Feed Conversion targeting in an FCC pilot plant using a non-linear MPC Strategy

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Abstract— **The main objective of this work is the development of an advanced control scheme for the Fluid Catalytic Cracking (FCC) Pilot Plant (PP) operated in the Chemical Process Engineering Research Institute (CPERI). This pilot plant is used for catalyst benchmarking, a very demanding procedure, that requires unit operation within a predefined span in order to match the industrial standards. For the tight, robust and efficient control of the FCC pilot plant a non-linear Model Predictive Control (MPC) strategy is implemented, along with an Extended Kalman Filter (EKF) for state and parameter estimation.**

I. INTRODUCTION

THE development and application of a reliable control scheme for the fluid catalytic cracking unit is one of the most challenging problems in chemical process industry. The application of a robust MPC strategy on the FCC unit appears as a much promising solution for the process optimization and profit maximization. However, the cost of developing a reasonably accurate first-principles model for the FCC process is usually prohibitive, as a result of the strong interactions and the high degree of uncertainty in the integrated riser-regenerator loop. The stochastic nature of the air distribution in the regenerator, the moderately defined flow regime of the gas-catalyst mixture in the riser, and the catalyst circulation throughout the unit form a complex, cyclic and constrained system. Furthermore, operational constraints set for safe and stable operation, product specifications and environmental restrictions formulate a complex control problem.

The problem in the pilot scale process is even more complicated. The operation of the pilot plant must follow a predefined profile, obeying the refinery standards. The catalyst benchmarking procedure requires the catalysts to be evaluated at constant conversion levels and riser reactor temperatures. Therefore, control of this pilot scale process faces several challenges:

--Riser temperature, controlled by the catalyst circulation rate, during closed loop PP operation, should satisfy a specified set-point that guarantees for constant selectivity in the product slate.

--Conversion of the gas-oil feed should meet a determined value for easy comparison (testing) of the variation of the examined catalysts activity and selectivity.

--Excess gas from the regenerator is subject to environmental constraints regarding the CO, SO_2, NOx emissions in commercial units and this pattern should be followed, or even examined, in the PP operation also.

The implementation of an MPC strategy appears, therefore, very promising, since the conventional control schemes, based on PID controllers, can not guarantee stability and accurate targeting of specified operating conditions, resulting to dubious productivity.

In previous work [1-3] a dynamic mathematical model has been developed and verified on the basis of steady state and dynamic experimental data of the FCC pilot plant of CPERI. The simulator predicts conversion, coke yield, and heat consumed by feed vaporization and catalytic reactions in the pilot riser reactor through the use of semi-empirical models

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developed in CPERI [1, 2]. The pilot regenerator reactor model uses the two-phase theory with a dilute phase model to account for post-combustion reactions [4, 5]. The effective manipulated variables in the PP are the catalyst circulation rate, feed preheat temperature, combustion air flow rate (and temperature), and gas-oil feed flow rate (though in an industrial unit it is driven by the need for target production), whereas the gas-oil composition and the catalyst quality are considered as disturbances. The interest is in controlling the regenerator and riser temperatures, conversion (feed basis), and coke yield (feed basis). However, the variables that can be measured online in the PP are the riser and regenerator temperature, the regenerator flue gas, the system pressure and pressure drops. Conversion and coke yield are therefore inferred by the available process measurements and the modeling relations. Thus, it is possible to implement a feedback control scheme that performs optimization through a cost function around the desired operational point. In this scheme constraints on the emissions of the regenerator (CO, NOx, and SO_2) are easily implemented. As the PP regenerator operates under full combustion mode the goal of minimum to zero CO emissions is easily achieved, yet for the other two goals the effect of the optimal operating point of the PP should be explored.

The development of the control structure underwent two main stages, the simulation study and the implementation to the real process level. The first was done by creating a framework with two instances of the model: an original entity of the simulator, as the "Virtual Process" (VP) and another one in the MPC scheme. A disturbance, such as a change in catalyst quality, was implemented in the VP to test the efficiency and robustness of the MPC. Having chosen and verified the most functional control structure followed by a suitable tuning (e.g., objective function weighting factors) the study resulted to a reliable MPC scheme to be applied on the actual pilot plant. Control parameter updates were obtained using the process measurements and the dynamic model. The optimal piecewise constant future control actions were calculated through dynamic programming over desired prediction and control horizons. The sensitivity of the performance of the online optimal non-linear MPC with respect to the duration of the control intervals and the prediction and control horizons was examined in conjunction to the effort for the numerical solution.

