INTEGRATING REAL-TIME OPTIMIZATION INTO THE MODEL PREDICTIVE CONTROLLER OF THE FCC SYSTEM

A. C. Zanin[1], M. Tvrzská de Gouvêa[2] and D. Odloak[*3]

1.Petrobras, Advanced Control Group, Av. Chile, 65 Sala 2102, 20035-900, Rio de Janeiro(RJ)-Brazi, zanin@petrobras.com.br
2.Universidade Presbiteriana Mackenzie, Departamento de Engenharia de Materiais, Rua da Consolação 896, Prédio 6 – Escola de Engenharia, 01302-907, São Paulo (SP), Brazil, miriam@lscp.pqi.ep.usp.br
3.University of São Paulo, Chemical Engineering Department, Av. Prof. Luciano Gualberto, trv.3, 380, 05508-900, São Paulo (SP) , Brazil, odloak@usp.br[1]

Abstract: In this paper attention has been paid to the establishment of a proper real-time optimization strategy for the FCC unit. The majority of the approaches published in the literature make use of steady-state data. If the plant is highly disturbed updating the optimal operating point may be not easily achieved. In this study procedures are shown on how to overcome this problem and how to make use of the linear model predictive controllers (MPC) extending them to include optimization of the predicted steady-state operational point. Three such optimization strategies are presented that rapidly accommodate measured disturbances while avoiding off-sets. The paper also shows results from the industrial implementation of one of these strategies at the refinery of São José in Brazil. The optimizing controller was integrated into the control package SICON, which was developed by Petrobras. Plant results show that the new controller is able to drive the process smoothly to a more profitable operating point overcoming the performance obtained by the existing advanced controller.

Keywords: model based control, process optimization, optimizing controller, FCC unit

1. Introduction

Globalization has led to the necessity of optimizing the operation of the chemical plants. This is the typical scenario of an oil-refinery where little improvements in the operation of the process may lead to large economical benefits.

The FCC process is one of the most important systems of the oil refinery. Several papers in the literature deal with how to model, control and optimize it (McFarlane et al. 1993, Arbel et al.,1995, Ellis et al. 1998). Some optimization approaches follow the hierarchically layered optimization strategy (Ying & Joseph, 1999), in which there is an upper optimization layer that establishes an optimal operational point for the process unit. This optimal operational point is implemented by an advanced controller that has to maintain some outputs at their optimal set-points. There is another strategy to process optimization known as the 1-layer approach or as the optimizing controller where the economical optimization problem is solved together with the control problem (Tvrszká de Gouvêa & Odloak, 1998a).

As far as the design of a control strategy is in regard, some steps must be followed. The first one is to select suitable process model. In this paper, the FCC model is based on the work of Moro & Odloak (1995) Secondly one has to establish the optimization structure and model its components. This is one of the main points of this paper, where the aim is to compare different control and optimization integration strategies and to implement the most suitable one. It is presented experimental results corresponding to a typical operation day of the system and shows that there is a substantial difference between the economic benefits obtained with the optimized controller and the existing conventional QDMC-type controller (Garcia & Morshedi, 1986).

2. The Process Control Structure

A thorough description of the FCC system can be found elsewhere (Tvrzská de Gouvêa & Odloak, 1998a, Zanin, 2001) and therefore here presentation will be restricted to the system inputs and outputs that are considered by the existing model predictive controller. The industrial system has seven inputs, which are the following:

(u_1)-the flowrate of air introduced into the FCC catalyst regenerator
(u_2)-the opening of the regenerated catalyst valve
(u_3),(u_4) the flowrates of feed streams introduced into the FCC reactor (riser).
(u_5)-the delta pressure between reactor and regenerator
(u_6)-the suction pressure of the wet gas compressor
(u_7)-the temperature of the combined feed stream

There are six controlled outputs in the FCC system studied here. These outputs are the following:
(y_1)-the temperature of the regenerator dilute phase
(y_2)-the regenerator dense phase temperature
(y_3)-the pressure drop on the catalyst control valve)
(y_4)-the riser (reactor) temperature
(y_5)-the opening of gas compressor control valve
(y_6)-the opening of the air blower control valve

