Journal of
Chemical Engineering & Process Technology

Selatnia et al., J Chem Eng Process Technol 2014, 5:4
DOI: 10.4172/2157-7048.1000197

Research Article Open Access

Modeling and Output Feedback Distributed Control for an Absorption Packed Column

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Abstract

This work consists of modeling, simulating and finally multiple models control of an industrial absorption packed column designated to remove CO_2, from natural gas. The multiple models approach is an elegant way of turning nonlinear problems into linear ones. We used in this paper the output feedback distributed control (ODC) coupled with local linearization of the model of the absorption packed column. We compared the results with those obtained with the traditional PID control and the results are satisfactory.

Keywords: Multiple models; PDC control; Methyldiethanolamine (MDEA) Absorption packed column; LMI; Lyapunov function.

Introduction

The absorption packed column is a physicochemical separation unit largely used in the chemistry industry. It consists of a tube where we send gas mixtures in order to separate one or more compounds from the principal mixture. It is largely used for the separation of acid gases (CO_2, H_2S) from natural gas.

The model presented in this paper is a dynamic model of the absorption packed column and consists of a set of nonlinear partial differential equations; it is elaborated starting from considerations on CO_2 and MDEA mass balance in gas and liquid phases and considers also the energy balance [1,2]. We finally obtain a nonlinear distributed parameters system.

Few studies were carried out on modelling and controlling the absorption column. Crosby and Durbin [3] studied the performance of a state controller. Roffel [4] developed a sub-optimal output controller with state inequality constraint. Darwish and Fantin [5] used a decentralized command with pole placement. Petrovsky [6] developed a multivariable PI regulator. Najim [7] developed a self-adjusting regulator in the case of CO_2 absorption by a diethanolamine solution and also multilevel learning control [8]. It took again the problem later on with predictive control [9].

Figure 1: The absorption packed column of In Salah Gas (ISG).

Few studies have also been published concerning the modelling and simulation of CO_2 absorption by aqueous solutions of MEA or MDEA on pilot and industrial columns [10-12].

For the model developed in our study, it seemed interesting for us to use the multiple models approach for the command of the absorption packed column because it enables us to obtain good performances for complex dynamics processes. We develop in first stage the PID regulation to compare the performances of the classical techniques with the performances of the Takagi-Sugeno multiple model approach.

Modeling and Open Loop Simulation of the Industrial Absorption Packed Column

The absorption packed column presented here is located at Khrechba and is part of the In Salah Gaz project, it removes CO_2 from natural gas by using an aqueous solution of methyldiethanolamine (MDEA) as a washing liquid, It is a packed type column measuring 8 meter height and 4 meter in diameter with Pall rings to improve the surface of contact between phases. For a better elimination of CO_2 from the natural gas, the liquid flow (water+MDEA) is counter-current with gas flow. The working pressure and temperature is respectively 71.5 bar at 55°C [2].

At contact between liquid and gas phase occurs on the surface of the Pall rings, CO_2 passes from the gas phase to the liquid phase; this diffusion is accelerated by chemical reaction of CO_2 with the MDEA in the liquid phase. The liquid flow (water+MDEA) and the CO_2 concentration in the gas mixture are respectively selected as control variable and output variable (Figure 1).

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Received May 16, 2014; **Accepted** May 28, 2014; **Published** June 02, 2014

Citation: Selatnia M, Illoul R, Boucherit MS (2014) Modeling and Output Feedback Distributed Control for an Absorption Packed Column. J Chem Eng Process Technol 5: 197. doi: 10.4172/2157-7048.1000197

Model equations

In order to simplify the model, the following assumptions are done [2,13]:

- There is no resistance in gas phase
- The reaction between CO_2 and MDEA is fast (Ha>5)
- Axial dispersion is negligible in the gas phase and the liquid phase
- The MDEA does not pass in gas phase

The mass balance on an elementary section dz of the column for CO_2 in the gas phase is written [2,13,14]:

Quantity of aqueous solution at input Z=quantity of aqueous solution at the output (z+dz)+quantity of aqueous solution transferred from the liquid phase to the gas phase+accumulation.

This gives:

$$(GC_{Ag})_z=(GC_{Ag})_{z+dz}+\varphi S\,dz+S\frac{dC_{Ag}}{dt}dz \quad (1)$$

Where G (m^3/s) is the volumic gas flow, ϕ the CO_2 flow transferred from the gas phase to the liquid phase, S the section of the column and C_{Ag} (mol/m^3) the CO_2 concentration in the gas phase. Given $U_G=G/S$ (m/s) the gas flow velocity, we obtain then:

$$U_g\frac{dC_{Ag}}{dz}+\varphi=-\frac{dC_{Ag}}{dt} \quad (2)$$

The chemical reaction between CO_2 and the MDEA is [10-12]:

$$CO_2+R_1R_2NCH_3+H_2O \rightarrow R_1R_2NCH_4^{+}+HCO_3^{-} \quad (3)$$

The reaction rate rA has the following form [14,15]:

$$r_A=kC_{AL}\,C_{BL} \quad (4)$$

Where k is the constant for reaction rate [14,15]:

$$k=2{,}9610^5\exp\left(-\frac{5332.8}{T}\right) \quad (5)$$

C_{AL} is the CO_2 concentration in the liquid phase and C_{BL} the MEA concentration in the liquid phase. The mass balance for CO_2 in the liquid phase gives finally:

$$\varphi=[kC_{AL}\,C_{BL}] \quad (6)$$

Which means that the totality of CO_2 transferred to the liquid phase reacts with the MDEA.

