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Comparative Analysis between Multimodel and Neural State Observation Approach of Nonlinear Systems. Application to Induction Motors.

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***Abstract*— This paper deals with comparative analysis between two state observation methods: the multimodel and the neural state observation approaches. The multimodel state observer is deduced from the fusion of linear state observers for the local models of the process. This fusion is based on the concept of validity of each observer. The observation gain is obtained by the resolution of the Linear Matrix Inequalities (LMI) derived from the stabilization criterion using the Lyapunov approach.**

As for the neural state observer, it is based in one hand on neural identification of the non-linear system, and in the other hand on a pole placement technique for calculating the gains of state observation. For neural identification, we use a neural network with nonlinear parameters (RNPNL). This RNPNL is a multilayer feedforward neural network using the sigmoïdal activation function and the modified error backpropagation learning algorithm.

The proposed state observation techniques are applied to the nonlinear model of the induction motor to reconstruct the non-measurable state variables and in particular the rotor flux.

***Keywords*— Multimodel state observer, neural state observer, LMIs, induction motor**

I. 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, the state observation of dynamic systems depends on the complexity of the system and tools implemented. If we can characterize and implement quickly and easily a state observer for a linear and stationary process, it is not at all even on a non-linear or uncertain or time-varying parameters [6], [7], [8]. It is then necessary to use other advanced methods of state observation [9], [10].

In this way, the multimodel approach appears as an interesting method to easier the representation of the complex system by using a set of simple models [11], [12], [13], [14].

On the other hand, neural network techniques have showing a good promise as competitive methods for signal processing, power systems and other applications [15], [16], [17]. Indeed, these techniques are efficient for approximating a wide range of nonlinear functions [18], [19].

In this article, we are interested by the observation of nonlinear dynamical systems using two approaches that are multimodel and neural networks. The approach of multimodel state observation is based on the calculus of the validities. The observation gains are obtained by the resolution of LMI constraints.

The neural state observation approach is based on the fact that artificial neural networks have the universal approximation property. Indeed, the objective is to design a neural network to approximate the non-linear part of the state observer through the back-propagation algorithm, by adding some correction terms to the neural network (NN) weights tuning in order to guarantee the stability of the state observer and the NN weights errors [20], [21].

These two approaches: multimodel state observer and neural state observer are applied to a physical process constituted by an induction motor. This type of motor has a nonlinear multivariable structure, making it difficult to control [7], [22]. In addition, its internal state variables are not always accessible to the measurement and in particular the rotor flux, hence, new techniques of state observation are needed [8], [23].

In this work, we intend to prove the importance and the performance of advanced methods of state observation as neural approach. This study is based on the comparison between conventional and non-conventional techniques of state observation. 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 thanks to three particularly interesting characteristics: adaptive, massively parallel and capable of generalization. Instead to the conventional multimodel state observation approach which present different difficulties as the annoying calculation, the choice of models base and the appropriate fusion technique.

This paper is organized as follows: the multimodel state observation of nonlinear systems is presented in the second section, and then the neural state observation is considered in the third section. The last section is devoted to the comparison, by numerical simulation, of the multimodel state observer and the neural observer of process studied.

II. MULTIMODEL STATE OBSERVER

Consider the uncertain complex process described by the equations:

$$\begin{cases} x(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \quad (1)$$

where A is the state matrix, B is the input matrix and C is the output matrix. x is the state vector, y is the output vector and u is the input vector.

This system can be described by several models (M_i) $(i = 1, \dots, i)$. Each of these models is represented by the following linear state equations:

$$\begin{cases} x_i(t) = A_i x_i(t) + B_i u_i(t) \\ y_i(t) = C_i x_i(t) \end{cases} \quad i = 1, \dots, i \quad (2)$$

where N is the number of the base models, x_i, u_i et y_i denote respectively the state, the input and the output vectors of the local model M_i.

The reconstruction of the non measurable state variables is based on the Luemberger observer which has the following form:

$$\begin{cases} \hat{x}_i(t) = A_i \hat{x}_i(t) + B_i u_i(t) + L_i[y(t) - \hat{y}_i(t)] \\ \hat{y}_i(t) = C_i \hat{x}_i(t) \end{cases} \quad (3)$$

where $\hat{x}_i$ and $\hat{y}_i$ are respectively the estimated state and output vectors of x_i and y_i.

