Nonlinear Dynamics and Systems Theory, **14** (2) (2014) 162–174

Indirect Adaptive Fuzzy Control of Multivariable Nonlinear Systems Class with Unknown Parameters

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Received: October 5, 2013; Revised: April 9, 2014

Abstract: This paper develops an adaptive fuzzy control of nonlinear system class. In this method, we investigated the possibilities offered by the fuzzy systems of Takagi-Sugeno type in terms of approximation capacity of the continuous nonlinear functions and we exploited the Lyapunov theory to establish a parametric adaptation law, ensuring the total stability of the system. Finally, simulation results are presented to show the effectiveness of this kind of controller.

Keywords: *fuzzy systems; fuzzy adaptive law; permanent magnet synchronous motors; current controlled inverter.*

Mathematics Subject Classification (2010): 03B52, 93C42, 94D05.

1 Introduction

The vast majority of conventional control techniques have been devised for linear time-invariant systems that are assumed to be completely known and well understood. In most practical instances, however, the systems to be controlled are nonlinear, time-varying and the basic physical processes in them are not completely known a priori. These types of model uncertainties are extremely difficult to manage, even with the conventional techniques. For these systems, the linear control exhibits generally poor performances and the recourse to a nonlinear adaptive control can be a judicious solution. Besides, the theory of fuzzy logic has also been applied successfully for the control of nonlinear systems. In general the control strategy used for fuzzy logic controller is based on expert knowledge, so the fuzzy logic controller has the ability to emulate the human strategies control [1–5] and [6]. Moreover, it would be necessary that the control strategy can perform the control objectives even if the parameters of the system evolve or are badly

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known. In order to solve this problem, we develop an adaptive fuzzy controller which is able to modify the control law according to the evolution of the system parameters.

During the past two decades, many works have been devoted to the development of the fuzzy logic controllers [7–10] based on the Takagi−Sugeno (T−S) model or the fuzzy dynamic models. The basic idea of these methods is: 1) To represent the complex nonlinear system by a family of local linear models, each linear model exhibits the dynamics of the complex system in one local region. Then, to construct a global nonlinear model by aggregating all the local models through the fuzzy membership functions. 2) To design the local controllers based mainly on each local model, which is much easier than on the global region for the nonlinear system. Then, the global controller can be aggregated from the local controllers. It was also proven that the fuzzy system is capable to approximate any nonlinear functions over a convex compact region [11]. Based mainly on this property, the fuzzy logic system is applied in the area of the adaptive control where the unknown nonlinear functions are approximated by a fuzzy basis functions and its parameters are updated on line to cope with uncertainties.

Many researchers have considered adaptive fuzzy control of nonlinear dynamical systems. The methods appeared in the literature could be derived into two groups: indirect methods and direct methods. An indirect adaptive controller tries to identity the dynamics of the system, and then generates a control input based on certainty equivalent principle [13,14,16,30–32]. Direct adaptive controller, on the other hand, directly adjusts the parameters of a controller to archive control objectives [12, 30–32]. The approaches presented in [12, 15, 17–19, 31, 32] are limited to SISO nonlinear systems with constant control gain. In the paper [30], the authors propose a direct adaptive control by using either fuzzy systems or neural networks for uncertain SISO nonlinear systems with state dependent control gain. In their proof of stability, the authors assume that the time derivative of the control gain is bounded from above by a known function, which is difficult to find for unknown systems.

In this paper, we develop a new stable fuzzy adaptive control for a class of MIMO nonlinear systems in order to confer high robustness to the controller in the presence of parametric uncertainties and dominant uncertain nonlinearities. The fuzzy systems are used to approximate the model of controlled system. The approximation theory and the Lyapunov method are used together to construct, in first stage, the fuzzy adaptive control law and to establish, in second stage, the convergence of the tracking error and the boundedness of the adaptive. The method is applied by simulation to the problem of tracking speed or position of the permanent magnet synchronous motor (PMSM).

This paper is organized as follows: in Section 2 the used fuzzy logic system is briefly described and Section 3 is devoted to the problem statement. The proposed fuzzy adaptive scheme for a class of MIMO nonlinear system is developed in Section 4. In Section 5, the performances of the proposed scheme are evaluated by simulation for the case of PMSM. The conclusion is presented in Section 5.

2 Description of the Used Fuzzy Logic System

The fuzzy logic system incorporates generally four principal components: fuzzifier, fuzzy rules base, inference engine and defuzzifier [20–22]:

– Fuzzifier maps crisp points in the input space into fuzzy sets in the input space.