The mass balance for the MDEA in the liquid phase gives:

$$(LC_{Bl})_z=(LC_{Bl})_{z+dz}-[k\,C_{Al}\,C_{Bl}]\,S\,dz-S\frac{dC_{Bl}}{dt}dz \quad (7)$$

Where L is the volume liquid flow. By taking account of (5) and noting by $U_L=L/S$ (m/s) the mean liquid flow velocity, we obtain:

$$U_l\frac{dC_{Bl}}{dz}-\varphi=-\frac{dC_{Bl}}{dt} \quad (8)$$

Our absorption packed column is finally described by the following set of partial derivative equations:

$$\begin{cases}U_g\dfrac{dC_{Ag}}{dz}+\varphi=-\dfrac{dC_{Ag}}{dt}\\ U_L\dfrac{dC_{BL}}{dz}-\varphi=-\dfrac{dC_{BL}}{dt}\end{cases} \quad (9)$$

The procedure to compute flow ϕ is given in [2] according to [14-16].

We have finally to consider the boundary conditions which for gas phase are the CO_2 concentration at the column bottom or input concentration C_{AGe} and for liquid phase the MEA concentration at the column top or input concentration C_{BLe}.

$$\begin{cases}C_{Ag}\big|_{z=0}=C_{Age}\\ C_{BL}\big|_{z=h}=C_{BLe}\end{cases} \quad (10)$$

Chemical reactions within the industrial column induces a strong heat emission and the appearance of a temperature gradient throughout the column; the temperature variation is approximately 5°C between the input and the output of the column, which leads us to establish an energy balance in order to describe the temperature changes which affects the various concentrations along the column [16]:

$$\begin{cases}U_g\dfrac{\partial T_g}{\partial z}+\dfrac{a.h_{g/l}(T_l-T_g)}{\left[\sum_i cp^g{}_i C^g{}_i\right]}=\dfrac{\partial T_g}{\partial t}\\ -U_L\dfrac{\partial T_l}{\partial z}+\dfrac{1}{\sum_i cp^l{}_i C^l{}_i}\left[\Delta H_r r_A-a.h_{g/l}(T_l-T_g)\right]=\dfrac{\partial T_l}{\partial t}\end{cases} \quad (11)$$

With:

C_i^g: concentration in gas phase at the interface (mol/m^3)

C_i^l: concentration in liquid phase at the interface (mol/m^3)

cp_i^g: Specific heat in the gas phase at the interface (J/mol.K)

$h_{g/l}$: coefficient of heat transfer (convection) ($J/m^2.K.s$)

T_l: Liquid temperature (K)

T_g: Gas temperature (K)

ΔH_r: enthalpy of the reaction (J/mol)

cp_i^l: specific heat in the liquid phase at the interface (J/mol.K)

We finally takes into account the boundary conditions for the temperature which are the temperatures for gas and the liquid at the column input.

$$\begin{cases}T_g\big|_{z=0}=T_{ge},\dfrac{\partial T_l}{\partial z}\Big|_{z=0}=0\\ T_l\Big|_{z=h}=T_{le},\dfrac{\partial T_g}{\partial z}\Big|_{z=h}=0\end{cases} \quad (12)$$

Model validation

A test was carried out on our industrial absorption column to compare the output CO_2 concentration given by the model with the real one and this for a step input variation of 10 t/h. the data were collected on a horizon of 6800 seconds. The results are grouped in Figure 2 where we represent respectively, the flows of MDEA and gas at the output and then the concentrations of CO_2 at the column output either experimental or given by the model [2]. We note that the model dynamics of the CO_2 concentration at the column output agree with the experimental results.

Open loop Simulation of the industrial column

By considering the equations (2) and (8), the dynamic model of the absorption column is that of a nonlinear, distributed parameters system. The results from open loop simulations are presented in Figures 3 and 4.

Simulations show that the system is stable. It presents a dead time

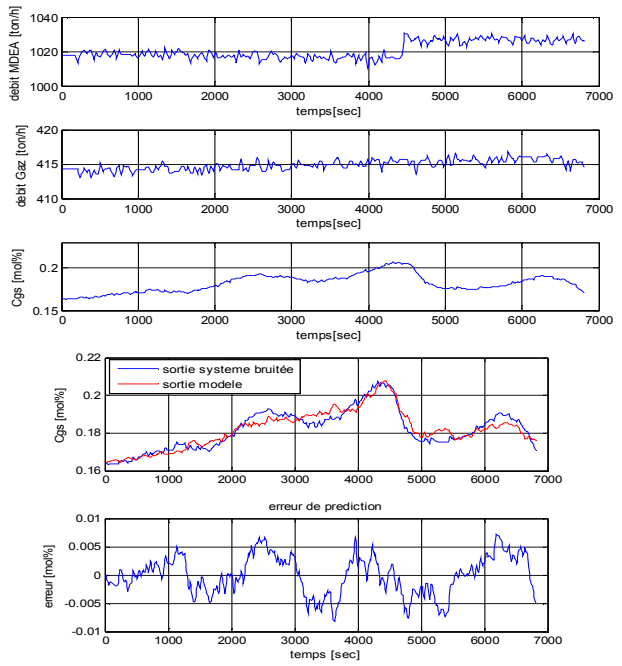

Figure 2: Output CO_2 Concentrations from the system and the model.

