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DETECTION OF ANOMALOUS BEHAVIOR AND PERFORMANCE ASSESSMENT OF PREDICTIVE CONTROLLERS

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Abstract: This study focuses on performance assessment of model predictive control systems. A statistical methodology based on costs functions is proposed to determine a performance index which is amenable for monitoring an MPC using a benchmarking (historical) behavior and confidence control charts. An alternative methodology based on the predictability of the error is proposed for performance monitoring the MPC. The proposed methodologies are used to evaluate a DMC used to control a chemical reactor when significant changes in the process dynamics and controller tuning are introduced.

Keywords: Process control, predictive control, controller performance, loop monitoring, performance benchmarking, fault diagnosis, costs functions.

1. INTRODUCTION

Predictive controllers are sensitive to performance degradation and anomalous behavior in their lifetime due to a number of reasons, typically modelling errors and poor tuning. The driving force of controller performance assessment, monitoring and diagnosis is to ensure that a MPC performs according to their model-based design specifications. This means that controlled variables meet their operating targets such as specifications on output variability, effectiveness in constraint enforcement and proximity to economic optimal operation. Typically the controller should work well over a wide range of operating conditions whilst dealing with unknown effects of unmeasured disturbances which may result in an actual controller behavior which is far from the expected performance based on the nominal controller design. In the literature, a number of approaches have been proposed for detecting significant deviations from the desired behavior of the predictive control system and guessing the possible causes of malfunctioning using performance indices based on cost functions. (Harris et al., 1999; Kesavan and Lee, 1997; Patwardhan et al., 1997; Schäfer and Cinar, 2002, 2004; Zhang and Henson, 1999).

The availability of a process model makes possible to calculate in real-time a cost function from the measured and manipulated variables and compare it to the predicted cost used by the controller. Schäfer and Cinar (2004) propose a performance measure based on the ratio of historical and achieved (actual) performance is used for loop monitoring and a ratio of design and achieved performance is used for diagnosis. An alternative suggested by Zhang and Henson (1999) is to compare the actual cost function with the one obtained using a linear model.

For performance monitoring, one attractive alternative is to compare the observed process behavior with a benchmark target using a desirable cost function from the commissioning step (Ghraizi, et al., 2003; Schäfer and Cinar, 2002, 2004). The use of cost functions can also be applied to the detection of anomalous behavior by comparison with cost values which are descriptive of loop malfunctioning, e.g. poor tuning or local process-model mismatch. In this work, the usefulness of control charts for performance monitoring based on characterizing the expected variability is presented. To illustrate the applicability of the proposed technique performance monitoring of a DMC controller in a chemical reactor is analyzed.

2. PERFORMANCE INDICES

The availability of an internal model in the controller design opens the possibility to tackle performance monitoring and diagnosis based on different ratios of cost functions. One alternative is to compare the cost function as predicted internally by the controller, J_{Cont}, to the actual cost function, J_{real}, calculated using the implemented inputs and observed process outputs. The resulting index IC_{Cont} is indicative of the validity of the predictions made by the internal model. Fig. 1 provides a schema of the variables involved in estimating this index using the internal model in a DMC and measurable disturbances. A significative change in the operating conditions may render the internal model inappropriate which will be readily detected by a shift in IC_{Cont}

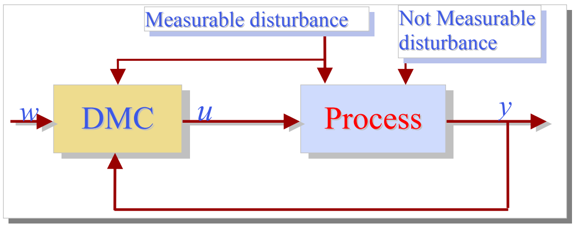

Fig. 1: Performance index calculation schema

Similarly, a benchmark index IC_{cont_hist} characterizing the desired behavior may be defined using the ratio between a historical cost function J_{real_hist} and the controller historical cost function J_{Cont_hist}. Tuning parameters in the cost function are: prediction horizon, $N2$, control horizon, Nu, equal concern errors γ to weight differently control objectives and move suppression factors β that affect the energy of control actions.

