GPC Controller Performance Monitoring and Diagnosis Applied to a Diesel Hydrotreating Reactor

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Abstract: Control systems tend to lose performance over time if their responses are not monitored and thus there is no support information on to how to make adjustments on them. Reliable controllers have complementary systems to identify and diagnose reductions in performance and also to implement predetermined solutions vis-à-vis the desirable type of output. The goal of this work was to analyze controller performance monitoring and causes diagnosis methods based in two indexes: historical benchmark and model based performance measurement. These methods were applied to situations of degraded performance simulated in the predictive control of a hydrotreating reactor, aiming the identification of the reduction in the controller performance and the discrimination of its causes. The obtained results can also be extended to several other chemical processes, once that the investigated process presents first order with dead-time dynamics, typical of these processes.

Keywords: 1. Process control. 2. Performance reduction detection and diagnosis. 3. Control audit. 4. Refinery.

1. INTRODUCTION

In recent years, the performance requirements for process plants have become increasingly difficult to satisfy. Stronger competition, tougher environmental and safety regulations, and changing economic conditions have been key factors in tightening product quality specifications. A further complication is that modern plants have become more difficult to operate because of their complex and highly integrated processes. The largest emphasis recently given to safety has naturally improved the importance of the process control area. Without process control systems integrated with computers, it would be impossible to operate modern plants safely and lucratively while achieving product quality and environmental requirements. Therefore, it becomes important for chemical engineers to have an understanding both of the theory and of the process control practice. (Seborg, Edgar and Mellichamp, 2004).

Controller performance assessment and monitoring are necessary in order to assure the process control effectiveness and profit of the plant. The initial design of control systems includes many uncertainties caused by approximations in process model, estimations of disturbance dynamics and magnitudes, and assumptions about operating conditions. Many factors can cause their abrupt or gradual performance deterioration overtime. Around 60% of all industrial controllers have some kind of performance problem (Schäfer and Cinar, 2004).

All controllers need to be retuned as the dynamic of the process suffer natural or continuous alterations. The controllers performance should be monitored, because, even though they may have been adequately adjusted, it is expected that their performance decays along years due to variations in the materials, deterioration of the instrumentation, changes in the plant, etc. This reduction in the performance should also be diagnosed, enabling the identification of the needs to readjust the controller tuning parameters.

The main benefit of applying advanced control strategy to catalytic processes in refineries can be related to quality giveaway. For hydrotreating units, quality giveaway is mainly obtained by reducing over-desulphurization. Experimental results showed clearly that the sulfur content of the product is strongly related to the severity of the reaction, which is determined by reactor bed temperatures and the residence time. Operating at higher temperatures yields better product quality, but at the same time shortens the catalyst cycle. Therefore, the better the reaction control is (so as to guarantee only the necessary conversion), the better the utilization of the catalyst cycle and the lower the operational cost of the process (Lababidi, Alatiqi and Ali, 2004). Additionally, in case of accident, the replacement of a reactor and the reconstruction of other damaged equipments can take up to 12 months and the cost of lost production can exceed US$ 50 millions (Ancheyta and Speight, 2007).

2. CONCEPTUAL ASPECTS

This work is structured under three main themes: dynamic process control, process control performance assessment and diesel hydrotreating.

2.1 Model Predictive Control – Generalized Predictive Control

The general set of the available Generalized Predictive Control (GPC) algorithms cover a large variety of control goals in contrast to other methods, so that some of them can even be considered GPC specific cases.

In the SISO case (single-input u, single output y), a linearized time-invariant discrete process is assumed, where the relations between input and output are described by the following equation:

$$A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t-1) \quad (1)$$

A and B are polynomials in the backward shift operator q^{-1} with, respectively, degrees m and n, and d is the dead-time.

With the premise that all process natural disturbances can be characterized by a stochastic disturbance, the principle of the superposition can be used to represent all disturbances as a unique influence in the output. Then, the process can be described by the following CARIMA (controlled auto-regressive and integrated moving average) model:

$$A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t-1) + C(q^{-1})e(t)/\Delta \quad (2)$$

where C is also a polynomial in the backward shift operator q^{-1}, $e(t)$ is an uncorrelated random sequence and $\Delta(q^{-1})$ is the differencing operator $1 - q^{-1}$.