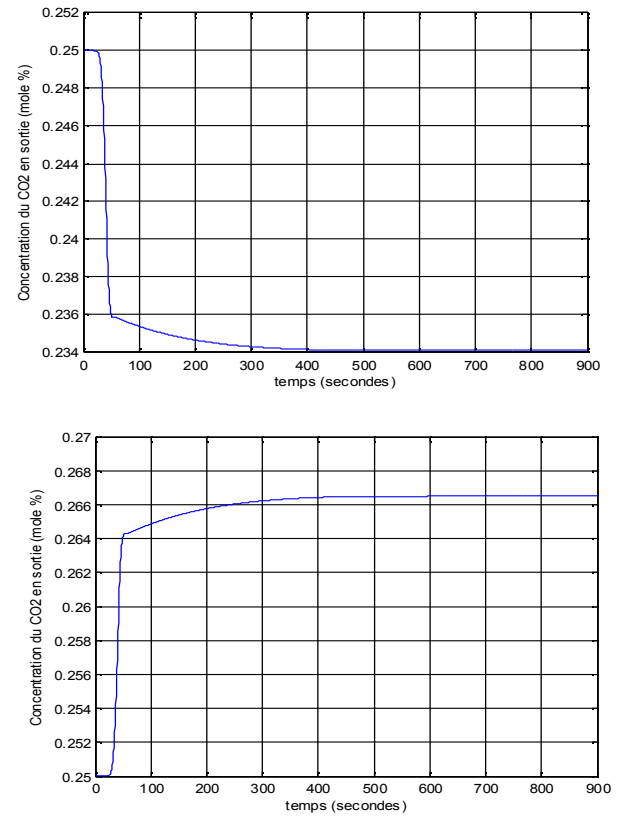

Figure 3: Output CO_2 Concentration for an input step disturbance of ± 5% on gas concentration.

in response to a step input disturbance on the CO_2 concentration due to the gas propagation along the absorption column.

PID Regulation of the Industrial Absorption Packed Column

We apply a PID regulation to the dynamic model of our absorption packed column. We chose a sampled control with a sampling period of 10 seconds. The reference for the input CO_2 concentration is s 0.25 mole%, which corresponds to a concentration of 7.05 mole CO_2/m^3. The parameters of the PID regulator were optimized using trial and error.

The simulation results are satisfactory; the PID regulator cancels the permanent error and ensures a quick response due to the derivative action. The regulation shows a net asymmetrical behaviour between responses to positive and negative step input disturbances due to the strong non linearity of the relationship between the input and the output.

Multiple Models Control of the Industrial Absorption Packed Column

Introduction

The multiple models are a nonlinear modeling technique which allows achieving a good compromise between precision and model complexity. In the light of the numerous work related to it in recent years [17-20], it arises a great interest, especially in applications dealing with simulation and control. It can also be seen as a particular fuzzy modeling technique [21,22], corresponding to a Takagi Sugeno (TS) approach [23]. A TS model is a composed of a finite number of linear models

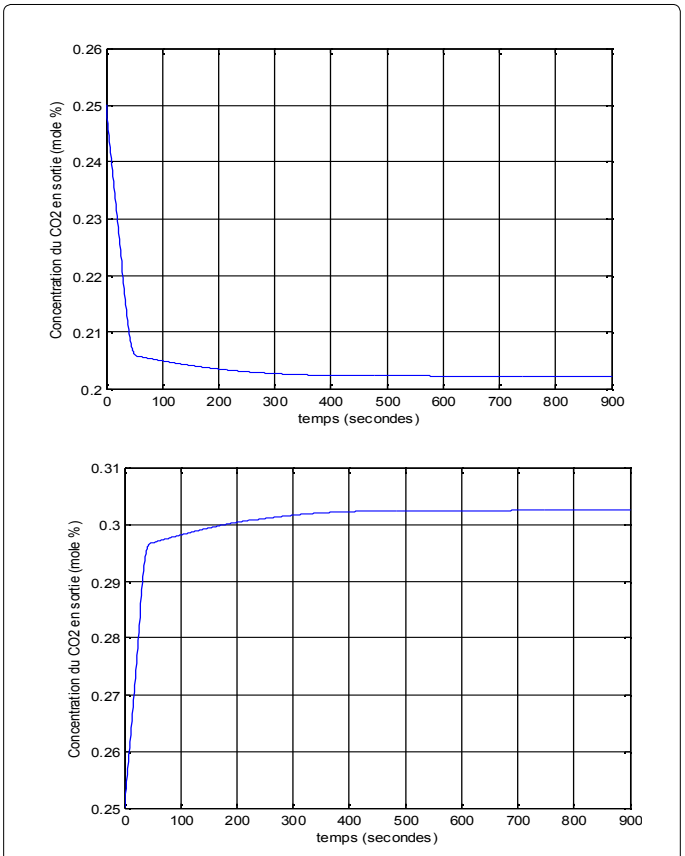

Figure 4: Output CO_2 Concentration for an input step disturbance of ± 10% on gas flow.