At any given time t, the real cost function J_{real} is based on input-output process data in the $N2$-1 previous sampling times. The value of J_{real} is descriptive of the actual capability a MPC to achieve the control objectives and the control energy employed. Cost function calculations are made using the receding horizon as

$$J_{real}(t) = \sum_{i=1}^{Nout} \gamma_{(i)} \sum_{j=1}^{N2} \left[y_{(i)}(t+j-N2) - w_{(i)}(t+j-N2) \right]^2 + \sum_{i=1}^{Nin} \beta_{(i)} \sum_{j=1}^{N2} \left[\Delta u_{(i)}(t+j-N2) \right]^2 \qquad (1)$$

where, y are the controlled (measured) variables, Δu are the step changes to manipulated variables, w are the desired output values, γ and β are weighting matrices. The values of w, γ and β are constant over each calculating window.

The historical cost function Jreal_hist is calculated in a similar way but using historical input-output data for an MPC working properly. Based on the sample mean and variance of the cost function it is possible to define the upper and lower limits for the control band in the control chart and they are calculate as follows:

$$\bar{J}_{real\_hist} \pm 2\sigma^2 \qquad (2)$$

Which can help detecting any abnormal deviations from expected performance as shown in Fig. 2.

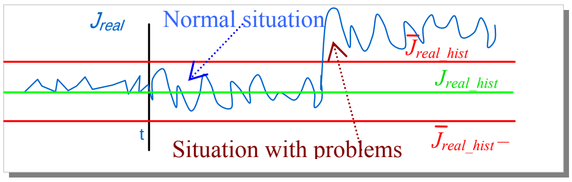

Fig. 2: Monitoring Jreal using a benchmark

σ is the variance of J_{real_hist} calculated

$$\sigma^2_{Jreal\_hist} = \frac{1}{n-1} \sum_{i=1}^{n} \left(J_{real\_hist}(i) - \bar{J}_{real\_hist} \right)^2 \qquad (3)$$

The cost function J_{Cont} for the controller is related to the deviation between value prediction of controlled variables and their references along with control efforts involved in tracking the reference w. This cost function is used internally by the MPC to synthesize the sequence of control actions. To calculate J_{Cont} predictions over the prediction horizon along with the expected evolution of controlled variables are used:

$$J_{Cont}(t) = \sum_{i=1}^{Nout} \gamma_{(i)} \sum_{j=1}^{N2} \left[\hat{y}_{(i)}(T+j\,|\,T) - w_{(i)}(T+j\,|\,T) \right]^2 + \sum_{i=1}^{Nin} \beta_{(i)} \sum_{j=1}^{Nu} \left[\Delta u_{(i)}(T+j\,|\,T) \right]^2 \qquad (4)$$

Where $T = t$-$N2$, $\hat{y}$ are predicted process outputs, Δu are the increments of the manipulated variables, w desired output references, γ y β are the weighting matrices. $N2$ is the prediction horizon, Nu is the control horizon, Nin is the number of manipulated variables, and $Nout$ is the number of controlled variables.

The cost functions J_{real} and J_{Cont} can be combined in a performance index IC_{Cont} descriptive of the difference between internal model predictions used by the controller with the ones computed directly from measurements:

$$IC_{Cont}(t) = \frac{J_{Cont}(t)}{J_{real}(t)} \qquad (5)$$

The evolution of the above index provides about the degradation of model predictions used by the controller. Similarly, a performance index can be defined using a historical benchmark for the controller defined in a similar way as in (5)

$$IC_{Cont\_hist}(t) = \frac{J_{Cont\_hist}(t)}{J_{real\_hist}(t)} \qquad (6)$$

The performance index IC_{Cont} can be monitored using benchmark control bands as shown in Fig. 3.

