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Fuzzy Supervision for a Multimodel Generalized Predictive Control based on Performances Index

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Abstract. In this paper, we develop a direct adaptive generalized predictive control based on performances index and we show the limits of this control law in the presence of a highly non stationary system. We present thereafter a method for validities estimation in the case of multimodel generalized predictive control ($MGPC$). This method is based on an online evaluation of the elementary GPC control laws performances through a fuzzy supervisor which evaluates the pertinence of each local control using a performances index and its variation. The satisfactory obtained results are compared to those registered in the classical residus approach case and show a very good closed loop performances in terms of tracking and regulation.

Keyword: Multimodel, Generalized Predictive Control, Performances Index, Validities, Fuzzy Supervisor, Time-Varying Parameters.

1 Introduction

The increasing complexity of industrial processes and the higher performance requirements, make the implementation of adaptive structure necessary. Many methods were developed to adapt the controller in function of the evolution of the task to be solved. The controller has to determine, at each instant, the correct situation of the system and choose the appropriate control decision. In fact, the controller parameters are adjusted using the estimated plant parameters. In addition, direct adaptive generalized predictive control ($DAGPC$) based on performances index is one of the few techniques able to cope with constraints and modelling errors in an explicit manner [1, 6]. It has proved to be efficient and successful for industrial applications. Moreover, for systems with time-varying parameters, acceptable performances may be maintained with adaptive controllers. However, the application of conventional adaptive control, is not suitable and it decreases considerably the performances in the presence of an important parameters variation [1, 3, 6, 16, 17]. To overcome this problem, it is necessary to introduce an intelligent modelling and control strategies. Indeed, multimodel and

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multicontrol approaches are considered to be very suitable and able to identify and control, complex systems with high performances.
The multimodel and multicontrol approaches are known as powerful techniques to overcome difficulties encountered in conventional modelling and control techniques. These approaches are useful for the industrial processes which are, often, complex (nonlinear or/and non stationary). The basic idea of the above approaches is the decomposition of the process's full operation range into a number of operating regimes. In each operating regime a simple local model or controller is applied. These local models, called model's library, are then combined in some way to yield a global model [4, 5, 8, 10, 18, 20, 24]. The advantages of these approaches appear in the simplicity of the local models and consequently in the facility of the adequate control law implementation. They can have different structures or/and reduced orders. To each local model is associated a validity degree $v_i(k)$ evaluating its pertinence to describe the system in its full operating area. The applied controller is a combination between the local controllers ponderated by the validities of the corresponding local models, or a switching between all of these. So the validities computation is among the main issues to consider in the multimodel and multicontrol approaches.
Several validities computation methods were proposed in the literature. These methods are classified according to the manner of obtaining the models, which are related to the process available knowledge [4, 5, 8, 10, 13, 15, 23, 22, 24]. Referring to the literature, the residue approach is the main known approach dealing with the validities' computation. In this last approach, the residue is frequently formulated by the geometric distance between the real output and the local models outputs [4, 5, 10, 24].
A fuzzy method for the validities estimation described in [8] is developed in presence of a model library based on Kharitonov's algebraic approach. This method introduces, besides the four extreme models, an other model called average model, determined as an average of the boundary models. The validity of each model of the library is provided by a fuzzy inference expressing the correlation between the considered model with respect to the average model. This method is exploitable only with presence of Kharitonov's model basis. Also a method of validities computation inspired from the fuzzy version of the algorithm "c-means" (the "k-means" classification algorithm) is described in [19, 24]. This method is based on the minimisation of a quadratic criterion based on the difference between the obtained classes'centres and the output of system. Other method that use a fuzzy supervision for the online validities'estimation is described in [10, 12, 13]. In this method each model of the base is associated with a fuzzy supervisor to generate the related validity $v_i(k)$ appealing to the residue and its variation.
In this work we propose a method for the validities estimation based on the evaluation of the elementary control performances. The question is an on line fuzzy supervision of the elementary control law validities using a computation of both performances index and its variation.
The paper is organized as follow: Firstly we develop a direct adaptive general-

ized predictive control based on performances index. An example of simulation is given thereafter to show the limits of this control law in the presence of a highly non stationary system. In the third section, we propose a solution for these problems through the synthesis of a multimodel generalized predictive control. A comparative study between two approaches for the validities'computation will be, also, detailed in this paper. The first approach is based on the classical residue approach therefore the other one exploits a fuzzy supervisor for an on-line validities estimation based on the performances index. A simulation example illustrating the efficiency of the proposed strategy is given. We finish the present work by a conclusion.