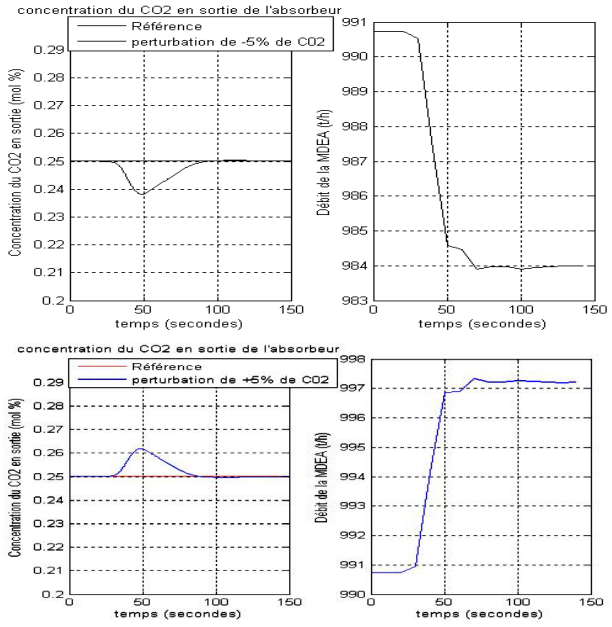

Figure 5: Output CO_2 Concentration and washing liquid flow for an input step disturbance of ± 5% on gas concentration.

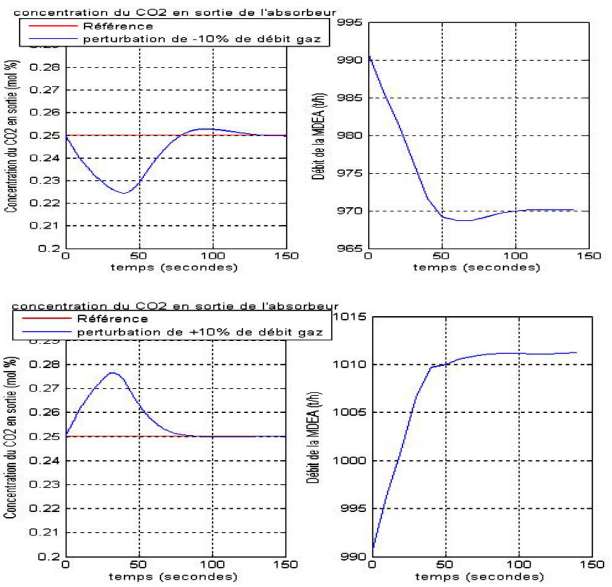

Figure 6: Output CO_2 Concentration and washing liquid flow for an input step disturbance of ± 10% on gas flow

connected with nonlinear functions called membership functions and verifying the convex mapping property (i.e. they are non-negative and their sum is equal to 1). It allows us to solve various problems of control, observation and diagnosis for nonlinear systems with linear techniques.

The approach associated with multiple models in control is known as the Parallel Distributed Compensation (PDC) [24]. This method is based on a set of linear controllers designed for each linear model, and stability of the overall closed loop is guaranteed via a Lyapunov function common to all the linear models.

In this paper, we identify the absorption packed column as a multiple model of the TS type and proposes a control based on State feedback Distributed Control (PDC) (Figures 5 and 6).

Problem formulation

The Multiple model approach: The multiple models have three basic structures: Coupled states (TS), uncoupled states [25] and hierarchical structure. The coupled states Structure (TS) is the most popular in the analysis and synthesis of the multiple models. it is written in the following form:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{M} \mu_i(z(t))(A_i x(t) + B_i u(t)) \\ y(t) = \sum_{i=1}^{M} \mu_i(z(t)) C_i x(t) \end{cases} \quad (13)$$

$x(t) \in R^n$ being the state vector, $u(t) \in R^m$ the input vector, $y(t) \in R^p$ the output vector $z(t) \in R$ is the decision variable or premises and the matrices $A_i \in R^{n \times n}$, $B_i \in R^{n \times m}$ et $C_i \in R^{p \times n}$, $\forall i = 1,2\ldots\ldots..,$ M are constant and supposed to be known.

The activation function or membership function μ_i (z (t)) determines the degree of activation of the i^{th} local model. It allows a progressive passage from this model to the other close local models. These functions can depend of the measurable variables of the system (the input and output signals) or of the non-measurable variables of the system (the states). They can be of triangular or Gaussian form and satisfy the properties of convex mapping:

$$\begin{cases} \sum_{i=1}^{M} \mu_i(z(t)) = 1, \forall t \\ 0 \le \mu_i(z(t)) \le 1, \forall i = 1,\ldots\ldots,M, \forall t \end{cases} \quad (14)$$

The multiple models can be viewed as universal approximations since any nonlinear system can be approximated by a multiple models representation with sufficient accuracy and this simply by increasing the number of sub-models. In practice, a reduced number of sub-models can be sufficient to obtain a satisfactory approximation, and we can use the tools of linear systems analysis to achieve this goal.

There are three approaches largely used in the literature allowing us to obtain a TS model: Identification, transformation by nonlinear sectors [26], or linearization. This last one is used in this work (Figure 7).

