(z_j) = \frac{1}{1 + \exp^{-z_j}}$$

The output of output node m is a weighted sum of its inputs, that is

$$y_k = \sum_j w_{kj} a_j$$

where w_{kj} is the weight between the j^{th} hidden and the k^{th} output node.

The NN equation may be conveniently expressed in matrix format by defining $x^T = [x_1, x_2, \dots, x_n]$, $y^T = [y_1, y_2, \dots, y_m]$, and weight matrices $W^T = [w_{kj}]$, $V^T = [v_{ji}]$. The threshold vector $\mu = [\mu_1, \mu_2, \dots, \mu_s]$ can be included as the first column of V^T , so that V^T contains both the weights and thresholds of the first to second layer connections. Then

$$y = W^T \sigma(V^T x)$$

However, several algorithms of multilayer neural networks training have been proposed in the literature of which most popular is the error backpropagation algorithm used extensively in NN applications [12].

The training is considered as a problem of optimization of a nonlinear function able to present the local minima and a global minimum. Indeed, it comprises of changing weights and thresholds so as to minimize the mean squared error between the actual outputs and the desired outputs in a gradient descent manner [10].

3. Neural network observer of nonlinear systems

In this section, the proposed neuro-observer structure and the observing error equations are described. Indeed, a feedforward neural network is used to replace the nonlinear function that has known structure and unknown weights.

Consider the nonlinear system

$$\begin{cases} \dot{x}(t) = Ax + g(x, u) \\ y(t) = Cx(t) \end{cases} \quad (1)$$

where

$x(t) \in \mathbb{R}^n$ is the state vector ;

$u(t) \in \mathbb{R}^{m_u}$ is the input vector ;

$y(t) \in \mathbb{R}^{m_y}$ is the output vector ;

$g(x, u)$ is an unknown nonlinear function;

A is a Hurwitz matrix;

The pair (A, C) is observable.

A state observer for (1) can be described by

$$\begin{cases} \dot{\hat{x}}(t) = A\hat{x} + \hat{g}(\hat{x}, u) + L(y - \hat{y}) \\ \hat{y}(t) = C\hat{x}(t) \end{cases} \quad (2)$$

where \hat{x} , \hat{y} denote respectively the state and the output observer. L is the observer gain selected such that $(A - LC)$ is a Hurwitz matrix.

The key to designing a neuro-observer is to employ a neural network to identify the nonlinearity and a conventional observer to reconstruct the state [22], [19], [23]. The following graphics depicts the structure of the proposed neural network observer.

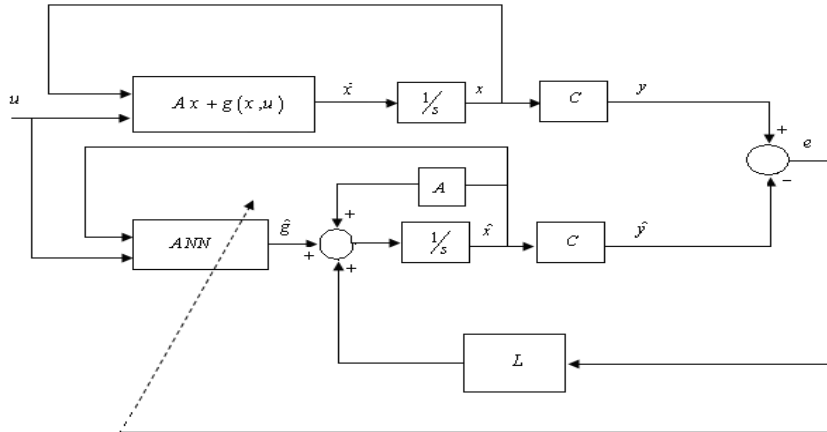


Figure 2. Structure of the designed neural network observer

Furthermore, a NN with one hidden layer is sufficient for identifying and modeling a nonlinear system with any degree of nonlinearity [7], [24].

The main property of the NN used here is the function approximation property [25]. Let $\gamma(x)$ be a smooth function from \mathbb{R}^n to \mathbb{R}^m . Then it can be shown that, as long as x is restricted to a compact set of $x \in \mathbb{R}^n$, for a sufficiently large number of hidden-layer neurons s , there exist weights and thresholds such that any continuous function on a compact set can be represented as follows [14]:

$$\gamma(x) = W \sigma(Vx) + \varepsilon(x) \quad (3)$$

where $\varepsilon(x)$ is the NN approximation error satisfying $\|\varepsilon(x)\| \leq \varepsilon_N$. With ε_N the bounding function known on a compact set S . Moreover, for any positive number ε_N one can find a NN such that $\|\varepsilon(x)\| \leq \varepsilon_N$ for all $x \in S$ [17], [14].

