MULTI-MODELS ADAPTIVE CONTROL

C. LUPU, C. PETRESCU*

Lucrarea prezintă o structură de sistem de reglare multi-model. Avantajele acestui sistem de reglare, comparativ cu cele ale unuia clasic, vor fi demonstrate pe un proces neliniar de control al nivelului dintr-un rezervor. Sunt prezentate metode recente de identificare recursivă în buclă închisă şi reglare utilizând o structură tip R-S-T ce pot garanta performanțele sistemului.

Implementarea în cadrul unui sistem de conducere de timp real a metodelor şi structurilor propuse confirmă şi susțin oportunitatea utilizării structurilor adaptive de tip multi-model în cazul proceselor neliniare şi a celor cu variații importante ale parametrilor.

A multiple models adaptive control system 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 methods in open and closed-loop identification and a. 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.

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

Introduction

Since 90's years different approaches of multi-model control have been developed. The Balakrishnan's and Narenda's first papers [1], which proposed several stability and robustness methods using classical switching and tuning algorithms, have to be mentioned. Later, the research in this field determined the extension and the improvement of multi-model control concept.

Magill and Lainiotis introduced the model representation through Kalman filters [2]. 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 was focused on nonlinear systems with time variable. Landau and Karimi [8], [9] have some contributions regarding the use of several particular parameter adaptation procedures, namely CLOE (Closed Loop

* Prof., prof., Dept. of Automatics and Computer Science, University POLITEHNICA of Bucharest, Romania

Output Error). The multi-model control version proposed by Narenda is based on neural networks. Finally, Dubois, Dieulat and Borne apply fuzzy procedures for switching and sliding mode control.

We propose a multi-model control procedure with closed loop identification for model parameter re-estimation and with adaptive control design after each switching operation.

Next, this paper emphasizes a new procedure for the multi-model control systems design which leads to quality improvement of the real time nonlinear control systems.

We consider the set of the models:

$$\boldsymbol{M} = \{M_1, M_2, M_3 \ldots M_n\}$$

and the class of correspondent controllers:

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

integrated in the closed-loop configuration, presented in Fig. 1.

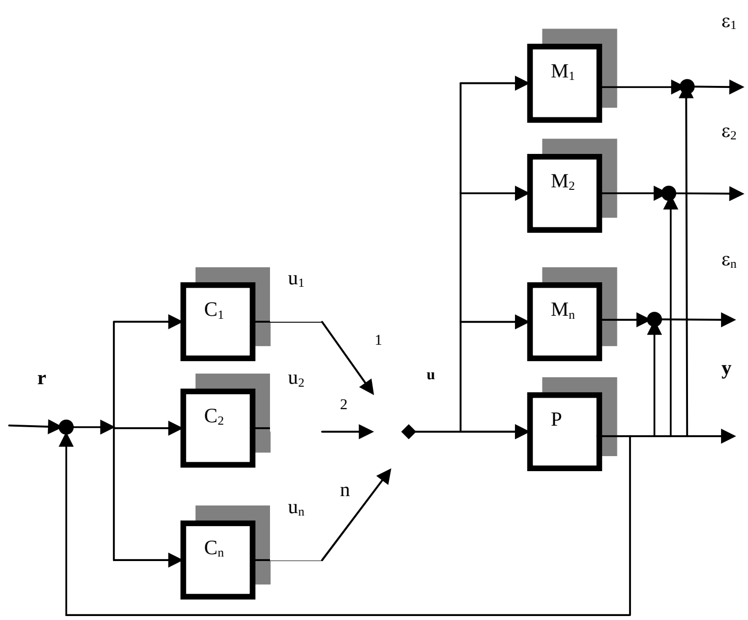

Fig. 1. Multi-Model Control Schema

The input and output of the plant ***P*** are ***u*** and ***y*** respectively. The $\boldsymbol{M_i}$ ***(i=1,2,… n)*** models are a priori evaluated. For each model $\boldsymbol{M_i}$ we are designing the controller $\boldsymbol{C_i}$ so that the pair ($\boldsymbol{M_i}$, $\boldsymbol{C_i}$) ensures the nominal performances.

The main idea of the multi-model adaptive control consists in choosing the best model included in ***M*** to apply the correspondent controller and continuing in the adaptive way towards current operating point of the plant.

In order to use this mechanism the identification problem is developed in two steps:

a) The model with 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) Using the adaptive strategy for real time control system, the parameters of the model are adjusted and the new control algorithm is computed (tuning – step).