Using convex analysis for regulator synthesis, the multiple models allows us to obtain control laws by the simultaneous resolution of a finite number of Linear Matrix Inequalities (LMI). In this case, the number of LMI inequalities is polynomial with respect to the number

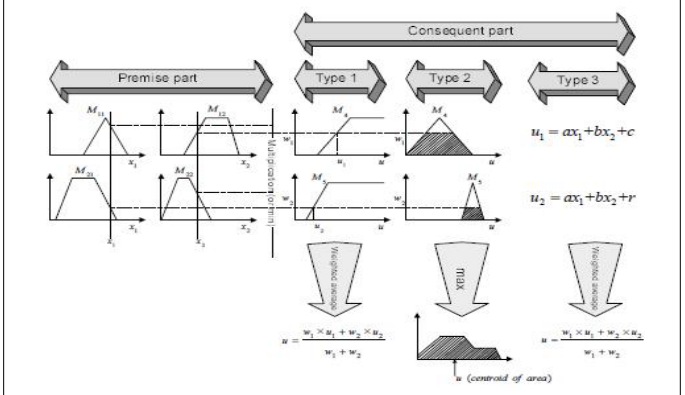

Figure 7: PDC control for TS multiple models.

of local models. Thus, it is advisable to minimize the number of local models to limit the conservatism of the method.

In the case of TS multiple models, this technique of regulator synthesis corresponds to the PDC method, It supposes that all the linear sub-models are at least stabilizable. Subsequently, they will also be supposed commendable.

Given the TS model given by equation (13), a control law resulting from PDC synthesis will thus be the combination of linear control laws for each sub-model, given by:

$$u(t) = -\sum_{i=1}^{M} \mu_i(z(t))\, F_i x(t) \tag{15}$$

Applying this control law to the TS multiple model, we obtain in closed loop:

$$\begin{cases} \dot{x}(t) = (A_z - B_z F_z)\, x(t) \\ y(t) = C_z x(t) \end{cases} \tag{16}$$

Or, in a more explicit way:

$$\{\dot{x}(t) = \sum_{i=1}^{M}\sum_{j=1}^{M} \mu_i(z(t))\mu_j(z(t))(A_i - B_i F_j)\, x(t) \tag{17}$$

The stability conditions for the closed loop system amounts to find a control gain F_j such that the derivative of the candidate Lyapunov function associated with the system is negative. Stabilizing the system thus amounts to solve the following problem:

Find a positive definite matrix P and F_i matrices, i=1. , M such that:

$$(A_z - B_z F_z)^T P + P(A_z - B_z F_z) < 0 \tag{18}$$

We notice that this inequality is nonlinear with respect to P and F_i. By using the congruence of the symmetrical full row matrix:

$$X = P^{-1} \tag{19}$$

We get:

$$XA^T_z + A_z X - XF^T_z B^T_z - B_z F_z X < 0 \tag{20}$$

By using the bijective variable change

$$M_i = F_i X,\ i=1,\ldots,M, \tag{21}$$

The problem becomes LMI in variables X and M_i.

$$\gamma_{ij} = XA^T_i - M^T_j B^T_i + A_i X - B_i M_j < 0 \tag{22}$$

We finally get:

$$\sum_{i=1}^{M}\sum_{j=1}^{M} \mu_i(z(t))\mu_j(z(t))\gamma_{ij} \tag{23}$$

And we can express the following result:

Theorem 4.1 [24] Given a continuous TS model, the PDC control law (14) and the γ_{ij}, if it exists a positive definite matrix X and M_i matrices, such that (21) is satisfied for all *i,j*=1,…, M, then the closed loop is overall asymptotically stable. Moreover, if the problem has a solution, the gains of the PDC control are given by:

$$F_i = M_i X^{-1} \tag{24}$$

And the PDC control is:

$$u(t) = -\sum_{i=1}^{M} \mu_i(z(t))\, F_i x(t) \tag{25}$$

If $F_i=F$, $\forall i=1,\ldots,M$, then we define a linear control law. In practice, to determine the matrix P and the control gain F_i, we have to solve (21) for all *i,j*=1,…, M. In the particular case where the multiple models verify the positive co linearity of the input matrices, that is:

$$B_i = B,\ \forall i \in I_n \tag{26}$$

The closed loop multiple models system of (16) is rewritten without the crossing terms $B_i F_j$:

$$\dot{x}(t) = \sum_{i=1}^{M} \mu_i(z(t))(A_i - B_i F_i)\, x(t) \tag{27}$$

The stability conditions of theorem 4.1 reduce then to the stability of the dominant models: P > 0,

$$(A_i - B_i K_i)P + P(A_i - B_i K_i) < 0,\ \forall i=1,\ldots,M \tag{28}$$

Substituting Bi by B, the control law leads to similar conditions.

Multiple models identification

The structural identification of a multiple models representation consists in the determination of the local models structures and the operation zones (or validity zones) for each local model [25]. The local models can be of various structures but in general we use simple structures, such as linear models.