It is assumed that the ideal weights W and V are bounded by known values, so that $\|W\|_F \leq W_M$ and $\|V\|_F \leq V_M$ [17], [26].

According to the approximation property of NN, the smooth nonlinear function $g(x, u)$ in the system (1) can be represented by NN with constant ideal weights W and V as follows:

$$g(x, u) = W \sigma(Vz) + \varepsilon(x)$$

where $z = [x \ u]$.

Thus, the NN functional estimates for $g(x)$ is given by

$$\hat{g}(\hat{x}, u) = \hat{W} \sigma(\hat{V} \hat{z})$$

The proposed observer is then given by

$$\begin{cases} \dot{\hat{x}}(t) = A \hat{x} + \hat{W} \sigma(\hat{V} \hat{z}) + L(y - \hat{y}) \\ \hat{y}(t) = C \hat{x}(t) \end{cases} \quad (4)$$

Defining the state and output estimation error as $e = x - \hat{x}$ and $e_y = y - \hat{y}$ yields the error dynamics as follows:

$$\begin{cases} \dot{e}(t) = Ax + W \sigma(Vz) - A\hat{x} - \hat{W} \sigma(\hat{V} \hat{z}) - L(y - \hat{y}) + \varepsilon(x) \\ e_y(t) = Ce(t) \end{cases} \quad (5)$$

By adding $W \sigma(\hat{V} \hat{z})$ to and subtracting from (5), we can write

$$\begin{cases} \dot{e}(t) = G e + e_W \sigma(\hat{V} \hat{z}) + \xi(t) \\ e_y(t) = C e(t) \end{cases} \quad (6)$$

where

$e_W = W - \hat{W}$, the NN weights estimation error;

$G = A - LC$;

$\xi(t) = W [\sigma(Vz) - \sigma(\hat{V} \hat{z})] + \varepsilon(x)$ is a bounded disturbance term $\|\xi(t)\| \leq \bar{\xi}$ for some positive constant $\bar{\xi}$ due to the boundedness of the sigmoidal function and the ideal weights (V, W) [27].

4. Stability analysis of the neural network observer

To train the network, a proper learning rule is defined in such a way that the stability of the observer is guaranteed. Furthermore, the weights updating mechanism, using standard Lyapunov technique, is based on the error backpropagation algorithm for which are added some correction terms in order to guarantee the stability of the state observer and the NN weights errors.

This task can be realized using the development presented in [7], but with some added modifications in the NN weights tuning. Moreover, the used correction terms are borrowed from [14], which use a radial basis activation function and deal with the control problem.

The modified NN weights tuning, taking in account the modification term, are provided as follows:

$$\dot{\hat{W}} = S e \sigma^T(\hat{V} \hat{z}) - k S \|e\| \hat{W} \quad (7)$$

$$\dot{\hat{V}} = \left(\hat{W} \sigma(\hat{V} \hat{z}) (1 - \sigma(\hat{V} \hat{z})) \right)^T T e \hat{z}^T - k T \|e\| \hat{V} \quad (8)$$

where

- $S = -\eta_1 G^{-T} C^T C$, $S = S^T > 0$;
- $T = -\eta_2 G^{-T} C^T C$, $T = T^T > 0$;
- $\eta_1, \eta_2 > 0$ are the learning rate and k is a small positive number.

The introduction of the matrices S and T in the correction terms permit to simplify the stability study.

The learning rules (7) and (8) in terms of the weight errors $e_W = W - \hat{W}$ and $e_V = V - \hat{V}$ can be written as follows:

$$\dot{e}_W = -S e \sigma^T(\hat{V} \hat{z}) + k S \|e\| \hat{W} \quad (9)$$

$$\dot{e}_V = -\left(\hat{W} \sigma(\hat{V} \hat{z}) (1 - \sigma(\hat{V} \hat{z})) \right)^T T e \hat{z}^T + k T \|e\| \hat{V} \quad (10)$$

Select the positive definite Lyapunov function candidate, used in [7], [6], such as

$$\mathcal{G} = \frac{1}{2} e^T P e + \frac{1}{2} \text{tr} \left(e_W^T S^{-1} e_W \right) + \frac{1}{2} \text{tr} \left(e_V^T T^{-1} e_V \right) \quad (11)$$

with $P = P^T > 0$ satisfying

$$G^T P + P G^T = -Q \quad (12)$$

for some positive-definite matrix Q .