2 Performances Index in the case of Generalized Predictive Control

We consider the system described by the following equation:

$$D(q^{-1})A(q^{-1})y(k) = q^{-d}B(q^{-1})D(q^{-1})u(k) + C(q^{-1})v(k). \tag{1}$$

Where $y(k)$ is the process output and $u(k)$ is the control signal applied to the system, d is the process time delay. $A(q^{-1})$ and $C(q^{-1})$ are monic polynomials with respective order n_A, n_c. $B(q^{-1}) = b_0 + ... + b_{n_B}q^{-n_B}$, $D(q^{-1}) = 1 - q^{-1}$.

The matrix form [1] of the predictor $\underline{\hat{Y}}$ is given by:

$$\underline{\hat{Y}} = R^{**}\underline{DU} + G^{**}\underline{Y} + Q^{**}\underline{DU}_p \tag{2}$$

with:

$$\begin{aligned}
&\underline{\hat{Y}} = [\hat{y}(k+HI/k)\ldots\hat{y}(k+HP/k)]^T;\\
&\underline{DU} = [Du(k-1)\ldots Du(k-n_B)]^T;\\
&\underline{Y} = [y(k)\ldots y(k-n_A)]^T;\\
&\underline{DUp} = [Du(k)\ldots Du(k+HP-1)]^T;
\end{aligned}$$

HI, HP and HC are, respectively, the horizons of initialization, prediction and control. The matrix R^{**}, G^{**} et Q^{**} are derived by solving diophantine equations, with unique solution [1].

$$\begin{aligned}
\dim[R^{**}] &= (HP - HI + 1, n_B)\\
\dim[G^{**}] &= (HP - HI + 1, n_A + 1)\\
\dim[Q^{**}] &= (HP - HI + 1, HP)
\end{aligned}$$

Let's define a prediction vector which depends on present and past measurements:

$$\underline{E\hat{Y}}_a = \underline{\hat{Y}}_a - \underline{YC} = R^{**}\underline{DU} + G^{**}\underline{Y} - \underline{YC} \tag{3}$$

with:

$\underline{\hat{Y}}_a = R^{**}\underline{DU} + G^{**}\underline{Y}$

$\underline{YC} = [y_c(k+HI)\dots y_c(k+HP)]^T$ is a set point vector.
The prediction $\underline{E\hat{Y}}_p$ depending on the future control sequence is defined by:

$$\underline{E\hat{Y}}_p = Q^{**}\underline{DU}_p \tag{4}$$

The dimension of the vector $\underline{DU}_p$ is reduced to $(HC,1)$ and, consequently, the $(HP-HC)$ columns of the matrix Q^{**} are not taken in account. We obtain the new matrix Q_*. The objective of the adaptive generalized predictive control is to calculate the optimal sequence control by minimizing the following criterion:

$$J = \frac{1}{2}\left\{\sum_{j=HI}^{HP}\left[\hat{y}(k+j/k) - y_c(k+j)\right]^2 + \lambda\sum_{j=0}^{HC-1} Du(k+j)^2\right\} \tag{5}$$

with:
λ is a ponderation factor. $\hat{y}(k+j/k)$ and $y_c(k+j)$ are respectively the j step output predictor and the reference signal.
The determination of the vector $\underline{DU}_p$ requires to put the criterion (5) under a matrix form:

$$J = \left[Q_*\underline{DU}_p + \underline{E\hat{Y}}_a\right]^T\left[Q_*\underline{DU}_p + \underline{E\hat{Y}}_a\right] + \underline{DU}_p^T\lambda\underline{DU}_p \tag{6}$$

