View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Agora University Editing House: Journals

INT J COMPUT COMMUN, ISSN 1841-9836
8(3):395-406, June, 2013.

An Approach to Fuzzy Modeling of Electromagnetic Actuated Clutch Systems

C.-A. Dragoş, R.-E. Precup, M.L. Tomescu, S. Preitl, E.M. Petriu, M.-B. Rădac

Claudia-Adina Dragoş, Radu-Emil Precup,
Stefan Preitl, Mircea-Bogdan Rădac
"Politehnica" University of Timişoara
Department of Automation and Applied Informatics
Bd. V. Parvan 2, 300223 Timisoara, Romania
claudia.dragos@aut.upt.ro, radu.precup@aut.upt.ro,
stefan.preitl@aut.upt.ro, mircea.radac@aut.upt.ro

Marius L. Tomescu
Aurel Vlaicu University of Arad
Romania, 310330 Arad, Elena Dragoi, 2
tom_uav@yahoo.com

Emil M. Petriu
University of Ottawa
School of Electrical Engineering and Computer Science
800 King Edward, Ottawa, ON, K1N 6N5 Canada
petriu@eecs.uottawa.ca

Abstract: This paper proposes an approach to fuzzy modeling of a nonlinear servo system application represented by an electromagnetic actuated clutch system. The nonlinear model of the process is simplified and linearized around several operating points of the input-output static map of the process. Discrete-time Takagi-Sugeno (T-S) fuzzy models of the processes are derived on the basis of the modal equivalence principle; the rule consequents of these T-S fuzzy models contain the state-space models of the process. Three discrete-time T-S fuzzy models are suggested, compared and validated by simulation results.
Keywords: Discrete-time Takagi-Sugeno fuzzy models, electromagnetic actuated clutch system, linearization, operating points, simulation results.

1 Introduction

The process taken into consideration and modeled in this paper is an electromagnetic actuated clutch system as a representative nonlinear system application. Therefore the derivation of accurate models is a challenging problem. Several approaches to fuzzy modeling of nonlinear servo systems are given in the literature. They belong to the general framework of nonlinear process models [1], [2], [3], [4], [5]. A parallel distributed compensation scheme is proposed in [6] with focus on fuzzy reference models; the linear matrix inequalities are formulated and solved in order to linearize the errors between the feedback system and the nonlinear reference model. The nonlinear system behavior is modeled in [7] by the division of the phase plane into sub-regions and a linear model represented either in state-space or ARX model form is assigned for each regions; the linear models are next expressed as fuzzy models. A DSP-based fuzzy-linear-model robust tracking control is developed in [8] for a piezoelectric servo system with dominant hysteresis in terms of the weighted combination of N fuzzy linear pulse transfer functions; the fuzzy model is included in a dead-beat control system. An ANFIS-based neuro-fuzzy model for a low inertia servomotor is suggested in [9], and several comparisons between the performance of the system with the standard motor model and its neuro-fuzzy model are carried out in the framework of

Copyright © 2006-2013 by CCC Publications

adaptive control. Fuzzy feedback linearization and fuzzy sliding mode control applications are given in [10] and [11].
This paper offers discrete-time dynamic Takagi-Sugeno (T-S) fuzzy model of an electromagnetic actuated clutch system. The computation of the T-S fuzzy models starts with the derivation of the continuous-time models which are obtained on the basis of the local linearization of the process models at five operating points (o.p.s). The local models are next discretized accepting a zero-order hold, and these local models are placed in the rule consequents of the T-S fuzzy model of the process.

Our approach is advantageous because it is relatively simple and it can be incorporated in many fuzzy control structures [12], [13], [14], [15], [16], [17], [18], [19]. Three fuzzy models are offered and compared using simulation results.
The paper is organized as follows: Section 2 is dedicated to the mathematical modeling of the process, the computation of T-S fuzzy models is synthesized in Section 3. Simulation results are presented in Section 4 to validate the new T-S fuzzy models. The concluding remarks are highlighted in Section 5.

2 Process Modeling

The mathematical modeling of the electromagnetic actuator as part of electric drive clutches is based on the schematic structure of a magnetically actuated mass-spring-damper system presented in Figure 1 [20]. The state-space model of the nonlinear servo system is:

$$\begin{aligned}
&\dot{x}_1 = x_2, \\
&\dot{x}_2 = -\tfrac{k}{m}x_1 - \tfrac{c}{m}x_2 + \tfrac{k_a x_3^2}{m(k_b+d-x_1)^2}, \\
&\dot{x}_3 = -\tfrac{R(k_b+d-x_1)}{2k_a}x_2 x_3 + \tfrac{1}{k_b+d-x_1}x_2 x_3 + [(k_b+d-x_1)/2k_a]V, \\
&y = 1000x_1,
\end{aligned} \tag{1}$$

where x_1 is the position, i.e., the mass position, x_2 is the mass speed, x_3 is the current, V is the control signal, y is the measured position (output), k is the stiffness of the spring, c is the coefficient of the damper, R is the electromagnetic coil resistance, and k_a, k_b are the constants in the relation between the magnetic flux and the current. The numerical values of the process parameters are listed in [21].

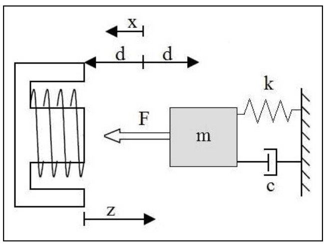

Figure 1: Schematic structure of a magnetically actuated mass-spring-damper system [20].