The time derivative of (11) is given by

$$\dot{g} = \frac{1}{2} e^T P e + \frac{1}{2} e^T P \dot{e} + tr(e_w^T S^{-1} \dot{e}_w) + tr(e_v^T T^{-1} \dot{e}_v) \quad (13)$$

By substituting (9), (10) and (12) into (13), it yields

$$\begin{aligned} \dot{g} = & -\frac{1}{2} e^T Q e + e^T P [e_w \sigma(\hat{V}\hat{z}) + \xi] + tr(-e_w^T e \sigma(\hat{V}\hat{z})^T + k e_w^T \|e\| \hat{W}) \\ & + tr(-e_v^T T^{-1} (\hat{W} \sigma(\hat{V}\hat{z})(1 - \sigma(\hat{V}\hat{z})))^T T e \hat{z}^T + k e_v^T \|e\| \hat{V}) \end{aligned} \quad (14)$$

In order to simplify the stability analysis \hat{z} is replaced by $\text{sgn}(\hat{z})$ since $\text{sgn}(\hat{z})$ is bounded but this is not necessarily true for \hat{z} [7]. Where $\text{sgn}(\hat{z})$ is the sign function characterized by

$$\text{sgn}(\hat{z}) = \begin{cases} 1, & \text{for } \hat{z} > 0 \\ 0, & \text{for } \hat{z} = 0 \\ -1, & \text{for } \hat{z} < 0 \end{cases}$$

Hence, the equality (14) becomes

$$\begin{aligned} \dot{g} = & -\frac{1}{2} e^T Q e + e^T P [e_w \sigma(\hat{V}\hat{z}) + \xi] + tr(-e_w^T e \sigma(\hat{V}\hat{z})^T + k e_w^T \|e\| \hat{W}) \\ & + tr(-e_v^T T^{-1} (\hat{W} \sigma(\hat{V}\hat{z})(1 - \sigma(\hat{V}\hat{z})))^T T e \text{sgn}(\hat{z})^T + k e_v^T \|e\| \hat{V}) \end{aligned} \quad (15)$$

In order to demonstrate that (15) is a negative semi definite function, we can rely on the following inequalities cited in [7] and recalled here as

$$\begin{aligned} tr(e_w^T (W - e_w)) & \leq W_M \|e_w\| - \|e_w\|^2 \\ tr(e_v^T (V - e_v)) & \leq V_M \|e_v\| - \|e_v\|^2 \end{aligned} \quad (16)$$

and

$$tr(-e_w^T e \sigma(\hat{V}\hat{z})^T) \leq \sigma_m \|e_w^T\| \|e\| \quad (17)$$

Notice that (17) is obtained since $tr(AB^T) = B^T A$ for two columns vectors A and B .

On the other hand, by using $\sigma_m(1 - \sigma_m) \leq \sigma_m$, $\|\hat{W}\| = \|W - e_w\| \leq W_M + \|e_w\|$ and (17), then the following inequality holds:

$$tr(-e_v^T T^{-1} (\hat{W} \sigma(\hat{V}\hat{z})(1 - \sigma(\hat{V}\hat{z})))^T T e \text{sgn}(\hat{z})^T) \leq \|e_v\| \|T\|^{-1} \sigma_m (W_M + \|e_w\|) \|T\| \|e\| \quad (18)$$

The use of (16), (17) and (18) yields the following inequality:

$$\begin{aligned} \dot{g} \leq & -\frac{1}{2}\lambda_{\min}(Q)\|e\|^2 + \|e\|^T \|P\| (\|e_W\| \sigma_m + \bar{\xi}) + \sigma_m \|e_W\|^T \|e\| + k \|e\| (W_M \|e_W\| - \|e_W\|^2) \\ & + k \|e\| (V_M \|e_V\| - \|e_V\|^2) + \|e_V\|^T \|T^{-1}\| \sigma_m (W_M + \|e_W\|) \|T\| \|e\| \end{aligned} \quad (19)$$

where $\lambda_{\min}(Q)$ denotes the minimum eigen-value of Q .

By defining $2K_1 = \|T\| \|T^{-1}\| \sigma_m$ and by adding and subtracting $K_1^2 \|e_W\|^2 \|e\|$ and $\|e_V\|^2 \|e\|$ to the right hand side of (19), we get

$$\begin{aligned} \dot{g} \leq & -\frac{1}{2}\lambda_{\min}(Q)\|e\|^2 + \|e\| \left[\|P\| \bar{\xi} - \|e_W\|^2 (k - K_1^2) + \|e_W\| (\|P\| \sigma_m + \sigma_m + kW_M) \right. \\ & \left. - \|e_V\|^2 (k - 1) + \|e_V\| (2K_1 W_M + kV_M) - (K_1 \|e_W\| - \|e_V\|)^2 \right] \end{aligned} \quad (20)$$