– Fuzzy rules base contains the fuzzy rules interpreting the behavior of a given system; it is the central element from which the other components interpret and combine these rules to form the final output.

– Inference engine exploits an approximate reasoning procedure in order to map fuzzy sets in the input space into fuzzy sets in the output space.

– Defuzzifier extracts crisp points in the output space from fuzzy sets in the output space.

A FLS can be seen as a mathematical application of the input towards the output. This application is very rich in its mathematical formulation by the existence of various mathematical interpretations concerning the fuzzy rules, the fuzzy inference and the defuzzifier. It is significant to note that the implementation of the adaptive fuzzy control, in real time, requires that the mathematical model of the FLS must be simple. In our case, we are interested in the FLS of Sugeno-Takagi model, developed initially to model system from numerical data [22]. In this case the consequences rules are numerical functions, which depend on the values of the crisp input variables.

In this section, we give a mathematical formulation of used fuzzy systems and fuzzy basis functions in the case of Sugeno-Takagi model. Denote by $x_{sf_1}, \ldots, x_{sf_n}$ the inputs of the FLS, and by y_{sf} its output. Each variable x_{sf_i} is related to m_i fuzzy sets F_i^j defined on U_i. Moreover, it is assumed that for any value of x_{sf_i} on U_i, there exists at least one fuzzy set among F_i^j ($i = 1, \cdots, n$ and $i = 1, \cdots, m$) for which the membership degree is non null. The rule base of the FLS incorporates $\prod_1^n m_i$ rules of the form:

$$\begin{array}{l} R_l : \text{if } \; x_{sf_1} \; \text{ is } \; F_1^{l_1} \; \text{ and ... and } \; x_{sf_i} \text{ is } F_i^{l_i} \; \text{ and ... and } \; x_{sf_n} \; \text{ is } \; F_n^{l_n}, \\ \text{then } y_{sf_l}(x) = a_0^l + a_1^l x_{sf_1} + ... + a_n^l x_{f_n} \end{array} \tag{1}$$

with $l = 1, ..., M$; $i = 1, ..., n$ and $1 \leq l_i \leq m_i$.
Indeed, the base of fuzzy rules contains all the combinations of the fuzzy sets related to the input variables. By considering the rules of the form (1) and using the product to interpret the fuzzy implication and the T-norm, therefore the expression of the FLS output is involved by the following relation [21, 24, 25]:

$$y_{sf} = \frac{\sum\limits_{l=1}^{M} \mu_l \cdot y_{sf_l}}{\sum\limits_{l=1}^{M} \mu_l}, \tag{2}$$

where μ_l stands for the firing strength of the R_l rule, which is given by:

$$\mu_l = \prod_{i=1}^{n} \mu_{F_i^{l_i}}(x_i), \quad 1 \leq l_i \leq m_i, \tag{3}$$

and $\mu_{F_i^{l_i}}$ is the membership function of variable x_i associated to fuzzy set $F_i^{l_i}$. This function is selected as Gaussian function:

$$\mu_{F_i^j}(x_{sf_i}) = \exp\left\{-0.5\left(v_i^j\left(x_{sf_i} - c_i^j\right)\right)\right\}, \tag{4}$$

where c is the average, v is the inverse of the variance. If the premises parameters are fixed *apriori*, only the conclusion parameters can be freely adjustable. Thus, the final output can be rewritten in the form:

$$y_{sf} = W(x_{sf}) \cdot A, \tag{5}$$

where A is a vector gathering the parameters a_i^j and $W(x_{sf})$ is a vector of basis fuzzy functions.

3 Problem Statement

Consider a class of MIMO non-linear systems described by the following set of differential equations (for $i = 1, \cdots, m$):

$$\begin{aligned} \dot{x}_i &= f_i(x) + g_i(x) \cdot u_i, \\ y_i &= x_i, \end{aligned} \tag{6}$$

where $f_i(x)$ and $g_i(x)$ are unknown functions, whereas $x = [x_1, \ldots, x_m]^T$, $u = [u_1, \ldots, u_m]$ and $y = [y_1, \ldots, y_m]$ are the system state, the control input and the plant output respectively. The control objective is to force the output vector $x = [x_1, \ldots, x_m]^T$ to follow the specified desired trajectory $x_d = [x_{d1}, \ldots, x_{dm}]^T$. Define the tracking error vector $e(t)$ as:

$$e(t) = x(t) - x_d(t).$$

Therefore, we should design a fuzzy adaptive control law $u(t)$ such that $e(t)$ converges to a small neighbourhood of zero. To this end, the following assumptions are assumed:

Assumption 3.1 Let:
- $f_i(x) \in \mathbb{R}$ and $g_i(x) \in \mathbb{R}$ are bounded smooth nonlinear functions,
- The state vector is available,
- The reference signal x_d and its derivation $\dot{x}_d$ are known bounded signals.

