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 has been proved an efficient 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. Moreover, 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 (the yield of gasoline, LPG, dry gas and coke) and riser 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.

--Feed conversion should meet a determined value for easy comparison (testing-ranking) of the variation of the examined catalysts activity and selectivity.

--Excess gas from the regenerator is subject to environmental constraints regarding the CO, SO₂, 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 PID based control schemes as implemented on the CPERI FCC PP can not guarantee the accurate targeting of specified operating conditions, thus 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 CPERI FCC PP. The effective manipulated variables in the PP (and its simulator) are the catalyst circulation rate, feed preheat temperature, combustion air flow rate (and temperature), and gas-oil feed flow rate, whereas the gas-oil composition and the catalyst quality are considered as disturbances. The major interest lies in the control of the riser temperature and the fee conversion. 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 along the unit segments. Conversion and coke yield...
(the most important variable in the system integration) are therefore inferred by the available process measurements and the modeling relations. In this manner, 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 SO2) can be 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. This paper investigates a simulated application within a framework with two instances of the model: an original entity of the simulator, as the “Virtual Process” (VP) and another one as the “Process Simulator” (PS) in the MPC scheme. A deliberate model mismatch (e.g., change in catalyst quality) was used to test the efficiency and robustness of the MPC. Having chosen and verified the most functional control structure followed by suitable tuning (e.g., objective function weighting factors) the study resulted in a reliable MPC scheme to be applied on the actual PP.

II. 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 lifeline. The riser reactor operates in pseudo-isothermal plug flow conditions, whereas the regenerator operates in full combustion mode under pseudo-adiabatic conditions. The PP resembles the valve operated FCC units with two slide valves regulating the catalyst circulation, one at the exit of the regenerator standpipe and one at the exit of the stripper standpipe. 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 surplus of combustion air flow. Secondary PID control loops regulate the process pressure, and the power supply to electrical heaters to ensure adiabatic operation. These secondary sub-problems are tightly controlled and assumed not to interact with the main control objectives of the integrated system.

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 at constant riser temperature. This practice is especially adopted for gathering comparable results in terms of catalyst selectivity, so any experiment not fulfilling that requirement is useless. Thus, the overall control objective translates to the elimination of repetitive PP experiments.

B. Pilot Process Control Objectives

The approach presented in this project is focused on improving the control performance of the unit through manipulation of the riser. This is dictated by the operational conditions of the 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 was 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, because it defines the dynamics of the unit. MPC requires an 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 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 through recycle. Therefore, modeling and monitoring of 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 [4,5]. In general, the process model should be accurate enough to maintain good prediction properties over the range of operating conditions of interest. The ability of the PP model to simulate accurately the dynamics of the PP has been demonstrated previously [1-3].

A robust control system relies on a suitable selection 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. At this point, it is useful to present a brief analysis of the system. The riser sub-section can be described by 5 basic equations:

\[
y_1 = f_1\left(\hat{W}_f, W_f, \hat{W}_c, \hat{W}_c, P_{RS}, T_{RX}, p(F), p(C)\right)
\]

\[
y_2 = f_2\left(\hat{W}_f, \hat{W}_f, \hat{W}_c, P_{RS}, T_{RX}, p(F), p(C)\right)
\]

\[
\hat{W}_f \times f_f\left(T_{PR}, T_{RX}, p(F)\right) + \hat{W}_c \times f_c\left(T_{D_{REG}}, T_{RX}, p(C)\right)
\]

\[
+ \hat{W}_c \times f_f\left(T_{D_{REG}}, T_{RX}, p(N)\right) + \Delta H_{vap} + \Delta H_{\text{crack}} = 0
\]

\[
\Delta H_{\text{vap}} = \hat{W}_f \times f_f\left(\hat{W}_f, \hat{W}_f, T_{PR}, T_{RX}, T_{D_{RS}}, p(F)\right)
\]

\[
\Delta H_{\text{crack}} = \hat{W}_f \times f_f\left(y_1, T_{RX}, p(F)\right)
\]

Practically, the system of equations (1)-(5) concisely describes the mass and energy balances of the riser section [3]. The operational variables (unknowns) in this system are 14, namely the conversion (\(y_i\)), the coke yield (\(y_c\)), the feed, inert and catalyst rates (\(W_f\), \(\hat{W}_f\), \(W_c\)), 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 (\(T^l_{D_{REG}}\)), the feed vaporization enthalpy (\(\Delta H_{\text{vap}}\)), the energy consumed by the cracking reactions (\(\Delta H_{\text{crack}}\)), and the properties or quality indices of the feed (\(p(F)\)), inert (\(p(N)\)) and catalyst (\(p(C)\)).