The multimodel observer for the global system is given by:

$$\begin{cases} \hat{x}(t) = A\hat{x}(t) + Bu(t) + L[y(t) - \hat{y}(t)] \\ \hat{y}(t) = C\hat{x}(t) \end{cases} \quad (4)$$

where $\hat{x}$ and $\hat{y}$ are the estimated state and output vectors of x and y.

L represents the multimodel observer gain determined by the fusion of the gains L_i of the local observers which are weighted by the validity v_i [24], [25] as following:

$$L = \sum_{i=1}^{N} v_i L_i \quad (5)$$

The validities are given by the expression:

$$v_i = \frac{1 - r_i}{N - 1} \qquad \mathrm{i} = 1, \dots, \mathrm{N} \quad (6)$$

where r_i is the residue of the model M_i, which is a quantity characterized the behavior of the model (M_i) compared to the process, given by the expression:

$$r_i = \frac{\|y - \hat{y}\|}{\sum_{i=1}^{N} \|y - \hat{y}\|} \quad (7)$$

In order to favor the most pertinent models to the detriment of the worst ones, it is interesting to use the following strengthened and normalized validities [26]:

$$V_i = \frac{v_i^s}{N - 1} \qquad i = 1, \dots, i \quad (8)$$

where:

$$v_i^s = v_i \prod_{j=1, j \neq s}^{N} (1 - v_j) \qquad i = 1, \dots, i \quad (9)$$

N is the number of base models.

The matrices A, B, C are obtained by fusion of those of the models M_i, $i = 1, \dots, i$, such that:

$$\begin{cases} A = \sum_{i=1}^{N} V_i A_i \\ B = \sum_{i=1}^{N} V_i B_i \\ C = \sum_{i=1}^{N} V_i C_i \end{cases} \quad (10)$$

we consider $\varepsilon = x - \hat{x}$ the observation error.

The stability of the global system is conditioned by the convergence of the observation error to zero.

$$\hat{\varepsilon}(t) = \sum_{i=1}^{N} V_i^2 (A_i - L_i C_i)\varepsilon(t) + 2\sum_{i<j}^{N} V_i V_j \left(\frac{A_i - L_i C_j + A_j - L_j C_i}{2} \right) \varepsilon(t) \quad (11)$$

According to Lyapunov theory, the global asymptotic stability of the system (11) is ensured if there exists a positive definite function V such that V be negative definite.
We consider the quadratic function of Lyapunov [27]:

$$V(t) = \varepsilon(t)^T P \varepsilon(t) \tag{12}$$

Indeed, the equation (11) is asymptotically stable if there exist a common positive definite matrix P such that [28] :

$$\begin{cases} P > 0 \\ G_{ii}^T P + P G_{ii} < 0 \\ \dfrac{(G_{ij} + G_{ji})^T}{2} P + P \dfrac{(G_{ij} + G_{ji})}{2} \leq 0 \end{cases} \tag{13}$$

where: $G_{ii} = A_i - L_i C_i$ and $G_{ij} = A_i - L_i C_j$.

The observation gain can be obtained from the resolution of LMI constraints (13).

III. NEURAL STATE OBSERVER

In this section will propose the principle of designing a neural state observer.

The key to design a neuro-observer is to employ a neural network to identify the nonlinearity and a conventional observer to reconstruct the state [29], [30].

The following graphic depicts the structure of the proposed neural network observer.

