MULTI-MODEL ADAPTIVE CONTROL SYSTEMS

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Abstract: *A system with multiple models and adaptive control will be presented. The advantages of this control with respect to the classical control will be illustrated on a level control system with nonlinear model plant. A recent recursive method in open and closed-loop identification and an R-S-T controller design has been proposed to guarantee the performances in the adaptive control scheme. The real time control system implementation confirms the opportunity of using the multi-models adaptive control architecture in the case when the nonlinear plant model introduces a typical large parameter variation. The article presents also an method to switch the algorithms. The obtained results for tested instalation show that the control strategy based on a single model and on a single controller generates a time response that is more affected by noise than the response given by an adaptive strategy. The multiple models adaptive control procedure proposed has the following advantages: a more precise model is chosen for the closed loop operating system, the R-S-T adaptive control ensures very good real time results for closed loop nonlinear system. It can be appreciate that the multiple models adaptive control can be recommended to improve the performances of the nonlinear control systems.*

Keywords *multi-models, closed-loop identification, R-S-T control, adaptive control, real time application*

1. INTRODUCTION

Since the 90's different approaches for the multi-model control strategy have been developed. The Balakrishnan's and Narenda's first papers which proposed several stability and robustness methods using classical switching and tuning algorithms have to be mentioned. Further research in this field determined the extension and improvement of the multi-model control concept. Magill and Lainiotis introduced the model representation through Kalman filters. In order to maintain the stability of minimum phase systems, Middelton improved the switching procedure using an algorithm with hysteresis. Petridis', Kehagias' and Toscano's work focused on nonlinear systems with time variable. Landau and Karimi have important contributions regarding the use of several particular parameter adaptation procedures, namely CLOE (Closed Loop Output Error). The multi-model control version proposed by Narenda is based on neural networks. Finally, Dubois, Dieulot and Borne apply fuzzy procedures for switching and sliding mode control.

In this paper a multi-model control procedure with closed loop identification for model parameter re-estimation and with adaptive control (re)design after each switching operation is proposed. This study emphasizes a new procedure for the multi-model control system design that assures improved performances for real time nonlinear control systems.

We consider the next set of models:

$$M = \left\{\mathcal{M}_1, \mathcal{M}_2, \mathcal{M}_3 \ldots \mathcal{M}_n\right\}$$

and the class of the correspondent controllers:

$$C = \left\{C_1, C_2, C_3 \ldots C_n\right\},$$

integrated in the closed-loop configuration, as presented in figure I.

The input and output of the process *P* are *u* and *y* respectively, and *r* is the set point of the system. The M_i (i=1,2,... n) models are a priori evaluated. For each model M_i a controller C_i is designed in order to assure the nominal performances for the pair (M_i, C_i).

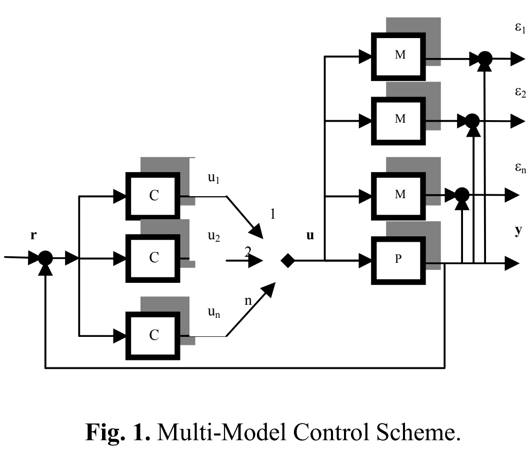

Fig. 1. Multi-Model Control Scheme.

The main idea of the multi-model adaptive control procedure is to chose the best model included in *M* that best approximates the process around a current operating point, to apply the correspondent controller and than to continue adaptively towards the current operating point of the process [9], [16].

In order to use this mechanism, the control problem is developed in two steps [4], [9]:

a) The model with the smallest error with respect to a performance criterion is chosen: *switching step*. After this operation the correspondent control input *u* is attached to the chosen model.

b) The corresponding controller is selected. Using the adaptive strategy for real time control system, the parameters of the model are adjusted by means of a recursive closed-loop identification technique (CLOE). The controller is also re-designed according to the final adaptive model obtained: *tuning step*.

The multi-model procedure can be used without the adaptive mechanism, in this case the tuning step being ignored [1]. Because the initial adaptive model is the fixed model C_i that best approximates the process around the current set point, the convergence of the adaptive mechanism is improved.