The linearization of the nonlinear servo system model (1) at five o.p.s $A_j(x_{10}, x_{20}, x_{30}, x_{40})$ (with j-the index of the o.p. $j = \overline{1,5}$, and 0-the index of the coordinates of the o.p.s, i.e., the state variables) leads to the linearized state-space models:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{b}\Delta V(t),$$
$$\Delta y(t) = \mathbf{c}^T\mathbf{x}(t),$$
$$\mathbf{x} = [\ x_1 = x \quad x_2 = \dot{x} \quad x_3 = i]^T,$$
$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{k}{m} + \frac{2k_a x_{30}^2}{m(k_b+d-x_{10})^3} & -\frac{c}{m} & \frac{2k_a x_{30}}{m(k_b+d-x_{10})^2} \\ \frac{Rx_{30}-V_0}{2k_a} - \frac{x_{20}x_{30}}{(k_b+d-x_{10})^2} & -\frac{x_{30}}{k_b+d-x_{10}} & -\frac{x_{20}}{k_b+d-x_{10}} - \frac{R(k_b+d-x_{10})}{2k_a} \end{bmatrix}, \quad (2)$$
$$\mathbf{b} = \begin{bmatrix} 0 \\ 0 \\ \frac{k_b+d-x_{10}}{2k_a} \end{bmatrix}, \mathbf{c}^T = [\ 1000 \quad 0 \quad 0\ ].$$

where $\mathbf{x}(t)$ is the system state vector, $\mathbf{A}$, $\mathbf{b}$ and $\mathbf{c}^T$ are the linearized system matrices, and t is the continuous time variable. The matrices of the discrete-time systems developed from (2) will be presented in the sequel.

3 Approach to Takagi-Sugeno Fuzzy Modeling

In order to capture both the static nonlinearity and the linear dynamics of the process, the derivation of a discrete-time dynamic T-S fuzzy model of the process is presented as follows. Figure 2 illustrates the structure of the T-S fuzzy model identification process.

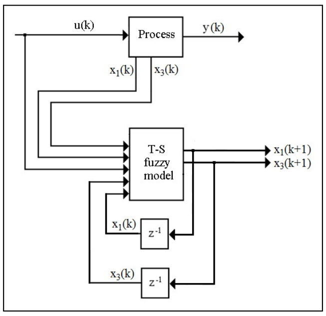

Figure 2: Structure of the discrete-time dynamic Takagi-Sugeno fuzzy model identification process.

The steps of our modeling approach are:

Step I. The definition of the membership functions of the input variables x_1 and x_3.

Step II. The choice of the settling time and the discretization of the continuous-time state-space models of the process which result in the discrete-time state-space models with the matrices $\mathbf{A}_{d,i}$, $\mathbf{B}_{d,i}$ and $\mathbf{C}_{d,i}$ and $\mathbf{C}_{d,i}$, $i = \overline{1,5}$.

Step III. The derivation of the T-S fuzzy model of the process, which has the state variables x_1 and x_3 as input variables, and the discrete-time state-space models of the process in the rule consequents.

The step I starts with the setting of the largest domains of variation of the two state variables used in all electromagnetic actuated clutch system operating regimes:

$$0 \leqslant x_1 \leqslant 0.004,\ 0 \leqslant x_3 \leqslant 10. \quad (3)$$

The fuzzification part of the T-S fuzzy model consists of the linguistic terms assigned to the input variables and defined as follows.

Three cases were considered for the input variable x_1 . The first two cases employ five linguistic terms, $LT_{x_1,j},\ j=\overline{1,5}$, with trapezoidal membership functions defined and referred to as $LT_{x_1,1}$, with the universe of discourse $[0.0019, 0.0023]$, $LT_{x_1,2}$, with the universe of discourse $[0.0021, 0.0027]$, $LT_{x_1,3}$, with the universe of discourse $[0.0023, 0.003]$, $LT_{x_1,4}$, with the universe of discourse $[0.0027, 0.0033]$ and $LT_{x_1,5}$, with the universe of discourse $[0.003, 0.004]$. The expressions of these trapezoidal membership functions are:

$$\mu_{TL_{x_3,j}}(x)=\begin{cases} 0, & x<a_{x_1,j} \\ 1+\frac{x-b_{x_1,j}}{b_{x_1,j}-a_{x_1,j}}, & x\in[a_{x_1,j},b_{x_1,j}) \\ 1, & x\in[b_{x_1,j},c_{x_1,j}) \\ 1-\frac{x-c_{x_1,j}}{d_{x_1,j}-c_{x_1,j}}, & x\in[c_{x_1,j},d_{x_1,j}) \\ 0, & x\geqslant d_{x_1,j} \end{cases},\ a_{x_1,j}<b_{x_1,j}\leqslant c_{x_1,j}<d_{x_1,j},\ j=\overline{1.5} \quad (4)$$

The modal values of the membership functions are the parameters $a_{x_1,j},\ j=\overline{1,5}$, $b_{x_1,j},\ j=\overline{1,5}$, $c_{x_1,j},\ j=\overline{1,5}$ and $d_{x_1,j},\ j=\overline{1,5}$. The values of these parameters are given in Table 1 for the first case and in Table 2 for the second case.

