International Journal of Computer Applications (0975 8887)
Volume 80 - No. 3, October 2013

Observer based and Quadratic dynamic matrix control of a fluid catalytic cracking unit: A comparison study

A.T. Boum
University of Lorraine
LRGP, UMR 7274, Nancy, France

M .A. Latifi
University of Lorraine
LRGP, UMR 7274, Nancy, France

J. P. Corriou
University of Lorraine
LRGP, UMR 7274, Nancy, France

ABSTRACT

This paper deals with the application of two computer based model predictive control algorithms to a complex process. This process is a fluid catalytic cracking unit (FCC). The FCC model used for this study is inspired from Lee and Skogestad. The algorithms used are quadratic dynamic matrix control(QDMC) and observer base model predictive control(OBMPC). A disturbance rejection is tested by introducing some change in the feed rate. Despite the important nonlinearities of the FCC, The two linear model predictive control algorithms are able to maintain a smooth multivariable control of the plant, while taking into account the constraints. But, OBMPC algorthm is more efficient in following the set points even in the present of disturbances than QDMC algorithm.

General Terms:

OBMPC, kalman filter, QDMC

Keywords:

simulation, constraint, Observer, fluid catalytic

1. INTRODUCTION

Fluid catalytic cracking (FCC) is one of the most important processes in a refinery, in particular due to its economic importance. This latter comes from the fact that fluid catalytic cracking is used to crack heavy atmospheric residues and vacuum distillate into lighter molecules that yield more valuable products such as gasoline, kerosene, light gas oil, . . . The FCC unit is a complex process [1] due to the composition of the feed, complex chemical reactions and dynamic mass and heat interactions between its main units, namely riser, separator and regenerator. The complex nature of this process, the environmental regulation and the gains that can come from an improvement in the optimal control of this process make it a challenge to science and engineering in the field of automation. The control of this process and the necessity to operate the plant close to constraints [20] [17] in order to maximize the gains call for an advanced control tool. Model predictive control (MPC) is presently used due to its capacity to easily handle multivariable processes while also taking into account hard and soft constraints with respect to the manipulated variables, their moves and the controlled variables. Furthermore, many variables in FCC processes must be followed such as the concentration of coke on the catalyst surface in the regenerator. FCC control has been done using different approaches [12, 18, 19, 23]. In practice, FCC units are frequently regulated by means of PID controllers based on the knowledge and experience of operators in the refinery.
In this work, two Model Predictive Control (MPC) algorithms of the FCC using two manipulated inputs and two controlled outputs are addressed [10]. This paper is organized as follows, Section 2 is related to the process description, Section 3 describes the model of FCC. Section 4 deals with model predictive control principles. Section 6 deals with the control of the FCC unit with the discussions of the simulation results.
Finally, the conclusions of the paper are presented in Section 7.

2. DESCRIPTION OF A MODERN FCC PROCESS

A modern FCC process mainly consists of three units (Figure 1). The cracking reactions of the hydrocarbon feed take place in the riser while the catalyst is reactivated in the regenerator by combustion of the coke deposited on the catalyst in the riser reactor.
The preheated feed is injected in the bottom part of the riser with a small quantity of vapor. The feed is vaporized at the contact of the hot catalyst. The hydrocarbon vapors undergo an endothermic reaction while rising to the top of the riser.
The temperature at the top of the riser is between 750 and 820K. The disengagement part of the reactor is used to separate the catalyst from the vapors, then the vapors enter the main fractionator. The spent catalyst is separated from the vapors by cyclones and flows in the extraction part where the remaining hydrocarbons on its surface are removed by stripping steam. The catalyst flows through a transport line to the regenerator.
In the regenerator, the catalyst is reactivated by burning the deposited coke using air entering at the bottom of the regenerator. This partial or total exothermic combustion reaction reactivates the catalyst and maintains the bed temperature between 950-980K for future gasoil cracking. The regenerated catalyst flows continuously in the riser through another circuit and the heat transported by the

catalyst is used to compensate the endothermic reactions in the riser.

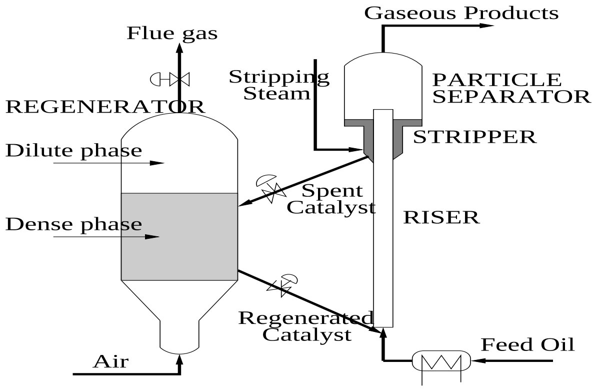


Fig. 1. Schematic diagram of FCC unit

3. MATHEMATICAL MODEL OF THE FCC

Many more or less detailed models are available in the literature for different purposes. The FCC model presently used is adapted from [13] with slight modifications by [3] and [11]. This model describes the main dynamical aspects of an FCC unit for a feedback control [2] and is adequate for predictive control because the main objectives of an FCC model are an acceptable description of the regenerator dynamics and also an acceptable description of gasoline yield [15].