2. MODEL SELECTION

The model-error at the *k* instant is defined as the difference between the output *y* of the process and the output y_i of the model M_i:

$$\varepsilon_i(k) = y(k) - y_i(k) \qquad (1)$$

For each model there is a controller that satisfies the control objective. The performance criterion used as selection rule is defined below:

$$J_i(k) = \alpha\varepsilon_i^2(k) + \beta\sum_{j=1}^{k} e^{-\lambda(k-j)} e_i^2(j) \qquad (2)$$

where α>0 and β>0 are the weighting factor and the long term accuracy for the instantaneous measurements, respectively; λ>0 is the forgetting factor.

The choice of the α , β and λ parameters depends on the process:

i) α=1 and β=0 → for the fast systems (good performances with respect to parameters changes, sensitive to disturbance);

ii) α=0 and λ=0 → for the slow systems (bad performances with respect to parameters changes, good performances with respect to disturbance) [9], [16].

3. CLOSE-LOOP RECURSIVE IDENTIFICATION

A closed-loop adaptive method (filtered closed loop error - FCLOE identification) with adjustable predictor is considered [4], [6]. This method computes the parameters of the model in order to minimize the closed loop output prediction error ε_{CL} using the filtered data *u* and *y*. A FCLOE identification scheme is presented in figure II.

The basic idea is to substitute (by filtering the process's input and output) the prediction error ε_{LS} with closed-loop output error ε_{CL}. The filter depends on the control algorithm. The FCLOE – algorithm in recursive least squares form is the following:

$$\begin{aligned}
&\hat{\theta}(k+1) = \hat{\theta}(k) + \mathbf{F}(k)\phi_f(k)\varepsilon_{LS}(k+1),\\
&\mathbf{F}(k+1) = \mathbf{F}(k) - \frac{\mathbf{F}(k)\phi_f(k)\phi_f(k)^T\mathbf{F}(k)}{1+\phi_f(k)^T\mathbf{F}(k)\phi_f(k)},\\
&\mathbf{F}(0) = \mathbf{I},\ \alpha>0,\\
&\varepsilon_{CL}(k+1) = \frac{y(k+1)-\hat{\theta}^T(k)\phi_f(k)}{1+\phi_f(k)^T\mathbf{F}(k)\phi_f(k)},
\end{aligned} \tag{3}$$

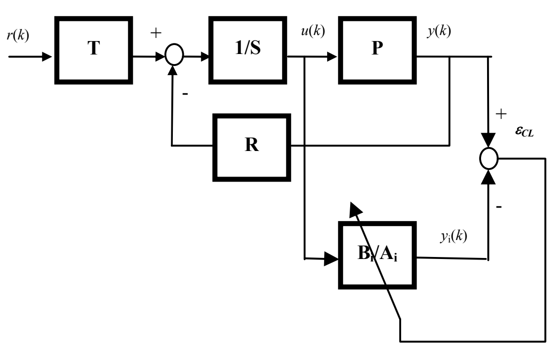

Fig. 2. Closed loop identification technique.

where:

$\hat{\theta}(k)$ is the parameter vector;

$\Phi_f(k)$ is the filtered observation vector;

$F(k)$ is the gain adaptation matrix;

ε_{CL} is the closed-loop prediction error.

4. MODEL BASED CONTROL (RE)DESIGN

For the model M_i a controller C_i is designed that satisfies the desired nominal performances. The controller C_i is computed using the RST polynomial algorithm with two degrees of liberty [6], [12], [17], as it is shown in the figure III.

This algorithm is used to solve in the same time, in rejection of disturbances and in reference tracking performances in the closed loop control systems.

The input $u(k)$ generated for the RST control algorithm is:

$$u(k) = \frac{T(q^{-1})}{S(q^{-1})}r(k) - \frac{R(q^{-1})}{S(q^{-1})}y(k) \tag{4}$$

The disturbances' rejection is ensured by the $R(q^{-1})$, $S(q^{-1})$ polynomials obtained solving the equation:

$$P_C(q^{-1}) = A(q^{-1})S(q^{-1}) + B(q^{-1})R(q^{-1}) \tag{5}$$

where

– pair ($A(q^{-1})$, $B(q^{-1})$) represents the process's model;

– $P_C(q^{-1})$ is the closed-loop characteristic polynomial.

The reference tracking performances are ensured by the choice of the $T(q^{-1})$ polynomial. For each model (A_i, B_i) a C_i control algorithm (R_i, S_i, T_i polynomials) will be computed respectively.