The respective schematic problem formulation for the regenerator (neglecting the dynamic clauses of the stripper) is as follows:

\[
c_{c,RG}^{(j)} = f_c\left(y_c, W_f, \hat{W}_f, T_{g,RG}, c_{c,RG}^{(j)}, c_{c,RG}^{(j-1)}, T_{c,RG}, T^l_{D_{REG}}, P_{RG}\right)
\]

\[
c_{c,RG}^{(j-1)} = f_c\left(y_c, W_f, \hat{W}_f, T_{g,RG}, c_{c,RG}^{(j)}, c_{c,RG}^{(j-1)}, T_{c,RG}, T^l_{D_{REG}}, P_{RG}\right)
\]

\[
\hat{W}_c \times f_c\left(T_{RX}, T^l_{D_{REG}}, p(C)\right)
\]

\[
\hat{W}_c \times f_c\left(T_{D_{REG}}, T^l_{D_{REG}}, p(G)\right) + \Delta H_{\text{comb}} = 0
\]

\[
\Delta H_{\text{comb}} = f_f\left(y_c, W_f, \hat{W}_f, W_c, c_{c,RG}^{(j)}, T_{g,RG}, T^l_{D_{REG}}, T^l_{D_{REG}}, P_{RG}, P(G)\right)
\]

The variables appearing in equations (6)-(9) are 8, namely the air flow rate (\(W_{d,RG}^{(j)}\)), composition (\(c_{d,RG}^{(j)}\)) and properties (\(p(G)\)), the composition of the regenerator flue gas (\(c_{d,RG}^{(j)}\)), the concentration of coke on the regenerated catalyst (\(c_{c,RG}^{(j)}\)), the average regenerator pressure (\(P_{RG}\)), the inlet temperature of the combustion air (\(T_{g,RG}^{(j)}\)) and the heat of combustion (\(\Delta H_{\text{comb}}\)). The system in its general form comprises 22 variables and 9 equations leading to 13 degrees of freedom. It is noted that the above analysis can describe the majority of the FCC pilot or industrial units.

The 13 independent variables of the FCC operation are as follows: 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, the pressure and the inlet air temperature and composition. In a typical industrial unit: the feed rate is driven by the need for maximum throughput as allowed by process constraints. Inert rate and quality variations are negligible, the temperature, the composition and the properties of the combustion air are ambient. The feed and catalyst qualities are considered as unknown disturbances. The reason for the latter is their stochastic nature, 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. These bounds are also present in the PP operation. More specifically, the feed and inert rates and qualities in the PP are constant so that the hydrocarbons partial pressure in the riser is kept constant. The combustion air rate of the pilot regenerator is controlled separately in order to satisfy the low emissions criterion. Finally, catalyst or/and feed quality are the unknowns during PP benchmarking experiments. The independent variables suitable for manipulation in the PP, for the purpose of benchmarking experiments, are the catalyst circulation rate (through the manipulation of the pressure differential and the valve position) and the feed preheat temperature.

The main control objective in both scales (PP and commercial) is the optimization of the feed conversion, while maintaining the riser temperature around a set point, which guarantees a constant effect of operating conditions on product selectivity. The riser temperature, feed conversion, feed preheat temperature and 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 (when all other input variables of the riser are 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 riser temperature measurements are obtained without online conversion measurements, conversion control can be performed using an inferred value calculated by equation (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.
III. 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 [4]. 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 predicted to the desired 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. These principles are graphically presented in Fig. 2.

![Basic principles in model-predictive control](image)

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 nonlinear MPC system (Fig. 3). The calculated error defines a bias term that can be used to correct the future predictions of the model. The bias model term encompasses contributions from model mismatch, unmeasured disturbances, and error in measurements. It can be assumed that this error will be persistent for the entire prediction horizon. One other approach is to add a parameter and state estimator 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. In both cases, 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.