3.1 Riser model

The riser is considered as plug flow reactor. The residence time of catalyst and feed in the riser is supposed to be a few seconds. Consequently, the riser is only described by spatial equations and considered as an algebraic system. The kinetic model makes use of a three lump scheme [24] to describe the cracking in the riser [4].
In the riser model, a dimensionless spatial variable is used, i.e. at bottom of riser $z = 0$ and at top of riser $z = 1$ corresponds to actual height L. The feed temperature $T_{ris}(z = 0)$ at the entry of the riser results from the heat balance

$$F_{cat,reg}\, C_{pcat}(T_{reg} - T_{ris}) = F_{feed}[C_{p,ol}(T_{boil} - T_{feed}) + \Delta H_{vap} + C_{p,og}(T_{ris}(0) - T_{boil})] \quad (1)$$

Mass balance of gas oil in the riser

$$\frac{dy_{go}}{dz} = -k_1\, y_{go}^2\, C_{owr}\, \phi\, t_c \quad (2)$$

where k_1 is the kinetic constant for gasoil consumption, C_{owr} is the catalyst to oil ratio, y_{go} is the mass fraction of gasoil in the riser, t_c is the residence time of the catalyst in the riser ϕ is the deactivation factor of the catalyst due to coke deposition
Mass balance of gasoline

$$\frac{dy_g}{dz} = (\alpha_2\, k_1\, y_{go}^2 - k3\, y_g)\, C_{owr}\, \phi\, t_c \quad (3)$$

Energy Balance in the riser

$$\frac{dT_{ris}}{dz} = \frac{\Delta H_{crack} F_{feed}}{(F_{cat,reg} C_{pcat} + F_{feed} C_{po} + \lambda F_{feed} C_{p,steam})} \frac{dy_{go}}{dz} \quad (4)$$

where ΔH_{crack} is the heat of reaction and F_{feed} and $F_{cat,reg}$ are the flow rates of the gasoil and catalyst respectively. The kinetic constants follow Arrhenius law. The deactivation of the catalyst by the coke deposition is given as

$$\phi = (1 - m\, C_{coke,reg})\, \exp(-\alpha\, t_c\, z\, C_{owr}) \quad (5)$$

The produced coke concentration is empirically given by

$$C_{coke,prod} = k_c \sqrt{\frac{t_c}{C_{rc}^N} \exp(\frac{-E_{acf}}{R T_{ris,1}})} \quad (6)$$

where $T_{ris,1}$ is the temperature at the riser outlet. The amount of concentration of coke leaving the riser is

$$C_{coke,ris,1} = C_{coke,reg} + C_{coke,prod} \quad (7)$$

3.2 Separator model

The residence time of catalyst in the separator is frequently of the order of one minute. This separator can be modelled as a perfectly mixed tank.
Mass balance of coke on catalyst

$$\frac{dC_{coke,sep}}{dt} = \frac{F_{cat,reg}\, (C_{coke,ris,1} - C_{coke,sep})}{m_{cat,sep}} \quad (8)$$

Energy balance

$$\frac{dT_{sep}}{dt} = \frac{C_{p,cat}\, F_{cat,reg}\, (T_{ris,1} - T_{sep})}{m_{cat,sep}\, C_{p,cat}} \quad (9)$$

3.3 Regenerator model

The regenerator model is inspired from Errazu [8]. It is made of a dense bed and a dilute zone. The regenerator is a fluidized bed where air bubbles cross the dense bed formed by the catalyst. This bed is considered as a CSTR. The temperature and amount of coke are considered uniform throughout the dense bed as well as the oxygen concentration. An important feature of the FCC is that the reactions in the riser are mainly endothermic whereas those in the regenerator are exothermic, thus the heat released in the regenerator is used by the riser by means of the transported catalyst. As the process involves a recycle, the behavior of a FCC is difficult to simulate correctly in steady state and transient state.
Mass Balance of coke on the catalyst

$$\frac{dC_{coke,reg}}{dt} = \frac{(F_{cat,spent}\, C_{coke,sep} - F_{cat,reg}\, C_{coke,reg}) - r_{cb}}{m_{cat,reg}} \quad (10)$$

Energy balance in the regenerator

$$\frac{dT_{reg}}{dt} = \frac{1}{(m_{cat,reg}\, C_{p,cat})}[(T_{sep}\, F_{cat,spent}\, C_{p,cat} + T_{air}\, F_{air,reg}\, C_{p,air} - T_{reg}\, (F_{cat,reg}\, C_{p,cat} + F_{air,reg}\, C_{p,air}) - \Delta H_{cb}\, \frac{r_{cb}}{M_{w,coke}}] \quad (11)$$

The kinetics of coke combustion is given by

$$r_{cb} = k_{cb}\,\exp(-\frac{E_{acb}}{RT_{reg}})\,x_{O2}\,C_{coke,reg}\,m_{cat,reg} \tag{12}$$

Mass balance of oxygen in the dense bed

$$\frac{dx_{O2}}{dt} = \frac{1}{m_{air,reg}}\,[F_{air,reg}/M_{w,air}\,(x_{o2,in} - x_{o2,reg}) \\ -((1+\sigma)\,n_{CH} + 2 + 4\,\sigma)/(4\,(1+\sigma))\,r_{cb}/M_{w,coke}] \tag{13}$$

A complete description can be found in [11]. The model is simulated in Fortran90.