If the functions $f_i(x)$ and $g_i(x)$ are well known the control input can be taken as [26]:

$$u^* = \frac{v_i - f_i(x)}{g_i(x)} \tag{7}$$

with

$$v_i = \dot{x}_{id} + \lambda_i e_i, \tag{8}$$

$$e_i = x_{id} - x_i, \lambda_i > 0, \quad i = 1, \ldots, m. \tag{9}$$

Introducing (7) into (6) leads to the tracking error dynamic equation:

$$\dot{e}_i + \lambda_i \cdot e = 0. \tag{10}$$

Since the coefficients λ_i are imposed such that $p + \lambda_i$ polynomial is Hurwitz, the tracking error vector $e(t)$ converges asymptotically to zero. In the case where the functions $f_i(x)$ and $g_i(x)$, involved in the dynamic model (6), are badly known, the implementation of the control law (7) is inoperative since it requires a precise model. To solve this problem an approach by a fuzzy logic system (FLS) is proposed. Our objective is to develop a model of identification and an adaptation law where the functions $f_i(x)$ and $g_i(x)$ are replaced by FLS. For this purpose, the dynamic of the system is rewritten, first of all, in the following form:

$$\dot{x}_i = \hat{f}_i\ (x; \theta_{f_i}) + \hat{g}_i(x; \theta_{g_i})\ u_i + \varepsilon_i. \tag{11}$$

Let $\hat{f}_i\left(x; \hat{\theta}_{fi}\right)$ and $\hat{g}_i\left(x; \hat{\theta}_{gi}\right)$ be the estimated of the functions $f_i(x)$ and $g_i(x)$, where $\hat{\theta}_{fi}$ and $\hat{\theta}_{gi}$ are a parameter vectors, whereas ε_i is a reconstruction error, it is given by:

$$\varepsilon_i = \left[f_i(x) - \hat{f}_i\ (x; \theta_{f_i})\right] + [g_i(x) - \hat{g}_i(x; \theta_{g_i})]\ u_i \tag{12}$$

such as:

$$\|\varepsilon_i\| \leq \bar{\varepsilon}_i.$$

Therefore, one can construct the following control input $u(t)$:

$$u(t) = \frac{v_i - \hat{f}_i\left(x;\hat{\theta}_{fi}\right)}{\hat{g}_i\left(x;\hat{\theta}_{gi}\right)}. \tag{13}$$

The control law (13) requires a FLS for reconstructing the functions $\hat{f}_i\left(x;\hat{\theta}_{fi}\right)$ and $\hat{g}_i\left(x;\hat{\theta}_{gi}\right)$ and an adaptation mechanism for the parameters $\hat{\theta}_{fi}$ and $\hat{\theta}_{gi}$ in order that this control ensures the convergence of the tracking error $e(t)$ to zero and the boundedness of all signals of the plant.

4 Control Synthesis

The FLS is principally used to estimate on line the nonlinear function given in (11). To this end, the functions $f_i(x)$ and $g_i(x)$ are ideally approximated by FLS such that:

$$\begin{aligned} f_i\left(x\right) &= W_{f_i}\left(x\right)\theta_{f_i i} + \varepsilon_{fi}, \\ g_i\left(x\right) &= W_{g_i}\left(x\right)\theta_{g_i i} + \varepsilon_{gi}, \end{aligned} \tag{14}$$

where $W_{f_i}\left(x\right)$ and $W_{g_i}\left(x\right)$ are basis functions [20], θ_{f_i} and θ_{g_i} are vectors of optimal parameters, while ε_{f_i} and ε_{g_i} are the unavoidable reconstruction errors satisfying the condition [27, 28]:

$$\begin{aligned} \|\varepsilon_{fi}\| &\leq \bar{\varepsilon}_{fi}, \quad \bar{\varepsilon}_{fi} > 0, \\ \|\varepsilon_{gi}\| &\leq \bar{\varepsilon}_{gi}, \quad \bar{\varepsilon}_{gi} > 0, \end{aligned} \qquad 1 \leq i \leq m. \tag{15}$$