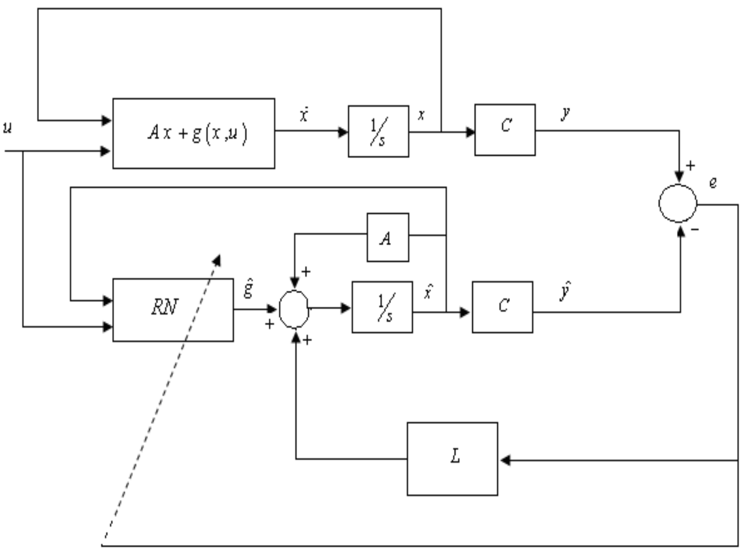

Fig.1 Structure of the designed neural network observer

Thus, for the design of a neural observer, we consider the nonlinear system governed in the state space by [30]:

$$\begin{cases} x(t) = A x + g(x,u) \\ y(t) = C x(t) \end{cases} \tag{14}$$

A is the Hurwitz matrix;
and $g(x,u)$ is an unknown nonlinear function.

The pair (A, C) is assumed observable. A nonlinear state observer of system (14) is described by the following equation:

$$\begin{cases} \hat{x}(t) = A\hat{x} + \hat{g}(\hat{x}, u) + L(y - \hat{y}) \\ \hat{y}(t) = C\hat{x}(t) \end{cases} \tag{15}$$

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

Thus, applying the universal approximation property, cited in [31], a multilayer RN is sufficient for the identification and modeling of the nonlinear function $g(x,u)$ of system (14) with constant weights W and V such as:

$$g(x,u) = W\ \sigma(V z) + \varepsilon(x) \tag{16}$$

where :

- $z = [x \quad u]$;
- $\sigma(.)$ represent the activation function of the hidden layer ;
- $\varepsilon(x)$ is the approximation error bounded $\|\varepsilon(x)\| \leq \varepsilon_N$,

and ε_N is a known function in a compact set S. Moreover, for any positive number ε_N , we can find a RN such that $\|\varepsilon(x)\| \leq \varepsilon_N$ for all $x \in S$.

Note that the ideal weights W and V are bounded by known values such as $\|W\| \leq W_M$ and $\|V\| \leq V_M$.

The activation function of hidden layer is sigmoïdal:

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

The sigmoïdal function is bounded by σ_m as:

$$\|\sigma(x)\| \leq \sigma_m$$

The nonlinear function g can be approximated by a multilayer RN according to the following model:

$$\hat{g}(\hat{x}, u) = \hat{W}\ \sigma(\hat{V}\hat{z}) \tag{17}$$

The proposed neural observer is then given by:

$$\begin{cases} \hat{x}(t) = A\hat{x} + \hat{W}\ \sigma(\hat{V}\hat{z}) + L(y - \hat{y}) \\ \hat{y}(t) = C\ \hat{x}(t) \end{cases} \tag{18}$$

To train the neural network, appropriate weights equations tuning are defined so that the stability of the proposed neural state observer is guaranteed [30]. These weights equations tuning are improved by correction terms as follows:

$$\hat{V} = \left(\hat{W}\ \sigma\left(\hat{V}\ \hat{z}\right)\left(I - \sigma\left(\hat{V}\ \hat{z}\right)\right)\right)^T T\ e\ \hat{z}^T - k\ T\ \|e\|\hat{V} \quad (19)$$

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

where:

- $e = x - \hat{x}$ is the error state estimation ;
- $T = -\eta_1 G^{-T} C^T C,\quad T = T^T > 0$;
- $F = -\eta_2 G^{-T} C^T C,\quad F = F^T > 0$;

IV. APPLICATION TO INDUCTION MOTOR

In this section, we apply the two precedent approaches to the model of the induction motor.