![Control block diagram of the process control structure](image)

The mathematical representation of the MPC algorithm is given by (10), 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.

\[
\min_{\mathbf{u}_{k+j-1}} J_{\text{MPC}} = \sum_{j=1}^{N_N} \left[ \mathbf{y}_{k+j} - \mathbf{y}_{k+j}^{\text{sp}} \right] \mathbf{wu}_{k+j-1}^2 + \sum_{j=1}^{N_P} \left[ \mathbf{u}_{k+j-1} - \mathbf{u}_{k+j}^{\text{sp}} \right] \mathbf{wu}_{k+j-1}^2 \\
\text{subject to:} \\
\dot{\mathbf{x}} = \mathbf{f} (\mathbf{x}, \mathbf{u}) \\
\mathbf{y} = \mathbf{g} (\mathbf{x}, \mathbf{u})
\]

(10)

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 corrected with the error bias term. Vector \( \mathbf{y}^{\text{sp}} \) denotes the desired response (set point) of the system output variables. The difference \( \mathbf{e}_{k+j-1} \) between the measured variables \( \mathbf{y}^{\text{meas}} \) and their predicted values \( \mathbf{y}^{\text{pred}} \) at time instance \( k \) is assumed to persist constant for the entire number of time intervals \( N_p \) of the prediction time horizon \( T_p \). \( T_c \) denotes the prediction horizon reached through \( N_c \) time intervals.

The tuning parameters of the controller are the weights \( \mathbf{w}^u \), \( \mathbf{w}^o \) and \( \mathbf{w}^{\text{meas}} \), 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. The selection of the appropriate prediction and control horizons is mainly dictated by the time scale characteristics of the system and the computational effort for the solution of the nonlinear dynamic program, whereas its effect on the control performance can be influenced with the choice of the weighting factors.
B. Extended Kalman Filter

Information acquired through process measurements can be used to correct the model states, \( x \), and parameters, \( \theta \), at each sampling interval. An Extended Kalman Filter [6] (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, \( x_0 \), as defined by the process balance equations are augmented with stochastic states, \( x^\prime \), that account for the model parameters and process disturbances. These additional states may vary with time in some stochastic manner. Since the functional relationship, \( f_\varepsilon \), for the stochastic state variables is rarely known, the most common assumption, provided that \( x^\prime \) 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, \( x^\prime \), into the state/parameter estimator can eliminate the bias between the mathematical model and the actual process and provide good and unbiased state estimates [7-10].

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

\[
\begin{align*}
\dot{x}_k &= \Phi_k x_{k-1} + \Gamma_k u_{k-1} + \Xi_k w_k \\
y_k &= H_k x_k + \Delta_k u_k + \Lambda_k v_k
\end{align*}
\]

where \( x_k \) is the augmented state vector, \( x^\prime_k \), and \( w_k = [w^\prime_k \, w^\ast_k] \), and \( v_k \) denote the process and measurement noise, respectively. Process and measurement noise are assumed to behave as zero mean Gaussian shocks with covariance matrices \( \Xi \) and \( \Lambda \), respectively. Matrix \( \Phi_k \) denotes the Jacobian of the system with respect to the states and is given by:

\[
\Phi_k = \begin{bmatrix} \Phi^\prime_k & \Phi^*_k \\ 0 & I \end{bmatrix}
\]

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

\[
x_{k+1/\ast_k} = x_{k+1/4} + K_k \{ y_{k+1} - H(x_{k+1/4}) \}
\]

\( K_k \) 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.

IV. 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 significantly lower impact on the process dynamics, compared to the two large vessels of the plant, the stripper and the regenerator. Roughly speaking, the large difference in the time constants, constitutes the behavior of the regenerator the dominating in the dynamic behavior of the integrated unit [11].

The pseudo-steady state and dynamic sub-models that constitute the PP dynamic simulator have been presented in the literature [1-3,12] and are not the subject of this paper. However, it is needed to clarify that the catalyst characteristics were represented by indices [2]. That is, the effects of catalyst type and quality were represented through a set of parameters (one for each product). These parameters are unknown and considered as unmeasured 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 and the EKF algorithms 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 and the PP recording S/W (Fig. 4).

Fig. 4. Block of process control operations.

B. MPC scheme

The formulation of the control problem results in a dynamic program. The objective function contains the integral of the squared error of the predicted trajectory for the controlled variables \( \hat{y}_i \) (incorporating the model predictions and the error correction term) from their desired trajectory \( \gamma_i^{\varepsilon} \), a move suppression factor on the manipulated variables that penalizes abrupt control actions and a steady state optimality factor that restricts the range of the possible solution within the operational limits and drives it towards a potentially desired solution in the plant optimization decision level.