4. MODEL PREDICTIVE CONTROL

4.1 Quadratic dynamic matrix control

Model Predictive Control (MPC) is a generic name for a class of multivariable algorithms that utilize a process model to predict the future behavior of the process and find corrective control moves required to drive the predicted outputs as close as possible to the desired trajectories while handling constraints. Historically, MPC was first implemented by [21], then Dynamic Matrix Control (DMC) was introduced [7]. Nowadays, many algorithms are used for model predictive implementation. The difference between them comes from the model used to represent the process, either step response, impulse response, or state space form. In the present work, step responses were used and the corresponding algorithms are briefly described. DMC [7] minimizes a quadratic criterion without taking into account the constraints so that an analytical solution results for the control vector. Quadratic dynamic matrix control (QDMC) [9] minimizes a more complete criterion in presence of linear constraints. In the present study, QDMC was used with constraints on the manipulated inputs and their variations.
For explanation purposes, DMC is first presented in a SISO framework [5,6]. A quadratic criterion taking into account the difference between the estimated output and the reference on the prediction horizon H_p is given by

$$J = \sum_{i=1}^{H_p} (\hat{y}(k+i|k) - y^{ref}(k+i))^2 \tag{14}$$

This criterion is minimized with respect to the variation of $\Delta u(k)$ of the input considered over a control horizon H_c.
The prediction of the ouput based on past and future inputs is

$$\hat{y}(k+l|k) = \\ \underbrace{y_{ss} + \sum_{i=l+1}^{H_m-1} h_i \Delta u(k+l-i) + h_M(u(k+l-M) - u_{ss})}_{\text{past inputs effect}} \\ + \underbrace{\sum_{i=1}^{l} h_i \Delta u(k+l-i)}_{\text{future inputs effect}} + \underbrace{\hat{d}(k+l|k)}_{\text{predicted disturbances}} \tag{15}$$

where h_M is the model horizon which must be larger than or equal to the prediction horizon. The output prediction based on past inputs is defined as

$$y^*(k+l|k) = y_{ss} + \sum_{i=l+1}^{M} \Delta u(k+l-i) \tag{16}$$

The vector of output predictions $\hat{y}(k+l|k)$ is related to the vector of ouput predictions $y^*(k+l|k)$ based on past inputs, to the vector of inputs $\Delta u(k)$ and to the vector of predicted disturbances as

$$\begin{bmatrix} \hat{y}(k+1|k) \\ \vdots \\ \hat{y}(k+H_p|k) \end{bmatrix} = \begin{bmatrix} y^*(k+1|k) \\ \vdots \\ y^*(k+H_p|k) \end{bmatrix} + \\ A \begin{bmatrix} \Delta u(k) \\ \vdots \\ \Delta u(k+H_c-1) \end{bmatrix} + \begin{bmatrix} \hat{d}(k+1|k) \\ \vdots \\ \hat{d}(k+H_p|k) \end{bmatrix} \tag{17}$$

where $\boldsymbol{A}$ is the dynamic matrix made of step response coefficients h_i of the plant outputs to the manipulated inputs.
For a multivariable system of dimension $n_u \times n_y$ the dynamic matrix is simply composed of submatrices as

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{A}_{11} & \dots & \boldsymbol{A}_{1n_u} \\ \vdots & & \vdots \\ \boldsymbol{A}_{n_y1} & \dots & \boldsymbol{A}_{n_yn_u} \end{bmatrix} \tag{18}$$

According to past equations, the vector of future input moves is given as

$$\Delta\boldsymbol{u}(k) = [\Delta u_1(k)^T \dots \Delta u_{n_u}(k)^T]^T \tag{19}$$

which is the least-squares solution of the following linear system

$$\begin{bmatrix} y^{ref}(k+1) - y^*(k+1|k) - \hat{d}(k|k) = e(k+1) \\ \vdots \\ y^{ref}(k+H_p) - y^*(k+H_p|k - \hat{d}(k|k) = e(k+H_p) \end{bmatrix} = \\ \boldsymbol{e}(k+1) = \boldsymbol{A}\Delta\boldsymbol{u}(k) \tag{20}$$

In the absence of constraints, the least-squares solution is

$$\Delta\boldsymbol{u}(k) = (\boldsymbol{A}^T\,\boldsymbol{A})^{-1}\boldsymbol{A}^T e(k+1) \tag{21}$$

In order to take into account the constraints, quadratic dynamic matrix control (QDMC) is used instead of DMC. Furthermore, a modification of the quadratic criterion as the sum of a performance term and an energy term is introduced in QDMC. Hard constraints affecting the manipulated variables and their moves are taken into account

$$\begin{aligned} \boldsymbol{u}_{min} \le \boldsymbol{u} \le \boldsymbol{u}_{max} \\ \Delta\boldsymbol{u}_{min} \le \Delta\boldsymbol{u} \le \Delta\boldsymbol{u}_{max} \end{aligned} \tag{22}$$