The optimal vector $\underline{DU}_P$ is written as follows:

$$\underline{DU}_P = -M\left[R^{**}\underline{DU} + G^{**}\underline{Y} - \underline{YC}\right] \tag{7}$$

with:

$$M = [Q_*^T Q_* + \lambda I_{HC}]^{-1}Q_*^T = \begin{bmatrix} \underline{m_1}^T \\ \underline{m_2}^T \\ \vdots \\ \underline{m_{HC}}^T \end{bmatrix} \tag{8}$$

We can write the equation (7) under the following matrix form:

$$M\underline{YC} = MG^{**}\underline{Y} + \underline{DU}_P + M\ R^{**}\underline{DU} = \theta^T\phi(k) \tag{9}$$

avec :

$$\theta^T = [MG^{**}\ I_{HC}\ MR^{**}]$$
$$\phi(k) = \left[y(k)\dots y(k-n_A)\ \ \underline{DU}_P^T\ \ Du(k-1)\dots Du(k-n_B)\right]^T$$

θ, ϕ (k) are, respectively, the matrix of parameters with dimension (n_A+n_B+1+HC, HC) and the input-output measurements vector with dimension $(n_A+HC+n_B+1,1)$.
We define the prediction vector $X_p(k+HP)$, which contains the predicted output and the future control sequence.

$$X_p(k+HP) = [\underline{\hat{Y}}^T\,\underline{DU}_p^T]^T \tag{10}$$

We define also the target vector $X_c(k+HP)$ from $X_p(k+HP)$, with the same dimension, composed of reference vector $\underline{YC}$ and zero vector Φ. Considering the fact that the output vector $\underline{\hat{Y}}$ has to converge to the reference vector while the control signal $\underline{DU}_P$ has to tend to zero, so defined by:

$$X_c(k+HP) = [\underline{YC}^T \quad \Phi^T]^T \tag{11}$$

So, We can define the error of "reaching target" as follows:

$$e(k+HP) = [X_p(k+HP) - X_c(k+HP)] \tag{12}$$

Finally a weighting matrix L with dimension $(HP - HI + HC + 1, HC)$, is defined to create a cancellation dynamics of the performances error:

$$\begin{aligned} e_f(k+HP) &= L^T e(k+HP) \\ &= L^T\left[X_p(k+HP) - Xc(k+HP)\right] \\ &= L^T X_p(k+HP) - L^T X_c(k+HP) \\ &= Ip_r(k+HP) - Ip_d(k+HP) \end{aligned} \tag{13}$$

with:
$Ip_r(k+HP)$ is the real performances indicator and $Ip_d(k+HP)$ is the desired one.
$L^T = [M \quad \lambda Z]$.
$Z = [Q_*^T Q_* + \lambda I_{HC}]^{-1},\ M = ZQ_*^T$.

2.1 Limit of the Direct adaptive generalized predictive control law based on a performances index

The objective of the direct adaptive generalized predictive control $DAGPC$ is to determine directly the parameters of the regulator using an adaptive algorithm which minimizes the performances index $\Im(k+HP)$ at each sampling time. The performances index to be minimized is a quadratic cost function $\Im$ defined by [6] :

$$\begin{aligned} \Im\,(k+Hp) &= \mathrm{e}_f(k+Hp)^T \mathrm{e}_f(k+Hp) \\ &= \left[Ip_r(k+HP) - \hat{\theta}^T(k+HP-1)\,\phi(k)\right]^T \times \\ &\qquad \left[Ip_r(k+HP) - \hat{\theta}^T(k+HP-1)\,\phi(k)\right] \end{aligned} \tag{14}$$

The parameters of regulator are updating through the gradient algorithm given by:

$$\hat{\theta}(k+HP) = \hat{\theta}(k+HP-1) - \frac{\Gamma}{2}\frac{\partial \Im(k+HP)}{\partial \hat{\theta}(k+HP-1)} \tag{15}$$

with Γ is a matrix of adaptation gain.
According to the equation (14), we can write the equation (15) as follow:

$$\hat{\theta}(k+HP) = \hat{\theta}(k+HP-1) + \Gamma\ \phi(k)\ e_f(k+HP)^T \tag{16}$$