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. Variable bounds and path constraints imposed by the system physical limitations and the product specifications are considered for violation along the optimal control path. Weights \( w \) express the relative significance of each term in the performance index:

\[
J_k = \sum_{i=1}^{n_v} w_i^v \left[ \frac{1 - y_{ki}^v(t)}{y_{ki}^v(t_i)} \right]^2 + \\
\sum_{i=1}^{n_u} w_i^u \left( \Delta u_i(t_i) \right)^2 + \sum_{i=1}^{n_y} w_i^y \left( 1 - \frac{\hat{y}_i(t_i)}{y_i(t_i)} \right)^2 \tag{13}
\]

The prediction \((N_P)\) and control \((N_C)\) horizons were selected equal to 20 and 10 minutes, respectively. The length of the prediction horizon was chosen close to the time necessary for the PP to reach the new steady state after imposing a typical change. However, shorter prediction horizons make the control scheme less susceptible to unmeasured disturbances. 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 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. The control profile was considered as piecewise constant with the manipulated variables changing every 2 minutes. The length between two consecutive control actions \((\Delta t_C)\) 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.

C. Simulation Study

The model predictive controller was initially tested on a simulated case study. This MPC framework included 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 “Process Simulator” (PS). This case study fully resembles the actual control problem in the real pilot process level. More specifically, different parameters that describe the effect of catalyst activity and selectivity on feed conversion and coke yield have been used in the VP and the PS. Two different sets of catalyst parameters from the PP experimental database were used for the VP and the PS models. Such a model structure made the simulated example equivalent to a typical catalyst benchmarking experiment. The PS model states and parameters were updated using the EKF and all available process measurements.

The indices of a catalyst with higher activity 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 accurately predicted by the model, was intentionally considered different between the VP and PS models. In the VP a higher non-catalytic coke intercept was used. This was done to examine the performance of the MPC scheme to an unmodeled disturbance in the EKF scheme. Moreover, significant artificial noise was added to the VP measurements to test the EKF effectiveness. Finally, large weighting factors were used in the feed preheat temperature move suppression factor to account for the sluggishness of the preheater.

![Fig. 5. MPC actions and VP and PS responses.](image-url)
algorithm was able to overcome the influence of the introduced disturbances and lead the VP to the desired conversion ($y_{sp} = 65\%$) and riser temperature ($T_{sp} = 527^\circ C$). The bias term ($e_k$ of (10) (also referred to as constant additive disturbance [14]) and the EKF estimator were used for correcting the PS error.

![Graph showing VP dynamic responses to MPC actions.]

**Fig. 6.** VP dynamic responses to MPC actions.

As shown in Fig. 5, the VP started at a state of 72\% feed conversion. The first action of the MPC was to lower the catalyst circulation rate and to increase the feed preheat temperature, as calculated by the dynamic optimization problem. The aggressive decrease in catalyst rate led the riser temperature to a rapid decrease. Moreover, 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, because of the higher catalyst coke selectivity. The latter resulted in an increase of the regenerator temperature (Fig. 6(a)) and subsequently the riser temperature (Fig. 5(d)). The control loop was continued for a period of 50 min. In the final steady state both the feed conversion and the riser temperature criteria were fully satisfied. The filtered and non-filtered PS behaviors are presented in Figs. 5-6. It is evident that the EKF was able to absorb the majority of the artificial noise introduced, to rapidly correct the model predictions and to eliminate the non-filtered disturbance by state corrections. Thus, it contributed to a smoother control actions profile. The steady state offset of the non filtered PS predictions is owed to the (non-filtered, non-modeled) difference in the non-catalytic coke intercept implemented. Overall, the nonlinear MPC structure achieved the desired steady state within 50 min, and this period would have been lower for a case with smaller range of change in the feed preheat.

**V. CONCLUSIONS**

An advanced nonlinear model predictive control strategy that calculates the optimal sequence of manipulated variables over a specified control horizon has been developed for a pilot-sized FCC unit that is used for experimental catalyst evaluation. The control problem formulation considers the unknown catalyst properties as constant disturbance to the nonlinear model of the MPC. The implementation of the nonlinear MPC scheme in conjunction with an EKF showed extreme robustness to changes in the catalyst activity and selectivity. The application of the nonlinear MPC-EKF scheme allowed for an accurate targeting of the desired feed conversion with poor knowledge of the catalyst effect. In conclusion, the proposed control strategy is expected to succeed to a more efficient control procedure that follows prescribed operating conditions, improving this way the overall productivity of the catalyst evaluation and decreasing the unit operating cost. Preliminary results of the MPC implementation to the real PP process level verify its robustness.

**REFERENCES**