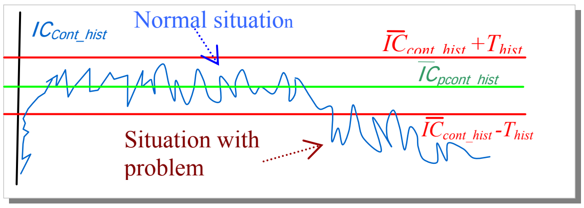

Fig. 3: Monitoring the controller performance index using a benchmark of desirable behavior

The performance index IC_{Cont} typically exhibits statistical variations due to unmeasured disturbances and unmodelled noise. This fact may affect the inferences made about the control system state using this index. To overcome this problem it is better to resort to a moving average of IC_{Cont} which filters the effect of random variability. The moving average is calculated as:

$$\overline{IC}_{Cont}(t) = (1-\theta) IC_{Cont}(t) - \theta \overline{IC}_{Cont}(t-1) \quad (7)$$

Where $0 \le \theta \le 1$ a forgetting factor such as a small value of is θ emphasizes the most recent values of the index (no memory). As θ increases towards 1 the importance of previous values also increases making the index average less sensitive for quick detection of sudden changes indicative of abnormality.

For a properly working controller both cost functions in the quotient (index) will have similar values and IC_{Cont} tends to 1 within the control bands defined by the historical benchmark. As the controller behavior deteriorates, the value of IC_{Cont} will drift away from the normal variability of a well-performing MPC.

An alternative methodology for performance monitoring is the idea of predictability of controller behavior. The main concept is that if a controller works properly and the prediction horizon b has been chosen appropriately, the behavior of a perfectly working controller cannot be predicted beyond the interval of time during which any disturbance entering the loop up to a present time is supposed to be compensated. On this ground, there may exist different alternatives to detect patterns of predictability in the time series associated to controller errors and manipulated variable changes. It is worth noting that as seen from time t, the controller error after time $t+b$ of a properly working controller cannot be distinguished from a random walk stochastic process see Fig 4. Over the control horizon, the controller behavior is fully predictable since it corresponds to its own control policy built-in by design.

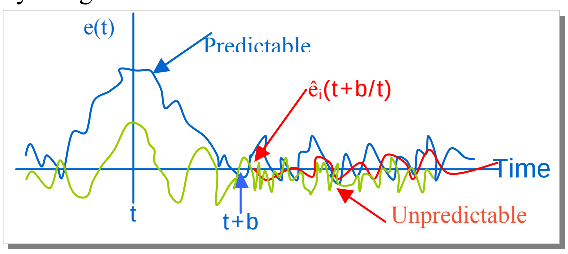

Fig. 4. On the predictability of the controller error.

It is worth discussing first the meaning of the control horizon b for a regulatory control task. Whatever the internal workings of a predictive controller, the value of b represents a sound engineering decision that takes into account, among other things, process dynamics, type of loop service and acceptable control energy. Let's denote by a scalar $e_i(t)$ the controller error whereas $\hat{e}_i(t)$ stands for the prediction of such error based on past error values, and possibly, control actions generated by the controller. The difference between the actual and predicted controller errors is the residue $r_i(t)$ whose means and variance provide relevant information regarding the predictability of a controller behavior.

The calculation of a performance index from a given data set demands some way of estimating future controller errors. The easiest way to do this is to propose a regression model of the following form:

$$\begin{aligned}\hat{e}_{i(t+b)} &= a_0 + a_1 e_{i(t)} + a_2 e_{i(t-1)} + \\ &+ \ldots + a_m e_{i(t-m+1)}\end{aligned} \quad (8)$$

Where m is the model order and a_j are the parameters to be fitted upon data using for example least-square regression. The Predictability Index (IC_{mv}) is calculated such the follow

$$IC_{mv}(t) = \sum_{i=1}^{Nout} f_i IC_i(t) \quad (9)$$

Where IC_i is the performance index of each one of the controlled variables and f_i it is a weight vector that is used to give different importance to each one of the index IC_i in dependence of each one of the controlled variables, $Nout$ it is the number of the controlled variables.