Defining K_2 and K_3 as

$$K_2 = \frac{\|P\| \sigma_m + \sigma_m + kW_M}{2(k - K_1^2)}$$

$$K_3 = \frac{2K_1 W_M + kV_M}{2(k - 1)}$$

Then, $K_2^2 \|e\|$ and $K_3^2 \|e\|$ are added to and subtracted from (20)

$$\begin{aligned} \dot{g} \leq & -\frac{1}{2}\lambda_{\min}(Q)\|e\|^2 + \|e\| \left[\|P\| \bar{\xi} + (k - K_1^2) K_2^2 + (k - 1) K_3^2 \right. \\ & \left. - (k - K_1^2) (K_2 - \|e_W\|)^2 - (k - 1) (K_3 - \|e_V\|)^2 - (K_1 \|e_W\| - \|e_V\|)^2 \right] \end{aligned} \quad (21)$$

Assuming $k \geq K_1^2$ and $k \geq 1$, then it follows:

$$\begin{cases} -(k - K_1^2) (K_2 - \|e_W\|)^2 \leq 0 \\ -(k - 1) (K_3 - \|e_V\|)^2 \leq 0 \\ -(K_1 \|e_W\| - \|e_V\|)^2 \leq 0 \end{cases}$$

Therefore, (21) becomes

$$\dot{g} \leq -\frac{1}{2}\lambda_{\min}(Q)\|e\|^2 + \|e\| \left[\|P\| \bar{\xi} + (k - K_1^2) K_2^2 + (k - 1) K_3^2 \right] \quad (22)$$

We obtain the following condition on $\|e\|$ to guarantee that \dot{g} is negative semi-definite such that

$$\|e\| > \frac{2 \left[\|P\| \bar{\xi} + (k - K_1^2) K_2^2 + (k - 1) K_3^2 \right]}{\lambda_{\min}(Q)} \quad (23)$$

Thus, according to the standard Lyapunov theorem, we can demonstrate that the observation error e is uniformly ultimately bounded [28].

In order to show the boundedness of the weight errors e_w , the equation (9) is recalled here as follows:

$$\begin{aligned} \dot{e}_w &= -S e \sigma^T(\hat{V} \hat{z}) + k S \|e\| \hat{W} \\ &= -S e \sigma^T(\hat{V} \hat{z}) + k S \|e\| W - k S \|e\| e_w \end{aligned} \quad (24)$$

First, since e , $\sigma(\hat{V} \hat{z})$, C are all bounded and G is a Hurwitz matrix then the term $-S e \sigma^T(\hat{V} \hat{z})$ is bounded. Therefore, (24) is considered as a linear system with bounded input $(-S e \sigma^T(\hat{V} \hat{z}) + k S \|e\| W)$ with the fact that the ideal weight W is fixed. Second, since the quantity $k S \|e\|$ is positive, then the system with bounded input (24) is stable. Hence, the boundedness of e_w is guaranteed.

In the same way, while putting the equation (10) under the following form:

$$\begin{aligned} \dot{e}_v &= -\left(\hat{W} \sigma(\hat{V} \hat{z})(1 - \sigma(\hat{V} \hat{z}))\right)^T \text{Tesgn}(\hat{z})^T + k T \|e\| \hat{V} \\ &= -\left(\hat{W} \sigma(\hat{V} \hat{z})(1 - \sigma(\hat{V} \hat{z}))\right)^T \text{Tesgn}(\hat{z})^T + k T \|e\| V - k T \|e\| e_v \end{aligned} \quad (25)$$

The system (25) represents a stable bounded input linear system since all its arguments are bounded including $\sigma(\cdot)$ and the quantity $k T \|e\|$ is positive. Hence e_v is bounded.

5. Application of the proposed neuro-observer to the rotor flux observation of an induction motor

In this section, we deal with the reconstruction of the rotor flux of an induction motor by using the proposed artificial neural network.

5.1. Induction motor model

The Park's model of an induction motor, considered in the $\alpha - \beta$ frame with the hypothesis of not saturated magnetic circuits, is described by five nonlinear differential equations given by [29], [30] as follows:

$$\begin{cases} \dot{x}(t) = A x + g(x, u, t) \\ y(t) = h(x, t) \end{cases} \quad (26)$$

where

$x = [I_{s\alpha} \ I_{s\beta} \ \Phi_{r\alpha} \ \Phi_{r\beta} \ \omega]^T$ is the state vector composed by two components of the stator current $I_{s\alpha}$ and $I_{s\beta}$, two component of the rotor flux $\Phi_{r\alpha}$ and $\Phi_{r\beta}$ and the rotor speed ω ;
 $u = [V_{s\alpha} \ V_{s\beta}]^T$ is the control vector composed by two components of the stator voltage $v_{s\alpha}$ and $v_{s\beta}$;

$y = [I_{s\alpha} \ I_{s\beta} \ \omega]^T$ is the output vector.