The CARIMA model may be considered the most appropriated model for many industrial applications with non-stationary disturbances. In practice, it has two main types of disturbance: occurrence of random steps in random intervals (e.g. changing of the product quality) and Brownian motion which is met in plants that depend on the energy balance (Clarke, 1988).

The following Diophantine Equation is employed for the development of the solution:

$$C(q^{-1}) = E(q^{-1})A(q^{-1})\Delta + q^{-d} * F(q^{-1}) \quad (3)$$

where, E and F are polynomials in the backward shift operator q^{-1} with degrees $d\text{-}1$ and m, respectively.

Multiplying the term $E(q^{-1})\Delta q^{j}$ in the components of (2); considering $C(q^{-1}) = 1$ (alternatively C is truncated and absorbed inside the polynomials A and B); and, assuming the future error values equal to zero, because they do not depend on the past values of $y(t)$ and $u(t)$, the following equation is obtained:

$$y(t+j) = G(q^{-1})\Delta u(t+j-d-1) + F(q^{-1})y(t) \quad (4)$$

where, $G(q^{-1}) = E(q^{-1})B(q^{-1})$.

In the GPC, the predictions $y(t+j)$ are estimated in order to compare them with a reference trajectory, and to calculate the optimum control actions. The system outputs will be influenced by signals in $u(t)$ after of the sampling periods $d+1$, due to the system dead-time of d sampling periods.

The following cost function is assumed:

$$J = (Gu + f - w)^T (Gu + f - w) + \lambda u^T u \quad (5)$$

where, w is the reference trajectory or *set-point* and λ is a weighting sequence.

Assuming that there are no constraints in the control signals, the minimum of J can be met by equating the J gradient to zero. Therefore, the following result is used in order to obtain the future control actions:

$$\Delta u = (G^T G + \lambda I)^{-1} G^T (w - f) \quad (6)$$

2.2 Predictive Control Performance Monitoring and Diagnosing

In order to perform performance reduction diagnosis of the controller, its performance shall initially be monitored preferable on-line. There is a set of techniques conceived for this purpose, named controller performance monitoring (CPM) techniques.

The objective of the CPM is to develop and implement technologies that provide information of the plant to determine if the appropriated performance and the characteristics of behavior are being reached through the controlled variables. For the case SISO, the normalized performance index is an elegant method, which compares the theoretic absolute lower limit in the output variability with the achieved values. This index could configure itself as a benchmark appropriated to measure the performance of a feedback control system (Cinar, Palazoglu and Kayihan, 2007).

Nevertheless, mostly for multivariable MPC controllers, other CPMs methods have been studied based in the calculation of the cost function, which in most cases is the objective function minimized to determine the MPC's strategy. Cinar, Palazoglu and Kayihan (2007) introduced two methods based on monitoring of the cost function values for the controller performance reduction diagnosis, called of historical benchmark and model-based performance measurement.

The cost function J_{ach} is obtained with plant real values that can be described in the following form:

$$J_{ach} = \frac{1}{Pc}\left\{\sum_{j=1}^{Pc}\left[e^T(k+j-Pc)Qe(k+j-Pc) + \Delta u^T(k+j-Pc)R\Delta u(k+j-Pc)\right]\right\} \quad (7)$$

Where, Pc is the moving horizon of past data; $e(k)$ is the vector of control errors at time k (difference between the controlled variable and the reference trajectory); Δu is the change in manipulated variables at time k; and, Q and R are weighting matrices representing the relative importance of each controlled and manipulated variable.

The historical benchmark requires a priori knowledge of good performance during a certain time period according to some expert assessment. The cost function applied in historical benchmark has the same form of (7), where the input and output data are taken from that period. So, the value achieved through this function is constant until a better performance is reached (Schäfer and Cinar, 2004).

The historical benchmark index is described by the following expression, which supports the control performance reduction or increase detection:

$$\gamma_{his}(t) = J_{his} / J_{ach}(t) \tag{8}$$

The model-based performance measure index compares the achieved performance with the performance in the design case that is characterized by inputs and outputs given by the model (Schäfer and Cinar, 2004).

The model-based performance measure index is described by the following expression:

$$\gamma_{des}(t) = J_{des}(t) / J_{ach}(t) \tag{9}$$

Both cost functions used in the calculation of the model-based performance measure index have the same form of (7).