In order to show the limit of the Direct adaptive generalized predictive control law based on a performances index, we consider a second order non stationary system described by the following equation:

$$y(k) = -a_1(k)\, y(k-1) - a_2(k)\, y(k-2) + b_1(k)\, u(k-1) + b_2(k)\, u(k-2) \tag{17}$$

The parameters $(a_i(k),\ b_i(k))$ are a time varying parameters.

2.2 Case of faintly non stationary system

In a first case, we consider a faintly variation of the parameters $(a_i(k), b_i(k))$. A direct adaptive generalized predictive control, with a retained synthesis parameters ($HP = 8$, $HC = 2$, $HI = 1$, λ=1), is synthesized. The application of this control law to the considered system gave the results represented by the figure 1. This figure illustrates the evolutions of the system output $y(k)$ and of the reference trajectory $y_c(k)$. We remark that the system output follows with notable precision the desired reference trajectory.

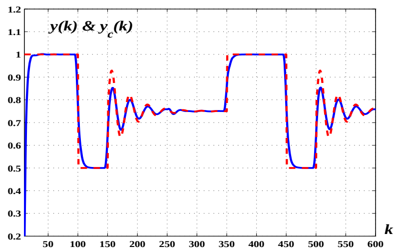

Fig. 1. The evolutions of the desired and the real outputs. (Faintly non stationary system)

2.3 Case of highly non stationary system

In presence of an important non stationary system, given by the figure 2, the performances of direct adaptive generalized predictive control $DAGPC$ is considerably deteriorated. It's due to the inability of this control law to act according to parametric variations and to the modelling errors. This is illustrated by the figure 3 witch lets appear a big error between the process output and the desired reference trajectory.

In order to overcome these problems, we propose to apply the multimodel approach. Indeed, the highly non stationary system can be represented by a set of N local models called models'base. We associate to each model a local Generalized Predictive Control. The effective control $u(k)$ applied to the process can be a result of a fusion between all these elementary control laws $u_i(k)$.

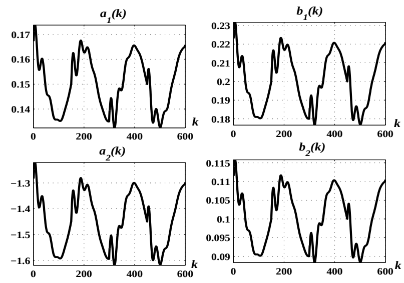

Fig. 2. Evolutions of the parameters.

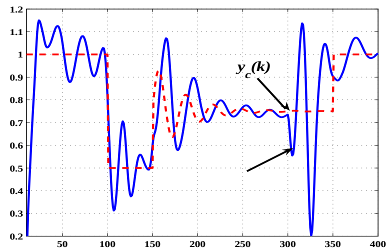

Fig. 3. The evolutions of the desired and the real outputs. (Important parameters variation case).

3 Synthesis of multimodel generalized predictive control based on Performances Index

The main objective that will lets us to consider the strategy of the multimodel control, is to avoid the adaptive aspect. Indeed, there is a number of problems associated with the application of the *DAGPC*. It may produces instable behavior of the overall system when the process presents a relatively important parameters variation, non linearity and/or when it is perturbed by external disturbances. The classical idea of the multimodel approach consists to select, at any instant, the appropriate model and the corresponding controller. In fact, the control signal applied to the system is a combination between all the proposed controllers. Each controller has the validity domain of the corresponding local model which is chiffred by a validity'degree. These validities'degrees are exploited in the fusion step to obtain the effective multimodel control. The methods of validity calculation existing in the literature are based on the evaluation of the pertinence of the models in the description of the system global behavior and pass generally by the residues calculation. The residue is formulated by the distance between the output of the system and the outputs of partial models.