Consequently, the functions $\hat{f}_i\left(x;\hat{\theta}_{fi}\right)$ and $\hat{g}_i\left(x;\hat{\theta}_{gi}\right)$ which are the approximation of $f_i(x)$ and $g_i(x)$ can be defined under the form:

$$\begin{aligned} \hat{f}_i\left(x;\hat{\theta}_{fi}\right) &= W_{f_i}\left(x\right)\hat{\theta}_{f_i}, \\ \hat{g}_i\left(x;\hat{\theta}_{gi}\right) &= W_{g_i}\left(x\right)\hat{\theta}_{g_i}. \end{aligned} \tag{16}$$

Proposition 4.1 *We use the following serial-parallel identification model:*

$$\dot{\hat{x}}_i = -\alpha_i\,\hat{x}_i + \alpha_i\,x + \hat{f}_i\,\left(x;\theta_{f_i}\right) + \hat{g}_i\left(x;\theta_{g_i}\right)\,u_i \tag{17}$$

where α_i is given positive scalar. The whole identification scheme is shown in Figure 1.

The goals of identification are the following: Specify the fuzzy systems $\hat{f}_i\left(x;\hat{\theta}_{fi}\right)$ and $\hat{g}_i\left(x;\hat{\theta}_{gi}\right)$, and develop an adaptive law for the parameters $\hat{\theta}_{fi}$ and $\hat{\theta}_{gi}$ such that: a) all signals involved in the identification model must be uniformly bounded, i.e., it must be guaranteed that $\hat{x} \in L\infty$, $\left(\hat{\theta}_f\theta_f^T\right) \leq M_f$, and $\left(\hat{\theta}_g\theta_g^T\right) \leq M_g$ (the input u and the system state x are uniformly bounded by assumption), and b) the error $e_i = x_i - \hat{x}_i$ should be as small as possible.

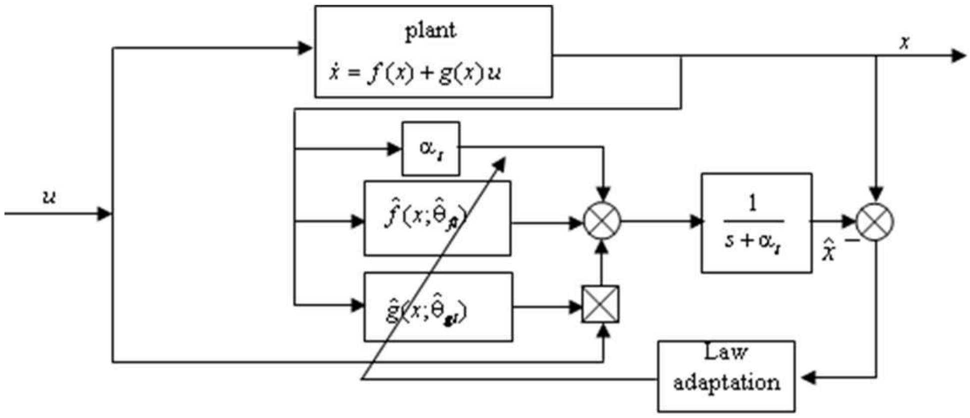

Figure 1: Identification model using fuzzy systems.

While having the fuzzy model (11), under the assumptions (A-3.1), and if the system (6) is conducted by the control law:

$$u(t) = \frac{v_i - \hat{f}_i\left(x; \hat{\theta}_{fi}\right)}{\hat{g}_i\left(x; \hat{\theta}_{gi}\right)} \tag{18}$$

and the parameters $\hat{\theta}_{fi}$ and $\hat{\theta}_{gi}$ are updated under the law:

$$\begin{aligned} \dot{\hat{\theta}}_{f_i} &= \eta_{f_i} W_{f_i}^T(x)\, e_i - k_i \left\| e_i \right\| \hat{\theta}_{f_i} \\ \dot{\hat{\theta}}_{g_i} &= \eta_{g_i} W_{g_i}^T(x)\, e_i\, u_i - k_i \left\| e_i \right\| \hat{\theta}_{g_i} \end{aligned} \tag{19}$$

where η_{fi} , η_{gi} and k_i are positive constants. Therefore, the tracking error converges asymptotically to zero and the state vector $\hat{x}$ and the parameters $\hat{\theta}_{fi}$ and $\hat{\theta}_{gi}$ are bounded.