These constraints can be gathered as a system of linear inequalities incorporating the dynamic information concerning the projection of constraints

$$\boldsymbol{B}\,\Delta\boldsymbol{u}(k) \le \boldsymbol{c}(k+1) \tag{23}$$

In the presence of constraints (22), the QDMC problem can be formulated as quadratic programming such as

$$\min_{\Delta u(k)} \left[\frac{1}{2}\Delta\boldsymbol{u}(k)^T\boldsymbol{H}\Delta\boldsymbol{u}(k) - \boldsymbol{g}(k+1)^T\Delta\boldsymbol{u}(k)\right] \tag{24}$$

subject to constraints (22). $\boldsymbol{H}$ is the Hessian matrix which is equal to

$$\boldsymbol{H} = \boldsymbol{A}^T \boldsymbol{\Gamma}^T \boldsymbol{\Gamma} \boldsymbol{A} + \boldsymbol{\Lambda}^T \boldsymbol{\Lambda} \tag{25}$$

where $\boldsymbol{A}$ is the dynamic matrix, $\boldsymbol{\Gamma}$ is a diagonal matrix of weights for the outputs, $\boldsymbol{\Lambda}$ is a diagonal matrix of weights for the inputs, $\boldsymbol{g}$ is the gradient vector which is equal to

$$\boldsymbol{g}(k+1) = \boldsymbol{A}^T \boldsymbol{\Gamma}^T \boldsymbol{\Gamma} \boldsymbol{e}(k+1) \tag{26}$$

This quadratic programming problem can be solved efficiently by available subroutines [22]. The present MPC code has been developed in Fortran90 and is able to take into account any number of inputs and outputs, any type of constraints, with respect to the inputs, their moves or the outputs [5, 6]. The version used in this article is based on step responses.

4.2 Observer based model predictive control

We will present for explanation purpose, the main equations related to OBMPC [5].
OBMPC was developed by [14] and expanded by [16]. In the case of a multivariable system with n_u inputs and n_y outputs the matrix S_i is defined as

$$\boldsymbol{S_i} = \begin{bmatrix} h_{1,1,i} & h_{1,2,i} & \dots h_{1,n_u,i} \\ h_{2,1,i} & h_{2,2,i} & \dots h_{2,n_u,i} \\ \vdots & \vdots & \dots \vdots \\ h_{n_y,1,i} & h_{n_y,2,i} & \dots h_{n_y,n_u,i} \end{bmatrix} \tag{27}$$

where $h_{k,l,i}$ is the coefficient at the instant i of the output k corresponding to the step input l.
At time k, the inputs to be determined are u(k) and the future control.
In the absence of disturbance, the state space form corresponding to the step response can written as

$$\begin{aligned} Y(k) &= \Phi Y(k-1) + S\Delta u(k-1) \\ y^*(k|k) &= \Psi Y(k) \end{aligned} \tag{28}$$

The future outputs are predicted by means of a state observer such as the optimal Kalman filter with the gain matrix K.
The objective function to be minimyse is

$$J = \|\Gamma(Y(k+1|k) - R(k+1|k)\|^2 + \|\Lambda \Delta U(k|k)\|^2 \tag{29}$$

with

$$\begin{aligned} \Delta U(k|k) &= \Phi Y(k-1) + S\Delta u(k-1) \\ Y(k+1|k) &= [y_f(k+1|k)^T \dots y_f(k+H_p|k)^T]^T \\ R(k+1|k) &= [r(k+1|k)^T \dots r(k+H_p|k)^T]^T \end{aligned} \tag{30}$$

where R is the reference trajectory.
In the absence of constraints, the leasquare solution of OBMPC is expressed as

$$\Delta U(k|k) = [S_{H_p}^T \Gamma^T \Gamma S_{H_p} + \Lambda^T \Lambda]^{-1} S_{H_p}^T \Gamma^T \Gamma [R(k+1|k) - \Phi_{H_p} \hat{Y}(k|k)] \tag{31}$$

Only $\Delta u(k|k)$ the first component of $\Delta U(k|k)$ is implemented

4.2.1 *Kalman Filter.*

The observer used for the OBMPC control is a descret descret Kalman filter. We will briefly describe it algorithm. Let consider a dynamic sctochastic system :

$$\begin{aligned} x_{k+1} &= A_k x_k + B_k u_k + G_k w_k \\ y_k &= C_k x_k + v_k \end{aligned} \tag{32}$$

where w_k et v_k are white noise, with known covariance Q_k et v_k:

$$\begin{aligned} E[w_k w_j^T] &= Q_k \delta_{kj} \\ E[v_k v_j^T] &= R_k \delta_{kj} \\ E[v_k w_j^T] &= 0 \end{aligned} \tag{33}$$

The Kalman filter can be used to calculate the prediction according to the equations:

$$\begin{aligned} \hat{x}_{k+1} &= A_k \hat{x}_k + B_k u_k + K_k [y_k - C_k \hat{x}_k] \\ \hat{y}_k &= C_k \hat{x}_k \end{aligned} \tag{34}$$

where K_k is the Kalman gain matrix, y_k is the real measure carried out at time k. Kalman filter is implemented by going trough two steps
The prediction step

$$\begin{aligned} \hat{x}_{k+1|k} &= A_k \hat{x}_{k|k} + B_k u_k \\ P_{k+1|k} &= A_k P_{k|k} A_k T + G_k Q_k G_k \end{aligned} \tag{35}$$

The correction step

$$\begin{aligned} \hat{x}_{k+1|k+1} &= \hat{x}_{k+1|k} + K_{k+1}(y_k + 1 - C_{k+1} \hat{x}_{k+1|k}) \\ P_{k+1|k+1} &= (I - K_{k+1} C_{k+1}) P_{k+1|k} (I - K_{k+1} C_{k+1} T + K_{k+1} R_{k+1} K_{k+1} \end{aligned} \tag{36}$$