The factor f is established like a relationship between the value of the weight γ that it is used to give different importance to the controlled variable and the total sum the weight factor of all the controlled variables of the control loop,

$$f_i = \frac{\gamma_i}{\sum_{i=1}^{Nout} \gamma_i} \quad (10)$$

The Predictability Index $(IC)_i$ for each error is calculated to bear some similarity with the one proposed by Harris (1989) to measure the current performance regarding the best performance that can be achieved using a minimum variance controller,

$$IC_i(t) = 1 - \frac{\sigma_r^2(t)}{\sigma_e^2(t)} \quad (11)$$

Where, σ_r and σ_e are the variance of the residue and the error, respectively. Similar calculations can be used to define a measure of the predictability of controller outputs. For a given interval of time, if a controller does not exhibit a predictable behavior beyond the control horizon, $\sigma_r \approx \sigma_e$ gives rising to a near zero value of IC_i. As the controller behavior is more predictable σ_e increases relative to σ_r, which in turn increases IC_i. For a controller exhibiting an easily predictable behavior (e.g., output saturation) $\sigma_r << \sigma_e$ and $IC_i = 1$. It is possible to define confidence intervals for sample estimators of the predictability index, which allows using control charts to detect excursions associated to loop malfunctions. The estimate to the confidence interval is carried out according to the following equation:

$$P\left(\frac{\hat{\sigma}_r^2}{\hat{\sigma}_e^2}F^{-1}_{0.5\alpha,n-1} \le \frac{\sigma_r^2}{\sigma_e^2} \le \frac{\hat{\sigma}_r^2}{\hat{\sigma}_e^2}F_{0.5\alpha,n-1}\right) = 1-\alpha \qquad (12)$$

Where α is the level of confidence, n is the size of the group of the data.

3. SIMULATION RESULTS

In this section, performance monitoring of model predictive controllers is discussed using simulated data for a continuous chemical reactor where the exothermic reaction A → B occurs. The controller is DMC and process a schema is given in Fig. 5.

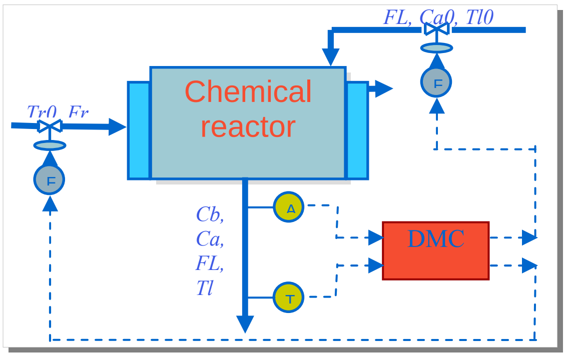

Fig. 5: CSRT controlled with a DMC

The controlled variables are the reactor temperature Tl and outflow product B concentration, whereas as manipulated variables the DMC uses inflow rate Fl of the reagent A entering the reactor and cooling flow rate Fr. There also exists a measurable disturbance, Tr0, the temperature of Fr, and two disturbances which cannot be measured: concentration Ca0 and temperature Tl0 for the incoming reagent.

For DMC performance monitoring and diagnosis three different scenarios have been simulated. Firstly, normal operating condition is considered. Later on, a change in process dynamics due to a significant variation of the heat transfer coefficient is considered. Finally, the influence of controller tuning on the DMC behavior is simulated to assess the effect on its performance.