The identification leads to a family of functions parameterized by the parameters vector $\underline{\theta}_i$ defining the structure of the ith local model, and the parameters vector $\underline{\beta}_i$ characterizing the zone of validity of this local model. The parametric estimate consists in determining for each local model *i* the parameters vector: $\underline{\Theta}_i = \left[\underline{\theta}_i^T \quad \underline{\beta}_i^T\right]^T$

The parametric estimation (also called training) is done on the basis of minimization of a functional binding the inputs and outputs system to the characteristics parameters of the model.

$$J_G = \frac{1}{2}\sum_{k=1}^{N}(y_s(t) - \hat{y}(t))^2 = \frac{1}{2}\sum_{k=1}^{N}\left[y_s(t) - \sum_{i=1}^{M}\omega_i(\zeta(t),\beta_i)\, f_i(\varphi(t),\theta_i)\right]^2 \tag{29}$$

In order to simplify the model, we chose linear sub-models of ARX type (auto regressive with exogenous inputs) with 3 inputs (system MISO):

- Liquid Flow U_l [ton/h]
- Gaz flow *Ug* [ton/h]
- Input CO_2 concentration C_{ge} [mol%]

The chosen local models are second order ones, they are written in the following form:

$$C_{gsi}(t+1) = A_{i1} C_{gs}(t) + A_{i2} C_{gs}(t-1) + B_i U_l(t) + C_i U_g(t) + D_i C_{ge}(t) + P_i + e_i(t+1) \tag{30}$$

With:

i=1,…. ,M : local model indices

$C_{gsi}(t+1)$ *:output* (concentration of CO_2) of local model i

$e_i(t+1)$: Gaussian white noise

A_{i1}, A_{i2}, B_i, C_i, D_i, P_i : parameters of local model i

We chose Gaussian membership functions with the decision variable $\xi(t) = C_{gs}(t)$ being the system output at time t.

The expression of the membership function is:

$$\omega_i\left(C_{gs}(t),[c_i,\sigma]\right) = \frac{exp\left(-\frac{(C_{gs}(t)-c_i)^2}{2\sigma^2}\right)}{\sum_{i=1}^{M} exp\left(-\frac{(C_{gs}(t)-c_i)^2}{2\sigma^2}\right)} \tag{31}$$

Where c_i is the mean. And σ the standard deviation for the Gaussian membership function

The global identification diagram is shown in Figure 8.

Training data (Figure 9)

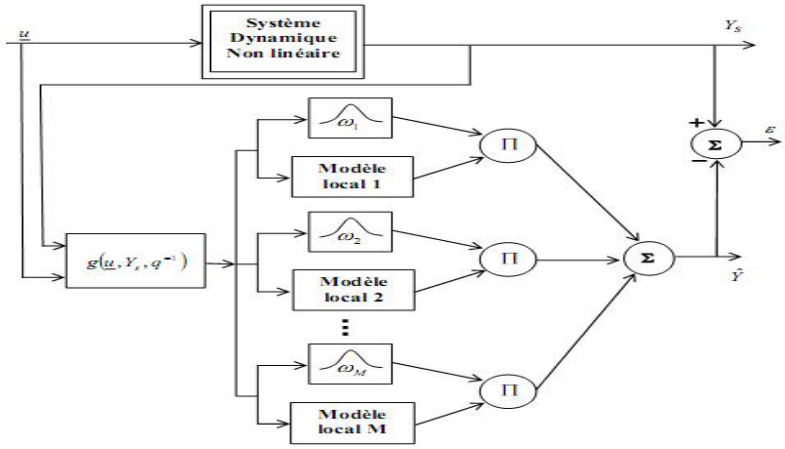

Figure 8: Structure of the multiple models identification.

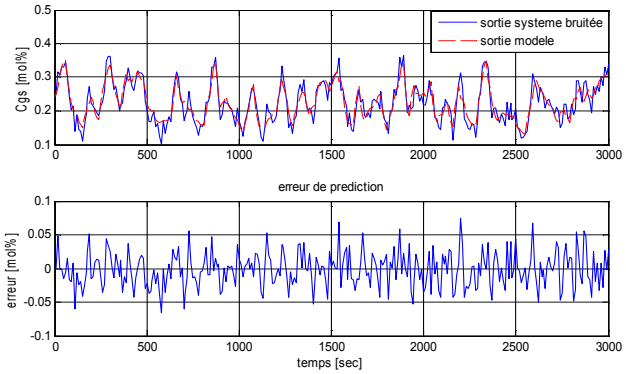

Figure 9: Training with the ARX structure.

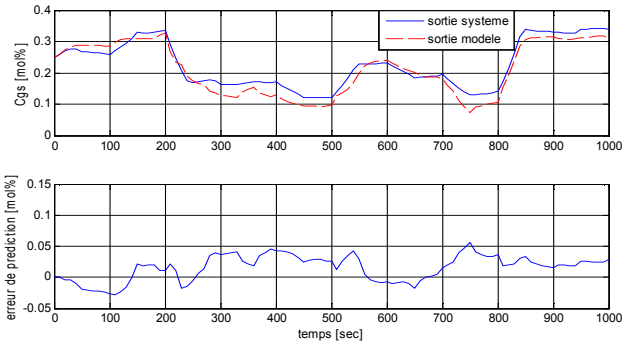

Figure 10: Validating with the ARX structure.