I. FCC Pilot Plant Control Objectives

A. Pilot Plant Description

The FCC pilot plant of CPERI (Fig. 1) operates in a fully-circulating mode and consists of a riser reactor, a fluidized bed regenerator, a stripper and a liftline. The riser reactor operates in pseudo-isothermal plug flow conditions, whereas the regenerator operates in full combustion mode under pseudo-adiabatic conditions. Two slide valves, one at the exit of the regenerator standpipe and one at the exit of the stripper standpipe regulate the catalyst circulation throughout the unit. The regenerator standpipe slide valve manipulates the catalyst circulation to control the riser temperature, whereas the stripper slide valve operates for constant stripper level (i.e. stripping volume). An on-line oxygen analyzer monitors the excess of oxygen and controls the combustion air flow rate. The process pressure, the control valves and the power supply to electrical heaters are controlled by numerous algorithmic PID controllers.

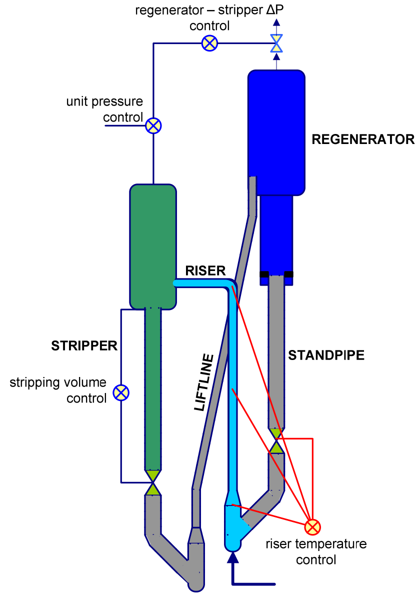

Fig. 1. Schematic diagram of the FCC pilot plant of CPERI

The main task of the PP is catalyst benchmarking. The goal is to maintain the operation within a narrow predefined window in order to achieve standard feed conversion. This practice is especially adopted for gathering comparable results in terms of catalyst selectivity, so any experiment not fulfilling that requirement is useless. In this way, the overall control objective translates to the elimination of repetitive and useless experiments.

B. Pilot Process Control Objectives

The approach presented in this project will focus on improving the control performance of the unit through manipulation of the riser. That is dictated by the operational conditions of the CPERI pilot regenerator, which allows a small margin for optimization, since the primary target for minimal polluting emissions is, in any case, achieved through full combustion of the coke under excess air conditions. So, as a first step, the optimal control case will be explored without imposing additional constraints (minimal CO emissions or specified regenerator temperature) considering the regenerator operation. Still, the regenerator operation significantly interacts with the riser. The regenerator defines the dynamics of the unit. MPC of the riser cannot be achieved via a stand-alone riser model. It requires an integrated accurate model of the riser-regenerator system, mainly, because both vessels interact with each other through stream recycling. As shown in Fig. 1, any variation in the coke/catalyst output stream of the riser is eventually led to the regenerator. The regenerator operation in turn, is notably affected by the transition of the input, resulting in dynamically changing operating conditions and output composition, which are fed back to the riser as a recycle stream affecting it again. Therefore, modeling and monitoring the regenerator is essential for controlling the riser. The effect of the model accuracy on the controlling efficiency has been extensively discussed in Model Predictive Control theory [6]. In general, the process model should be accurate enough to maintain good prediction properties over the range of operating conditions of interest. The model used for this project has been developed and presented in detail in previous publications [1-3], where its ability to simulate accurately the dynamics of the PP has been demonstrated.

A robust control system prerequisites a suitable choice of controlled (output) and manipulated (input) variables. The manipulated variables should be the ones that highly affect the unit outputs, while allowing operational flexibility and successfully alleviating the disturbances effects. The controlled variables should be chosen in correspondence to the control objectives (yield maximization, temperature stability etc.). At this point, it is useful to present a brief analysis of the system. The riser sub-section is described by 5 basic equations:

$$y_x = f_x\left(\dot{W}_F, \dot{W}_C, \dot{W}_N, P_{\mathrm{RS}}, T_{RX}, p(F), p(C)\right) \quad (1)$$

$$y_c = f_c\left(\dot{W}_F, \dot{W}_C, \dot{W}_N, P_{\mathrm{RS}}, T_{RX}, p(F), p(C)\right) \quad (2)$$

$$\begin{aligned}&\dot{W}_F \times f_F\left(T_{PR}, T_{RX}, p(F)\right) + \dot{W}_C \times f_C\left(T^{(t)}_{D:\mathrm{RG}}, T_{RX}, p(C)\right)\\&+ \dot{W}_N \times f_N\left(T_{D:\mathrm{RS}}, T_{RX}, p(N)\right) + \Delta H_{vap} + \Delta H_{crack} = 0\end{aligned} \quad (3)$$

$$\Delta H_{vap} = \dot{W}_F \times f_v\left(\dot{W}_F, \dot{W}_C, T_{PR}, T_{RX}, T_{D:\mathrm{RS}}, p(F)\right) \quad (4)$$

$$\Delta H_{crack} = \dot{W}_F \times f_k\left(y_x, T_{RX}, p(F)\right) \quad (5)$$