Indeed, these methods lack sometimes a precision. To overcome this problem, we propose, a method for the validities estimation based on a fuzzy supervisor which evaluates the pertinence of each local control using a computation of performances index and its variation.

3.1 Determination of a models'base

The determination of a models'base is confided to the method based on the Kohonen networks [21, 24]. The application of this approach requires firstly to determine the number of clusters. The classification of an identification data set is the second stage. Then, there is a stage of structural and parametric estimation. In order to determine the local models that can reproduce the behavior of the system [14, 21, 24].
The application of this method to an identification data set picked out on the highly non stationary system, yields to three second-order systems described by the following transfer functions:

$$H_1(q^{-1}) = \frac{0.0978q^{-1} + 0.2011q^{-2}}{1 - 0.4414q^{-1} + 0.1383q^{-2}} \tag{18}$$

$$H_2(q^{-1}) = \frac{0.1q^{-1} + 0.1922q^{-2}}{1 - 0.4775q^{-1} + 0.1614q^{-2}} \tag{19}$$

$$H_3(q^{-1}) = \frac{0.1003q^{-1} + 0.2065q^{-2}}{1 - 0.4353q^{-1} + 0.1484q^{-2}} \tag{20}$$

3.2 Validities estimation based on classical residue approach

The validities of models M_i ($i = 1, ..., N$) are calculated using the residues approach formulated by the relations (21), (22) and (23):

$$r_i(k) = |y(k) - y_i(k)|\,; \quad i \in [1, N]. \tag{21}$$

$y(k)$ and $y_i(k)$ represent respectively the system and the models M_i outputs.
Practically, it is recommended to use the following normalized expression of the residue:

$$r'_i(k) = \frac{r_i(k)}{\sum\limits_{j=1}^{N} r_j(k)} \tag{22}$$

The validity which varies in the contrary sense of the residue, can then be expressed by:

$$v_{m_i}(k) = \frac{1 - r'_i(k)}{N - 1} \tag{23}$$

In the case where the residue approach is adopted for a highly non stationary system the performances of multimodel generalized predictive control, based on classical residue approach, is considerably deteriorated, the figures 4 and 5, show respectively the evolutions of the desired reference trajectory $y_c(k)$, the system output $y(k)$ and of the control law $u(k)$. It is clear that the system output is far from tracking the desired reference trajectory. Moreover, the variance of control signal is considered relatively important. The evolution of the validities'degrees relative to each model is presented in figure 6.

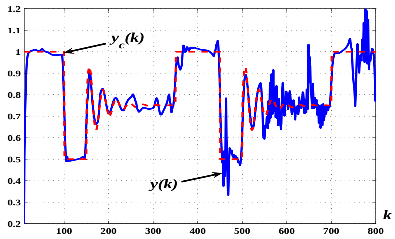

Fig. 4. The evolutions of the desired and the real outputs. (Classical residue approach).

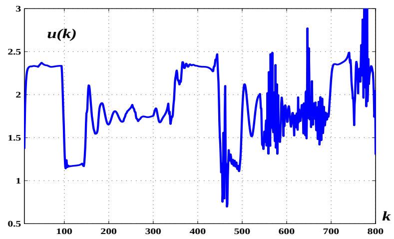

Fig. 5. The Evolution of control sequence $u(k)$. (Classical residue approach).

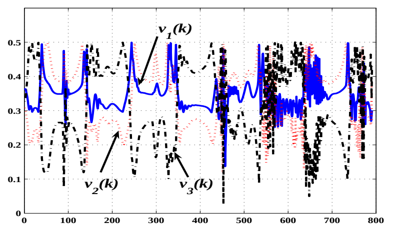

Fig. 6. Evolutions of the different validities in the classical residue approach case.