The optimal gain is

$$K_k = P_{k|k} C_k T R_k - 1 \tag{37}$$

5. IDENTIFICATION

In order to identify the FCC process, step responses are used. The coefficients of the step responses are used to build the dynamic matrix. Step inputs are successively applied to the FCC model and the outputs are sampled with a sampling period of 250s in order to obtain the step response coefficients. The model horizon is equal to 60.
The relationship between each input i and output j at instant k is given by

$$h_{ij,k} = \left(\frac{\Delta y_j}{\Delta u_i} \right)_k \tag{38}$$

The identified step responses are represented in Figures 2, 3. The indicated normalized time is the number of sampling periods. The manipulated inputs are respectively the regenerated catalyst flow rate u_1 and the air flow rate to the regenerator dense bed u_2. The controlled outputs are the temperature at the top of the riser y_1 and the regenerator temperature y_2. The step responses to u_1 show an algebraic effect followed by an inverse response. The algebraic effect is due to the immediate influence of the catalyst flow rate variation as the dynamic influence is neglected in the riser. The inverse response is more complex, the temperature first decreases due to the endothermic reactions in the riser, then it increases due to the exothermic reactions in the regenerator, but with a larger time constant in this latter. The influence of u_2 is simpler and the responses are close to those of first-order transfer function responses.

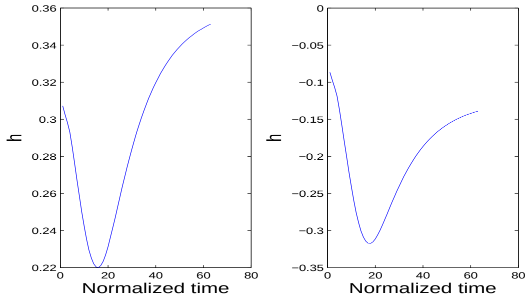


Fig. 2. Coefficients of the step responses between u_1 and y_1 (left) and between u_1 and y_2 (right)

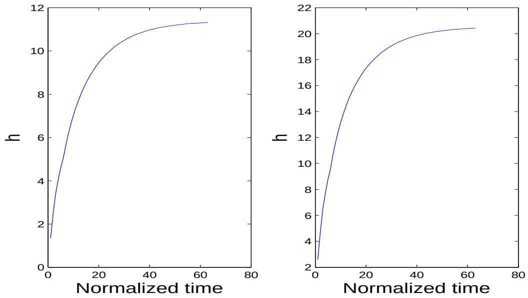


Fig. 3. Coefficients of the step responses between u_2 and y_1 (left) and between u_2 and y_2 (right)

6. CONTROL OF THE FCC PROCESS

As the process is multivariable and as imposed constraints on the manipulated variables are considered, the QDMC and OBMPC algorithms are used. The controlled outputs are the riser temperature and the regenerator temperature. The manipulated inputs are the air flow rate to the regenerator and the regenerated catalyst flow rate.

6.1 Simulation results and discussions

The simulations have been carried out with the conditions 6.1 As well as the MPC code written in Fortran90 [6], the process code is also written in Fortran90. Constraints are imposed on the manipulated variables (Table 6.1). The set points are known in advance, i.e. at initial time $t = 0$, all the set points profiles are already known. The set points were chosen desynchronized to emphasize the coupling effects. Two cases have been studied (Table 6.1). The simulations results (Figures 4(a), 4(b), 5(a), 5(b)) show that, despite changes in the set points, the outputs follow their respective set points with small deviations, lower than 1 or 2K at the most, while the manipulated variables remain within the constraints.

The results (Figures 8(a), 8(b), 9(a), 9(b)) show the performance of the controller even when the weights on the outputs are significantly reduced. The manipulated inputs are still within the constraints and the output still follow the set points in an acceptable manner.

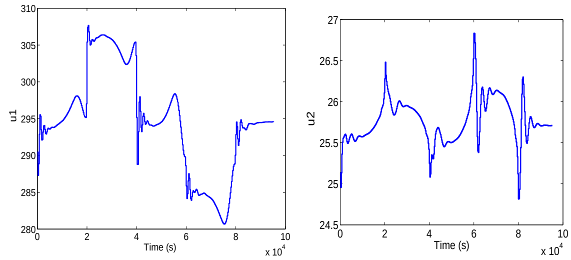
The coupling effects between inputs and outputs are visible on Figures 4(a),5(b) and on Figures 4(b),5(a) , but for example output 1 rapidly joins its stable set point after some transient behavior whereas output 2 tracks its new set point. Thus, the Quadratic Dynamic Matrix controller used with the identification through step

Table 1. Simulations conditions

Parameter	QDMC	OBMPC
Platform	PC Linux Ubuntu	PC linux ubuntu
Software	Fortran90	Fortran90
Execution time	10mn	10mn

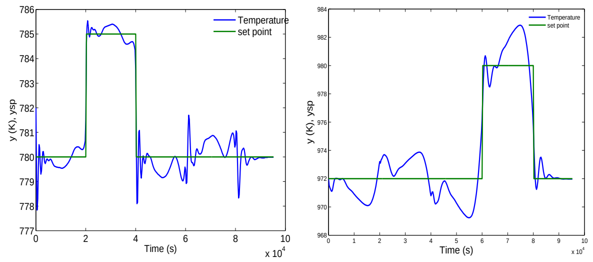
Table 2. MPC parameters

Parameter	Case 1	Case 2
Sampling period	250s	250s
Prediction horizon	63	63
Control horizon	3	3
Min-Max constraints on input 1	[269 , 325]	[269 , 325]
Min-Max constraints on input 2	[25 , 52]	[25 , 52]
Γ diagonal values	8 8	4 4
Λ diagonal values	1 1	1 1