3. The Optimization Strategy

Modeling the optimization strategy should start with the optimizer layer. In this paper the economic objective, which is sought, is the maximum production of liquefied petroleum gas (LPG). The conversion model of Tvrzská de Gouvêa & Odloak (1998b) is adopted to estimate the yield of LPG, which depends on both process variables and properties of the feed streams. The latter will typically vary depending on the petroleum used and on how much heavy oil is recycled. Since process variables are related to each other, a suitable steady-state process model is in need and in this paper the model presented in Tvrzská de Gouvêa & Odloak (1998b) based upon the model of Moro & Odloak (1995) is adopted.

The economic objective function can be written as follows:

$$\min f_{eco} = -(u_3 + u_4)\times(LPGV) \qquad (1)$$

s. t. constraints defined by the conversion and process models as well as bounds on the decision variables.
LPGV is the volumetric yield of LPG.

If one wants the closed loop to have a faster response, it seems reasonable that the advanced controller should solve the optimization problem of minimizing (2) subjected to the constraints (3) to (6).

$$\min_{\Delta u(k+j),\ j=0,\ldots m-1} \sum_{i=1}^{p}\left\|W_1\left(y(k+i)-r\right)\right\|_2^2+\sum_{j=0}^{m-1}\left\|W_2\Delta u(k+j)\right\|_2^2 + \left\|W_4\left(u(k-1)+\sum_{j=0}^{m-1}\Delta u(k+j)-u_s\right)\right\|_2^2 \qquad (2)$$

$$-\Delta u^{\max} \le \Delta u(k+j) \le \Delta u^{\max}; \qquad j=0,\ldots,m-1 \qquad (3)$$

$$u^{\min} \le u(k-1)+\sum_{j=0}^{i}\Delta u(k+j) \le u^{\max} \ ; \ i=0,\ldots,m-1 \qquad (4)$$

$$y(k+i)=\left[y(k+i)\right]_k+\sum_{j=0}^{\min[i,m-1]} s^*(i-j)\Delta u(k+j) \qquad i=1,\ldots p \qquad (5)$$

$$\left[y(k+i)\right]_k = \left[y(k+i+1)\right]_{k-1}+s(i)\Delta u(k-1) + \left(y^p(k)-\left[y(k+1)\right]_{k-1}-s(1)\Delta u(k-1)\right); \ i=1,\cdots,n \qquad (6)$$

where, W_1, W_2 and W_4 are weighting factors, m and p are, respectively, the prediction and control horizons, k is the present time instant, $k+i$ is a sampling step where the controlled outputs are predicted, y is the predicted output, r is the output reference value defined according to equation (7), $\Delta u(k)=u(k)-u(k-1)$ is the control move, u is the manipulated input, u_s is the input value corresponding to the optimal operating point, $s(i)$ is the i^{th} coefficient of the step response of the process, $s^*(i)$ corresponds to the modified $s(i)$ coefficients as in (7), n is the number of coefficients of the step response of the system, y^p is the measured output of the system.

$$\begin{cases} If \quad \left[y(k+i)\right]_k \ge y^{\max} \Rightarrow \begin{cases} r=y^{\max} \\ s^*(j)=s(j); \quad j=1,\ldots,p \end{cases} \\ If \quad \left[y(k+i)\right]_k \le y^{\min} \Rightarrow \begin{cases} r=y^{\min} \\ s^*(j)=s(j); \quad j=1,\ldots,p \end{cases} \\ If \quad y^{\min} < \left[y(k+i)\right]_k < y^{\max} \Rightarrow \begin{cases} r=\left[y(k+i)\right]_k \\ s^*(j)=0; \quad j=1,\ldots,p \end{cases} \end{cases} \qquad (7)$$