Validating data (Figure 10)

Implementation of the method and simulation results

The decision variable z(t) is in our case the state vector *x(t)* output gas concentration of the industrial column C_{gs},

$x(t)=[C_{gs}(t)\ C_{gs}(t-1)]^T$. A multiple models with four sub-models can easily be obtained in the form:

$$\dot{x}(t) = \sum_{i=1}^{4} \mu_i(x(t))\,(A_i - B_iF_i)\,x(t) \qquad (31)$$

With the memberships functions $\mu_i(x(t))$ either triangular or Gaussian. The parameter of the four models is:

$$A_1=\begin{pmatrix}-0.4436\\0.5744\end{pmatrix} A_2=\begin{pmatrix}-0.4772\\-0.2732\end{pmatrix} A_3=\begin{pmatrix}-1.8937\\0.3093\end{pmatrix} A_4=\begin{pmatrix}0.5339\\-0.2304\end{pmatrix}$$
$$B_1=(-0.0006)\,B_2=(-0.0006)\,B_3=(-0.0006)\,B_4=(-0.0006) \qquad (32)$$
$$C_1=C_2=C_3=C_4=\begin{pmatrix}1\\0\end{pmatrix}$$

And the State Feedback Distributed Control (PDC) is:

$$U_L(t)=-\sum_{i=1}^{4}\mu_i\,(C_{gs}(t))\,F_i x(t)+U_{Lin} \qquad (33)$$

U_L is the liquid flow velocity, and U_{Lin} the mean flow velocity corresponding to the chosen operating point of the column.

The F_i feedback gains are determined by resolution of *LMI* in order to ensure good regulation performances, less than a 0.25% variation of CO_2 around the operating points.

The selected gain is finally $F_{i=}$[980 985 995 1002]t/h

Closed loop simulation:

Case (a): triangular membership functions

The column simulation shows us the output CO_2 concentration for step input disturbances on either the gas flow or the CO_2 concentration. The evolutions of the output CO_2 concentration and the corresponding control are on Figures 11-13

Case (b): Gaussian membership functions

The evolutions of the output CO_2 concentration and the corresponding control are on Figures 14-16

Discussions

The oscillations of the output CO_2 concentration for the industrial column are mainly due to fuzzy control, but the operating point of is quickly reached in less than 50 seconds . We note on all the curves (5, 6 and 11-16) that disturbance is always rejected with both PID and PDC regulation. But comparison of the peak values as well as the oscillations show us that PDC control acts more quickly than PID control.

Conclusion

In this paper, a TS multiple models obtained by linearization was

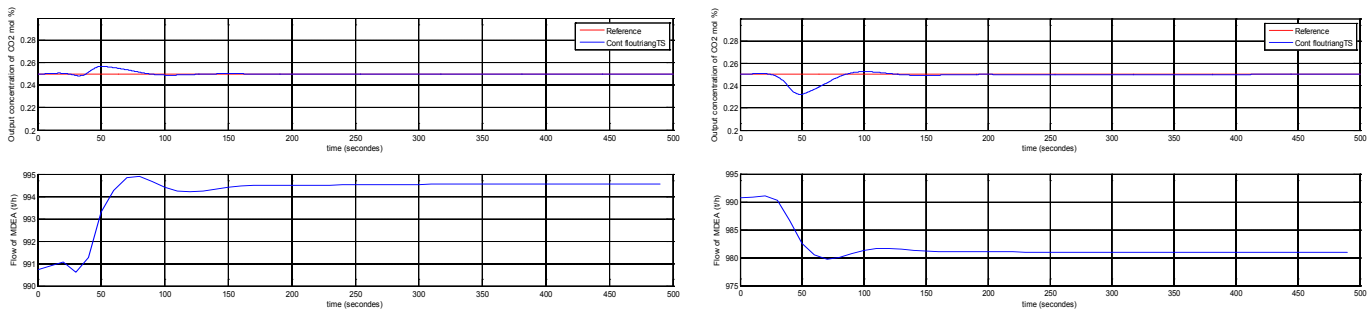

Figure 11: Output CO_2 Concentration and washing liquid flow for a step input disturbance of ± 5% on gas concentration.

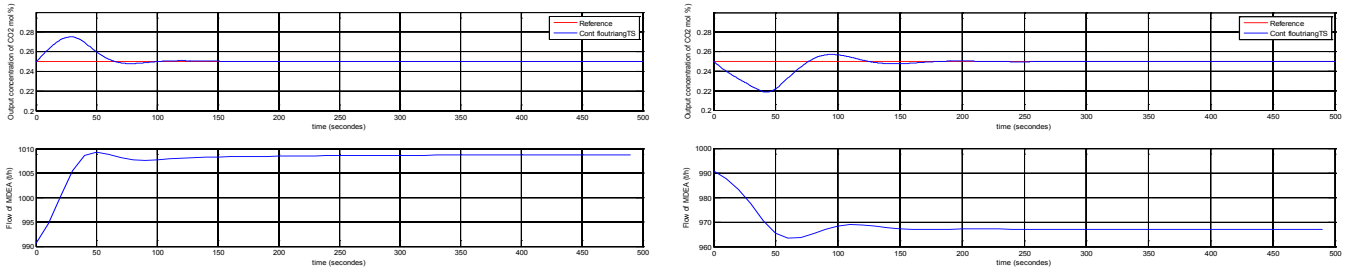

Figure 12: Output CO_2 Concentration and washing liquid flow for a step input disturbance of ± 10% on gas flow.