4 Fuzzy Supervision of the Multimodel Generalized Predictive Control based on Performances Index

The proposed method considers a fuzzy supervision for the online validities' estimation. Each local controller is associated with a fuzzy supervisor to generate the related validity $v_i(k)$ appealing to the performances index $\Im_i(k)$ and its variation $\Delta\Im_i(k)$. The objective of the control law is to maintain the real performances indicator close to the desired one. So the idea consists to find, at every sampling time, the elementary control $u_i(k)$ witch provides the nearest performances (measured by the elementary performances indicator $Ip_i(k+HP)$) to the real one (measured by the real performances indicator $Ip_r(k+HP)$). The application of this elementary control $u_i(k)$ could bring the system to the desired performances (measured by the desired performances indicator $Ip_d(k+HP)$). let's define a performances error $e_{\Im_i}(k+HP)$ by:

$$\begin{aligned} e_{\Im_i}(k+HP) &= Ip_r(k+HP) - Ip_i(k+HP) \\ &= L^T X_p(k+HP) - L_i^T X_i(k+HP) \end{aligned} \tag{24}$$

with:
$X_p(k+HP) = [\underline{\hat{Y}}^T \ \underline{DU}_p^T]^T$.
$L_i^T = [M_i \quad \lambda Z_i]$, $\quad Z_i = [Q_{i_*}^T Q_{i_*} + \lambda I_{HC}]^{-1}$, $\quad M_i = Z_i Q_{i_*}^T$.
$X_i(k+HP) = [\underline{\hat{Y}}_i^T \ \underline{DU}_{p_i}^T]^T$. $\underline{\hat{Y}_i} = R_i^{**}\underline{DU} + G_i^{**}\underline{Y}_i + Q_i^{**}\underline{DU}_p \qquad i \in [1, N]$.
Therefore, we can write the performances index by the following equation:

$$\Im_i(k+HP) = \mathrm{e}_{\Im_i}(k+HP)^T \mathrm{e}_{\Im_i}(k+HP) \tag{25}$$

The supervisor is illustrated by figure 7. Each element of supervision is composed of three functions which are the fuzzyfication, the fuzzy inference and the defuzzyfication [2, 8, 10, 12, 13].

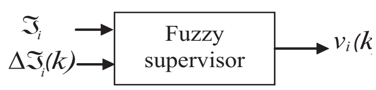

Fig. 7. The fuzzy supervisor scheme.

4.1 Fuzzyfication

The fuzzyfication consists to convert the normalized real inputs ($\Im_{i_n}(k)$, $\Delta\Im_{i_n}(k)$) to fuzzy input. Indeed, to each normalized input of the supervisor, we associate n_e fuzzy sets described by triangular membership functions centered on the numbers Nce_j.
The performances index $\Im_i(k)$ is normalized in the interval [0,1] and we have:

$$\Im_{i_n}(k) = \frac{\Im_i(k) - \Im_{\min}}{\Im_{\max} - \Im_{\min}} \ ; \ Nce_i = \frac{i-1}{n_e - 1} \qquad 1 \le i \le n_e$$

The variation of the index performances $\Delta\Im_i(k)$ is normalized in the interval [-1,1] and we have:

$$\Delta\Im_{j_n}(k) = \frac{\Delta\Im_j(k) - \frac{\Delta\Im_{\max} - \Delta\Im_{\min}}{2}}{\frac{\Delta\Im_{\max} - \Delta\Im_{\min}}{2}} \;\; ; \; Nce_j = -1 + \frac{j-1}{\frac{n_e - 1}{2}} \qquad 1 \leq j \leq n_e$$

Three fuzzy sets have been reserved for each supervision input ($ne = 3$) in the present case.

4.2 Fuzzy inference

The Fuzzy inference phase consists to apply a set of linguistic rules, provided by a priori elaborated rule basis, to the fuzzy inputs in order to evaluate the supervisor output $v_i(k)$. The elaboration of the rule basis witch manage the online supervision of the validities requires a phase of experimentation. The rule basis is presented in the table 1.

$\Im_i(k)$

	$v_i(k)$	S	M	L
$\Delta\Im_i(k)$	N	VL	L	VS
	Z	VL		
	P	VL	S	VS

Table 1: Inference table for the fuzzy supervisor.

with:
* Z: Zero, N: Negative, P: Positive, S: Small, M: Medium, L :Large
* VS: Very Small, VL: Very Large.