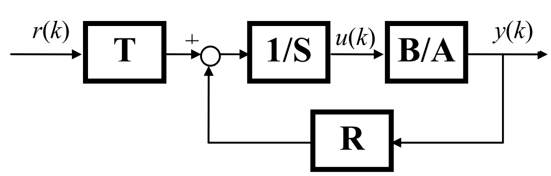

Fig. 3. RST control algorithm.

In parallel with the close-loop identification procedure, an adaptive pole placement method is used in order to achieve the desired performances in closed-loop [6], [12]. There are two possible approaches for the adaptive RST control algorithm design:

4.1 Disturbances' rejection adaptive algorithm:

1. Re-identification of the model M_{k+1} using the identification algorithm (3), where the filtered data is $\Phi_f(k) = \frac{S}{P_C}\Phi(k)$:

$$\mathcal{M}_{k+1} = \frac{B_{k+1}\left(q^{-1}\right)}{A_{k+1}\left(q^{-1}\right)} \quad (6)$$

2. Evaluation of the pair $R_{k+1}(q^{-1})$, $S_{k+1}(q^{-1})$ from equation:

$$P_C\left(q^{-1}\right)=A_{k+1}\left(q^{-1}\right)S\left(q^{-1}\right)+B_{k+1}\left(q^{-1}\right)R\left(q^{-1}\right) \quad (7)$$

3. Computation of the input $u(k+1)$:

$$u(k+1) = \frac{T(q^{-1})}{S_{k+1}(q^{-1})}r(k) - \frac{R_{k+1}(q^{-1})}{S_{k+1}(q^{-1})}y(k) \quad (8)$$

4.2 Reference tracking adaptive algorithm:

1. Identification of the model M_{k+1}:

$$\mathcal{M}_{k+1} = \frac{B_{k+1}\left(q^{-1}\right)}{A_{k+1}\left(q^{-1}\right)} \quad (9)$$

2. Computation of the $P_{C\ k+1}(q^{-1})$ polynomial using the equation:

$$P_{Ck+1}\left(q^{-1}\right)=A_{k+1}\left(q^{-1}\right)S\left(q^{-1}\right)+B_{k+1}\left(q^{-1}\right)R\left(q^{-1}\right) \quad (10)$$

3. Computation of the $T_{k+1}(q^{-1})$ polynomial with the relation:

$$T_{k+1}\left(q^{-1}\right) = \frac{P_{k+1}(1)}{B_{k+1}(1)}P_{C\ k+1}\left(q^{-1}\right) \quad (11)$$

4. Computation of the input $u(k+1)$:

$$u(k+1) = \frac{T_{k+1}\left(q^{-1}\right)}{S\left(q^{-1}\right)}r(k) - \frac{R\left(q^{-1}\right)}{S\left(q^{-1}\right)}y(k) \quad (12)$$

The main experimental results from real time multi-models adaptive control system are presented on experimental results section.

5. ALGORITHMS SWITCHING

Corresponding to multi-model structure's function logic, after finding the best algorithm for the current process's functioning point, the next step consists on switching the control algorithm. Two essential conditions must be verified with respect to this operation:

- To be designed so that no bumps in the applications of the control law are encountered;
- To be (very) fast.

Shocks determined by the switching operation cause non-efficient and/or dangerous behaviors. Moreover, slow switching determines boiling down the control algorithm's action zone, which involves only the system's performances' alteration.

These are the main problems to be solved when designing the algorithms' switching block. Firstly, from structurally point of view, this block may contain all algorithms' implementation, or, secondly, at least the algorithms' coefficients. The switching operation is done based on the information provided by the system's state or position identification block. This information consists of a trigger-signal to start the operation and the number of the algorithm that will become active.

5.1 Classical solutions

Present solutions solve more or less this problem and they are based on maintaining in active state all the control algorithms, also called "warm state". This supposes that every algorithm receives information about the process output y(k) and set the point value (eventually filtered) r(k), but only the control law $u_i(k)$ is applied on the real process, the one chosen by the switching block. This solution does not impose supplementary function logic for the system's architecture and, for these reasons, it

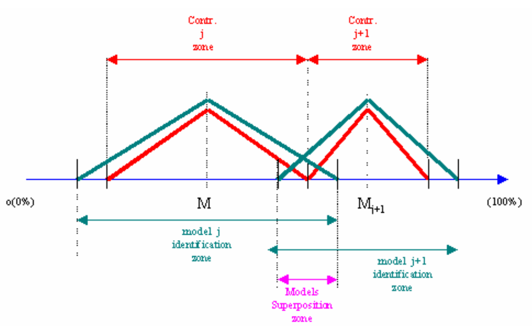

Fig. 4. Superposition of identification zones for two neighbor-models and their corresponding control actions

gives the possibility of switching very fast the algorithms. The drawback of this approach is that when designing the multi-model structure several supplementary steps are necessary.