The optimizing controller will typically correspond to a non-linear non-convex programming problem whose dimension may be large. So, a robust numerical algorithm must be at hand to solve the optimization problem (Tvrzská de Gouvêa and Odloak, 1998c). However, one nice feature of the optimizing controller approach is that the structure of an existing linear advanced controller may be maintained. Only one more term has to be included in the cost function of the controller. This term corresponds to the economic objective of the system. As for the constraints, steady-state process and conversion models must be included together with some more bound constraints (on steady-state values). So discussion of how to model the strategy may be limited on how to incorporate the economical term in the objective function. If the objective function of the predictive controller has a term that compares the predicted outputs to their reference values, inclusion of the economic term is quite simple. One simply has to include the economic function f_{eco} defined in eq. (1) into the objective function weighted by a factor (W_3) that is needed to tune the strategy. In this paper the predictive advanced controller to be modified is based on the range control concept, i.e., it is a QDMC type controller where no fixed reference values exist and the controlled outputs are controlled by ranges. The approach used here to prevent unfeasibility in the control and optimization problem is to use a control horizon larger than one and a sufficiently large bound on the “last” control move in the control horizon. One heuristic attempt to solve the off-set problem which results from leaving the control moves which are not implemented rather free is to modify the objective function by including terms that weight the difference between the predicted solution and the implemented one. The idea is to establish an optimal operating point that will define an optimal bound on the economic objective function. Then, this value will be compared to a prediction of the economic objective function based on the actual implemented control actions as can be seen in eq. (8) where the term weighted by W_6 appears. Another way to avoid off-sets is to force the implemented control actions to their predicted optimal value, which is achieved by the inclusion of the term weighted by W_5 in eq. (8). So, the objective function becomes the following:

$$\begin{aligned} \min_{\Delta u(k+i);\, i=0,\dots,m-1} & \sum_{j=1}^{p} \left\| W_1 \left(y(k+j) - r \right) \right\|_2^2 + \\ & + \sum_{i=0}^{m-1} \left\| W_2 \Delta u(k+i) \right\|_2^2 + W_3 f_{eco} + \\ & + \left\| W_5 \left(u(k+m-1) - (u(k-1) + \Delta u(k)) \right) \right\|_2^2 + \\ & + W_6 \left[f_{eco}(u(k+m-1), y(k+\infty)) - f_{eco}(u(k), y'(k+\infty)) \right]^2 \end{aligned} \quad (8)$$

where, W_5 and W_4 are weighting factors, $y(k+\infty)$ and $y'(k+\infty)$ correspond to the predicted outputs at steady-state taking into account, respectively, the manipulated inputs evaluated at the end of the control horizon and at the next sampling step.

4. Comparing the Optimization Strategies

In this section the performance of the layered optimization strategy defined by equations (1) to (6) will be compared to the optimizing controller defined in equation (8) together with constraints (2) and (6) and the rigorous nonlinear steady-state model of the process. The layered strategy will be named 2-layers approach, the optimizing controller with W_5=0 will be denoted as 1-layer approach with correction in u and finally the optimizing controller with W_6=0 will be referred to as the 1-layer approach with correction in f_{eco}. Since in the real operation of the plant disturbances will be present, all simulations were performed under the presence of the disturbances, which correspond to real disturbances of the FCC system of the refinery of São José.

The dynamic responses are shown for some important process variables like the temperatures of the feed, of the riser and the dense phase of the regenerator (u_7, y_4 and y_2) and the flowrate of gasoil (u_3) because their behavior is followed by other variables.

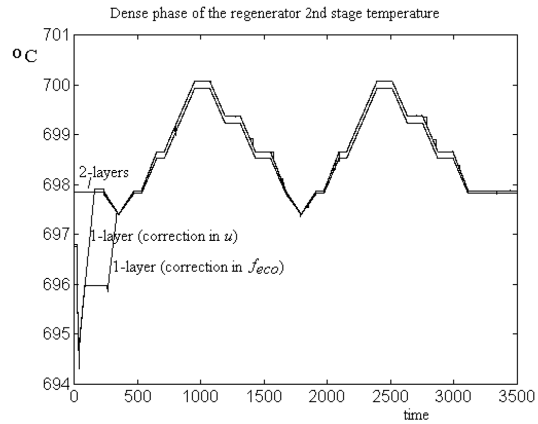


Fig. 1-Predicted optimal value of the regenerator temperature.