1. Choice of the model

The model-error at the *k* instant is defined as the difference between the output $\boldsymbol{y_i}$ of the model $\boldsymbol{M_i}$ and the output ***y*** of the plant:

$$\varepsilon_i(k) = y(k) - y_i(k) \tag{1}$$

The performance criterion which is used as the selection rule is defined below:

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

where $\alpha>0$ and $\beta>0$ are the weighting factors on the instantaneous measures and the long term accuracy; $\lambda>0$ is the forgetting factor.

The choosing of the α , β and λ parameters depends of the plant:

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

2. Closed-loop recursive identification

A closed-loop adaptive method (filtered closed loop error- FCLOE identification) for the adjustable predictor is considered [9], [5]. This method computes the parameters of the model in order to minimize the closed loop output prediction error $\boldsymbol{\varepsilon_{CL}}$ using the filtered data $\boldsymbol{u}$ and $\boldsymbol{y}$. A FCLOE identification scheme is presented in Fig. 2:

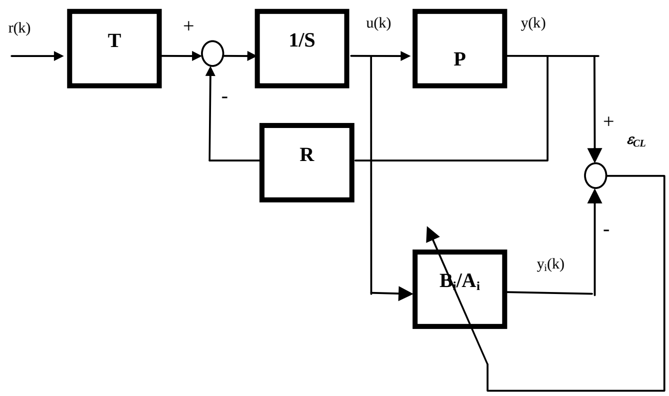

Fig. 2. Close loop identification technique

The basic idea is to substitute (by filtering of *u* and *y*) the prediction error $\boldsymbol{\varepsilon_{LS}}$ with closed-loop output error $\boldsymbol{\varepsilon_{CL}}$. The filter depends of the control algorithm. The FCLOE – algorithm in least squares recursive form is the following:

$$\theta(k+1)=\theta(k)+F(k)\phi_f(k)\varepsilon_{LS}(k+1) \tag{3}$$

$$F(k+1)=F(k)-\frac{F(k)\phi_f(k)\phi_f(k)^T F(k)}{1+\phi_f(k)^T F(k)\phi_f(k)} \quad F(0)=\alpha I,\ \alpha>0 \tag{4}$$

$$\varepsilon_{CL}(k+1)=\frac{y(k+1)-\theta^T(k)\phi_f(k)}{1+\phi_f(k)^T F(k)\phi_f(k)} \tag{5}$$

where ,

$\theta(k)$ 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 $\boldsymbol{M_i}$ model we design a controller $\boldsymbol{C_i}$ that satisfies the desired nominal performances [9]. The RST polynomial algorithm with two degrees of liberty, for $\boldsymbol{C_i}$ controller is proposed (see Fig. 3):

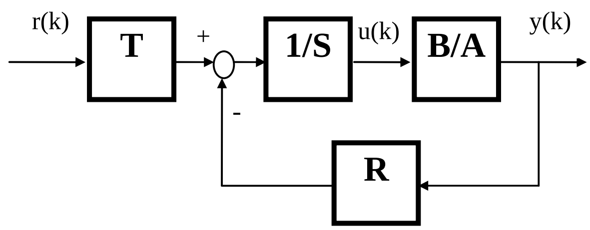

Fig. 3. RST control algorithm

In this case the input *u(k)* is:

$$u(k)=\frac{T(q^{-1})}{S(q^{-1})}r(k)-\frac{R(q^{-1})}{S(q^{-1})}y(k) \tag{6}$$

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

$$P_C(q^{-1})=A(q^{-1})S(q^{-1})+B(q^{-1})R(q^{-1}) \tag{7}$$

where,
- pair ($A(q^{-1})$, $B(q^{-1})$) represents the plant model;
- $P_C(q^{-1})$ is the closed-loop characteristic polynomial.

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

The adaptive pole placement method is used for achieved performances in closed-loop.