The functions $g(x, u)$, $h(x)$ and the matrix A are given by

$$g(x, u, t) = \begin{bmatrix} \beta \omega \Phi_{r\beta} + \gamma V_{s\alpha} \\ -\beta \omega \Phi_{r\alpha} + \gamma V_{s\beta} \\ \omega \Phi_{r\beta} \\ -\omega \Phi_{r\alpha} \\ -\mu \Phi_{r\beta} I_{s\alpha} + \mu \Phi_{r\alpha} I_{s\beta} - \frac{p}{J} C_r \end{bmatrix}; \quad h(x) = \begin{bmatrix} I_{s\alpha} \\ I_{s\beta} \\ \omega \end{bmatrix}$$

and

$$A = \begin{bmatrix} -\Lambda & \omega_s & \beta\alpha_r & 0 & 0 \\ -\omega_s & -\Lambda & 0 & \beta\alpha_r & 0 \\ M\alpha_r & 0 & -\alpha_r & 0 & 0 \\ 0 & M\alpha_r & 0 & -\alpha_r & 0 \\ 0 & 0 & 0 & 0 & -\alpha_m \end{bmatrix}$$

The different parameters, characterizing the induction motor modeling, are given by

$$\alpha_r = \frac{R_r}{L_r}, \alpha_s = \frac{R_s}{L_s}, \alpha_m = \frac{f}{J}, \beta = \frac{M}{\sigma L_s L_r}, \eta = \frac{1}{\sigma}, \mu = \frac{pM}{JL_r}, \gamma = \frac{1}{\sigma L_s}, \xi = \frac{p}{J}$$

where L_r and L_s are the rotor and stator inductance, M is the mutual inductance, $\sigma = 1 - \frac{M^2}{L_r L_s}$ is the Blondel coefficient, R_r and R_s are the rotor and stator resistances, p is the pair pole number, f is the viscous friction, J is the rotor inertia moment and C_r is the load torque. Notice that the model of the induction motor (26) is strongly nonlinear with unmodeled dynamics and parameter variations.

5.2 Neural Network flux observer of induction motor

The artificial neural network was applied for the state observation of an induction motor characterized by the following numerical parameters [31]:

Parameter of IM	Values
R_r	1 Ω
R_s	1.1 Ω
L_r	156.8 mH
L_s	155.4 mH
p	2
J	0.013 Kgm^2
M	150 mH

To test the robustness of the proposed observation approach, an unknown variable physical parameter, represented by the load torque C_r with the value of $35Nm$, is applied on the nonlinear system in the interval $0.1 \leq t \leq 0.3$.

In this paper, two neural networks are employed: One to estimate the rotor flux and the other to estimate the load torque.

It is to be announced that the two used ANN are a multi-layer feedforward neural network with the error back-propagation learning algorithm and a sigmoidal activation function.

The first one is a three layer neural network where the input layer contains seven neurons, fifteen neurons in the hidden layer and the output layer contain two neurons which represent the two components of the rotor flux $\Phi_{r\alpha}$ and $\Phi_{r\beta}$.

The second one is a four-layer neural network with two hidden layers containing respectively twenty-two and fifteen neurons. The input layer involves five neurons and the output layer contains one neuron which represents the load torque C_r .

The inputs of each network are $I_{s\alpha}$, $I_{s\beta}$, $\hat{\Phi}_{r\alpha}$, $\hat{\Phi}_{r\beta}$, $v_{s\alpha}$, $v_{s\beta}$ and ω as illustrated in figure 1. The input and output layer neurons use linear activation functions and the hidden layer neurons have a sigmoidal transfer functions.

The initial weights of the network are selected as small random numbers.

The curves of the figure 2, 3 and 4 present the evolution of the actual rotor flux ($\Phi_{r\alpha}$, $\Phi_{r\beta}$), the actual load torque C_r , the rotor flux ($\hat{\Phi}_{r\alpha}$, $\hat{\Phi}_{r\beta}$) and the load torque \hat{C}_r obtained by using the neural network estimator.

As can be observed, despite nonlinearity and complexity of the induction motor model and the effect of the load torque considered as an external disturbance, the proposed neural network estimator is able to reconstruct accurately the rotor flux of the studied process. Besides robustness with respect to parameter variation, the proposed NN observer allows also the reconstruction of the load torque which is practically difficult to measure.

Notice that, the network of neurons is capable of high speed nonlinear computation due to its parallel structure [10]. Hence, ANN's are a self learning means of emulating the input/output relationships of very nonlinear systems. Thereby, the ANN state observation presents high performances to reconstruct the induction machine unavailable state variables and in particular the rotor flux.