Monitoring the model-based performance measure is useful in diagnosing causes that affect the design case controller. Two groups of causes may be devised. For instance, increases in unmeasured disturbances, actuator faults, or increase in the model mismatch do not influence the design case performance (group II causes). Accordingly, J_{des} remains constant while J_{ach} increases, reducing the model-based performance measure. Root cause problems such as input saturation or increase in measured disturbance, on the other hand, affect the design case performance as well (group I causes). This lead to an approximately constant value of the model-based performance measure, if the effect is quantitatively equal (Cinar, Palazoglu and Kayihan, 2007).

This diagnostic sequence assumes that only one source cause occurs. If γ_{des} doesn't change significantly, while the model performance and achieved performance decrease quantitatively equal, the diagnosis of the root cause is in the group I. If γ_{des} presents a considerable decrease, the diagnosis of the root cause is in the group II. In the case that multiple causes can occur simultaneously, the diagnosis logic becomes more complex.

Subgroups are defined to further distinguish between the root cause problems in group I. All changes in the controller (e.g. tuning parameters, estimator, constraints) are assumed to be performed manually. These changes are known and their effects can be monitored. However, the action taken is known and the root cause of the effect does not need to be identified by diagnosis tools (subgroup Ia causes). The remaining two root cause problems (change in measured disturbances and input saturation) belong to subgroup Ib. Additional information is needed to distinguish between the two root cause problems in subgroup Ib. Looking at the manipulated variables, input saturation can be determined by visual inspection. A saturation effect in a manipulated variable indicates input saturation as underlying root cause and rules out the increase in measured disturbances (Cinar, Palazoglu and Kayihan, 2007).

2.3 Diesel Hydrotreating

The hydrotrating unit considered in this work is the Trickle Bed Reactor (TBR) with two reactors in series, each reactor formed by two fixed bed, as showed in Figure 1.

The oil feed is combined with makeup hydrogen and recycle hydrogen and heated to the reactor inlet temperature. Heat is provided from heat exchange with the reactor effluent and by a furnace. The reaction of hydrogen and oil occurs in the reactors in the presence of the catalyst. To prevent reactor temperatures from getting too high, quench gas (cold recycled hydrogen gas) is added between reactors and between catalyst beds of multiple-bed reactors to maintain reactor temperatures in the desired range.

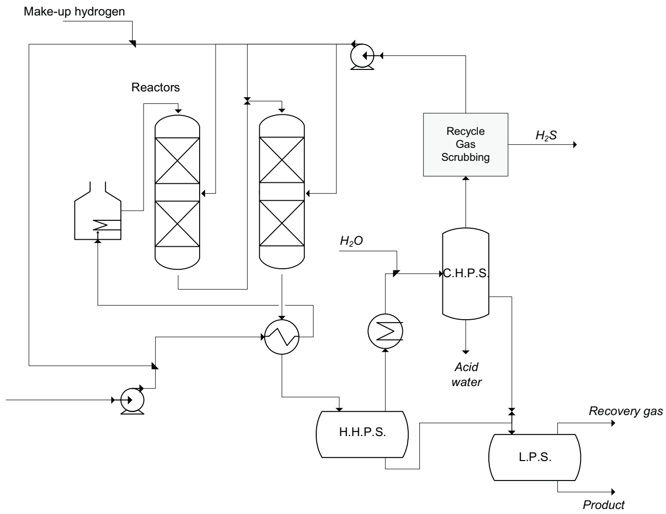

Figure 1 – Diesel hydrotreating process

The second reactor effluent is cooled (by exchange with the reactor feed) to recover the heat released from the hydrotreating reactions. After cooling, the reactor effluent is flashed in the hot, high-pressure separator (HHPS) to recover hydrogen and to make a rough split between light and heavy reaction products. The liquid from HHPS has its pressure lowered, than it is sent to the low-pressure separators, and on to the product fractionator. The HHPS vapor is cooled and water is injected to absorb hydrogen sulfide and ammonia produced in the reactors by the hydrotreating reactors. The mixture is further cooled to condense the product naphtha and gas oil and is flashed in the cold, high-pressure separator (CHPS). The CHPS separates the vapor, liquid water, and the liquid light hydrocarbons. The pressure of the hydrocarbon liquid is lowered and it is sent to the low-pressure separators. The water is sent to a sour water recovery unit for removal of the hydrogen sulfide and ammonia. The hydrogen-rich gas from the CHPS flows to the H_2S absorber. The purified gas flows to the recycle compressor where it is increased in pressure so that it can be used as quench gas and recombined with the feed oil. Liquid from the low-pressure separators is fed to the atmospheric fractionator, which splits the hydroprocessed oil from the reactors into the desired final products.