These supplementary conditions demand the matching of the control algorithm outputs' in the neighborhood switching zones. The superposition of models identification zones accomplishes this aspect. That can be seen on Fig. IV.
As a result of this superposition, the multi-model structure will have an increased number of models.

Another approaches [2], [10] propose mixing two or more algorithms' outputs. The "weighting" of each control law depends on the distance from the current process's operating point and the action zone of each algorithm. Based on this, the switching from an algorithm to another one is done using weighting functions with a continuous evolution in [0–1] intervals. This technique can be easily implemented using fuzzy approach. An example is presented on Fig. V.

This solution involves solving control gain problems, determinated by the mixing of the algorithms' outputs.

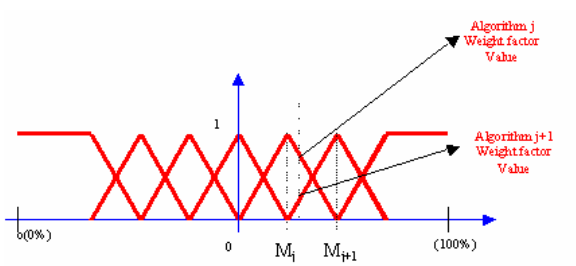

Fig. 5. Algorithms weighting functions for a specified operating position

5.2 Proposed solution

In this paper, it is used a solution that provides very good results for fast processes with nonlinear characteristics. The main idea is that, during the current functioning of multiple-models control systems with N model-algorithm pairs, it is supposed that just one single algorithm is to be maintained active, the good one, and all the other N-1 algorithms rest inactive. The active and inactive states represent automatic, respectively manual, regimes of a control law. The output value of the active algorithm coresponds to the manual control for all the other N-1 inactive algorithms. System's functioning scheme is presented on Fig. VI.

In the switching situation, when a "better" *Aj* algorithm is found, the actual *Ai* active algorithm is commuted in inactive state, and *Aj* in active state, respectively.

For a bumpless commutation, it must be solved the manual–automatic transfer problems, and the solution to this it is presented in [8].

This solution can be implemented in two variants – first - with all inactive algorithms holding on manual regime, or – second - just a single operating algorithm (the active one) and activation of the "new" one after the computation of the currently corresponding manual regime and switching on automatic regime. Both variants have advantages and disadvantages. Choosing one of them necessitates knowledge about the hardware performances of the structure. After a general view, the first variant seems to be more reasonable.

In all situations, it is considered that the active algorithm's output values represent manual commands for the "new" selected one.

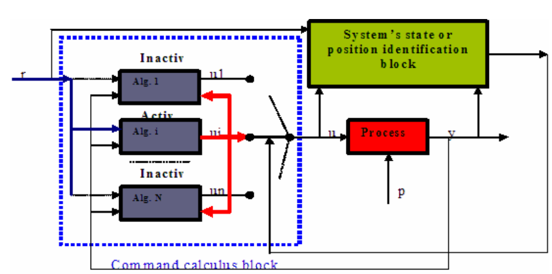

Fig. 6. Proposed solution for algorithm switcing

The only inconvenient of this solution is represented by the necessary big computation power when approaching high order systems, which is not, however, a problem nowadays.

6. EXPERIMENTAL RESULTS

We have tested the multi–model adaptive control strategy using an experimental installation presented in Fig. VII. The main goal is to control in closed loop the level in the Tank 1. There is a nonlinear relation between the level *L* and the flow *F*:

$$F = a\sqrt{2gL} \tag{13}$$

We consider three operating points P_1, P_2 and P_3 on the nonlinear characteristic $F = f$ (L) as it is presented in figure Fig.VII. The level values L_1, L_2, L_3 can be considered set points for the nominal level control system.