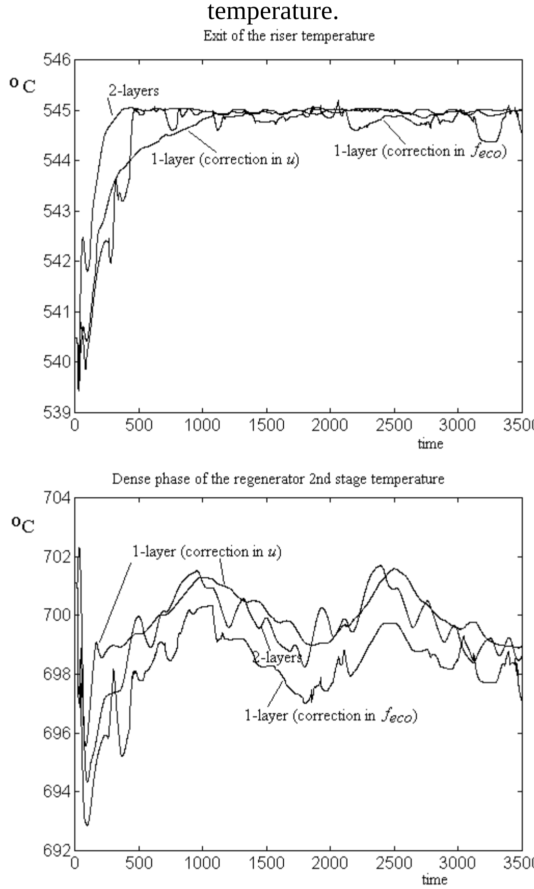


Fig. 2-Simulated reactor and reg. temperatures

Fig. 1 shows the predicted optimal value of the regenerator’s temperature. Note that all three strategies predict the same values since this is a variable that explicitly appears in the economical optimization problem. Also, all three approaches predict the same value for the temperature of the riser y_4, which was kept at its upper bound during the whole experiment of the campaign (i.e. at 545°C). Fig.2 shows the simulated dynamic responses of the riser and regenerator dense phase temperatures. The 1-layer approach with corrections on u produces the smoothest responses particularly if the reactor and regenerator temperatures are under regard. The 1-layer approach with corrections on f_{eco} suffers more the effect of model mismatch since a linear model is used for the prediction of the output variables in the term weighted by W_4. Fig. 3 shows the behavior of the economical objective, which is the production of LPG is shown. It can be seen that the three approaches produce similar results. The 2-layers approach produces a more rapid response in the beginning since reference values on the input variables are provided, whereas the 1-layer approach with correction in u provides the slowest response. However, the latter has the smoothest and less oscillatory response. So there is a tradeoff between choosing a rapid or smooth response. Since the FCC units are highly disturbed, it was decided to implement the 1-layer strategy with correction in u.

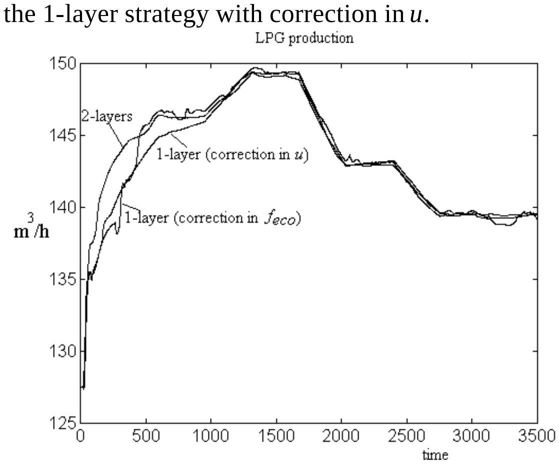


Fig. 3-Simulated behavior of the objective

5. Results from the Industrial System

It was decided by the engineers of Petrobras that the optimizing controller was to be implemented into the industrial FCC process. In this section the results of a "typical" operation day with the FCC unit controlled by the new controller are presented. It is not the aim to discuss the early commissioning steps, a discussion of which can be found elsewhere (Zanin et al., 2000) and neither the tuning procedure of the optimizing controller will be discussed. The tuning parameters used by the optimizing controller are presented in Table 1 where T is the sampling time. Observe that the weights contained in both W_1 and W_2 are quite different depending on the corresponding output or input. These factors are associated directly related to the importance of the variables related to them since the implemented controller uses engineering units and the inputs and outputs are not scaled.