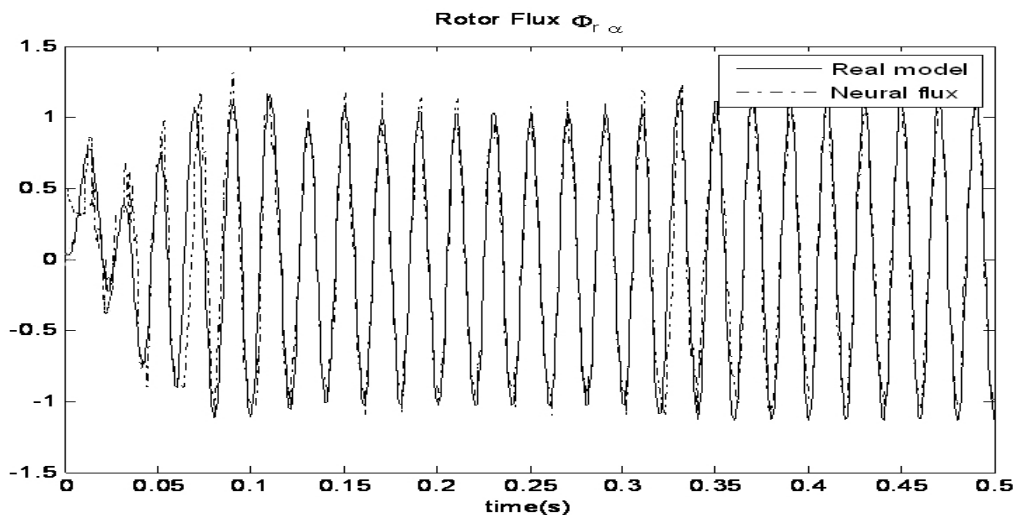


Figure 2. Evolution of the real state $\Phi_{r\alpha}$ and the neural flux observer $\hat{\Phi}_{r\alpha}$

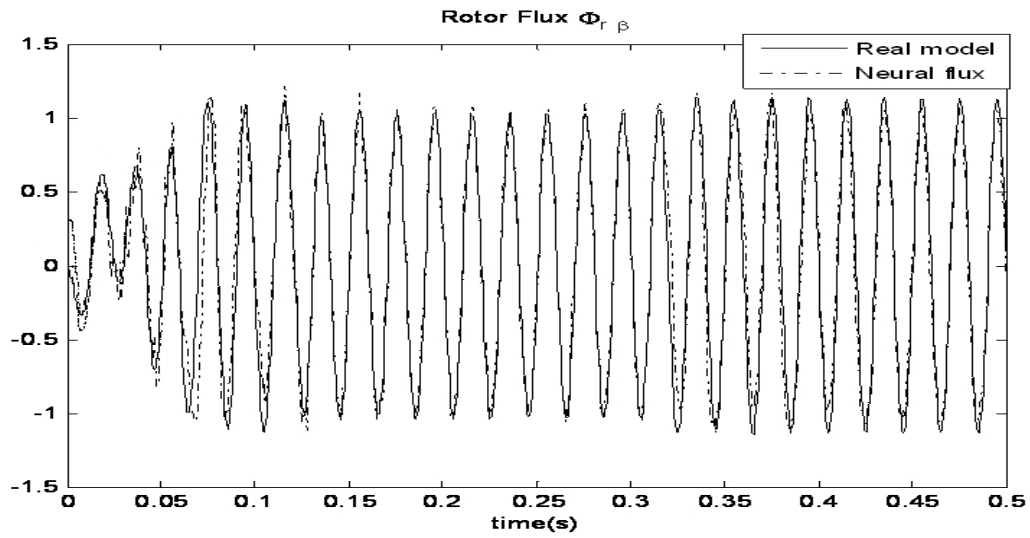


Figure 3. Evolution of the real state $\Phi_{r\beta}$ and the neural flux observer $\hat{\Phi}_{r\beta}$