We have identified three different models for the nonlinear process each corresponding to the chosen operating points (M_1 for the high level, M_2 for the medium level and M_3 for the low level):

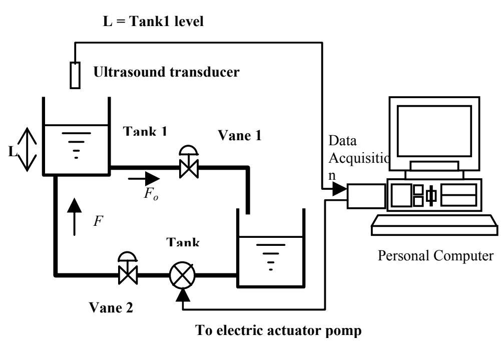

Fig. 7. Level Control Experimental Installation.

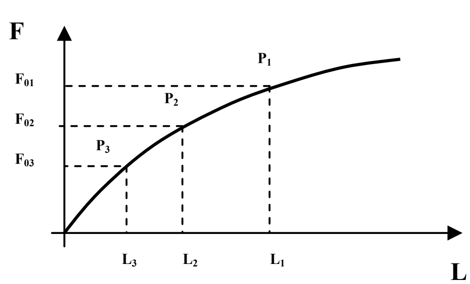

Fig. 8. Non linear characteristic *F* = *f*(L)

$$\mathcal{M}_1 = \frac{0.0086856q^{-1} + 0.000341q^{-2}}{1 - 0.94374q^{-1} - 0.02457q^{-2}} \tag{14}$$

$$\mathcal{M}_1 = \frac{0.0076444q^{-1} + 0.000341q^{-2}}{1 - 0.95172q^{-1} - 0.02322q^{-2}} \tag{15}$$

$$\mathcal{M}_3 = \frac{0.007144q^{-1} + 0.00074q^{-2}}{1 - 0.95502q^{-1} - 0.02238q^{-2}} \tag{16}$$

Three RST control algorithms were computed using a pole placement procedure for each identified models. The same nominal performances are given for all systems, by a second order standard dynamic system described by $\omega_0 = 0.05$, $\xi = 0.85$ (tracking performances) and $\omega_0 = 0.085$ and $\xi = 0.75$ (disturbance rejection performances) respectively, with a sampling period Te = 5s. The control algorithms are:

$$\begin{aligned} R_1\left(q^{-1}\right) &= 61.824 - 46.906q^{-1} \\ S_1\left(q^{-1}\right) &= 1.0 - 1.0q^{-1} \\ T_1\left(q^{-1}\right) &= 113.378 - 158.394q^{-1} + 59.933q^{-2} \end{aligned} \tag{17}$$

$$\begin{aligned} R_1\left(q^{-1}\right) &= 65.435 - 49.171q^{-1} \\ S_1\left(q^{-1}\right) &= 1.0 - 1.0q^{-1} \\ T_1\left(q^{-1}\right) &= 123.609 - 172.686q^{-1} + 65.341q^{-2} \end{aligned} \tag{18}$$

$$\begin{aligned} R_1\left(q^{-1}\right) &= 65.592 - 49.235q^{-1} \\ S_1\left(q^{-1}\right) &= 1.0 - 1.0q^{-1} \\ T_1\left(q^{-1}\right) &= 126.582 - 176.840q^{-1} + 66.912q^{-2} \end{aligned} \tag{19}$$

The desired poles placement in closed loop is presented in figure Fig. IX. Let as consider P_0 a new current operating point, between P_1 and P_2, near P_2, model M_3 being the last model active. The set point of level control system is L_0 placed between L_1 and L_2.

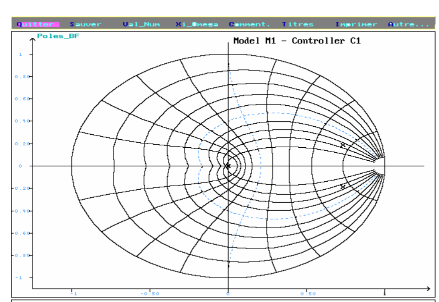

Fig. 9. Closed loop desired poles placement.

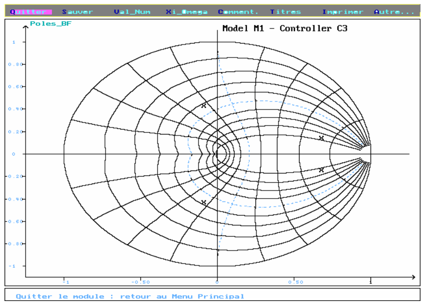

Fig. 10. Closed loop poles placement in P_0 using controller C_3.