Table 1
Parameters of input membership functions in the first case

Linguistic terms, $LT_{x_1,j},\ j=\{1,5\}$	Trapezoidal membership functions $a_{x_1,j},\ j=\overline{1,5}$	$b_{x_1,j},\ j=\overline{1,5}$	$c_{x_1,j},\ j=\overline{1,5}$	$d_{x_1,j},\ j=\overline{1,5}$
$LT_{x_1,1}$	0.0019	0.0019	0.0021	0.0023
$LT_{x_1,2}$	0.0019	0.0021	0.0023	0.0027
$LT_{x_1,3}$	0.0021	0.0023	0.0027	0.003
$LT_{x_1,4}$	0.0023	0.0027	0.003	0.00384
$LT_{x_1,5}$	0.003	0.00384	0.004	0.004

Table 2
Parameters of input membership functions in the second case

Linguistic terms, $LT_{x_1,j},\ j=\{1,5\}$	Trapezoidal membership functions $a_{x_1,j},\ j=\overline{1,5}$	$b_{x_1,j},\ j=\overline{1,5}$	$c_{x_1,j},\ j=\overline{1,5}$	$d_{x_1,j},\ j=\overline{1,5}$
$LT_{x_1,1}$	0.0019	0.0019	0.0021	0.0023
$LT_{x_1,2}$	0.0021	0.0023	0.0025	0.0027
$LT_{x_1,3}$	0.0025	0.0027	0.003	0.0033
$LT_{x_1,4}$	0.003	0.0033	0.0035	0.00384
$LT_{x_1,5}$	0.0035	0.00384	0.004	0.004

Five linguistic terms, $LT_{x_1,j},\ j=\overline{1,5}$, with trapezoidal and triangular membership functions are defined and employed in the third case, and referred to as $LT_{x_1,1}$, with the universe of discourse $[0.0019, 0.0023]$, $LT_{x_1,2}$, with the universe of discourse $[0.0021, 0.0027]$, $LT_{x_1,3}$, with the universe of discourse $[0.0023, 0.003]$, $LT_{x_1,4}$, with the universe of discourse $[0.0027, 0.0033]$, and $LT_{x_1,5}$, with the universe of discourse $[0.003, 0.004]$. The modal values of the trapezoidal membership functions are the parameters $a_{x_1,j},\ j\in\{1,5\}$, $b_{x_1,j},\ j\in\{1,5\}$, $c_{x_1,j},\ j\in\{1,5\}$ and $d_{x_1,j},\ j\in\{1,5\}$ given in Table 3.

Table 3
Parameters of trapezoidal input membership functions in the third case

Linguistic terms,	Trapezoidal membership functions			
$LT_{x_1,j},\ j=\{1,5\}$	$a_{x_1,j},\ j\in\{1,5\}$	$b_{x_1,j},\ j\in\{1,5\}$	$c_{x_1,j},\ j\in\{1,5\}$	$d_{x_1,j},\ j\in\{1,5\}$
$LT_{x_1,1}$	0.0019	0.0019	0.0021	0.0023
$LT_{x_1,5}$	0.0033	0.00384	0.004	0.004

The expressions of the triangular membership functions are:

$$\mu_{TL_{x_1,j}}(x)=\begin{cases}0, & x<a_{x_1,j}\\ 1+\frac{x-b_{x_1,j}}{b_{x_1,j}-a_{x_1,j}}, & x\in[a_{x_1,j},b_{x_1,j})\\ 1-\frac{x-b_{x_1,j}}{c_{x_1,j}-b_{x_1,j}}, & x\in[b_{x_1,j},c_{x_1,j})\\ 0, & x\geqslant c_{x_1,j}\end{cases},\ a_{x1,j}<b_{x1,j}<c_{x1,j},\ j=\overline{2,4} \tag{5}$$

where the modal values of the membership functions are the parameters $a_{x_1,j}$, $b_{x_1,j}$, and $c_{x_1,j}$, $j=\overline{2,4}$ presented in Table 4.

Table 4
Modal values of linguistic terms in the third case

Linguistic terms,	Trapezoidal membership functions		
$LT_{x_1,j},\ j=\overline{2,4}$	$a_{x_1,j}$	$b_{x_1,j}$	$c_{x_1,j}$
$LT_{x_1,1}$	0.0021	0.0023	0.0027
$LT_{x_1,3}$	0.0023	0.0027	0.003
$LT_{x_1,4}$	0.0027	0.003	0.0033

Figure 3 shows the membership functions of x_1 in these three cases: the first case in Figure 3 (a), the second case in Figure 3 (b) and the third case in Figure 3 (c).

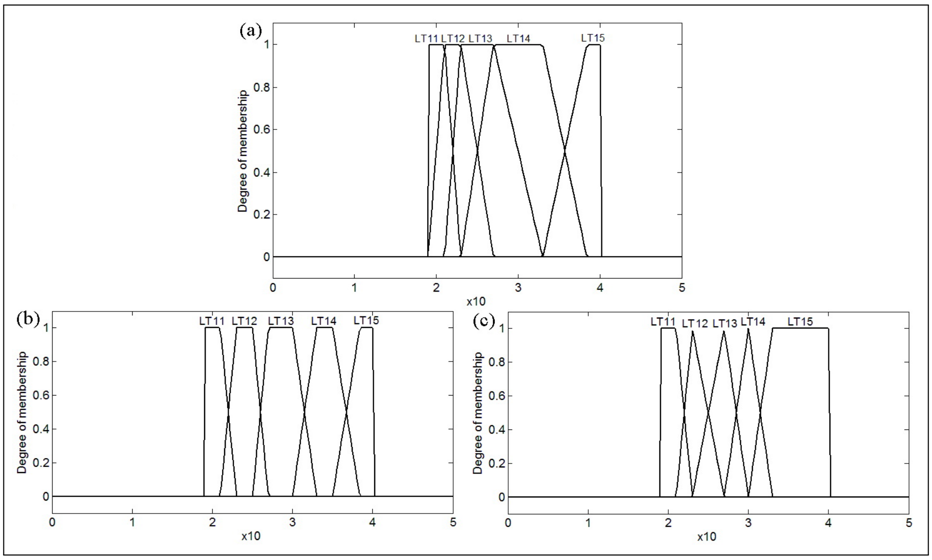

Figure 3: Membership functions of the input variable x_1 in the first case (a), in the second case (b) and in the third case (c).