Table 1 Tuning parameters of the controller

Tuning parameter	Value
T	1 min
m	2
p	20
W_1	*diag*(1., 2., 5., 3., 3., 1.)
W_2	*diag*(40., 1., 8., 1., 16., 40., 20.)
W_3	500.

At the particular operating day considered here, before the optimizing controller was switched on the system was controlled by the conventional linear MPC and some facts called ones attention:

- The plant was being operated close to its maximum capacity. The plant operators dictated strict operating bounds to the temperature of the riser and regenerator. Actually, the plant operators selected a range for the regenerator temperature of only about 3°C and the range for the temperature of the riser of only 1°C. Depending on the disturbances of the system, the maximum and minimum bounds for these temperatures were moved up or down to allow a larger feed flowrate or to relieve other operating constraints.
- The operator was also dictating the bounds on the feed flow rate to the converter and consequently he was trying to optimize the operation of the system using heuristic rules based on his own experience.

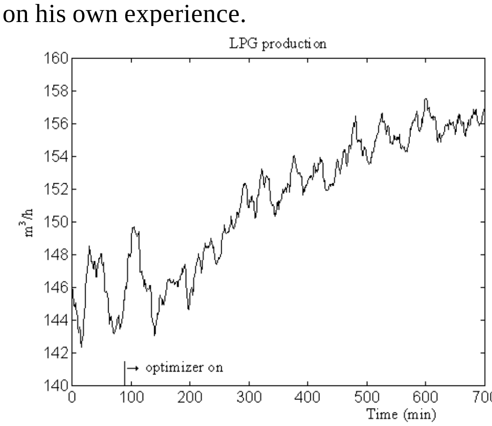


Fig.4-Plant economic objective

Results of the implementation are shown in figures 4 to 6. Observe that the control strategy was switched from the conventional linear MPC to the optimizing controller at time equal to 100min. At this point the range of the riser temperature (y_4) was enlarged to about 3°C to allow more space for the optimizer to work. The maximum bounds on the flowrates of gasoil and deasphalted oil were sequentially increased following staircase profiles. Particular attention should be given to Figure 8, which shows how the economic objective function varied along the time. The obtained LPG