The model adopted in this work to represent the HDT's process was the model presented by Carneiro (1992) which applies the concept proposed by Hlavácek (1982) in representing fixed beds through the CSTR-CELL model. The CSTR-CELL in series describes the adiabatic fixed bed reactors dynamic. In Figure 2, a scheme of this model is shown.

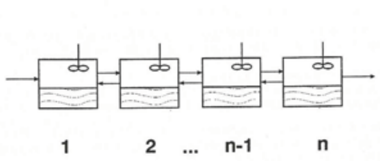

Figure 2 – CSTR-CELL reactor model

The CSTR-CELL reactor model considers mass and heat axial dispersion in the bed, mass diffusion and heat transportation between fluid and solid phases, as illustrated in Figure 3. The following assumptions are adopted in the CSTR-CELL: only one first order reaction – with respect to the mean concentration of a pseudo-reagent "A" in the solid phase porous – occurs and the reaction rate can be described by the Arrhenius equation; there is no volume variation in the reactor; the reactors are adiabatic; there is only one liquid and one solid phase with constant physical-chemical properties; there is only longitudinal transport phenomena; and, there are non-linear interactions between kinetic and thermal processes.

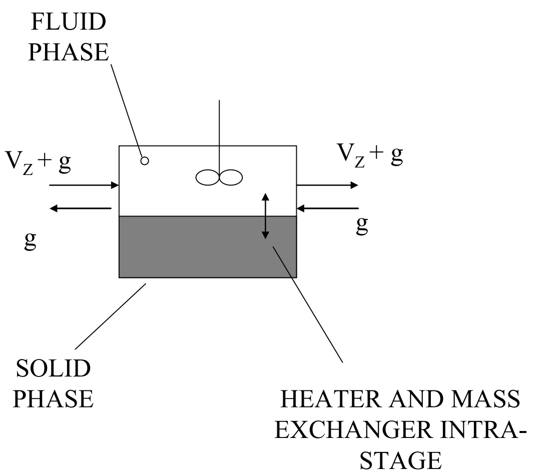

Figure 3 – CSTR-CELL stages

The Carneiro (1992) model was employed in this work for being at the same time able to represent the main process dynamics and simple, as it is composed by ordinary differential equations.

4. METHODOLOGY

This paper focus on the primary controller of the cascade control system applied to the first bed of the first reactor of the HDT unit, which can be seen in the top left hand corner of the diagram shown in Figure 4. This controller controls the bed outlet temperature through the manipulation of the set-point that is sent to the secondary controller. The secondary controller controls the inlet temperature of the bed through the manipulation of the fuel flow that enters the furnace.

The primary controller was performed by the GPC algorithm, using no explicit constraints and weighting in the cost function. The tuning parameters were the prediction horizon (N), the control horizon (NU) and the reference trajectory parameter (α).

The GPC was projected with a first order internal model with dead-time. The function considered for reference trajectory was a first order equation, which has only one tuning parameter: α. The larger α, the more cautious the control actions. If α is zero, the trajectory is constant and equal to the set-point, as can be noticed in the equation to follow:

$$w(t+1) = \alpha\, y(t) + (1-\alpha)SP \qquad (10)$$

As a default option, α was chosen in this study as equal to 0.7.