A. Multimodel state observer of induction motor

The Park model of the induction motor in a reference frame, and under the assumption of unsaturated magnetic circuits, is a nonlinear system which is presented in the following form [32], [33], [34]:

$$\begin{cases} X(t) = f(X,U,\theta,t) \\ Y(t) = g(X,t) \end{cases} \quad (20)$$

where :

$X = \begin{bmatrix} I_{s\alpha} & I_{s\beta} & \phi_{r\alpha} & \phi_{r\beta} & \omega \end{bmatrix}^T$ is the state vector composed by the two components of the stator currant i_{ii} and i_{ii} , the two component in the rotor flux $\phi_{r\alpha}$ and $\phi_{r\beta}$, the rotor speed i and the two components of the stator voltage $V_{s\alpha}$ and $V_{s\beta}$;

$U = \begin{bmatrix} V_{s\alpha} & V_{s\beta} \end{bmatrix}^T$ is the control vector;

$Y = \begin{bmatrix} I_{s\alpha} & I_{s\beta} & \omega \end{bmatrix}^T$ is the output vector.

θ(t) is the vector of parameters involving the stator and rotor resistances.

The function f(X,U) and g(X) are given by :

$$f(X,U) = \begin{bmatrix} \omega_s I_{s\beta} - \Lambda I_{s\alpha} + \beta\alpha_r\phi_{r\alpha} + \beta\omega\phi_{r\beta} + \gamma V_{s\alpha} \\ -\omega_s I_{s\alpha} - \Lambda I_{s\beta} - \beta\omega\phi_{r\alpha} + \beta\alpha_r\phi_{r\beta} + \gamma V_{s\beta} \\ M\alpha_r I_{s\alpha} - \alpha_r\phi_{r\alpha} + \omega\,\phi_{r\beta} \\ M\alpha_r I_{s\beta} - \alpha_r\phi_{r\beta} - \omega\,\phi_{r\alpha} \\ -\mu\phi_{r\beta} I_{s\alpha} + \mu\phi_{r\alpha} I_{s\beta} - \alpha_m\omega - \xi C_r \end{bmatrix} \text{ and}$$

$$g(X) = \begin{bmatrix} I_s \\ \omega \end{bmatrix}$$

with :

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

$$\alpha_m = \frac{F}{J} \text{ et } \Lambda = \alpha_s\,\eta + M\beta\,\alpha_r .$$

The nonlinear model, linearized around a nominal operating point characterized by the triplet (u0,x0,y0), is given by the following system:

$$\begin{cases} x(t) = A(\theta)x(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \quad (21)$$

The matrix $A(\theta)$, B and C can be written as follows:

$$A(\theta) = \begin{bmatrix} -\Lambda & \omega_s & \beta\alpha_r & \beta\omega_0 & \beta\phi_{r\beta_0} \\ -\omega_s & -\Lambda & -\beta\omega_0 & \beta\alpha_r & -\beta\phi_{r\alpha_0} \\ M\alpha_r & 0 & -\alpha_r & \omega_0 & \phi_{r\beta_0} \\ 0 & M\alpha_r & -\omega_0 & -\alpha_r & -\phi_{r\alpha_0} \\ -\mu\phi_{r\beta_0} & \mu\phi_{r\alpha_0} & \mu I_{s\beta_0} & -\mu I_{s\alpha_0} & -\alpha_m \end{bmatrix}$$

$$B = \begin{bmatrix} \gamma & 0 \\ 0 & \gamma \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} ;\quad C = \begin{bmatrix} \omega_1 & \omega_2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

with

$$\omega 1 = \sqrt{\frac{2}{3}}\left(\frac{I_{sd0}}{\sqrt{I_{sd0}^2 + I_{sq0}^2}}\right) \quad \text{and} \quad \omega 2 = \sqrt{\frac{2}{3}}\left(\frac{I_{sq0}}{\sqrt{I_{sd0}^2 + I_{sq0}^2}}\right)$$

The rotoric and statoric resistances are defined in the presented ranges:

$$\underline{R_r} \le R_r \le \overline{R_r}$$
$$\underline{R_s} \le R_s \le \overline{R_s}$$

The nominal values of resistances are given by:

$$R_{rn} = \frac{\underline{R_r} + \overline{R_r}}{2}$$
$$R_{sn} = \frac{\underline{R_s} + \overline{R_s}}{2}$$

We have so four local models taking in account the different combinations of ($\underline{R_r}, \overline{R_r}, \overline{R_s}, \underline{R_s}$) and an average model using R_{rn}, R_{sn}.