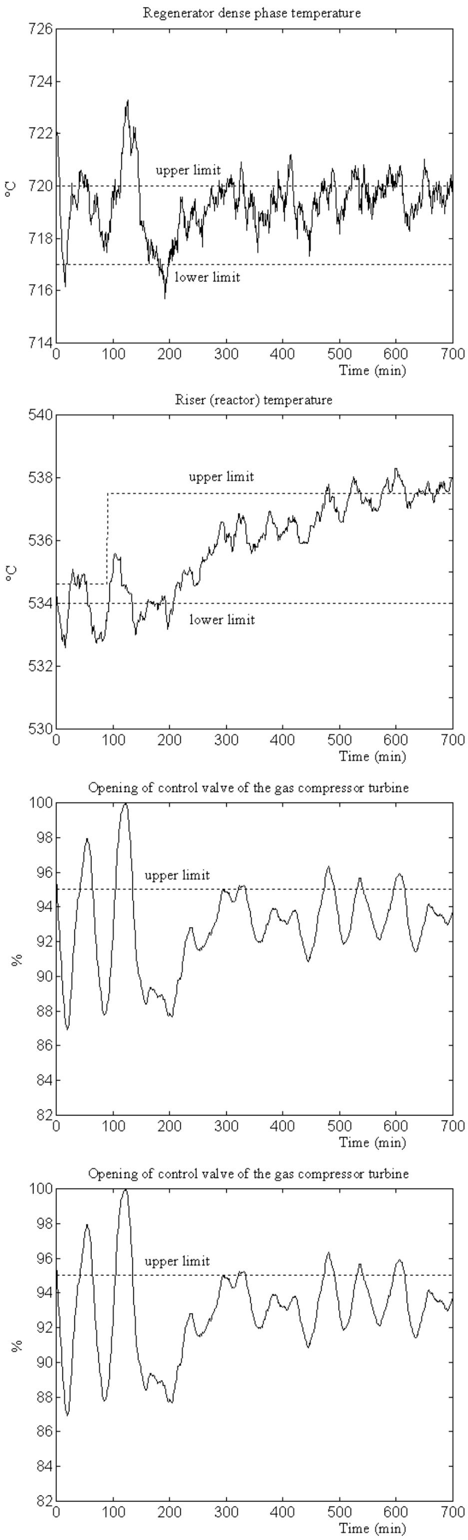


Fig.5-Plant controlled outputs

production began to increase smoothly and continuously immediately after the optimizing controller was started and an increase of about 10% in the LPG production was obtained after about 10h. Figures 5 and 6 present the corresponding values of the main outputs and inputs, respectively. It is clear that the conventional MPC helped with the operator heuristic was not optimizing the process satisfactorily. The optimizing controller succeeded in increasing production. It increased the flow rates of gasoil and deasphalted heavy oil and also pushing the unit to some of its constraints as the maximum riser temperature, the maximum regenerated catalyst valve opening and the minimum pressure in the main fractionator (gas compressor inlet pressure). It can be seen that all inputs were kept strictly inside their bounds since the constraints on these variables are imposed explicitly (hard constraints). This does not happen with the controlled outputs, which is an expected result, since the constraints in these variables are soft or the deviations from their bounds are included in the controller objective function.

6. Conclusion

This paper studies different ways of integrating the optimization of the process operation and the model predictive controller that is usually applied in oil refineries. New optimization strategies were established that are able to manage non-steady state data. Thus changes in the operational point can be captured before the plant is stabilized. One of these approaches made use of an optimizing controller, which has the advantage of incorporating all features of existing advanced controllers and makes the commissioning task easier. It is also shown how to model the latter strategies in order to avoid off-set problems and the simulations presented in the paper show that the dynamic response can be smooth and fast. Moreover, the results of the industrial application of one of the proposed strategies were also presented. The practical results indicate that the optimizing controller is able to improve considerably the economic benefits when compared to the conventional operating practice.

All the results presented in this paper are related to a project of implementing a real-time optimization strategy in the Refinery of São Josél.

Acknowledgment

Financial support was provided by FAPESP (under grants 96/2444-6, 97/07963-4, 98/14384-3 and 00/02937-0) and by Cnpq (grant 300860/97-8).

References

Arbel, A., Huang, I.H., Rinard, R. and A.V. Sapre (1995). Dynamics and control of fluidized catalytic crackers.1. Modeling of the current generation of FCC's. *Ind. Eng. Chem Res.*, 34, 1228-1243.

Ellis, R.C.; Xuan, L. and J.B. Riggs (1998). Modeling and optimization of a model IV fluid catalytic cracking unit. *AIChE Journal*, 44, 2068-2079.

Garcia, C. E. and Morshedi M. (1986), Quadratic programming solution of dynamic matrix control (QDMC), *Chem. Engng Commun*., 46, 73-87.

McFarlane, R.C., R.C. Reinnemann, J.F. Batee and C. Georkakis (1993). Dynamic simulation for a model IV fluid catalytic cracking unit. *Computers Chem Engng*, 17, 275-300.

Moro. L.F.L. and D. Odloak (1995). Constrained multivariable control of fluid catalytic converters. *J. of Process Control*, 5, 29-39.

Tvrzská de Gouvêa, M. and D. Odloak (1998a), One layer real time optimization of LPG production in the FCC unit: procedure, advantages and disadvantages, *Comp. Chem Engng*, 22, S191-198.