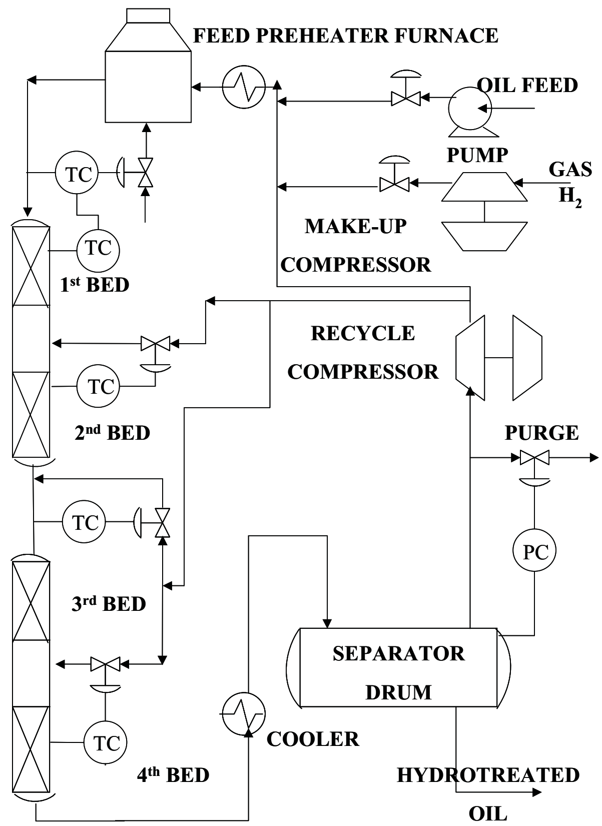

Figure 4 – Diesel Hydrotreating Unit Diagram (De Souza Jr., Campos and Tunala, 2009)

In respect to the assumed performance reduction scenarios, four cause diagnosis cases were tested based in the method presented previously: increased controlled variable variability (group II causes), mismatch between the model and the phenomenological model based simulator (group II causes), saturation of manipulated variable (group Ib causes) and change of the control tuning parameters (group Ia causes).

5. RESULTS

The events responsible for the reductions in performance were introduced in the 80^{th} sampling time, as can be observed in the following figures. Figures 5, 6, 7 and 8 present, respectively, the following situations: increase in the controlled variable variability, mismatch between the internal model of the controller and the phenomenological model based simulator, saturation of the manipulated variable and change of the control tuning parameter. In all figures, the first graph presents the cost functions calculated to obtain the historical benchmark and model-based performance measure indexes. The second graph presents the historical benchmark index (monitoring index), and the third graph presents the model-based performance measure index (diagnosis index).

With the controlled variable variability increased in 5 times (in the phenomenological simulator), the achieved cost function was increased, while the others remained at the same level, as shown in Figure 5. In consequence, both the monitoring and diagnosis indexes had their values reduced. So, these behaviors agree with the expected for causes belonging to the group II which is the case for increases in unmeasured disturbances.

Figure 6 represents the change of CARIMA model parameters – *a* and *b* of (2) – which were multiplied by 20, causing an increase of the achieved cost function. The cost function applied to the model remained at the same level, because the internal model of the controller was affected in the same way.

As the mismatch between the internal model of the controller and the phenomenological simulator belongs to the causes of group II, the monitoring and diagnosis indexes decrease as can be seen in Figure 6.

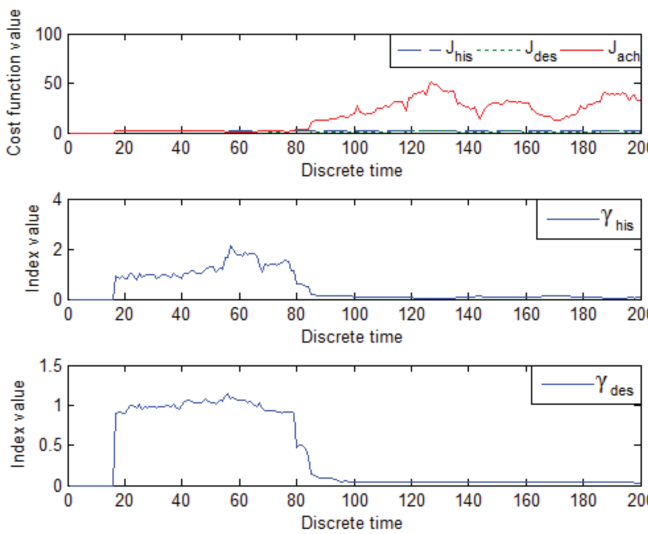

Figure 5 – Control performance reduction diagnosis caused by the controlled variable variability increase

When a constraint in the manipulated variable was applied to limit its lower value to 236.1ºC, the achieved cost function and the based-model cost function showed an increase which resulted in the decrease of the monitoring index and in the maintenance of the diagnosis index (see Figure 7). The observed behavior agrees with the causes belonging to group I, as was expected. Among the causes of group I, this particular cause can be diagnosed by monitoring the control actions, such as presented in the Figure 8, where from the 80^{th} sampling time ahead the manipulated variable did not decrease beyond the value -0.2.