Five linguistic terms, $LT_{x_3,j},\ j=\overline{1,5}$, are defined for the input variable x_3 . The first and the fifth one are modeled by trapezoidal membership functions, and the second, the third and the fourth one are modeled by trapezoidal membership functions. The universes of discourse of the membership functions of these linguistic terms are: $[4,8]$ for $LT_{x_3,1}$, $[5,9]$ for $LT_{x_3,2}$, for $[6,10]$, $LT_{x_3,3}$, $[7,11]$ for $LT_{x_3,4}$, and $[8,12]$ for $LT_{x_3,5}$. The expressions of the trapezoidal membership functions are:

$$\mu_{TL_{x_3,j}}(x) = \begin{cases} 0, & x < a_{x_3,j} \\ 1 + \frac{x - b_{x_3,j}}{b_{x_3,j} - a_{x_3,j}}, & x \in [a_{x_3,j}, b_{x_3,j}) \\ 1, & x \in [b_{x_3,j}, c_{x_3,j}) \\ 1 - \frac{x - c_{x_3,j}}{d_{x_3,j} - c_{x_3,j}}, & x \in [c_{x_3,j}, d_{x_3,j}) \\ 0, & x \geqslant d_{x_3,j} \end{cases}, \ a_{x_3,j} < b_{x_3,j} \leqslant c_{x_3,j} < d_{x_3,j}, \ j \in \{1,5\} \quad (6)$$

The modal values of the membership functions are the parameters $a_{x_3,j}$, $j \in \{1,5\}$, $b_{x_3,j}$, $j \in \{1,5\}$, $c_{x_3,j}$, $j \in \{1,5\}$, and $d_{x_3,j}$, $j \in \{1,5\}$, given in Table 5.

Table 5
Parameters of trapezoidal linguistic terms

Linguistic terms,	Trapezoidal membership functions			
$LT_{x_3,j}$, $j = \{1,5\}$	$a_{x_3,j}$, $j \in \{1,5\}$	$b_{x_3,j}$, $j \in \{1,5\}$	$c_{x_3,j}$, $j \in \{1,5\}$	$d_{x_3,j}$, $j \in \{1,5\}$
$LT_{x_3,1}$	4	4	6	8
$LT_{x_3,5}$	8	10	12	12

The expressions of the triangular membership functions are:

$$\mu_{TL_{x_1,j}}(x) = \begin{cases} 0, & x < a_{x_1,j} \\ 1 + \frac{x - b_{x_1,j}}{b_{x_1,j} - a_{x_1,j}}, & x \in [a_{x_1,j}, b_{x_1,j}) \\ 1 - \frac{x - b_{x_1,j}}{c_{x_1,j} - b_{x_1,j}}, & x \in [b_{x_1,j}, c_{x_1,j}) \\ 0, & x \geqslant c_{x_1,j} \end{cases}, \ a_{x1,j} < b_{x1,j} < c_{x1,j}, \ j = \overline{2,4}, \quad (7)$$

where the modal values of the membership functions are the parameters $a_{x_3,j}$, $b_{x_3,j}$, and $c_{x_3,j}$, $j = \overline{2,4}$, given in Table 6.

Table 6
Modal values of linguistic terms

Linguistic terms,	Trapezoidal membership functions		
$LT_{x_3,j}$, $j = \overline{2,4}$	$a_{x_3,j}$	$b_{x_3,j}$	$c_{x_3,j}$
$LT_{x_3,1}$	5	7	9
$LT_{x_3,3}$	6	8	10
$LT_{x_3,4}$	7	9	11

Figure 4 shows the membership functions of the input x_3.

The rule consequents of the T-S fuzzy models correspond to the discrete-time state-space models characterized by the matrices $\mathbf{A}_{d,i}$, and $\mathbf{B}_{d,i}$, $\mathbf{C}_{d,i}$, $i = \overline{1,5}$, detailed in Table 7. These models are obtained by discretization of the continuous-time state-space linearized models (1) using the sampling period $T_s = 0.001$ s.

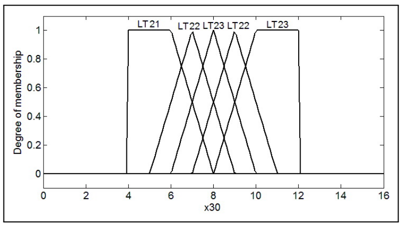

Figure 4: Membership functions of the input variable x_3.