Practically, the system of (1) - (5) concisely describes the mass and energy balances of the riser section [3]. The operational variables (unknowns) in this system are 14: the conversion (y_x), the coke yield (y_c), the feed rate ($\dot{W}_F$) the inert rate ($\dot{W}_N$), the catalyst circulation rate ($\dot{W}_C$), the pressure (P_{RS}) and the temperature (T_{RX}) of the reactor, the feed preheat temperature (T_{PR}), the temperature at the regenerator dense section ($T^{(t)}_{D:\mathrm{RG}}$), the feed vaporization enthalpy (ΔH_{vap}), the energy consumed by the cracking reactions (ΔH_{crack}), the properties or quality indices of the feed ($p(F)$), the inert ($p(N)$) and the catalyst (p(C)). The respective schematic problem formulation for the regenerator (neglecting the dynamic clauses of the stripper) is as follows:

$$c^{(t)}_{c:\mathrm{RG}} = f_c\left(y_c, \dot{W}_F, \dot{W}^{(l_D=0)}_{g:\mathrm{RG}}, c^{(l_D=0)}_{g:\mathrm{RG}}, c^{(l_F=1,\,t)}_{g:\mathrm{RG}}, c^{(t)}_{c:\mathrm{RG}}, \dot{W}_C, T^{(t)}_{D:\mathrm{RG}}, P_{\mathrm{RG}}\right) \quad (6)$$

$$c^{(l_F=1,\,t)}_{g:\mathrm{RG}} = f_g\begin{pmatrix} y_c, \dot{W}_F, \dot{W}^{(l_D=0)}_{g:\mathrm{RG}}, c^{(l_D=0)}_{g:\mathrm{RG}}, c^{(l_F=1,\,t)}_{g:\mathrm{RG}}, \\ c^{(t)}_{c:\mathrm{RG}}, \dot{W}_C, T^{(t)}_{D:\mathrm{RG}}, P_{\mathrm{RG}}, p(G) \end{pmatrix} \quad (7)$$

$$\begin{aligned}&\dot{W}_C \times f_C\left(T_{RX}, T^{(t)}_{D:\mathrm{RG}}, p(C)\right) +\\&\dot{W}^{(l_D=0)}_{g:\mathrm{RG}} \times f_g\left(T^{(l_D=0)}_{g:\mathrm{RG}}, T^{(t)}_{D:\mathrm{RG}}, T^{(l_F=1)}_{F:\mathrm{RG}}, p(G)\right) + \Delta H_{comb} = 0\end{aligned} \quad (8)$$

$$\Delta H_{comb} = f_r\left(y_c, \dot{W}_F, W^{(l_D=0)}_{g:\mathrm{RG}}, \dot{W}_C, T^{(l_D=0)}_{g:\mathrm{RG}}, T^{(t)}_{D:\mathrm{RG}}, T^{(l_F=1)}_{F:\mathrm{RG}}, P_{\mathrm{RG}}, p(G)\right) \quad (9)$$

The system of (6) - (9) briefly describes the regenerators extended system of equations [3]. The variables appearing here are 8: the air (for combustion) flow rate at the bottom of the regenerator ($\dot{W}^{(l_D=0)}_{g:\mathrm{RG}}$), the composition of the gas exiting from the regenerator top ($c^{(l_F=1,\,t)}_{g:\mathrm{RG}}$), the composition of coke on the regenerated catalyst ($c^{(t)}_{c:\mathrm{RG}}$), the average regenerator pressure (P_{RG}), the inlet temperature of the combustion air ($T^{(l_D=0)}_{g:\mathrm{RG}}$), the heat of the exothermic reactions (ΔH_{comb}) the combustion air composition ($c^{(l_D=0)}_{g:\mathrm{RG}}$) and its properties ($p(G)$). The system in its general form counts 22 variables and 9 equations, therefore 13 degrees of freedom. It is noted that the analysis presented, despite the generalities, requires full comprehension of the FCC unit operation and it can describe any pilot or industrial unit.

The 13 independent variables of the FCC operation are: the feed rate, the inert rate, the riser pressure, the catalyst circulation rate, the feed preheat temperature and the qualities of the feed, inert and catalyst, for the riser section. For the regenerator they are the air rate at the bottom, the pressure and the inlet air temperature, composition and properties. In a typical industrial unit: the feed rate is set to meet the unit maximum capacity, the inert rate and quality follow a predefined pattern in order to retain constant partial pressure of the hydrocarbons in the riser, the temperature, the composition and the properties of the combustion air are constant. These bounds are also followed in PP operation, although not always for the same reasons. More specifically in the pilot plant: the combustion air rate of the pilot regenerator is controlled separately in order to satisfy the low emissions criterion. Also, the feed and catalyst qualities are considered as unknown disturbances. The reason for the latter is their stochastic nature in industry, meaning that the complete feed quality description is usually unavailable, because it is a mixture of various refinery streams and the catalyst quality is changing perpetually due to the continuous addition of a small amount of fresh catalyst. Furthermore, catalyst or/and feed qualities are the usual unknowns during PP benchmarking experiments. Provided that the riser and the regenerator pressure are controlled by separate subsystems, the only independent variables suitable for manipulation in the PP, for the purpose of benchmarking experiments, are the catalyst circulation rate and the feed preheat temperature.