Figure 9 represents the control tuning change situation, where the prediction horizon varied from 4 to 50. In this situation, it can be observed that the indexes presented a similar behavior to the previous situation, due to the fact that this kind of cause also belongs to group I, where the same change affects the internal model and the model of the phenomenological simulator. This cause would not need to be diagnosed, because the modification in the tuning parameters of the controller – and, therefore, the reason of the performance reduction – would be previously known.

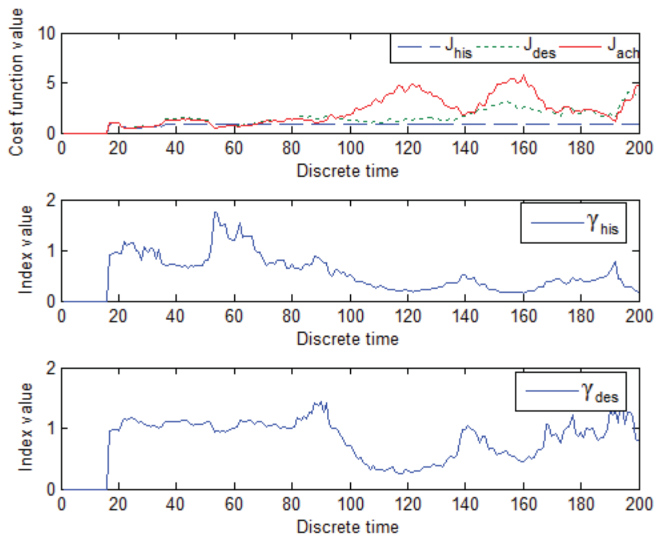

Figure 6 – Control performance reduction diagnosis caused by the mismatch between the model and the phenomenological model based simulator

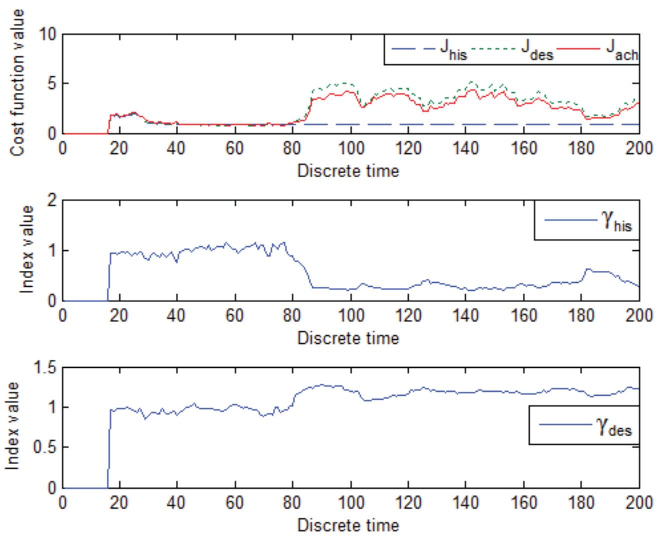

Figure 7 – Control performance reduction diagnosis caused by the saturation of the manipulated variable