Table 7
Numerical values of matrices of discrete-time state-space models

O.p.s	Numerical values of the matrices
1	$\mathbf{A}_{d1} = \begin{bmatrix} 0.9864 & 0.0007 & 0.0000062 \\ -24.3234 & 0.4847 & 0.011 \\ 3.018 & -0.1579 & 0.9816 \end{bmatrix}, \mathbf{B}_{d1} = \begin{bmatrix} 0.000000031 \\ 0.000088 \\ 0.0142 \end{bmatrix},$ $\mathbf{C}_{d1} = [1000 \quad 0 \quad 0]$
2	$\mathbf{A}_{d1} = \begin{bmatrix} 0.9869 & 0.0007 & 0.0000073 \\ -23.352 & 0.4847 & 0.013 \\ 3.4059 & -0.1856 & 0.9811 \end{bmatrix}, \mathrm{B}_{d1} = \begin{bmatrix} 0.000000036 \\ 0.000088 \\ 0.0142 \end{bmatrix},$ $\mathbf{C}_{d1} = [1000 \quad 0 \quad 0]$
3	$\mathbf{A}_{d1} = \begin{bmatrix} 0.9876 & 0.0007 & 0.0000086 \\ -22.0872 & 0.4847 & 0.0153 \\ 3.7379 & -0.2153 & 0.9807 \end{bmatrix}, \mathbf{B}_{d1} = \begin{bmatrix} 0.000000042 \\ 0.00012 \\ 0.0139 \end{bmatrix},$ $\mathbf{C}_{d1} = [1000 \quad 0 \quad 0]$
4	$\mathbf{A}_{d1} = \begin{bmatrix} 0.9885 & 0.0007 & 0.0000101 \\ -20.4072 & 0.4847 & 0.018 \\ 3.9765 & -0.2479 & 0.9801 \end{bmatrix}, \mathbf{B}_{d1} = \begin{bmatrix} 0.000000049 \\ 0.000139 \\ 0.0135 \end{bmatrix},$ $\mathbf{C}_{d1} = [1000 \quad 0 \quad 0]$
5	$\mathbf{A}_{d1} = \begin{bmatrix} 0.9897 & 0.0007 & 0.0000101 \\ -18.3864 & 0.4847 & 0.0209 \\ 4.1934 & -0.2814 & 0.9793 \end{bmatrix}, \mathbf{B}_{d1} = \begin{bmatrix} 0.000000055 \\ 0.000158 \\ 0.0132 \end{bmatrix},$ $\mathbf{C}_{d1} = [1000 \quad 0 \quad 0]$

The modal equivalence principle guarantees the equivalence between the fuzzy models and the nonlinear state-space models. That is the reason to express the rule base of the discrete-time dynamic T-S fuzzy models in the following general form:

$$R^i : \mathrm{IF} x_{1,k} \mathrm{IS} LT_{x_{1,j}} \mathrm{AND} x_{3,k} \mathrm{IS} LT_{x_{3,j}} \text{ THEN} \begin{cases} \mathbf{x}_{k+1} = \mathbf{A}_{d,i}\mathbf{x}_k + \mathbf{B}_{d,i}u_k \\ y_{k,m} = \mathbf{C}_{d,i}\mathbf{x}_k \end{cases}, \quad (8)$$
$$i = \overline{1, nR}, \; j = \overline{1, nLT},$$

where k is the index of the current sampling interval, i is the index of the current rule, j is the index of the current linguistic term, nR is the number of rules, nLT is the number of linguistic terms, $nR = nLT = 5$ in our discrete-time dynamic T-S fuzzy models.

The fuzzy controller employs the SUM and PROD operators and the weighted average defuzzification method. Other operators can be used [22], [23], [24], [25], [26], [27].

4 Experimental Results

The modeling approach presented in the previous sections is applied and exemplified in this section in order to obtain fuzzy models for the electromagnetic actuated clutch system. Three T-S fuzzy models were developed for this nonlinear process. Some comparisons were done to illustrate the difference between them. A part of the results is presented as follows. The simulation results include the evolutions of the position versus time (in Figure 5), the evolution of the measured position versus time (in Figure 6), the evolution of the modeling error versus time (in Figure 7), and the evolution of the current versus time (in Figure 8).
Figure 5 and Figure 6 present the evolution of both position and measured position y in four cases: nonlinear model (1) of the process, first T-S fuzzy model, second T-S fuzzy model and third T-S fuzzy model. These evolutions point out in all cases an aperiodical evolution with a small overshoot, but the fuzzy modeled responses exhibit a delay of 0.1 s and they exceed the steady-state values of the nonlinear model. The modeling error versus time is highlighted in Figure 7 to outline the difference between the nonlinear model and the fuzzy models.

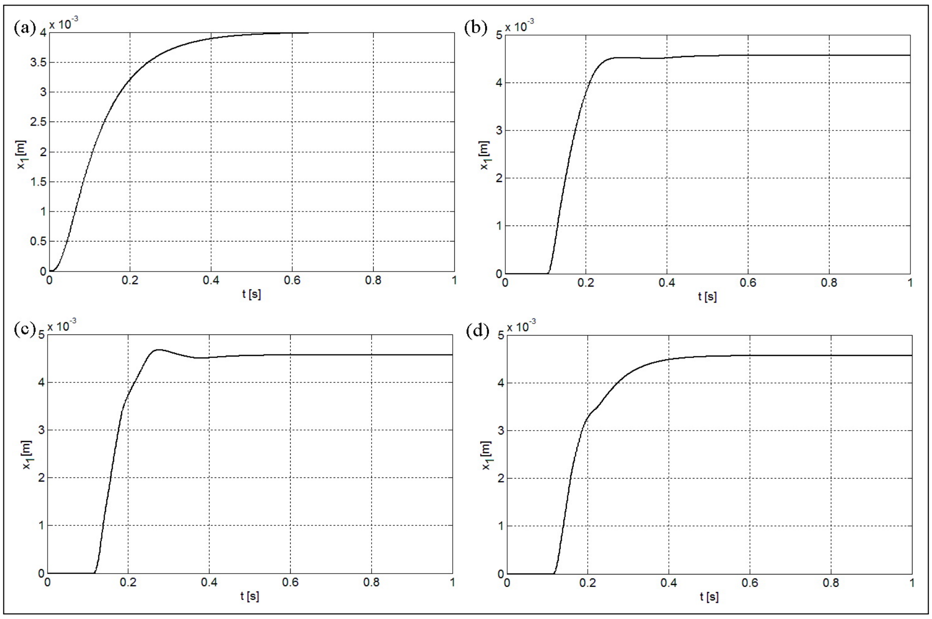

Figure 5: Position of nonlinear model (a), of first T-S fuzzy model (b), of second T-S fuzzy model (c) and of third T-S fuzzy model (d) versus time.