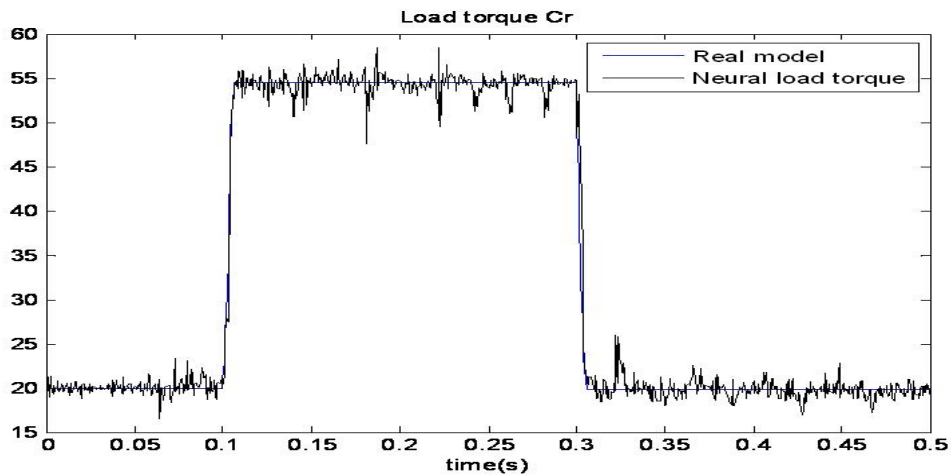


Figure 4. Evolution of the parameter C_r and the neural load torque observer

6. Conclusion

In this paper, we have developed a neural network observer for nonlinear dynamical systems. It is a three-layer feedforward artificial neural network, trained with the modified error backpropagation learning algorithm.

The Lyapunov's direct method is used in order to ensuring the stability of the proposed non-conventional observer and the neural network weight errors. Furthermore, some correction terms are provided to the NN weights to improve the robustness of the NN observer.

Moreover, the efficiency and the high performances of the proposed recurrent observer are due to the parallel architecture of the ANN's and the high capacity of training despite the presence of external disturbances.

It has been shown from the simulation results that the proposed recurrent observer is efficient and permits the rapid reconstruction of the state variables of an induction motor and especially the rotor flux despite the strong nonlinearities affecting the studied process and the emerged load torque considered as an external disturbance. In addition, the reconstruction of the load torque variation has been made possible using the proposed neural network observer.

References

- [1] G. C. Verghese, and R. Sanders, "Observers for flux estimation in induction machines", IEEE Transactions on Industrial Electronics, Vol. 35, 1988.
- [2] A.S. Tlili and N. Benhadj Braiek, "State observation of nonlinear and uncertain system: Application to induction motor", International Journal of Power and Energy Systems, Vol. 28, 2008, 252-262.
- [3] K. K. Busawon and M. Saif, "A state observer for nonlinear systems", IEEE Transactions on Automatic Control, Vol. 44, 1999.
- [4] J. Theocharis and V. Petridis, "Neural network observer for induction motor control", IEEE Control Systems, 1994.
- [5] A. Germani, C. Manes, and P. Pepe, "A new approach to state observation of nonlinear systems with delayed output", IEEE Transactions on Automatic Control, Vol. 47, 2002.
- [6] F. Abdollahi and H.A. Talebi, "A stable neural network observer with application to flexible joint manipulators", (ICONIP'02) Proceeding of the 9th International Conference on Neural Information Processing, Vol. 4, 2002, 1910-1914.
- [7] F. Abdollahi and H.A. Talebi, "A stable neural network observe-based observer with application to flexible joint manipulators", IEEE Transaction on Neural Network, Vol 1, 2006, 118-129.
- [8] K. Jain , Artificial neural networks, a tutorial, IEEE, 31-44.
- [9] K. Narendra and K. Parthasarathy, "Identification and control of dynamic system using neural networks", IEEE Transaction on Neural Network, Vol 1, 1990, 4-27.
- [10] T. Michael and R. Harley, "Identification and control of induction machines using artificial neural networks", IEEE Transaction on Industry Applications, Vol 31, 1995, 612-619.
- [11] K. Seong-Hwan, P. Tae-Sik, Y. Ji -Yoon and P. Gwi-Tae, "Speed sensorless vector control of an introduction motor using neural network speed estimation", IEEE Transaction on Industrial Electronics, Vol 48, 2001, 609-614.
- [12] M. Godoy and K. Bose, "Neural network based estimation of feedback signals for a vector controlled induction motor drive", IEEE Transaction on Industry applications, Vol 31, 1995, 620-629.
- [13] A. Toh, P. Nowicki and F. Achrafzadeh, "A flux estimator for field oriented control of an induction motor using an artificial neural network", IEEE, Canada, 1994, 585-592.
- [14] R. Selmic and L. Lewis, "Multimodel neural networks identification and failure detection of nonlinear systems", Proceeding of the 40th IEEE Conference on Decision and Control, Florida, USA, 2001, 3128-3133.
- [15] J. Olvera, X. Guan, and M. T. Manry, "Theory of monomial networks", Proceedings of Implicit and Nonlinear Systems, 1992, 96-101.
- [16] J. Park and I. W. Sandberg, "Universal approximation using radial-basis function networks", Neural Comp., vol. 3, 1991, 246-257.
- [17] F. Lewis, K. Liu and A. Yesildirek, "Neural net robot controller with guaranteed tracking performance", IEEE Transaction on Neural Network, Vol 6., 1995, 703-715.
- [18] Y.H. Kim, F.L. Lewis and C.T. Abdallah, "Nonlinear observer design using dynamic recurrent neural networks", Proceedings of the 35th Conference on Decision and Control, Kobe, Japan, 1996, 949-954.
- [19] J. Vargas and E. Hemerly, " Neural adaptive observer for general nonlinear systems", Proceedings of the American Control Conference, Chicago, 2000.