We assume that the R_r and R_s change in a range of ±50% of their nominal values as following:

$$0.688 \le R_r \le 2.065$$
$$0.415 \le R_s \le 1.245$$

We calculate the local gains of the five local models using the LMI constraints (13) applied to (21), leads to:

$$P=\begin{bmatrix} 0.3 & 0.24 & 0.16 & 0.35 & -0.104 \\ 0.24 & 0.25 & -0.15 & 0.38 & 0.82 \\ 0.16 & -0.15 & 259 & -26 & -0.1 \\ 0.35 & 0.38 & -26 & 412 & -0.61 \\ -0.104 & 0.82 & -0.1 & -0.61 & 0.46 \end{bmatrix}$$

$$L_1=\begin{bmatrix} -350 & 80 \\ -300 & -50.58 \\ 2.025 & 0.83 \\ -0.81 & 0.88 \\ 50.105 & 300.87 \end{bmatrix} \quad L_2=\begin{bmatrix} -338 & 80.55 \\ -256 & -60 \\ 1.025 & 0.243 \\ -0.75 & 0.78 \\ 49.105 & 230.58 \end{bmatrix}$$

$$L_3=\begin{bmatrix} -330 & 75 \\ -354 & -79.88 \\ 1.95 & 0.175 \\ -0.35 & 0.98 \\ 83.15 & 354 \end{bmatrix} \quad L_4=\begin{bmatrix} -255 & -7.023 \\ -345 & -65 \\ 2.29 & 1.2 \\ -1.2 & 0.43 \\ 85.47 & 354 \end{bmatrix}$$

$$L_5=\begin{bmatrix} -300 & -17.41 \\ -258.82 & -35 \\ 1.27 & 0.983 \\ -0.54 & 0.67 \\ 98.351 & 305.87 \end{bmatrix}$$

B. Neural state observer of induction motor

The Park model of the study motor is presented in this form:

$$\begin{cases} x(t) = Ax + g(x,u,t) \\ y(t) = h(x,t) \end{cases} \tag{21}$$

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

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

$$h(x,t)=\begin{bmatrix} I_{s\alpha} \\ I_{s\beta} \\ \omega \end{bmatrix}$$

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

The RN is three layers where the input layer contains 5 neurons, 15 neurons in the hidden layer and output layer contains two neurons that represent the two components of rotor flux $\Phi_{r\alpha}$ and $\Phi_{r\beta}$.

The input of RN consist of two components of the stator current $I_{s\alpha}$ and $I_{s\beta}$, the two components of the stator voltage $V_{s\alpha}$ and $V_{s\beta}$ and speed of rotation ω.

The learning rate γ_g and learning speed γ_m values are respectively 0.2 and 0.4.

The poles placement of the matrix $(A - LC)$ in:

$$[-200, -201, -202, -203, -204]$$

leads to the following gain observation:

$$L=\begin{bmatrix} 239.819 & -315.718 & 23.618 \\ 297.601 & 234.764 & 27.573 \\ 27.570 & -27.872 & 138.172 \\ -4.101 & 2.450 & -0.434 \\ -2.155 & -4.238 & -0.216 \end{bmatrix}$$

The curves of Figures 2 and 3 show the simulation results on the evolution of the rotor flux components $(\Phi_{r\alpha}, \Phi_{r\beta})$ and their estimated $(\hat{\Phi}_{r\alpha}, \hat{\Phi}_{r\beta})$ obtained using the multimodel observer and neuro-observer.

It is remarkable that the two observation approaches join quickly the real process with good performances and since the start of transient state of the motor.

It also appears from these simulations, that the neural state observer joins the actual process faster than the multimodel observer. Thus, we can conclude that the neural observer gives better performance when it comes to rebuilding the grandeur are not available for the measurement of nonlinear systems, it is more suited to this class of systems.