Figure 8 points out the evolution of the current in the same four cases: nonlinear model (1) of the process, first T-S fuzzy model, second T-S fuzzy model and third T-S fuzzy model. Figure 8 illustrates that the current exhibited by the T-S fuzzy models has a delay, but it reaches the steady-state value in approximately 0.5 s and with aperiodical response as that of the model (1). All responses point out a delay of 0.1 s which must be reduced. Moreover, the convergence of the modeling error to zero can be achieved by the optimization of the parameters of several parameters of the fuzzy models including input membership functions or parameters in the rule consequents. Various optimization algorithms can be implemented in this context [28], [29], [30], [31], [32], [33], [34], [35], [36].

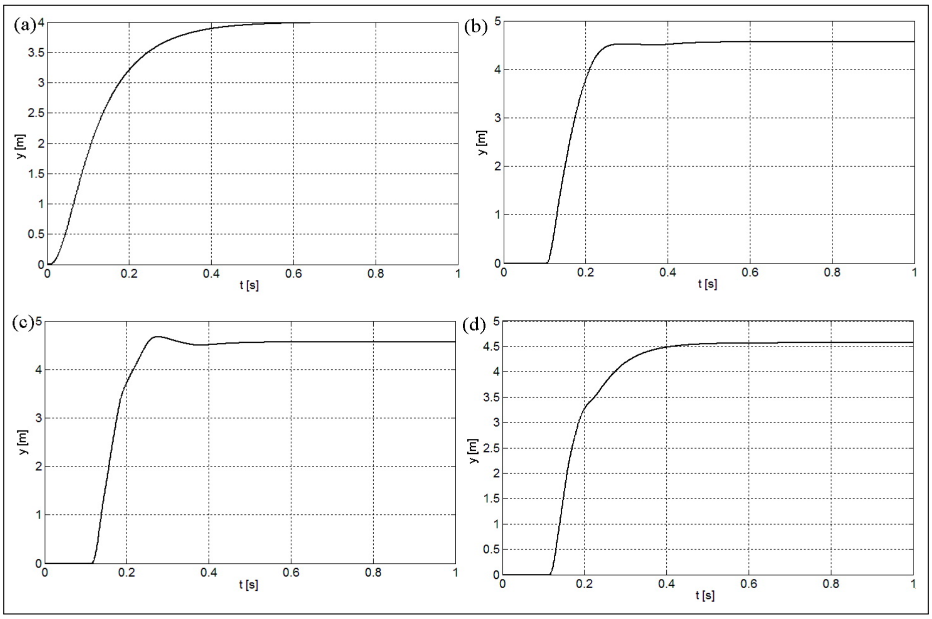

Figure 6: Measured position of nonlinear model (a), of first T-S fuzzy model (b), of second T-S fuzzy model (c) and of third T-S fuzzy model (d) versus time.

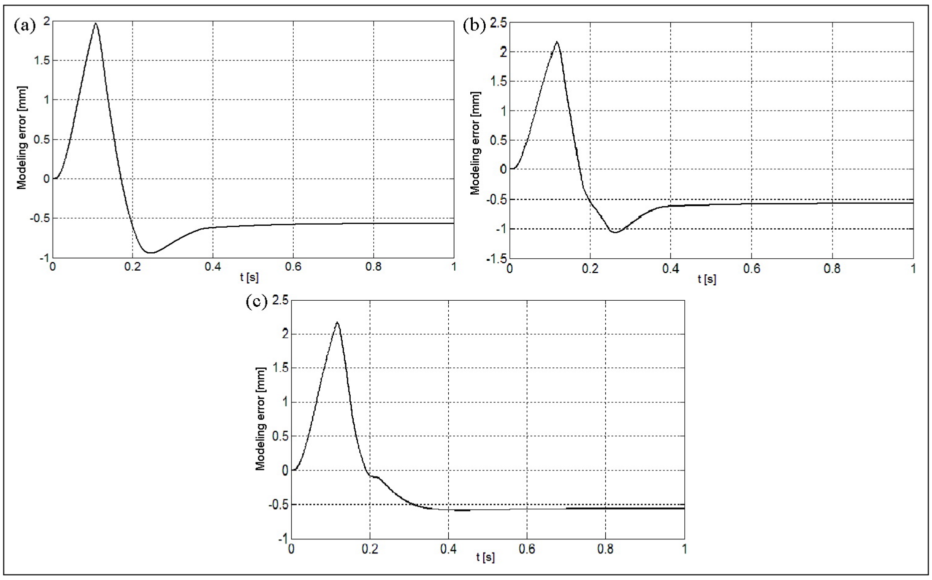

Figure 7: Modeling error of first T-S fuzzy model (a), of second T-S fuzzy model (b) and of third T-S fuzzy model (c) versus time.