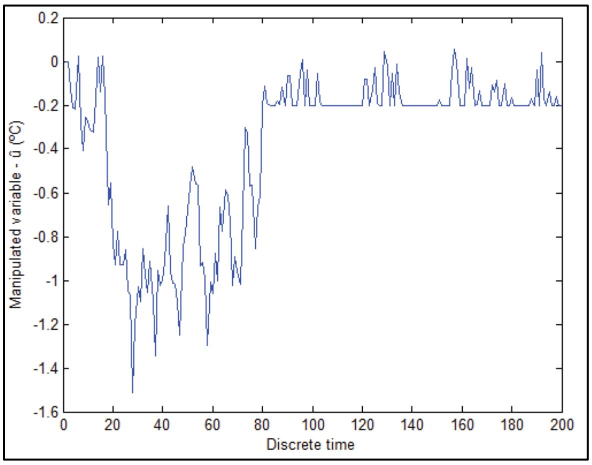

Figure 8 – Saturation of manipulated variable

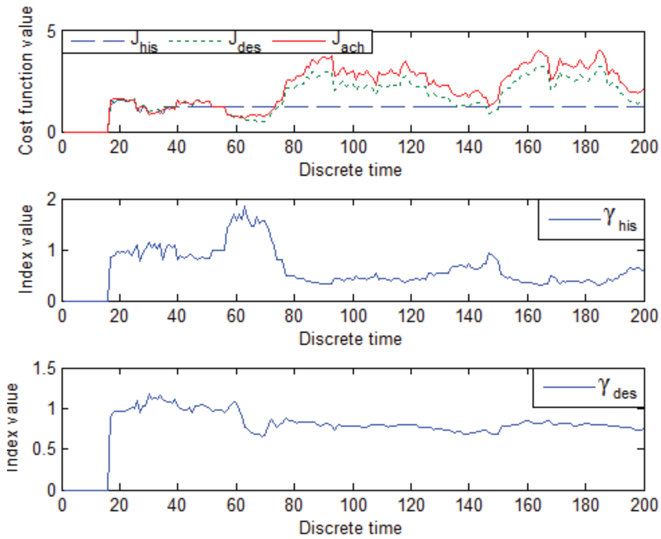

Figure 9 – Control performance reduction diagnosis caused by the change of the control tuning parameter

Even though some situations were potentially easier (e.g. the saturation of the manipulated variable) to detected and diagnose than others (e.g. the mismatch between the model and the phenomenological model based simulator), all the simulated scenarios were safely diagnosed. However, the situations studied in this paper were magnified in order to allow the verification of the differences that were expected for each case in the figures.

6. CONCLUSIONS

Monitoring and diagnosis methods were successfully applied to study control performance reduction scenarios using a GPC algorithm. Four types of performance reduction causes were diagnosed: increase in the controlled variable variability, mismatch between the model and the phenomenological simulator, saturation of manipulated variable and change in the control tuning parameter.

As future developments, it is suggested the implementation of operation support tools that enable the automatic performance monitoring and diagnosis.

Finally, it is expected that – with environmental concern, development of the industrial safety area and evolution of human intellectual capacity – more and more technologies will be developed in order to enable the correction, the prevention and, mostly, the failures prediction, allowing the man to dedicate his work to nobler activities, like process optimization.

REFERENCES

Ancheyta, J., Speight, J. G. (2007). *Hydroprocessing of heavy oils and residua*. CRC Press. USA.

Carneiro, H. P. (1992). Robust control of a fixed bed chemical reactor. 1992. 142 p. Dissertation (Chemical Engineering Master) – Engineering Pos-Graduation Program Coordination (COPPE), Federal University of Rio de Janeiro, Rio de Janeiro.

Cinar, A., Palazoglu, A., and Kayihan, F. (2007). *Chemical process performance evaluation*. CRC Press. USA.

Clarke, D. W. (1998). Application of generalized predictive control to industrial processes. *IEEE Control Systems Magazine*. April. p. 49 – 55.

De Souza Jr., M. B., Campos, M. C. M. M., and Tunala, L. F. (2009). Dynamic Principal Component Analysis Applied to the Monitoring of a Diesel Hydrotreating Unit. In Ferrarini, L. and Veber, C. (ed.). *Modeling, control and diagnosis of complex industrial and energy systems*. ISA, USA.

Hlavácek, V. (1982). *Fixed bed reactors, flow and chemical reaction*. Verlag Chemic. Germany.

Lababidi, H. M. S., Alatiqi, I. M., and Ali, Y. I. (2004). Constrained model predictive control for a pilot hydrotreating plant. *Chemical Engineering Research and Design*, v. 82 (A10), p. 1293 – 1304.

Schäfer, J. and Cinar, A. (2004). Multivariable MPC system performance assessment, monitoring and diagnosis. *Journal of Process Control*, v. 14, p. 113 – 129.

Seborg, D. E., Edgar, T. F., and Mellichamp, D. A. (2004). *Process dynamic and control*. Wiley, 2nd Edition. USA.

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