3.1 Results obtained for normal operating conditions

In Fig. 6 and Fig. 7 the effect of set-point changes for the controlled variables Cb and Tl have been simulated. Process and controller parameters are maintained constant throughout. As can be seen the settling time for the process is in the order of 45 min and the controller seems to handle successfully the load disturbances

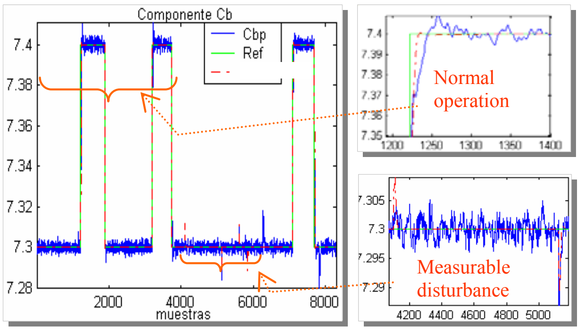

Fig. 6.DMC response for a set-point change in Cb

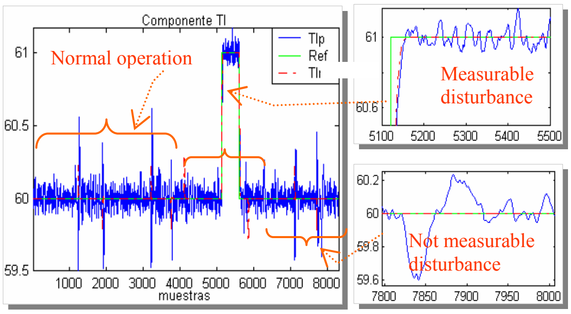

Fig. 7: DMC response for a set-point change in T1.

In Fig. 8 the cost function J_{real} along with its average and upper/lower confidence limits are depicted. For the chosen degree of confidence (95%) the relatively low value of J_{real} is indicative proper working of the controller when facing the load disturbances.

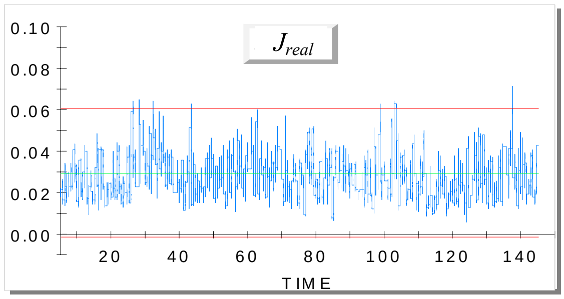

Fig. 8: Cost function Jreal.

In Fig. 9, the performance index IC_{Cont} has the same result as J_{real} and validate that the controller is working well.

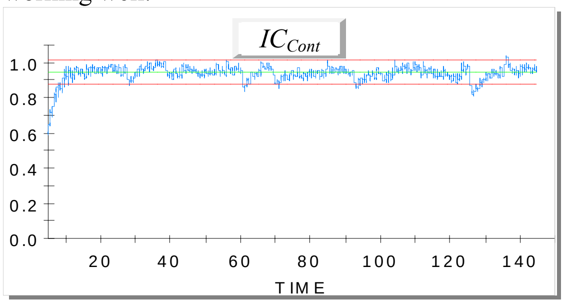

Fig. 9: Performance Index IC_{Cont}.

The Predictability Index IC_{mv} in Fig. 9 fully confirm good DMC behavior to handle both measurable and unknown disturbances.

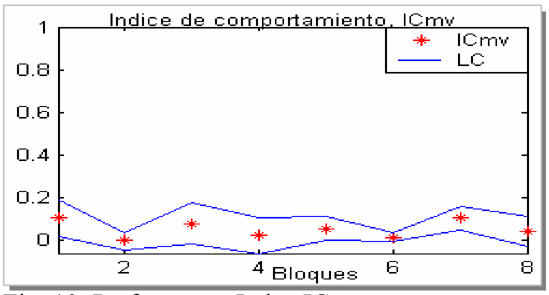

Fig. 10: Performance Index ICmv.

3.2 *Change in process dynamics*

To simulate a drastic change in the dynamic behavior of the procesa at t=41 h the value of the heat transfer coefficient is lowered from its nominal design value Of. 4300 kJ/(h*m2)*K to 2470 kJ/(h*m2)*K and maintaned in this latter value until the end of the simulation episode. The simulation experiment was carried out as follows. The first 38 hours (2000 sample values) were simulated under normal operating conditions. At t=72h load-type disturbances (measurable and unknown) are introduced. Each disturbance has been simulated for 34 hours with a sampling time of 1 min.