There are two possibilities for the adaptive design approach:

Disturbance rejection adaptive algorithm:

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

$$M_{k+1} = \frac{B_{k+1}\left(q^{-1}\right)}{A_{k+1}\left(q^{-1}\right)} \quad (8)$$

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

$$P_C(q^{-1})=A_{k+1}(q^{-1})S(q^{-1})+B_{k+1}(q^{-1})R(q^{-1}) \quad (9)$$

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

$$u(k+1) = \frac{T(q^{-1})}{S_{k+1}(q^{-1})} r(k) - \frac{R_{k+1}(q^{-1})}{S_{k+1}(q^{-1})} y(k) \quad (10)$$

Reference tracking adaptive algorithm:

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

$$M_{k+1} = \frac{B_{k+1}\left(q^{-1}\right)}{A_{k+1}\left(q^{-1}\right)} \quad (11)$$

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

$$P_{C\,k+1}(q^{-1})=A_{k+1}(q^{-1})S(q^{-1})+B_{k+1}(q^{-1})R(q^{-1}) \quad (12)$$

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

$$T_{k+1}(q^{-1}) = \frac{P_{k+1}(1)}{B_{k+1}(1)} P_{C\,k+1}(q^{-1}) \quad (13)$$

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

$$u(k+1) = \frac{T_{k+1}(q^{-1})}{S(q^{-1})} r(k) - \frac{R(q^{-1})}{S(q^{-1})} y(k) \quad (14)$$

The main experimental results from real time multi-models adaptive control system will be presented below.

5. Experimental results

We have evaluated the achieved performances of the adaptive multi–model control using an experimental installation as in Fig. 4. The main goal is to control in closed loop the level in Tank 1. There is a nonlinear relation between the level L and the flow F.

$$F = a\sqrt{2gL}\,. \tag{15}$$

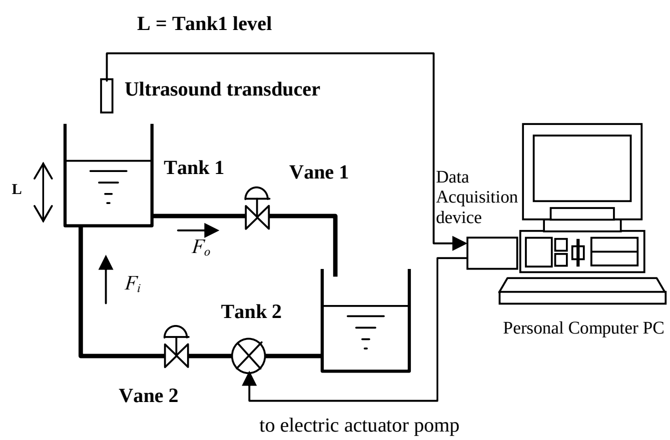

Fig. 4. Level Control Experimental Installation

We consider three plant operating points P_1, P_2, P_3 on the nonlinear diagram $F = f(L)$ as in Fig. 5. The level values L_1, L_2, L_3 can be considered the set – points of the nominal level control system.

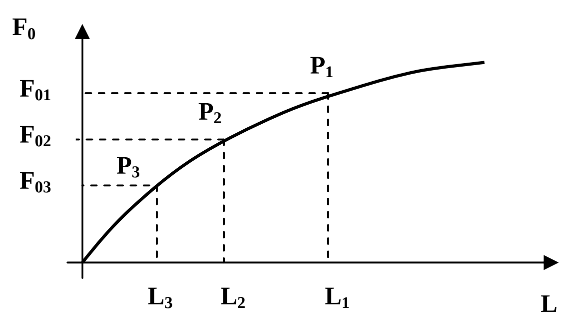

Fig. 5. Non linear characteristic $F = f(L)$

We have identified three different models of the nonlinear process in these operating points. M_1 for the high level, M_2 for the medium level and M_3 for the low level, where:

$$M_1 = \frac{0.08816 q^{-1}}{1 - 0.94233 q^{-1}}$$

$$M_2 = \frac{0.08092 q^{-1}}{1 - 0.92641 q^{-1}}$$

$$M_3 = \frac{0.07903 q^{-1}}{1 - 0.91757 q^{-1}}$$

In this case we have computed three correspondent R-S-T algorithms using a pole placement procedure. 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 time Te = 5s.