The main objective in both the pilot plant and the industry FCC process is the optimization of the riser conversion on feed basis, while maintaining the riser temperature around a set point, which guarantees a constant effect of operating conditions on product selectivity. The riser conversion, the riser temperature, the feed preheat temperature and the catalyst circulation rate are interrelated variables and comprise a system of equations ((1) - (5)), which under stable operation is uniquely defined (within the narrow bounds of the PP operation). The manipulated catalyst circulation rate obviously affects the conversion, but it also affects the heat build-up, consumption and loss of the system, having an impact on the riser temperature, as well. Riser temperature and feed conversion are correlated, meaning that for a given value of the riser temperature, conversion is uniquely defined and vice-versa (given that every other input variable of the riser is constant). The last fact provides two alternatives for the control problem: If riser conversion measurements are available then it can be directly controlled by manipulating the catalyst rate and feed preheat. In the most usual case that the riser temperature measurement is accessible and the online conversion measurement is unavailable, then conversion control can be performed using an inferred value calculated by (1).

On the basis of the above analysis, an MPC strategy can be implemented for the control of feed conversion and riser temperature through the proper manipulation of the catalyst circulation rate and the feed preheat temperature. This strategy should lead to the direct targeting of the desired conversion and reduce the number of required experiments with the same catalyst in catalyst evaluation tests.

II. Model Predictive Control

A. MPC Principles

Model predictive control is based on the fact that past and present control actions affect the future response of the process [6]. Having selected a time horizon extending into the future, the prediction of the process model is calculated, based on past control actions. The response of the model can then be compared to a desired trajectory if no further control actions are to be taken. The variation between the desired control trajectory and the predictions can therefore be minimized, through the calculation of a specified number of future control actions (Fig. 2). The control horizon (i.e. the period for which future control actions are calculated) may be selected smaller or equal to the prediction time horizon, during which the comparison of the desired to the predicted trajectories is performed. At each time interval the first optimal control action in the calculated sequence is implemented and a new measurement of the actual response of the process is obtained. The model-based predictive control principles are presented in Fig. 2.

The deviation of the model prediction from the actual response of the process is recorded and considered as the error of the process model, as shown in the block diagram of the MPC system (Fig. 3). The calculated error defines a bias term that is used to correct the future predictions of the model. The bias model term encompasses contributions from model mismatch, unmeasured disturbances, and measurement error. It is assumed that this error will be persistent for the entire prediction horizon. Thus, error feedback is maintained in the control system allowing integral action and elimination of steady-state offset. The block diagram describing the system is presented in Fig. 3.

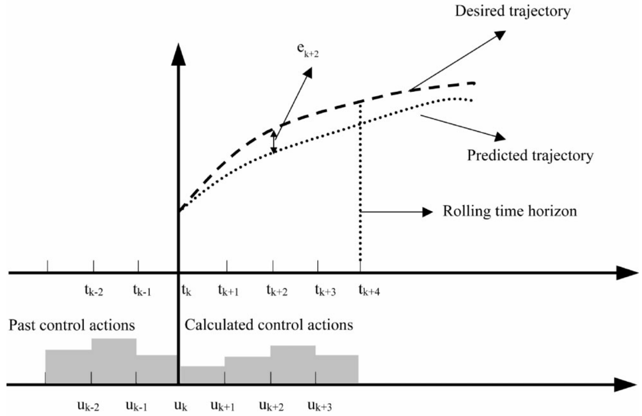

Fig. 2. The principles in model-predictive control.

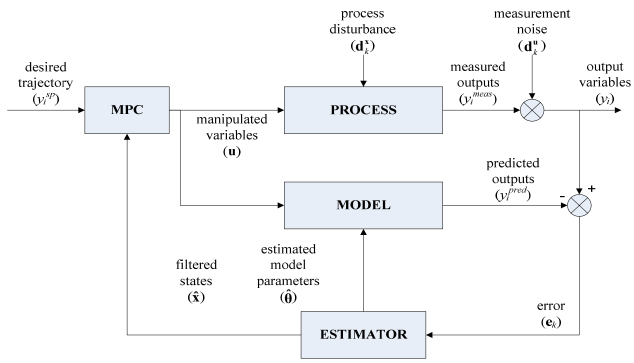

Fig. 3. Control block diagram of the process.

A parameter and state estimator can be added to enhance the model accuracy and the overall MPC robustness. For non-linear systems robust state and parameter estimation can be achieved through the use of an Extended Kalman Filter (EKF). The correction of the model parameters and states leads to the gradual minimization of the model - process mismatch.