5 Conclusions

The paper has proposed an approach to the fuzzy modeling of an electromagnetic actuated clutch system. This approach is important because it is easily applicable with adequate but not complicated generalizations to a wide category of industrial applications. Other similar T-S fuzzy models can be obtained in order to be further used in the T-S fuzzy controller design and tuning.

The future work will be dedicated to separating a part of the parameters of the input membership functions. These parameters will be obtained by different optimization algorithms which

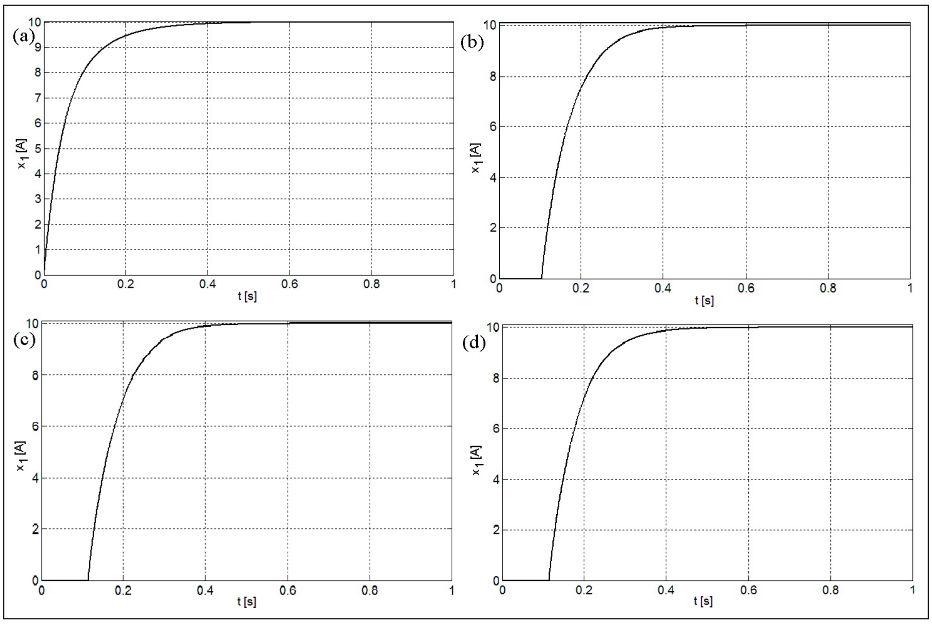

Figure 8: Current of nonlinear model (a), of first T-S fuzzy model (b), of second T-S fuzzy model (c) and of third T-S fuzzy model (d) versus time.

will solve the optimization problems with objective functions that depend on the modeling errors. The reduction of the modeling errors will be thus ensured.

Acknowledgements

This work was supported by a grant in the framework of the Partnerships in priority areas - PN II program of the Romanian National Authority for Scientific Research ANCS, CNDI - UEFISCDI, project number PN-II-PT-PCCA-2011-3.2-0732.

Bibliography

[1] Škrjanc, I.; Blažič, S.; Agamennoni O. (2005); Identification of dynamical systems with a robust interval fuzzy model, *Automatica*, 41(2):327-332.

[2] Johanyák, Z.C. (2010); Survey on five fuzzy inference-based student evaluation methods, in: Computational Intelligence in Engineering, I. J. Rudas, J. Fodor, J. Kacprzyk, Eds., *Studies in Computational Intelligence*, Springer-Verlag, Berlin, Heidelberg, 313:219-228.

[3] Vaščăk, J.; Madarász, L. (2010); Adaptation of fuzzy cognitive maps-a comparison study, *Acta Polytechnica Hungarica*, 7(3):109-122.

[4] Babu Devasenapati, S.; Ramachandran, K. I. (2011) Hybrid fuzzy model based expert system for misfire detection in automobile engines, *Int. J. of Artificial Intelligence*, 7(A11):47-62.

[5] Dzitac, I; Vesselényi, T; Tarcă, R. C. (2011) Identification of ERD using fuzzy inference systems for brain-computer interface, *INT J COMPUT COMMUN*, ISSN 1841-9836, 6(3):403-417.

[6] Taniguchi, T; Tanaka, K.; Yamafuji, K.; Wang, O.H. (1999) A new PDC for fuzzy reference models, *Proc. of 1999 IEEE Int. Conf. on Fuzzy Systems*, Seoul, Korea, 2:898-903.

[7] Eksin, I.; Erol, O.K. (2000) A fuzzy identification method for nonlinear systems, *Turkish Journal of Electrical Engineering and Computer Sciences*, 8(2):125-135.

[8] Hwang, V.-L.; Jan (2002) A DSP-based fuzzy robust tracking control for piezoelectric servosystems, *Proc. of 2002 IEEE International Conference on Fuzzy Systems*, Honolulu, HI, USA, 2:1410-1415.

[9] Mihai, D. (2004) Discrete fuzzy control loops based on a motor neuro-fuzzy model. Pushing too far a continuous logic?, *Proceedings of 2004 IEEE International Conference on Fuzzy Systems*, Budapest, Hungary, 2:587-592.

[10] Chien, T.-L.; Chen, C.-C.; Tsai, M.-C.; Chen, Y.-C. (2010) Control of AMIRA's ball and beam system via improved fuzzy feedback linearization approach, *Applied Mathematical Modelling*, 34(12):3791-3804.

[11] Cerman, O.; Hušek, P. (2012) Adaptive fuzzy sliding mode control for electro-hydraulic servo mechanism, Expert Systems with Applications, 39(11):10269-10277.