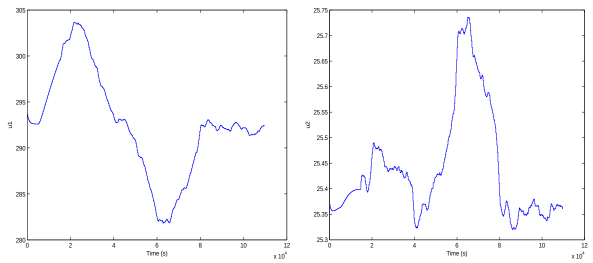
(a) Flow rate of regenerated catalyst u_1 (kg.s^{-1})
(b) Flow rate of air to the regenerator u_2 (kg.s^{-1})

Fig. 4. Manipulated variables (Case 1)



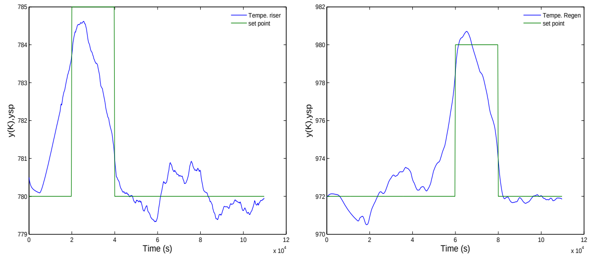
(a) Temperature at the top of the riser y_1 (K)
(b) Temperature in the regenerator y_2 (K)

Fig. 5. Controlled variables (Case 1)



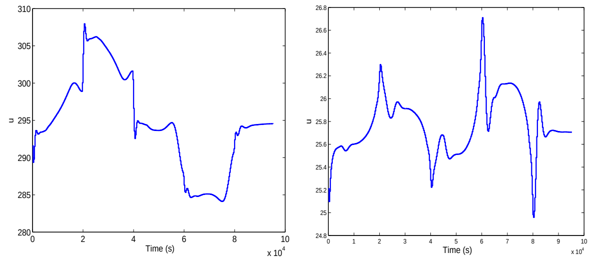
(a) Flow rate of regenerated catalyst u_1 (kg.s^{-1})
(b) Flow rate of air to the regenerator u_2 (kg.s^{-1})

Fig. 6. Manipulated variables obmpc



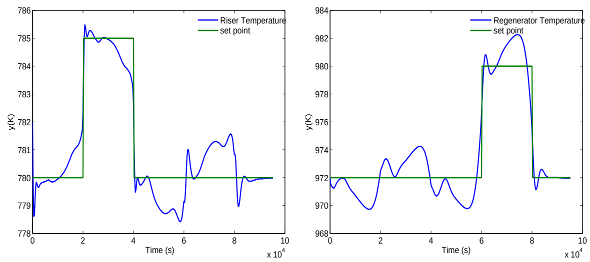
(a) Temperature at the top of the riser y_1 (K)
(b) Temperature in the regenerator y_2 (K)

Fig. 7. Controlled variables obmpc



(a) Flow rate of regenerated catalyst u_1 (kg.s^{-1})
(b) Flow rate of air to the regenerator u_2 (kg.s^{-1})

Fig. 8. Manipulated variables (Case 2)



(a) Temperature at the top of the riser y_1 (K)
(b) Temperature in the regenerator y_2 (K)

Fig. 9. Controlled variables (Case 2)

response coefficients is able to maintain the complex process outputs close to their respective variable sets points with very acceptable deviations.
The influence of the weights in the criterion has been studied (Table 6.1). They were introduced to give more importance to the performance part than to the energy part of the criterion. The consequence is that the tracking is very correct 5(a),5(b)
but that at the same time some rather steep variations of the inputs are imposed, such as clearly shown at set point changes. When the weights $\mathbf{\Gamma}$ are decreased,9(a),9(b)
the tracking is a little worse with larger deviations at set point changes, but it remains acceptable and the inputs are more smooth. Some important variables in the regenerator and separator such as the concentrations of coke on the catalyst in the separator and in the regenerator, the mole fraction of oxygen in the regenerator dense bed are shown in Figures 10, 11, 12. From Figures 10 and 11, it appears that the coke on catalyst is not completly burnt, in agreement with the hypothesis that the regenerator was assumed in partial combustion mode. The evolution of the coke content at the top of the riser is similar to that in the separator, and follows the same tendency as the coke in the regenerator, i.e. when the regenerator temperature increases, the coke content decreases and when the riser temperature increases, the coke content increases. The quantity of coke decreases with the increase of the flow rate of air in the regenerator.
Due to the fact that gasoline yield is strongly dependent on the temperature in the riser and the catalyst activity is also dependent on the temperature in the regenerator, the overall functioning of the FCC can be significantly improved by this tool.