Remark 4.1 The adaptation law (19) updates only the conclusion parameters. Indeed in our case, the designer specifies, in advance, the structure of FLS, the input variables, the fuzzy sets (or membership functions) and the number of rules. In practice, to make the "good choice" for all these FLS parameters, in advance, is a difficult task, apart for a skilled operator in the area of the controlled system. A common practice is an arbitrary defining the membership functions to cover the interest subset of the input space [12, 30–32]. One can think that this adaptation law also compensates, in a certain manner, for the inadequacy of the fuzzy sets and the insufficiency of the rules number.

5 Application to Permanent Magnet Synchronous Motor

5.1 Mathematical model of PMSM

The model of the permanent magnet synchronous motors (PMSM) is considered in the case of the usually allowed simplifying assumptions i.e.:

– The spatial distribution of stator winding is sinusoidal.

– The saturation is neglected.
– The damping effect is neglected.

Thus, in the synchronous $d-q$ reference form, the dynamic of PMSM is represented as follows:

$$\begin{aligned} &v_d = R_s i_d + L_d \tfrac{di_d}{dt} - pL_q\Omega\, i_q, \\ &v_q = R_s i_q + L_q \tfrac{di_q}{dt} + pL_d\Omega\, i_d + p\Omega\,\Phi_f, \\ &J\tfrac{d\Omega}{dt} = T_{em} - T_r - F_c\Omega, \\ &T_{em} = \tfrac{3}{2}p\left(\Phi_f i_q + (L_d - L_q)\ i_d i_q\right), \end{aligned} \tag{20}$$

where:

v_d, v_q	Stator voltage in $d-q$-axis;
i_d, i_q	Stator current in $d-q$-axis;
L_d, L_q	Stator inductance in $d-q$-axis;
R_s	Stator resistance;
p	Number of pole pairs;
Ω	Mechanical speed of motor
Φ_f	Flux created by the rotor magnets;
F_c	Viscous friction coefficient;
J	Total moment of inertia of the motor and load;
T_{em}, T_r	Electromagnetic torque and load torque;

5.2 Speed Control

In the case of surface-mounted PMSM ($L_d = L_q$), the electromagnetic torque depends solely on current in the q axis. For a given torque, the transferred power is optimized if the current in the direct axis is null ($i_d = 0$) [29]. Hence, the control objective is to force the current i_d to zero and to impose the demanded torque by controlling the current i_q. Physically by this strategy, the linked stator flux is maintained in quadrature with flux produced by the rotor magnets. The proposed schema of indirect adaptive fuzzy control, about the speed tracking of the PMSM, appears in Fig. 2.

From the reference speed Ω_{ref} and measured speed Ω, the fuzzy adaptive controller provides the desired current. The three-phase reference current is obtained from the $(d-q)$ stator reference current (i_{dref}, $i_{qref} = 0$) by using the inverter Park transformation. The actual stator current (i_a, i_b, i_c) is restricted in hysteresis bandwidth Δi around the three-phase reference currents by using an appropriate switching of the inverter legs. By using the equilibrium equation between the motor torque and the torque opposed by the mechanical part of the system, we can write:

$$\frac{d\Omega}{dt} = f(\Omega) + g(\Omega)\cdot i_q. \tag{21}$$

Using equation (30), the fuzzy identifier becomes:

$$\dot{\hat{\Omega}} = -\alpha\cdot\hat{\Omega} + \alpha\cdot\Omega + \hat{f}(\Omega;\hat{\theta}_f) + \hat{g}(\Omega;\hat{\theta}_g)\cdot i_q. \tag{22}$$

However, the estimated $\hat{f}(.)$and $\hat{g}(.)$ of the function $f(.)$ and $g(.)$ can be generated in the form:

$$\begin{aligned} &\hat{f}(\Omega;\hat{\theta}_f) = W_f(\Omega)\hat{\theta}_f, \\ &\hat{g}(\Omega;\hat{\theta}_g) = W_g(\Omega)\hat{\theta}_g. \end{aligned} \tag{23}$$