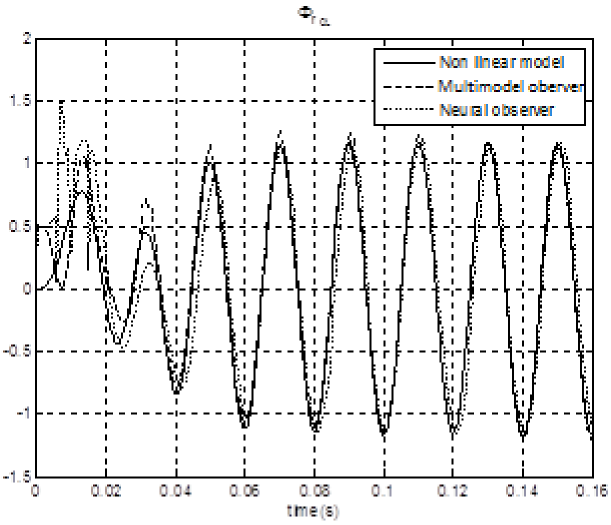

Fig.2 Evolution of $\Phi_{r\alpha}$ and its observers:

- Multimodel observer
- Neural observer

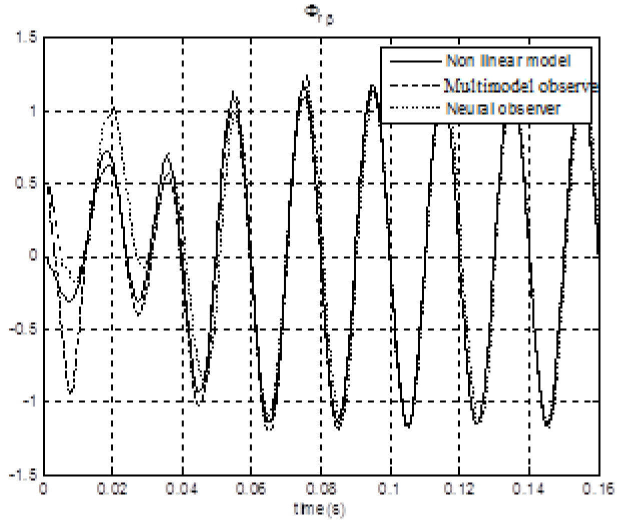

Fig.3 Evolution of $\Phi_{r\beta}$ and its observers:
- Multimodel observer
- Neural observer

V. CONCLUSION

In this paper, we have presented two types of state observers of nonlinear systems.

The first one, a multimodel observer, is based on linear fusion of partial observation laws using validities. The estimation of the validities uses the calculus of residues. The gain of such observer is obtained by the resolution of LMI constraints derived from the Lyapunov method.

The second type is a neural state observer based in one hand, on neural identification of the non-linear model of the studied process, and in the other hand, on a pole placement technique for calculating the gains of state observation.

It has been shown from the simulation results that the proposed state observers are efficients and permit the rapid reconstruction of the state variables of an induction motor and especially the rotor flux despite the strong nonlinearities affecting the studied process but with a light superiority of the neural observer compared to the multimodel state 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 and N. Benhadj Braiek, "State observation of nonlinear and uncertain system: Application to induction motor", *International Journal of Power and Energy Systems*, vol. 28, pp. 252-262, 2008.

[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] G. Garcier, E. Mendes and A. Razek, "State observation of a non linear systems. Application to (bio) chimical process", *AICHE journal, vol. 146*, pp. 282-288, 1999.

[7] C. Courties, "*Sur la commande robuste et LPV des systèmes à paramètres lentement variables*", *Thèse de Doctorat*, Toulouse, 1999.

[8] A.S. Tlili and E. Benhadj Braiek, "Observateurs d'état non linéaires et LPV des machines asynchrones", *CIFA'02*, Nantes, France, pp. 45-49, 2002.

[9] A. N. Lakhal, A. S. Tlili and N. Benhadj Braiek, "Stabilité non quadratique d'observateur d'état flou de type Takagi-Sugeno des systèmes non linéaires. Application à une machine asynchrone", JTEA'08, Hammamet, Tunisia, 2008.