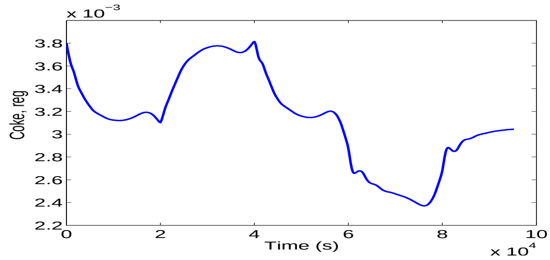


Fig. 10. Mass fraction of coke on catalyst in the regenerator

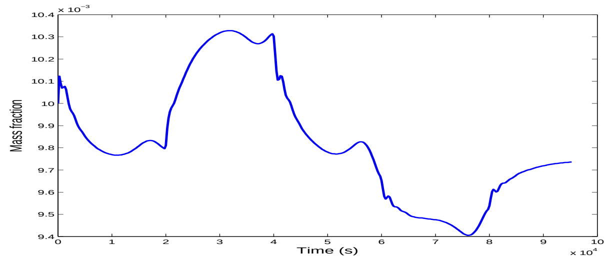


Fig. 11. Mass fraction of coke on catalyst in the separator

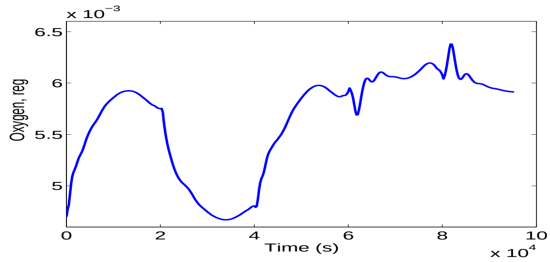
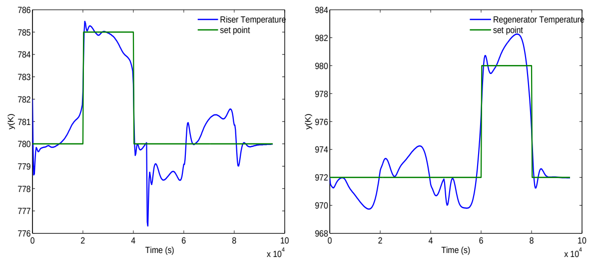


Fig. 12. Oxygen mole fraction in the regenerator

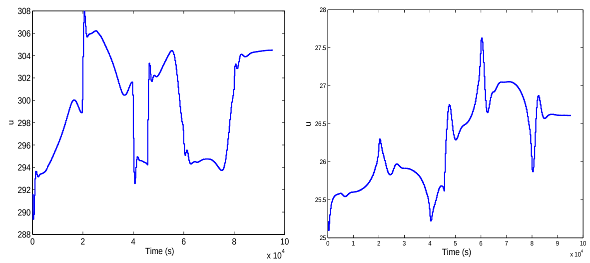
The influence of several disturbances can be studied. A first disturbance is introduced by a 5% increase of the feed flow rate at the bottom of the riser after 40000_s
The simulation results (Figures 13(b) 13(a)) show a good rejection of disturbance by the controller (Figures 14(a) 14(b)) show that the manipulated variables still remain within the constraints.



(a) Temperature at the top of the riser y_1 (K) in the case of feed disturbance

(b) Temperature in the regenerator y_2 (K) in the case of feed disturbance

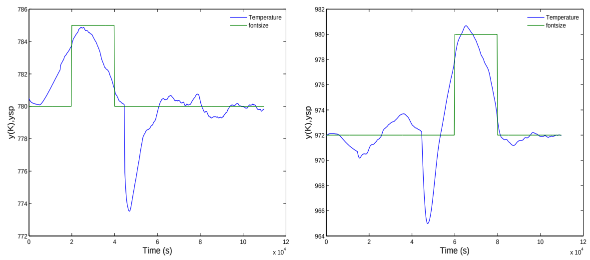
Fig. 13. Controlled variables in the case of feed disturbance with QDMC (5% increase of the feed flow rate at t=40000s)



(a) Flow rate of regenerated catalyst u_1 (kg.s^{-1}) in the case of feed disturbance

(b) Flow rate of air to the regenerator u_2 (kg.s^{-1}) in the case of feed disturbance

Fig. 14. Manipulated inputs in the case of feed disturbance with QDMC (5% increase of the feed flow rate at t=40000s)



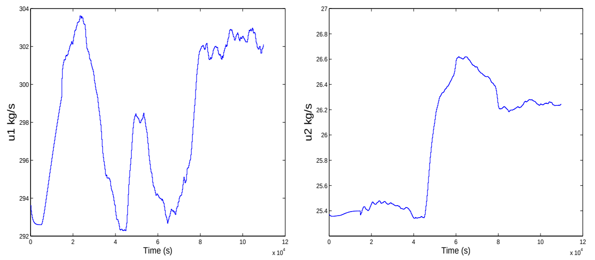
(a) Temperature at the top of the riser y_1 (K) in the case of feed disturbance

(b) Temperature in the regenerator y_2 (K) in the case of feed disturbance

Fig. 15. Controlled variables in the case of feed disturbance with OBMPC (5% increase of the feed flow rate at t=40000s)

7. CONCLUSION

In this work, Quadratic Dynamic Matrix Control and observer based model predictive control algorithms are implemented to control the FCC process with the regenerated catalyst flow rate and the flow rate of air to the regenerator as manipulated variables. The simulations results show a very good tracking of the set points despite set points changes and disturbances by both algorithms. But , however, We notice a superior tracking of the set points by the observer based model predictive control algorithm in the presence of disturbances.