[12] Precup, R.-E.; Preitl, S. (1999) Fuzzy Controllers, *Editura Orizonturi Universitare Publishers*, Timişoara.

[13] Orlowska-Kowalska, T.; Szabat, K.; Jaszczak, K. (2002) The influence of parameters and structure of PI-type fuzzy-logic controller on DC drive system dynamics, *Fuzzy Sets and Systems*, 131(2):251-264.

[14] Precup, R.-E.; Preitl, S.; Faur, G. (2003) PI predictive fuzzy controllers for electrical drive speed control: Methods and software for stable development, *Computers in Industry*, 52(3):253-270.

[15] Precup, R.-E.; Preitl, S.; Korondi, P. (2007) Fuzzy controllers with maximum sensitivity for servosystems, *IEEE Transactions on Industrial Electronics*, 54(3):1298-1310.

[16] Angelov, P.; Lughofer, E.; Zhou X. (2008) Evolving fuzzy classifiers using different model architectures, *Fuzzy Sets and Systems*, 159(23):3160-3182.

[17] Precup, R.-E.; Preitl, S.; Petriu, E.M.; Tar, J.K.; Tomescu, M.L.; Pozna, C. (2009) Generic two-degree-of-freedom linear and fuzzy controllers for integral processes, *Journal of The Franklin Institute*, 346(10):980-1003.

[18] Linda, O.; Manic, M. (2011) Interval yype-2 fuzzy voter design for fault tolerant systems, *Information Sciences*, 181(14):2933-2950.

[19] Khanesar, M. A.; Teshnehlab, M.; Kaynak, O. (2012) Control and synchronization of chaotic systems using a novel indirect model reference fuzzy controller, *Soft Computing*, 16(7):1253-1265.

[20] Di Cairano, S.; Bemporad, A.; Kolmanovsky, I.V.; Hrovat, D. (2007) Model predictive control of magnetically actuated mass spring dampers for automotive applications, *International Journal of Control*, 80(11):1701-1716.

[21] Dragoş, C.-A.; Preitl, S.; Precup, R.-E.; Petriu, E.M.; Stînean, A.-I. (2011) A comparative case study of position control solutions for a mechatronics application, *Proc. of 2011 IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, Budapest, Hungary:814-819.

[22] Angelov, P.; Buswell, R. (2003) Automatic generation of fuzzy rule-based models from data by genetic algorithms, *Information Sciences*, 150(1-2):17-31.

[23] Precup, R.-E.; Tomescu, M.-L.; Preitl, S. (2007) Lorenz system stabilization using fuzzy controllers, *INT J COMPUT COMMUN*, ISSN 1841-9836, 2(3):279-287.

[24] Johanyák, Z.C. (2010) Student evaluation based on fuzzy rule interpolation, *Int. J. of Artificial Intelligence*, A10(5):37-55.

[25] Vaščák, J.; Madarász, L. (2010) Adaptation of fuzzy cognitive maps-A comparison study, *Acta Polytechnica Hungarica*, 7(3):109-122.

[26] Sadighi, A.; Kim, W.-J. (2011) Adaptive-neuro-fuzzy-based sensorless control of a smart-material actuator, *IEEE/ASME Transactions on Mechatronics*, 16(2):371-379.

[27] Ho, T.H.; Ahn, K.K. (2012) Speed control of a hydraulic pressure coupling drive using an adaptive fuzzy sliding-mode control, *IEEE/ASME Transactions on Mechatronics*, 17(5):976-986.

[28] Precup, R.-E.; Preitl, S. (2004) Optimisation criteria in development of fuzzy controllers with dynamics, *Engineering Applications of Artificial Intelligenc*e, 17(6):661-674.

[29] Blažič, S.; Matko, D.; Škrjanc, I. (2010) Adaptive law with a new leakage term, *IET Control Theory* & *Applications*, 4(9):1533-1542.

[30] Sánchez Boza, A.; Haber-Guerra, R.; Gajate, A. (2011) Artificial cognitive control system based on the shared circuits model of sociocognitive capacities. A first approach, *Engineering Applications of Artificial Intelligence*, 24(2):209-219.

[31] Liu, T.; Hu, Z. (2011) Immune algorithm with memory coevolution, *Int. J. of Artificial Intelligence*, 7(A11):189-197.

[32] Niu, B.; Fan, Y.; Wang, H.; Li, L.; Wang, X. (2011) Novel bacterial foraging optimization with time-varying chemotaxis step, *International Journal of Artificial Intelligence*, 7(A11):257-273.

[33] Damanafshan, M.; Khosrowshahi-Asl, E.; Abbaspour, M. (2012) GASANT: An ant-inspired least-cost QoS multicast routing approach based on genetic and simulated annealing algorithms, *INT J COMPUT COMMUN*, ISSN 1841-9836, 7(3):417-431.

[34] Rankovic, V.; Radulovic, J.; Grujovic, N.; Divac, D. (2012) Neural network model predictive control of nonlinear systems using genetic algorithms, *INT J COMPUT COMMUN*, ISSN 1841-9836, 7(3):540-549.

[35] Bacanin, N.; Tuba, M. (2012) Artificial Bee Colony (ABC) algorithm for constrained optimization improved with genetic operators, *Studies in Informatics and Control*, 21(2):137-146.

[36] Ben Omrane, I.; Chatti, A.; Borne, P. (2012) Evolutionary method for designing and learning control structure of a wheelchair, *Studies in Informatics and Control*, 21(2):155-164.