The inference table associates n_s fuzzy sets (n_s linguistics variables) to the supervisor output variable (n_s=5), which are descried, also, by triangular membership functions. These functions are defined in the interval $[0, 1]$ and centered on the numbers Ncs_l:

$$Ncs_l = \frac{l-1}{n_s - 1} \qquad\qquad 1 \leq l \leq n_s$$

The ***MIN-MAX*** inference method is used for the evaluation of the fuzzy rules contribution. Therefore the supervisor's output is determined by calculation of the coefficients D_l given by the following formla:

$$D_l(k) = \underset{Regle\ \ l}{MAX}\left\{MIN\left[\mu_i(\Im_{i_n}), \mu_j(\Delta\Im_{i_n})\right]\right\}$$

with: $i, j = 1, ..., n_e$ *and* $l = 1, ..., n_s$.
Actually, the terms $D_l(k)$ corresponds to the heights of the trapezes gotten by leveling of the output triangular membership functions.

4.3 Defuzzyfication

To elaborate the numerical value of the supervisor output, we appeal to a defuzzyfication phase based on the gravity center method. This value $v_i(k)$ can be calculated using the formula given by:

$$v_i(k) = \frac{\sum_{l=1}^{ns} D_l(k) \times Ncs_l}{\sum_{l=1}^{ns} D_l(k)} \tag{26}$$

4.4 Simulation Example

The application of the proposed strategy on the same highly non stationary system is given thereafter. A comparative study with the classical residue approach, given by figures 4, 5 and 6, shows the contribution in precision of the proposed validities computation technique. This is illustrated by the figures 8 and 9. We remark that the output of system follows with precision the desired reference trajectory. The evolution of the validities'degrees relative to each control law is presented in figure 10. This last figure shows the zones of intervention of each local control law and its contribution in the global control. These results demonstrate the efficiency of the proposed approach based on fuzzy supervisor, in term of closed loop performances with regard of the classical residue approach.

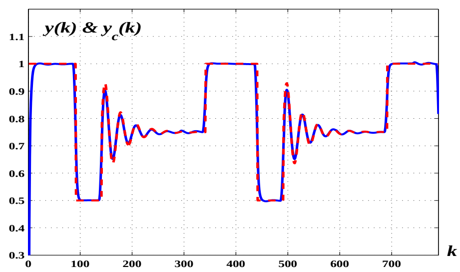

Fig. 8. The evolutions of the desired and the real outputs. (Fuzzy supervision).

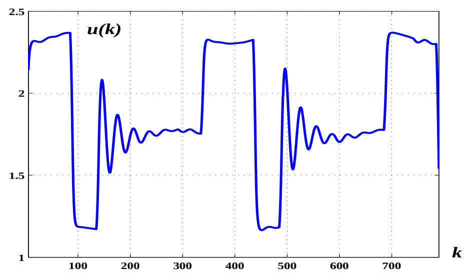

Fig. 9. The Evolution of control sequence $u(k)$. (Fuzzy supervision).

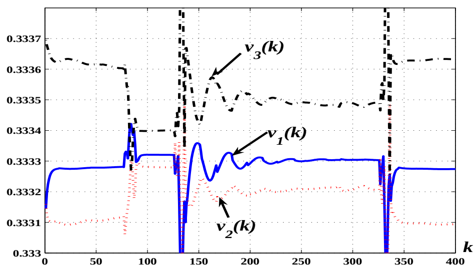

Fig. 10. Evolutions of the different validities. (Fuzzy supervision).

5 Conclusion

In this paper, we develop a direct adaptive generalized predictive control based on performances index. We showed the limits of this control law in the presence of a highly non stationary system. Thereafter, we dealt with one of the main issues to consider in the multimodel approach, which is the validities computation. A method based on a fuzzy supervisor which provide the validities referring to the performances index and its variation.

Referring to the simulation results, it appears that the proposed validities computation method improves the closed loop performances relatively to the case where the classical residue approach is used.

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