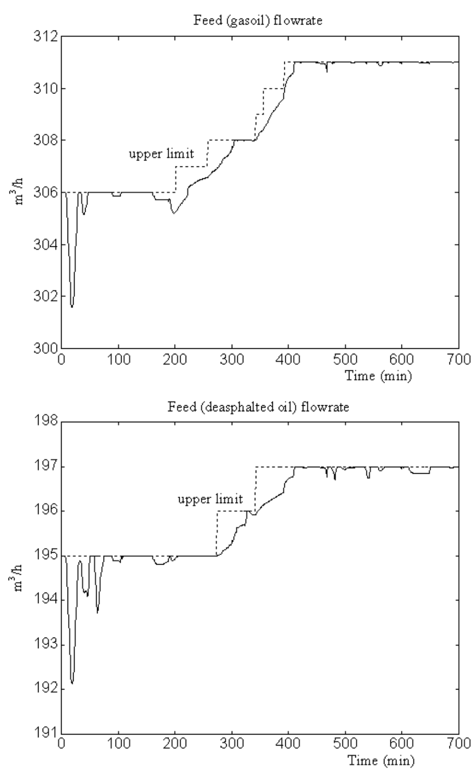
Tvrzská de Gouvêa, M. and D. Odloak (1998b). On-line maximization of LPG in the FCC unit. *Latin American Applied Research*, 28, 107-114.

Tvrzská de Gouvêa, M. and D. Odloak (1998c). A new treatment of inconsistent quadratic programs in a SQP-based algorithm, *Computers Chem Engng* , 22, 11, 1623-1651.

Ying, C-M. and Joseph, B. (1999). Performance and stability analysis of LP-MPC and QP-MPC cascade control systems. *AIChE Journal*, 45, 1521-1534.

Zanin A. C. (2001), Industrial implementation of a real-time optimizer, *PhD Thesis*, University of São Paulo, Brazil.

Zanin A. C., Trvzská de Gouvêa M. and Odloak D. (2000), Industrial implementation of real-time optimization strategy for maximizing production of LPG in a FCC unit, *Computers Chem Engng*., 24, 525-531.



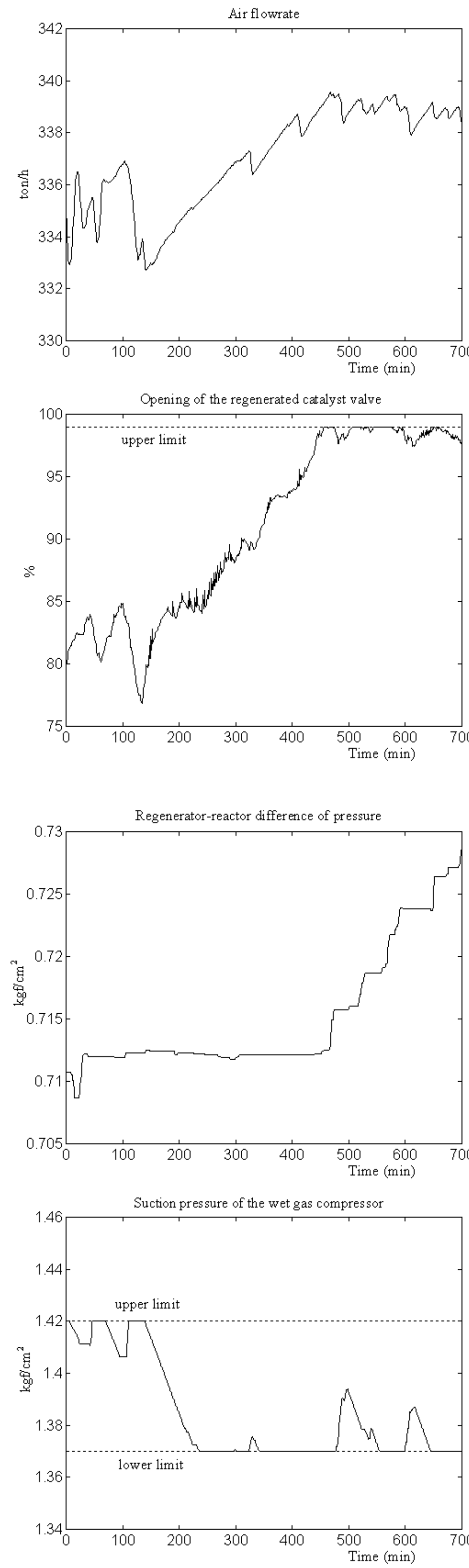


Fig. 6. Plant manipulated inputs