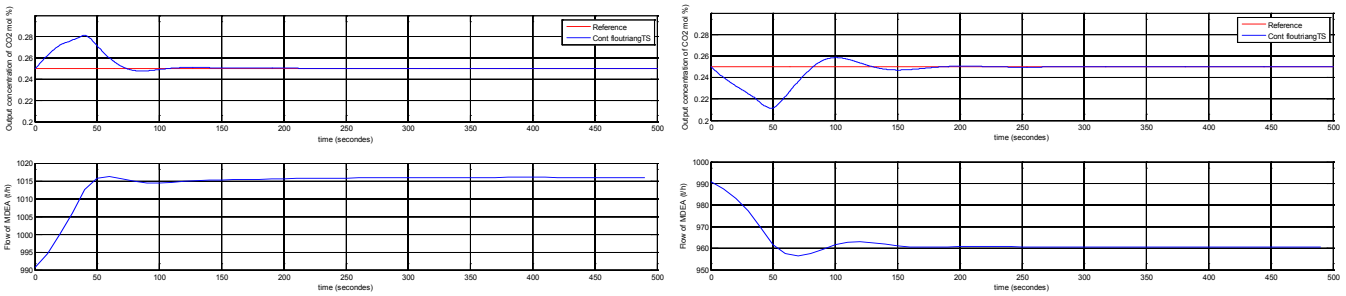

Figure 13: Output CO_2 Concentration and washing liquid flow for a step input disturbance of ± 5% on gas concentration and ± 10% on gas flow.

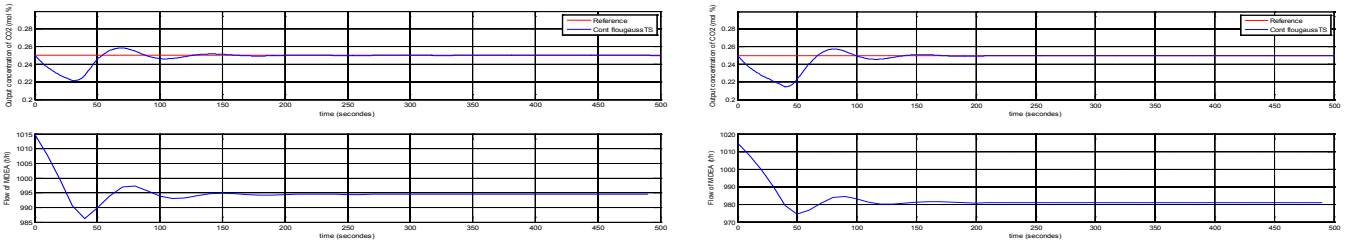

Figure 14: Output CO_2 Concentration and washing liquid flow for a step input disturbance of ± 5% on gas concentration.

used for the regulation of an industrial absorption packed column used for gas washing .We take a reduced number of sub models, four, to ease identification. The results obtained with state distributed feedback (PDC) are better than those by classical PID regulation, for a method which is not significantly complicated. Further investigations will be undertaken in the use of multiple models in control, multiple observers and multiple models in systems diagnosis.

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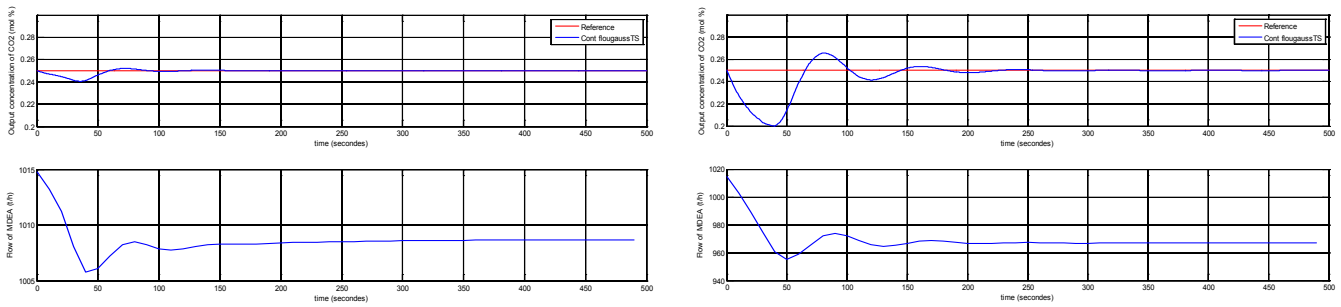

Figure 15: Output CO_2 Concentration and washing liquid flow for a step input disturbance of ± 10% on gas flow.

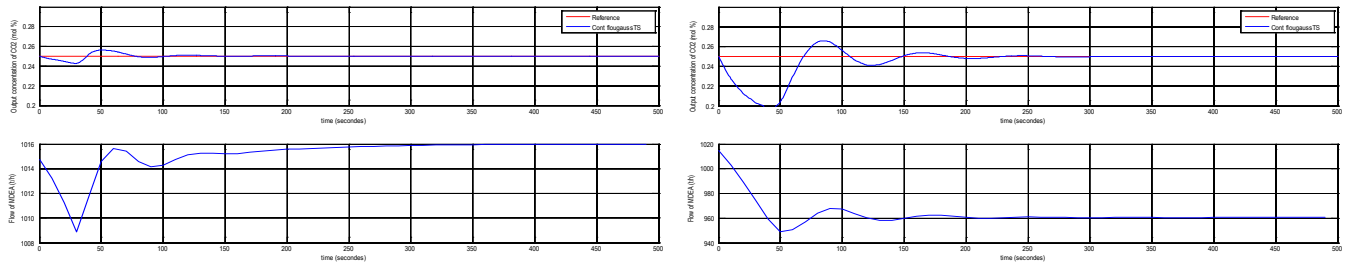

Figure 16: Output CO_2 Concentration and washing liquid flow for a step input disturbance of ± 5% on gas concentration and ± 10% on gas flow.

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