[10] A. N. Lakhal, A. S. Tlili and N. Benhadj Braiek, "Comparative Analysis between Fuzzy and Neural State Observation Approach of Nonlinear Systems. Application to Induction Motors", *International Review of Automatic Control, IREACO, vol.5*, No. 5, 2012.

[11] Z. Kardous, "Sur la modélisation et la commande des processus complexes et/ou incertains", *Thèse de Doctorat*, Ecole Centrale de Lille, 2004.

[12] A. M. Nagy Kiss, "Analyse et synthèse de multimodèles pour le diagnostic. Application à une station d'épuration", *Thèse de Doctorat*, Institut Nationale Polytechnique de Lorraine, 2010.

[13] H. Hamdi, " Approche multimodèle pour l'observation d'état et le diagnostic des systèmes singuliers non linéaires", *Thèse de Doctorat*, Ecole Supérieur des Sciences et techniques de Tunis, 2012.

[14] R. Orjuela, "Contribution à l'estimation d'état et au diagnostic des systèmes représentés par des multi-modèles", *Thèse de Doctorat*, Institut National Polytechnique de Lorraine, 2008.

[15] 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, pp. 620-629, 1995.

[16] 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*, pp. 585-592, 1994.

[17] 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*, pp. 3128-3133, Florida, USA, 2001.

[18] J. Olvera, X. Guan, and M. T. Manry, "Theory of monomial networks", *Proceedings of Implicit and Nonlinear Systems*, pp. 96-101, 1992.

[19] J. Park and I. W. Sandberg, "Universal approximation using radial-basis function networks", Neural Comp., vol. 3, pp. 246-257, 1991.

[20] 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*, pp. 25- 29, Japan, 2003.

[21] 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*, pp. 1539-1543, 1997.

[22] N. Benhadj Braiek and H. Jerbi, "Approche algébrique de linéarisation des systèmes non linéaires par retour d'état", *5ème CMMNI*, pp.510-516, Rabat, Maroc, 1995.

[23] A.S. Tlili and A. Salem, "Observateur mutimodèle de flux d'une machine asynchrone", *CTGE*, Tunis, Tunisie, pp. 49-59, 2004.

[24] Z. Kardous, "On the quadratic stabilization in discrete multimodel control", *IEEE Conference on Control Applications, CCA*, Turkey, 2003.

[25] F. Delmotte, " Analyse multimodèle", *Thèse de doctorat*, Lille, 1997.

[26] L.X. Wang, " Stable adaptive fuzzy control of nonlinear systems", *IEEE Trans. on Fuzzy Systems,* vol. 2, pp. 146-155, 1993.

[27] Z. Kardous, "Validity dependent stabilization criteria of multimodel control », MED, Turkey, 2004.

[28] A. N. Lakhal, A. S. Tlili and N. Benhadj Braiek, " On the stability of a multiobserver of induction motors", *Fourth International Multi-Conference on Systems Signals and devices,* SSD'07, Hammamet, Tunisia, 2007.

[29] A. Alessandri, C. Cervellera, A. E Grassia and M. Sanguineti, "Design of observers for continuous-time nonlinear systems using neural networks", *In Proceeding of American Control Conference*, Boston, Massachusetts, 2004.

[30] A. N. Lakhal, A. S. Tlili and N. Benhadj Braiek, “Neural network observer for nonlinear systems. Application to induction motors”, *International Journal of Control and Automation, vol. 3*, No. 1, 2010.
[31] K. Hornik, “Multilayer feedforward networks are universal approximators”, *Neural Networks, vol. 2*, pp. 359-366, 1989, USA.
[32] R. Ortega, C. Canudas and S. Seleme, “Nonlinear control of induction motors : torque tracking with unknown load disturbance”, *IEEE. Trans. Automat. Control, vol. 38*, pp. 1675-1680, 1993.
[33] H. Khalil and E.G. Strangas, “Robust speed control of induction motors using position and current measurements”, *IEEE Trans. Automat. Control,vol 41*, pp. 1216-1219, 1996.
[34] B. H. Mouna and S. Lassaâd, “ANN’s sensorless induction motor fuzzy logic speed control”, *Int.Review of Automatic Control, vol. 3, n.6,* pp. 651-657,2010.