(a) Flow rate of regenerated catalyst u_1 (kg.s^{-1}) in the case of feed disturbance

(b) Flow rate of air to the regenerator u_2 (kg.s^{-1}) in the case of feed disturbance

Fig. 16. Manipulated inputs in the case of feed disturbance with OBMPC (5% increase of the feed flow rate at t=40000s)

Nomenclature

Γ diagonal matrix of weights for the outputs
Λ diagonal matrix of weights for the inputs
λ mass fraction of vapor in the feed
$\boldsymbol{A}$ dynamic matrix
ϕ catalyst deactivation
σ molecular ratio of CO_2 to CO in the dense bed of the regenerator
$C_{coke,reg}$ mass fraction of coke in the regenerator
C_{pcat} heat capacity of catalyst
C_{rc}^N weight fraction of coke on regenerated catalyst
F_{feed} mass flow rate of feed $(kg.s^{-1})$
$F_{air,reg,mas}$ mass flow rate of air to regenerator $(kg.s^{-1})$
$F_{cat,reg}$ mass flowrate of catalyst (kg.s^{-1})
H_c control horizon
H_p prediction horizon
k_i kinetic constant
r_{cb} rate of coke combustion $(kg.s^{-1})$
T_{air} temperaure of air to regenerator (K)
T_{reg} temperature in the regenerator dense bed (K)
T_{ris} temperature in the riser (K)
T_{sep} temperature in the separator (K)

8. REFERENCES

[1] H. Ali, S. Rohani, and J.P. Corriou. Modelling and control of a riser type fluid catalytic cracking (FCC) unit. *Trans. IChemE.*, 75, part A:401–412, 1997.
[2] J. Alvarez-Ramirez, J. Valencia, and H. Puebla. Multivariable control configuration for composition regulation in a fluid catalytic cracking unit. *Chem. Eng. J.*, 99:187–201, 2004.
[3] J.S. Balchen, D. Ljungquist, and S. Strand. State-space predictive control. *Chem. Eng. Sci.*, 47(4):787–807, 1992.
[4] Corma and Martinez-Triguero. Kinetics of gas oil cracking and catalyst decay on SAPO-7 and USY molecular sieves. *App Catal*, 118:153–162, 1994.
[5] J.P. Corriou. *Commande des Procédés*. Lavoisier, Tec. & Doc., Paris, 2003.
[6] J.P. Corriou. *Process Control - Theory and Applications*. Springer, London, 2004.

[7] C.R. Cutler and B.L. Ramaker. Dynamic matrix control-a computer control algorithm. Houston,Texas, 1979. In AIChE Annual Meeting.

[8] A.F. Errazu, H.I. de Lasa, and F. Sarti. A fluidized bed catalytic cracking regenerator model grid effects. *Can. J. Chem. Engng.*, 57:191–197, 1979.

[9] C.E. Garcia and A.M. Morshedi. Quadratic programming solution of dynamic matrix control(qdmc). *Chem.Eng Comm*, 46:73–87, 1986.

[10] M. Hovd and S. Skogestad. Controllability analysis for the fluid catalytic cracking process. *AIChE Annual Meeting*, 1991.

[11] M. Hovd and S. Skogestad. Procedure for regulatory control structure selection with application to the FCC process. *AIChE J.*, 39(12):1938–1953, 1993.

[12] H. Kurihara. *Optimal Control of Fluid Catalytic Cracking Process*. PhD thesis, MIT, 1967.

[13] E. Lee and F.R.Jr. Groves. Mathematical model of the fluidized bed catalytic cracking plant. *Trans. Soc. Comput. Sim.*, 2:219–236, 1985.

[14] J.H. Lee, M. Morari, and C.E. Garcia. State-space interpretation of model predictive control. *Automatica*, 30:707–717, 1994.

[15] D. Ljungquist, S. Strand, and J.G. Balchen. Catalytic cracking models developed for predictive control purposes. *Modeling, Identification and Control*, 14(2):73–84, 1993.

[16] P. Lunström, J.H. Lee, M. Morari, and S. Skogestad. Limitations of dynamic matrix control. *Comp. Chem. Engng.*, 19(4):409–421, 1995.

[17] Mihaela-Hilda Morar and Paul Serban Agachi. The development of a MPC controller for a heat integreated fluid catalytic cracking plan. *STUDIA UNIVERSITATIS BABES-BOLYAI CHEMIA*, 54(4, 1):43–54, 2009.

[18] L.F. Lautenschlager Moro and D. Odloak. Constrained multivariable control of fluid catalytic cracking converter. *Journal of Process Control*, 5:29–39, 1995.

[19] L.F.L. Moro and D. Odloak. Constrained multivariable control of fluid catalytic cracking converters. *Journal of Process Control*, 5:29–39, 1995.

[20] C. I. C. Pinheiro, J. L. Fernandes, L. Domingues, A. J. S. Chambel, I. Graa, N. M. C. Oliveira, H. S. Cerqueira, and F. R. Ribeiro. Fluid catalytic cracking (fcc) process modeling, simulation, and control. *Ind. Eng. Chem. Res.*, 51:1–29, 2011.

[21] J. Richalet, A. Rault, J.L Testud, and J. Papon. Model predictive heuristic control: Applications to industrial processes. *Automatica*, 14:413–428, 1978.

[22] K. Schittkowski. NLPQL: A Fortran subroutine solving constrained nonlinear programming problems. *Ann. Oper. Res.*, 5:485–500, 1985.

[23] R. Shridar and D.J. Cooper. A novel tuning strategy for multivariable model predictive control. *ISA Transactions*, 36(4):273–280, 1998.

[24] V.W. Weekman and D.M. Nace. Kinetics of catalytic cracking selectivity in fixed, moving and fluid bed reactors. *AIChE J.*, 16(3):397–404, 1970.