The mathematical representation of the model-based predictive control algorithm is given by (10),where where $\mathbf{x}$, $\mathbf{u}$, $\mathbf{y}$ denote the vectors of the state, manipulated (i.e. control actions) and output variables of the system, respectively. Symbols $\mathbf{f}$ and $\mathbf{g}$ denote the sets of differential and algebraic model equations. Vector $\hat{\mathbf{y}}$ denotes the predictions for the system output variables that include the contribution of the bias term on the model predictions. Vector $\mathbf{y}^{sp}$ denotes the desired response (set point) of the system output variables.

$$
\min_{\mathbf{u}_{k+j-1}} \boldsymbol{J}_{MPC} = \sum_{j=1}^{N_P} \left\| \hat{\mathbf{y}}_{k+j} - \mathbf{y}_{k+j}^{sp} \right\|_{\mathbf{w}_{k+j}^{y}}^{2} + \sum_{j=1}^{N_C} \left\| \Delta \mathbf{u}_{k+j-1} \right\|_{\mathbf{w}_{k+j-1}^{\Delta u}}^{2} + \sum_{j=1}^{N_C} \left\| \mathbf{u}_{k+j-1} - \mathbf{u}_{k+j-1}^{ss} \right\|_{\mathbf{w}_{k+j-1}^{u}}^{2}
$$

subject to:

$$
\begin{aligned}
&\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x},\mathbf{u}) \\
&\mathbf{y} = \mathbf{g}(\mathbf{x},\mathbf{u}) \\
&\quad \mathbf{e}_{k+j-1} = \left(\mathbf{y}^{meas} - \mathbf{y}^{pred}\right)_{k+j-1} \\
&\quad \hat{\mathbf{y}}_{k+j} = \mathbf{y}_{k+j}^{pred} + \mathbf{e}_{k+j-1} \\
&\quad \mathbf{u}^{l} \le \mathbf{u}_{k+j-1} \le \mathbf{u}^{u} \\
&\quad N_C = \left(T_C - T_k\right)/\Delta t_C,\; N_P = \left(T_P - T_k\right)/\Delta t_P
\end{aligned} \tag{10}
$$

Vector $\mathbf{e}_k$ denotes the difference between the measured output variables $\mathbf{y}^{meas}$ and the predicted values $\mathbf{y}^{pred}$ at time instant k. The current formulation assumes that the error on the predictions will persist and remain constant for the entire length of the prediction time horizon. T_P and T_C denote the prediction and control horizons, reached through N_P and N_C time intervals, respectively.

The tuning parameters of the controller are the weights $\mathbf{w}^y$, $\mathbf{w}^u$ and $\mathbf{w}^{\Delta u}$, and the length of the prediction and control horizons. A long prediction horizon allows the control scheme to compensate for slower dynamics that affect the response of the system further into time. However, large prediction horizons make the control scheme more susceptible to unmeasured disturbances. On the other hand, a short control horizon may lead to aggressive control actions, as the controller attempts to correct the trajectory with a few moves through short time period.

The formulation of the control problem results in a dynamic program. The objective function contains the integral of the squared error of the controlled variables from the desired trajectory, a move suppression factor on the manipulated variables that penalizes high values in the rate of change for the control actions and a steady state optimality factor for restricting the range of the possible solution within the operational limits. The behavior of the manipulated variables is considered as a sequence of piecewise values that minimize the objective function. The prediction and control horizons are divided in equally spaced time intervals, during which the manipulated variables remain constant. Upper and lower bounds apply for the manipulated variables along the control horizon, as required by the physical limitation of the system (e.g., $\dot{W}_C$ cannot exceed its value for the respective maximum available valve opening or the minimum flow necessary for safe operation). The solution method involves successive iterations between the optimizer, that evaluates the optimal values of the manipulated variables, and the integrator, that calculates the dynamic response of the system and the sensitivity of the control actions to the control objectives. Variable bounds and path constraints are considered for violation along the optimal control path.

B. Extended Kalman Filter

The model states, $\mathbf{x}$, and parameters, $\boldsymbol{\theta}$, are updated every time a new set of measurements becomes available. Therefore, an Extended Kalman Filter [7] (EKF) is utilized due to the nonlinear nature of the process model. The dynamic process model is linearized and brought to its equivalent state space representation. The deterministic process states, $\mathbf{x}^d$, as defined by the process balance equations are augmented with stochastic states, $\mathbf{x}^s$, that account for the model parameters and process disturbances. These additional states may vary with time in some stochastic manner. Since the functional relationship, $\mathbf{f}^s$, for the stochastic state variables is rarely known, the most common assumption, provided that $\mathbf{x}^s$ does not change considerably with time, is to be set equal to a zero vector. Thus, the dynamic behavior of the stochastic state variables is usually modeled as a random walk process. The inclusion of meaningful and consistent non-stationary stochastic state variables, $\mathbf{x}_k^s$, into the state/parameter estimator can eliminate the bias between the mathematical model and the actual process and provide good and unbiased state estimates [8-11].