- [20] H. Kubota and K. Matsuse, "Speed sensorless field-oriented control of induction motor with rotor resistance adaptation", IEEE Transaction on Industry Application, Vol. 30, 1219-1224.
- [21] H. Khalil and E.G. Strangas, "Robust speed control of induction motors using position and current measurements", IEEE Transaction on Automatic Control, Vol. 41, 1996, 1216-1219.
- [22] F. Abdollahi and H.A. Talebi, "State estimation for flexible joint manipulators using stable neural networks", Proceedings of IEEE International Symposium on Computational Intelligence in Robotics and Automation, Japan, 2003, 25- 29.
- [23] P. A. Ioannou and M. M. Polycarpou, "Identification and control of nonlinear systems using neural networks models : design and stability analysis", Tech. Rep.91-01-09, Los Angeles.
- [24] S. Weerasooriya, M. A. El-Sharkawi, "Identification and control of a dc motor using back-propagation neural networks", IEEE Transactions on Energy Conversion, Vol. 6, 1991.
- [25] K. Hornik, M. Stinchcombe and H. White, "Multilayer feedforward networks are universal approximators", Neural Networks 2, 1989, 359-366.
- [26] Y. H. Kim, F. Lewis and C. T. Abdallah, "A dynamic recurrent neural network based adaptive observer for a class of nonlinear systems", Automatica, Vol 33, 1997, 1539-1543.
- [27] J. Vargas and E. Hemerly, "Robust neural adaptive observer for MIMO nonlinear systems", Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, 1999.
- [28] K. S. Narendra and A. M. Annaswamy, "Stable adaptive control", Prentice-Hall, Englewood Cliffs, NJ, 1989.
- [29] K. Tanaka, T. Ikeda and H. O. Wang, "Fuzzy regulators and Fuzzy Observers: Relaxed stability Conditions and LMI-Based Designs", IEEE Transaction on Fuzzy Systems, Vol. 6, 1998, 250-265.
- [30] R. Ortega, C. Canudas and S. Seleme, "Nonlinear control of induction motors: torque tracking with unknown load disturbance", IEEE Transaction on Automatic Control, Vol 38, 1993, 1675-1680.
- [31] M. Farza, H. Hammouri, C. Jallut and J. Lieto, "Reduced order observers for flux, rotor resistance and speed estimation for vector controlled induction motor drivers using the extending Kalman filter technique", IEE Electronic Power Application, vol. 45, 1999, 93-106.

Authors



Asma Najet Lakhali received her Master of Automatic from the Ecole Nationale d'Ingénieurs de Monastir in 2006. She is currently working toward the Ph.D. degree in Automatic, an Assistant Professor in the Faculté des Sciences de Bizerte and a member of the Processes Study and Automatic Control Laboratory (LECAP) in the Ecole Polytechnique de Tunisie. Her research interests include neural networks and fuzzy systems, observer of nonlinear dynamical systems with application on electromechanical processes.



Ali Sghaier Tlili received his Master of Systems Analysis and Numerical Treatment and his Ph.D. in Electrical Engineering, both from the Ecole Nationale d'Ingénieurs de Tunis in 1998 and 2003, respectively. He is currently an Assistant Professor in the Institut Supérieur d'Informatique de Tunis and a member of the Processes Study and Automatic Control Laboratory (LECAP) in the Ecole Polytechnique de Tunisie. His current research interests include nonlinear, decentralized, multi-model and fuzzy observer based control for nonlinear, uncertain and complex systems with application on electromechanical processes.



Naceur Benhadj Braiek was born in 1963. He obtained his Master of Electrical Engineering and Master of Systems Analysis and Numerical Processing, both from the Ecole Nationale d'Ingénieurs de Tunis in 1987, his Master of Automatic Control from the Institut Industriel du Nord (Ecole Centrale de Lille) in 1988, his Ph.D. in Automatic Control from the Université des Sciences et Techniques de Lille, France, in 1990, and his Doctorat d'Etat in Electrical Engineering from Ecole Nationale d'Ingénieurs de Tunis in 1995. Currently, he is Professor of Electrical Engineering at the Ecole Supérieure des Sciences et Techniques de Tunis. He is also Director of the Processes Study and Automatic Control Laboratory (LECAP) at the Ecole Polytechnique de Tunisie. His domain of interests is related to the modeling, analysis and control of nonlinear systems with applications on electrical processes.