If no adaptive or multi-model approach is used the performances obtained in P_0 with controller C_3 would be poor.
If a multi-model mechanism is provided according to this situation, the multi-model scheme will choose the best model (M_2) and will select the corresponding (C_2 –(R_2,S_2,T_2)) control algorithm. Using algorithm (R_2,S_2,T_2) the performances obtained are improved.

Applying also an adaptive structure, a new model and a new control algorithm are obtained in order to assure the exact imposed performances presented in figure Fig. IX. To better emphasize the advantages of using this procedure the time responses of the closed loop system with (Fig. XIII) and without (Fig. XIV) the multi-model adaptive scheme are shown.

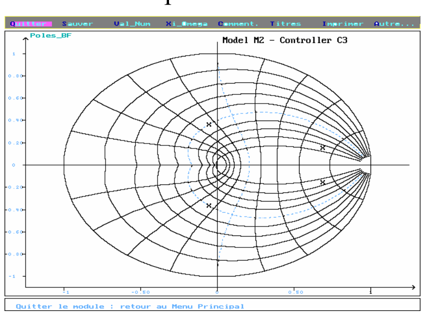

Fig. 11. Closed loop poles placement in P_0 using controller C_2.

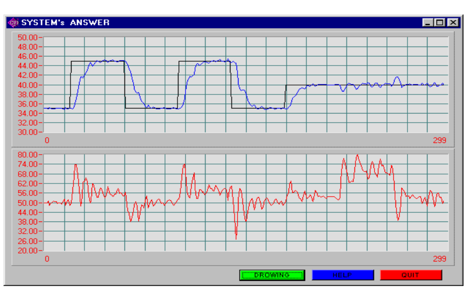

Fig. 12. Performances for P_0 operating point with (R_2,S_2,T_2) algorithm.

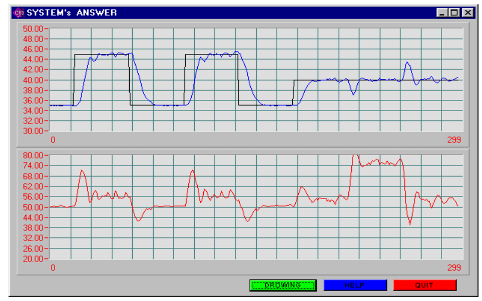

Fig. 13. Improved performances for P_0 operating point, using adaptive control procedure.

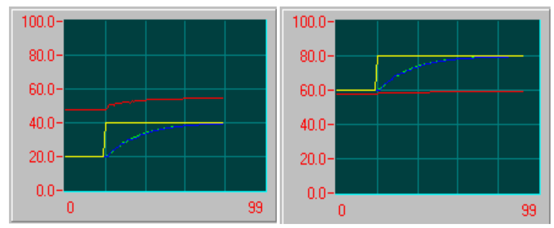

Fig. 14. a) switching test b) switching test

In the same time, few tests were effectuated to verify the switching between two algorithms. The switching procedure is determinated by the change of the set point value. These tests are:

a) from 20% (where algorithm 3 is active) to 40% (where algorithm 2 is active). The effective switching operation is done when the filtered set point (and process output) becomes greater than 30%. Fig. XIV(a) presents the evolutions.

b) from 60% (where algorithm 2 is active) to 80% (where algorithm 1 is active). The effective switching operation is done when the filtered set point (and process output) becomes greater then 70%. Fig. XIV(b) presents the evolutions.

In both tests, one can see that there are no shocks or there are very small oscillations in the control evolution by applying this approach. Increasing the number of models-algorithms to 4 or 5 could eliminate the small oscillations.

7. CONCLUSIONS

An application using a multiple models adaptive control procedure to control a nonlinear process has been presented. A mechanism based on the performance model-error criterion for the choice of the best model in switching phase is considered. The closed loop identification algorithm (CLOE) and the RST adaptive control algorithm are used.

The proposed multiple models adaptive control procedure has the following advantages: a more precise model is chosen for the closed loop operating system; the RST adaptive control mechanism ensures very good real time results for closed loop nonlinear systems.

The proposed switching method was successfully tested on a laboratory application with nonlinear characteristic, using a 3 multi-model/controller real-time software application. The first variant (with all algorithms active) of the approach was implemented, ensuring the fast switching (one step) between algorithms.

With regards to the results obtained in the paper, the switching method can be successfully recommended in multi-model real-time control structures for fast processes.

We appreciate that the multiple models adaptive control scheme can be recommended to improve the performances of the nonlinear control systems.

The application presented in this paper is also available as a virtual laboratory. The students can test the multi models adaptive control procedure remotely

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