Hence, the augmented state space model representation is as follows:

$$
\begin{aligned}
\mathbf{x}_k &= \boldsymbol{\Phi}\mathbf{x}_{k-1} + \boldsymbol{\Gamma}\mathbf{u}_{k-1} + \boldsymbol{\Xi}\mathbf{w}_k \\
\mathbf{y}_k &= \mathbf{H}\mathbf{x}_k + \boldsymbol{\Delta}\mathbf{u}_k + \boldsymbol{\Lambda}\mathbf{v}_k
\end{aligned} \tag{11}
$$

where $\mathbf{x}_k$ is the augmented state vector, $\mathbf{x}_k = \begin{bmatrix} \mathbf{x}_k^d \\ \mathbf{x}_k^s \end{bmatrix}$ and $\mathbf{w}_k = \begin{bmatrix} \mathbf{w}_k^d \\ \mathbf{w}_k^s \end{bmatrix}$, $\mathbf{v}_k$ denote the process and measurement noise, respectively. Process and measurement noise are assumed to behave as zero mean Gaussian shocks with covariance matrices $\mathbf{Q}$ and $\mathbf{R}$, respectively. Matrix $\boldsymbol{\Phi}_k$ denotes the Jacobian of the system with respect to the states and is given by: $\boldsymbol{\Phi}_k = \begin{bmatrix} \boldsymbol{\Phi}_k^{\mathbf{d}} & \boldsymbol{\Phi}_k^{\mathbf{s}} \\ \mathbf{0} & \mathbf{I} \end{bmatrix}$

When a new observation becomes available, the states are updated according to the following equation:

$$
\mathbf{x}_{k+1/k+1} = \mathbf{x}_{k+1/k} + \mathbf{K}_k \left\{ \mathbf{y}_{k+1} - \mathrm{H}\left(\mathbf{x}_{k+1/k}\right) \right\} \tag{12}
$$

$\mathbf{K}_k$ is the Kalman gain at time t_k computed recursively from the resulting Riccati equations. For increased accuracy of the EKF the process model is linearized in each time interval.

III. RESULTS

A. Process Model

The simulator of the PP includes three main sections: a pseudo-steady state model of the riser reactor, a dynamic model of the regenerator and a set of dynamic and pseudo-steady state models of the stripper, the regenerator standpipe, the liftline and the slide valves. For the specific case of the CPERI pilot plant, the dynamic effects of the riser, the cyclones, the liftline and the regenerator standpipe were neglected, as their operation has a significantly lower impact on the process dynamics, compared to the two large vessels of the plant, the stripper and the regenerator. The residence times of these two units are so much longer that the dynamic effect of the rest is suitably neglected. In both the pilot plant and a typical commercial unit, it is the behavior of the regenerator that dominates the dynamic and the steady state behavior of the integrated unit [12].

The pseudo-steady state and dynamic sub-models that constitute the dynamic simulator of the PP have been presented in the literature [1-4] and are not the subject of this paper. However, it is needed to clarify that, as the catalyst effect on the system can not be modeled, it was represented by indices [2]. That is, the effects of catalyst type and quality were expressed through an array of indices (one for each product) that was assigned to each catalyst to express its activity and selectivity. These indices are the unknowns or "constant disturbances" in the PP control problem formulation.

The dynamic material and energy balance equations form a system of Differential-Algebraic Equations (DAE) that is solved using the equation oriented environment of gPROMS [13]. The dynamic model, the MPC algorithm and the EKF module were merged in a compound module, formed by a gPROMS entity and a MATLAB module communicating through Excel files that serve as the bridge between the two programs.

B. Simulation Study

The model predictive controller was initially tested on a simulated case study. The MPC framework includes two instances of the model that were concurrently executed. The first instance, which represented the "Virtual Process" or "Virtual Plant" (VP), was depicted by a flawless version of the model. The second introduced a case study including significant amount of mismatch in the reaction kinetics in order to simulate a fictitious simulated process and was used to represent the "Simulator". Hence, in the following the expression "Virtual Process" or VP denotes the process, for which the flawless version of the model was used, and the expression "Simulator" denotes the model with the different kinetic constants. This case study actually included what is expected to be the control problem in the real pilot process level. More specifically, different indices that describe the effect of catalyst activity and selectivity on feed conversion and coke yield have been used in the VP model and the Simulator model. The indices used were those of real catalysts, different for each case (VP and Simulator) taken from the PP experimental database. With this structure the equivalent of a typical catalyst benchmarking experiment was fully reconstructed. The intervals for the control actions (i.e. manipulation of variables) were chosen equal to 2 minutes. The Simulator was updated using infrequent rate process measurement of the reactor temperature and the inferred conversion of the VP. The optimal piecewise constant future control actions were calculated through dynamic programming over the desired prediction and control horizons.