$R_1(q^{-1}) = 61.824 - 46.906\ q^{-1}$
$S_1(q^{-1}) = 1.0 - 1.0\ q^{-1}$
$T_1(q^{-1}) = 113.378 - 158.394\ q^{-1} + 59.933\ q^{-2}$

$R_2(q^{-1}) = 65.435 - 49.171 q^{-1}$
$S_2(q^{-1}) = 1.0 - 1.0\ q^{-1}$
$T_2(q^{-1}) = 123.609 - 172.686 q^{-1} + 65.341 q^{-2}$

$R_3(q^{-1}) = 65.592 - 49.235\ q^{-1}$
$S_3(q^{-1}) = 1.0 - 1.0\ q^{-1}$
$T_3(q^{-1}) = 126.582 - 176.840\ q^{-1} + 66.912\ q^{-2}$

Let as consider P_0 the current operating point, between P_1 and P_2, near P_2. The set-point of level control system is L_0 placed between L_1 and L_2. According to this situation, the multi-model scheme will choose the best model M_2 and will select C_2 (R_2,S_2,T_2) control algorithm. The use of this algorithm (R_2,S_2,T_2) on the plant will assure the performances presented in the Fig. 5.1.

The adaptive multi-model control procedure has improved the quality of the control. The new performances obtained with the real time adaptive control system are presented in Fig. 5.2. In fact, the improved performances are assured using the best starting selected system (M_2, C_2) and the adaptive procedure from P_2, towards P_0.

Each of the Figs. (5.1), (5.2) shows at the top the evolution of the set point *r* and the output *y,* and at the bottom the evolution the control *u,* respectively.

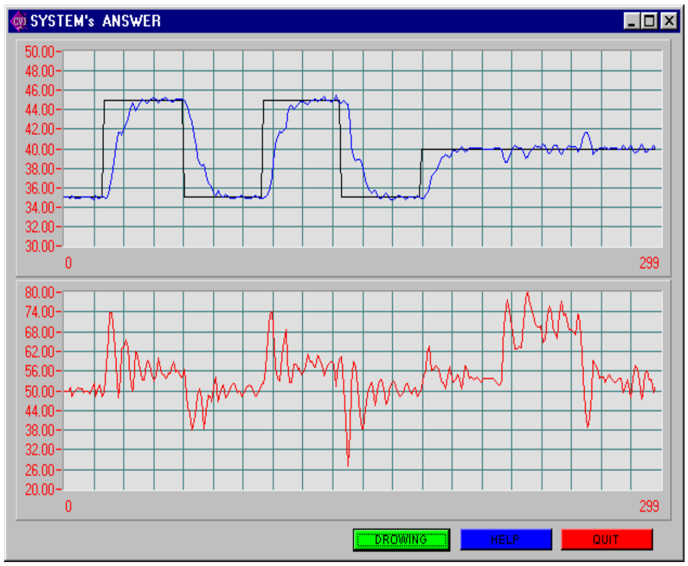

Fig. 5.1 Performances for P_0 operating point with (R_2,S_2,T_2) algorithm

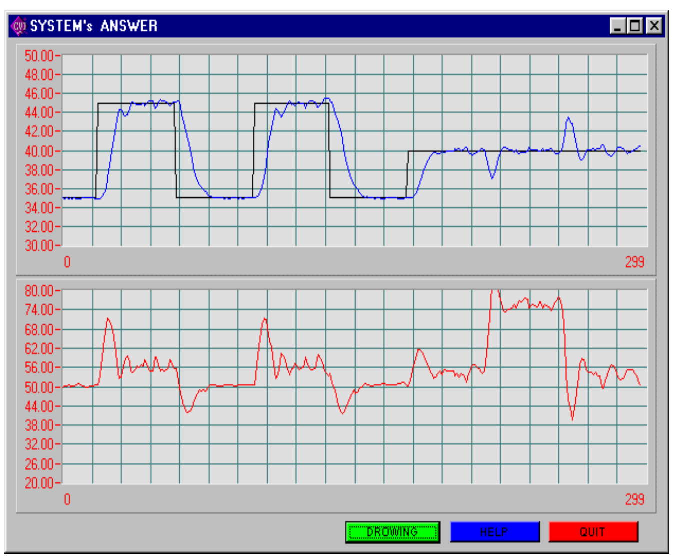

Fig. 5.2 Improved performances for P0 operating point, using adaptive control procedure

Conclusions

An application of the multiple models adaptive control to a nonlinear model plant 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 R-S-T adaptive control algorithm is used.

The multiple model 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.

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

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