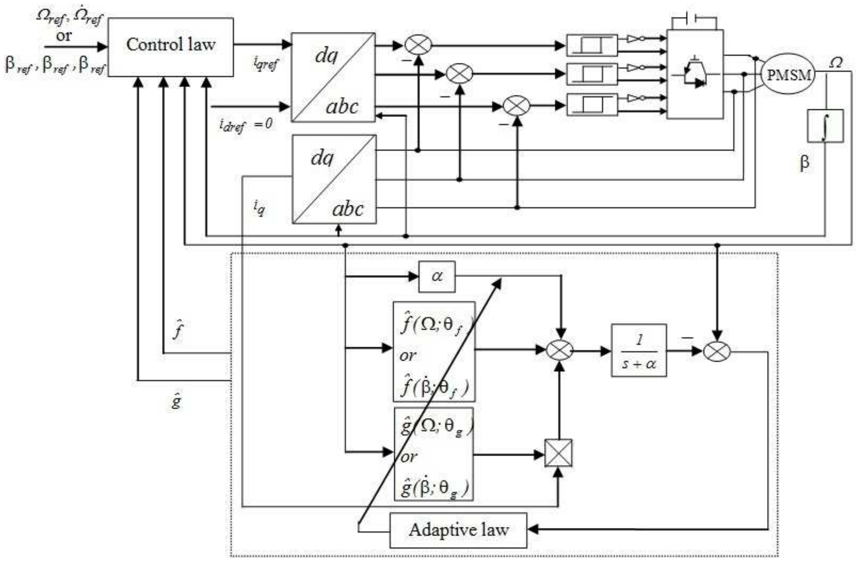

Figure 2: Indirect adaptive fuzzy control scheme of permanent magnet synchronous motor.

For this application, the fuzzy system has one variable at input and this variable is described by 3 membership functions.

The identification error is given as follows:

$$e(t) = \Omega - \hat{\Omega}. \tag{24}$$

The parameter adaptive law is given by:

$$\begin{aligned} \dot{\hat{\theta}}_f &= \eta_{f\Omega} W_f(\Omega)\, e - k_\Omega \,\|e\|\, \hat{\theta}_f, \\ \dot{\hat{\theta}}_g &= \eta_{g\Omega} W_g(\Omega)\, e\, i_{qref} - k_\Omega \,\|e\|\, \hat{\theta}_g, \end{aligned} \tag{25}$$

where $\eta_{f\Omega}$,$\eta_{f\Omega}$ and k_Ω are positive constants.

Consequently, the control law i_{qref} is given by:

$$i_{qref} = \frac{v - \hat{f}(\Omega; \hat{\theta}_f)}{\hat{g}(\Omega; \hat{\theta}_g)} \tag{26}$$

with

$$v = \dot{\Omega}_{ref} + \lambda(\Omega_{ref} - \Omega), \quad \lambda > 0.$$

5.3 Position control

The procedure used previously is renewed in the case of the tracking of trajectory position. Thus, we again consider the equation (21) where $\dot{\Omega}$ is replaced by position β, which leads to:

$$\ddot{\beta} = f(\dot{\beta}) + g(\dot{\beta}) \cdot i_q \tag{27}$$

with

$$\beta = \frac{d\Omega}{dt}.$$

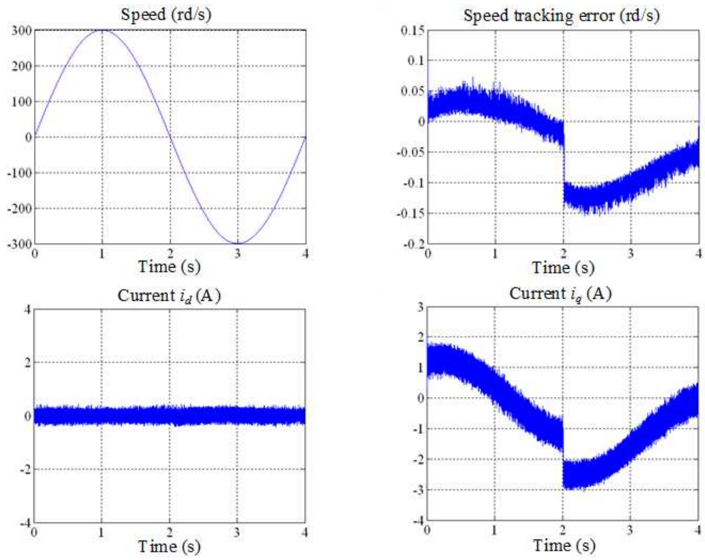

Figure 3: Speed tracking, with the nominal load torque is applied at $t = 2s$, of PMSM.