C. Validation of the MPC scheme

The different catalyst activity and selectivity between the Virtual Plant and the Simulator act as a constant disturbance in the process cycle. The goal for the MPC was to move the plant operation through a sequence of corrective control actions to the desired level of feed conversion and riser temperature. The following performance index was used:

$$\begin{aligned} J_k = & \sum_{i=1}^{n^y} w_i^y \int_{t_k}^{t_{k+1}} \left(1 - \frac{\hat{y}_i(t)}{y_i^{sp}}\right)^2 + \\ & \sum_{i=1}^{n^u} w_i^{\Delta u} \left(\Delta \hat{u}_i \left(t_{k/k-1}\right)\right)^2 + \sum_{i=1}^{n^u} w_i^u \left(1 - \frac{\hat{u}_i(t_k)}{u_i^{ss}}\right)^2 \end{aligned} \tag{13}$$

where $\hat{y}_i$ denotes the predictions of the respective variables i that incorporate the model prognosis and the error correction (i.e. difference between the measurement and the prediction at the previous time period) and y_i^{sp} the set points of the controlled variables. The second term of (13) denotes the move suppression factor, which penalizes abrupt changes in the manipulated variables. The last term denotes the steady state optimality factor and it aims to drive the MPC actions towards a potentially desired solution, dictated by the plant optimization decision level. Weights w express the relative significance of each term in the performance index.

The prediction (N_P) and control (N_C) horizons were selected equal to 20 and 10 minutes, respectively. The length of the prediction horizon is chosen close to the time necessary for the PP to reach the new steady state after imposing a typical change. The length of the control horizon was mainly driven by the computational time for solution that should be lower than the unit sampling interval. The control profile was considered as piecewise constant with the manipulated variables changing every 2 minutes. The length between two consecutive control actions (Δt_C) was chosen on the basis of the frequency of the available measurements. A new optimal sequence of 5 control actions was calculated every 2 minutes. This means that every 2 minutes a new control action was implemented and a new measurement was recorded. The time between two successive measurements was determined considering also the limitation imposed from the computation time required for the solution of the dynamic optimization and simulation of the process model. At each time interval the dynamic non-linear model was linearized and the EKF was applied. In the linearization the catalyst indices were considered as manipulated variables and then added to the linearized state vector.

The control problem, as posed above, was tested on a simulation environment, in which different catalyst indices ($p(C)$) were used for the Virtual Process and the Simulator. The indices of a catalyst with higher activity and selectivity and much higher coke selectivity were used in the VP. Moreover, the non-catalytic coke yield, which is a result of the feedstock quality and can be predicted by the model, was intentionally considered different between the PP and the Simulator. In the VP a higher non-catalytic coke yield was

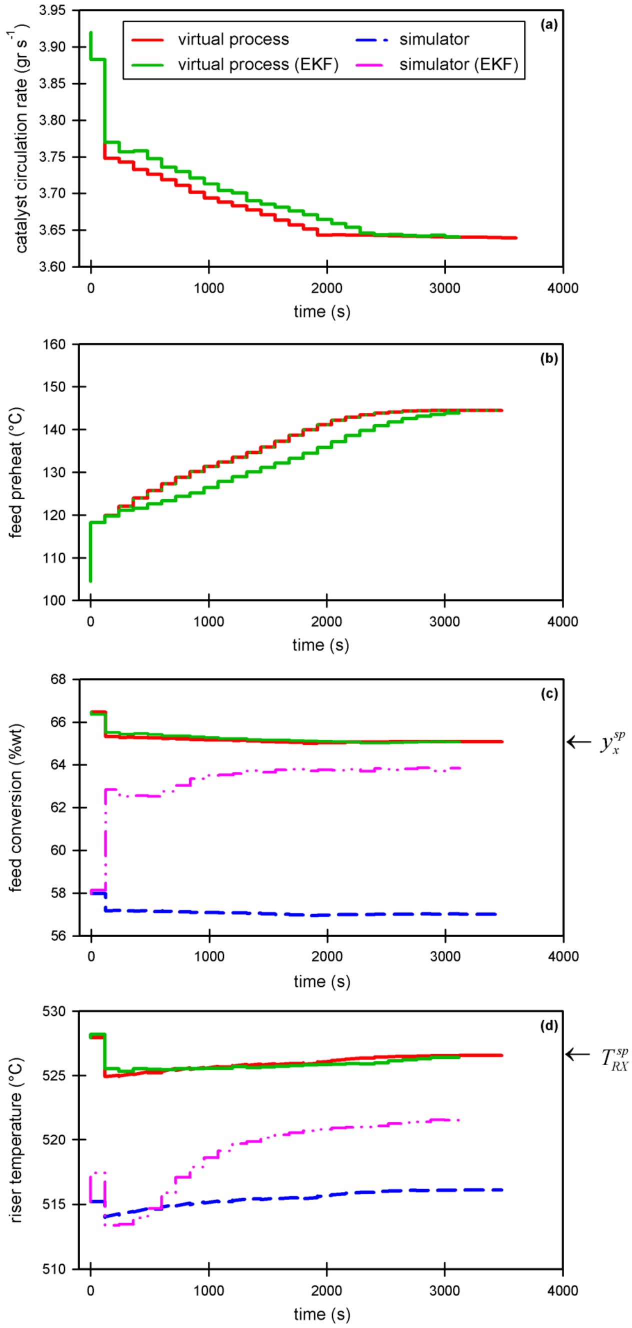

Fig.5. MPC actions and responses with and without the EKF.

used. This was done to examine the performance of the MPC scheme to a disturbance that was not filtered by the EKF. Finally, noise was added to the VP measurements to test the EKF efficiency. These significant differences caused an increase in the feed conversion of the VP and lower riser temperature, compared to those predicted by the Simulator. The task for the MPC algorithm was to lead the VP to the desired conversion ($y_x^{sp} = 65$ %wt) and riser temperature ($T_{RX}^{sp} = 526.7$ °C) under the influence of the disturbances introduced. The bias term (e_k of (10)) (also referred to as constant additive disturbance [14]) and the parameter estimation through the EKF were used for improving the Simulator accuracy.

As shown in Fig. 5, the VP initiated at 2% higher feed conversion than the desired one and riser temperature 2°C above its set point. The first action of the MPC was to lower the catalyst circulation rate and increase the feed preheat temperature, as dictated by the solution of the dynamic problem. The lower catalyst circulation rate led to lower coke yield (on feed basis), but higher overall ratio of coke rate over catalyst rate entering the regenerator. The latter resulted in increasing the regenerator temperature (Fig. 5(f)) and eventually the riser temperature (Fig. 5(d)). As the controlled variables are variables of the riser, which operates in pseudo-steady state, the MPC led the process very close to the desired set-points rapidly. Thereafter, using the information of the prediction horizon waited for the dynamics of the process (Fig. 6), while making small control actions to eliminate the VP - Simulator mismatch.

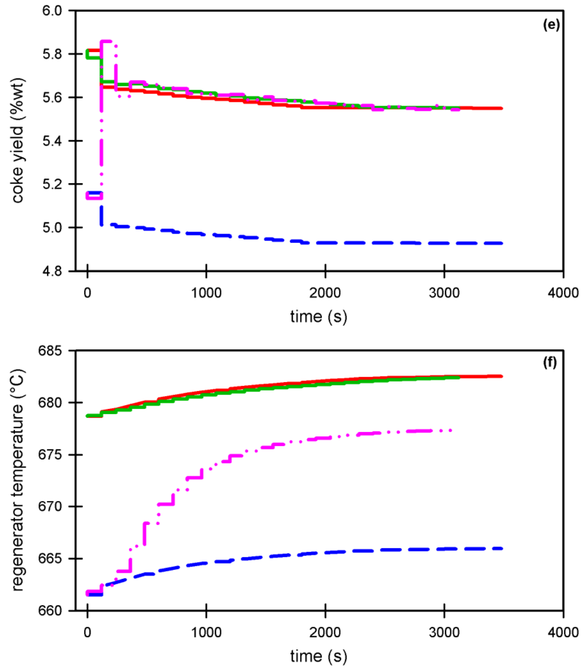

Fig. 6. PP dynamic responses to MPC actions with and without EKF.

The control loop was continued for a period of 40 min. In the final steady state both the feed conversion and the riser temperature criteria were fully satisfied. The results with the use of the EKF are also presented in Fig. 4. It is evident that the EKF was able to absorb the artificial noise introduced and to correct the model predictions, creating a smother control actions profile. The steady state offset of the filtered model predictions is owed to the feed quality disturbance implemented, which was not filtered. Overall, the MPC structure presented promises the establishment of the desired steady state within 40 min, which is very important for the PP operation.

IV. Conclusions

An advanced model predictive control strategy that calculates the optimal sequence of manipulated variables over a specified control horizon has been implemented in a pilot - sized FCC unit used for experimental catalyst evaluation. The implementation of the MPC scheme in conjunction with an EKF showed extreme robustness to changes in the feed quality and the catalyst activity and selectivity. The application of the MPC-EKF scheme allowed for an accurate targeting of the desired feed conversion with poor knowledge of the catalyst properties and selectivity. In conclusion, the proposed control strategy succeeded to a more efficient control procedure that follows prescribed operating conditions. Thus, it leaded to the elimination of additional and repetitive experiments with the same catalyst, in catalyst evaluation tests, improving this way the overall productivity of the catalyst evaluation and decreasing the unit operating cost.

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