Using the equation (27), the identification model is:

$$\ddot{\hat{\beta}} = -\alpha \cdot \dot{\hat{\beta}} + \alpha \cdot \dot{\beta} + \hat{f}(\dot{\beta}; \hat{\theta}_f) + \hat{g}(\dot{\beta}; \hat{\theta}_g) \cdot i_q. \tag{28}$$

In our application we allot three membership functions to the input $\dot{\beta}$ for the two fuzzy systems. The estimated functions are given by:

$$\begin{aligned} \hat{f}(\dot{\beta}; \hat{\theta}_f) &= W_f(\dot{\beta}) \cdot \hat{\theta}_f, \\ \hat{g}(\dot{\beta}; \hat{\theta}_g) &= W_g(\dot{\beta}) \cdot \hat{\theta}_g, \end{aligned} \tag{29}$$

where the vector parameters $\hat{\theta}_f$ and $\hat{\theta}_g$ are updated by:

$$\begin{aligned} \dot{\hat{\theta}}_f &= \eta_{f\beta} \cdot W_f(\dot{\theta}) \cdot e - k_\beta \cdot \|e\| \cdot \hat{\theta}_f, \\ \dot{\hat{\theta}}_g &= \eta_{g\beta} \cdot W_f(\dot{\theta}) \cdot e \cdot i_{qref} - k_\beta \cdot \|e\| \cdot \hat{\theta}_g, \end{aligned} \tag{30}$$

with e being the identification error, it is given by:

$$e = \dot{\beta} - \dot{\hat{\beta}}, \tag{31}$$

$\eta_{f\beta}$,$\eta_{g\beta}$ and k_β are positive constants.

By using the functions ($\hat{f}$ and $\hat{g}$) from the fuzzy system model (29) and in accordance with the control law, the control law i_{qref} is involved by:

$$v = \ddot{\beta}_{ref} + k_{1\theta}(\dot{\beta}_{ref} - \dot{\beta}) + k_{2\theta}(\beta_{ref} - \beta).$$

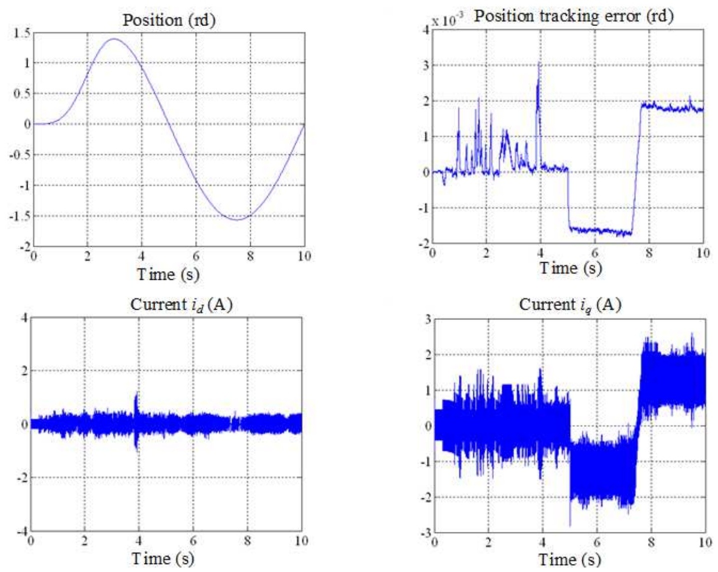

Figure 4: Position tracking, with the nominal load torque applied at $t = 5s$, of PMSM.

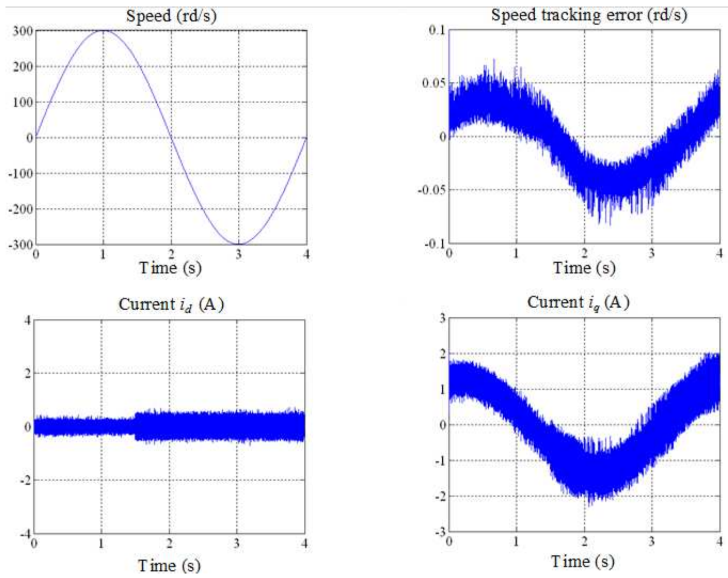

Figure 5: Speed tracking, with parameter variations at $t = 1.5s$, of PMSM.

5.3.1 Simulation results

The motor under tests is characterized by: $L_d = L_q = 0.0121\ H$, $\Phi_f = 0.013\ Wb$, $J = 0.0001\ kg \cdot m^2$, $F = 0.00005\ km^2/s$, $R_s = 3.4\ \Omega$ and $\Omega_n = 300\ rd/s$. The current-controlled inverter is fed by $70V$ continue voltage assumed constant. The proposed schema of the adaptive fuzzy controller is tested by simulation to perform the position and speed tracking of PMSM. The values of the control coefficients, which enabled us to

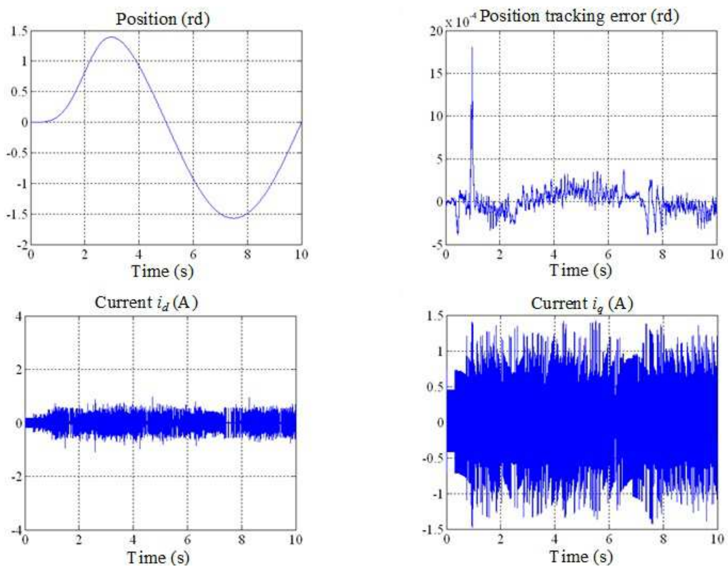

Figure 6: Position tracking, with parameter variations at $t = 1s$, of PMSM.

obtain satisfactory results, are collected in Table 1 and Table 2.

$\eta_{f\Omega}$	$\eta_{g\Omega}$	k_Ω	α	λ
50	50	0.5	5	10.85

Table 1: Speed control coefficients.

$\eta_{f\beta}$	$\eta_{g\beta}$	k_β	α	$k_{1\beta}$	$k_{2\beta}$
50	50	0.5	5	121	3694

Table 2: Position control coefficients.

The desired trajectories are imposed as:

$$\Omega_{ref} = 300 \sin\left(\frac{\pi}{2}t\right); \quad \beta_{ref} = \frac{\pi}{2}\left(1 - e^{-0.1\cdot t^3}\right)\sin\left(\frac{\pi}{5}t\right).$$

Figure 3 and Figure 4 give respectively the responses of the speed and position control in the case where the nominal load torque is applied. It appears that, the speed and position follow respectively their reference, the disturbance rejection is fast and the stator current is aligned on the q axis (i.e. $i_d = 0$). The robustness of the trajectories tracking of speed and position is carried out in the presence of the electric parameters variations. Indeed, these variations impose an increase of 100% of the stator resistances, a reduction of 50% of stator inductances and a reduction of 10% of the inductor flux. The obtained responses are represented in Figure 5 and Figure 6.

In spite of the application of these strong parameters variations the tracking speed and position are maintained with a weak tracking error. This shows clearly that this fuzzy adaptive control has the capacity to respond quickly to the evolution of the parameters and to their variations.

6 Conclusion

In this paper, we proposed an indirect fuzzy adaptive control scheme for a class of unknown nonlinear systems. In this controller, the adaptive fuzzy control law ensures the convergence of tracking errors and boundedness of the fuzzy logic system parameters. The application of the developed method is carried out for a permanent magnet synchronous motor. The obtained simulation results show that this adaptive control fuzzy law maintains the tracking errors in an acceptable interval with feasible control inputs in the presence of hard parameters variations or external disturbances.

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