In Fig. 11 and Fig. 12, the controlled variables are shown along with their desired reference values. It worth noting the increase of the process setting time from 42 min to almost 100 min. Even though, the performance is degraded due to a much poorer internal model, the DMC can handle quite well load disturbances.

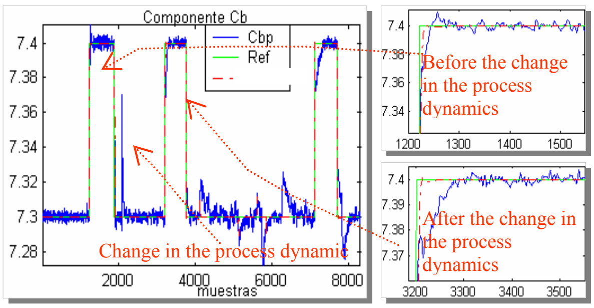

Fig. 11: DMC of product composition with degraded internal model prediction under load disturbances.

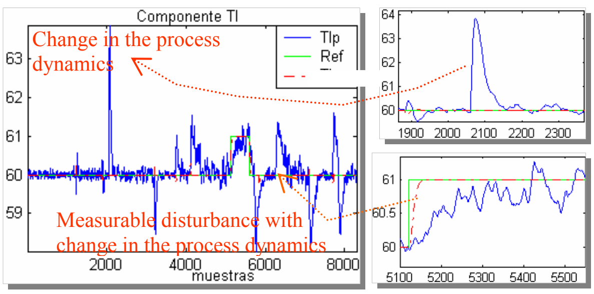

Fig. 12: Behavior of T1 when the process dynamics is changed.

In Fig. 13 the cost function J_{real}, performance index IC_{Cont} are showned, as expected, as soon as the process dynamics is changed, the time series for both indices drift away from the normal (expected) variability. As soon the DMC can recover control, the control charts reflect a return to "under-control".

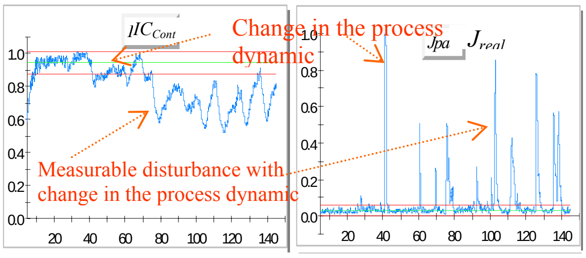

Fig. 13: Detecting a drift in process dynamics.

Fig. 9 reveal how the controller's state worsenits as soon as the process dynamics is changed and olso showned how the value of the index IC_{mv} change and the level of the uncertainty increases in this situation.

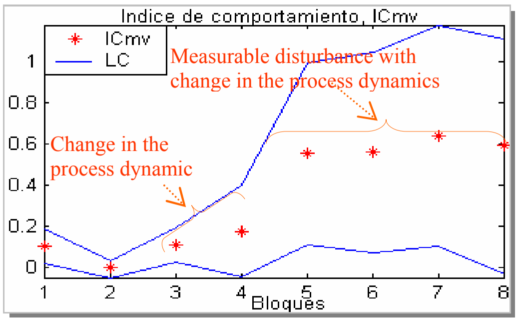

Fig. 14: Performance Index IC_{mv}.

3.3 *Change in tuning parameters*

The original values of the tuning parameters were γ=[2.0 1.0 0.8], β=[0.5 0.5], α=[0.03 0.099 0.09], and have been changed to the following ones: γ=[2 8 1], β=[0.999 0.999], α=[2 2 1]. The new values for weighting errors and controller agresiveness drastically effect the performance of the DMC. However, performance degradation reflected in very different ways in the process and controller cost functions, respectively.

Simulation studies were done following a similar procedure to that of Section 3.2. At t=41 h, tuning parameters of the DMC has been changed and maintained throughout the rest of the simulation. Results obtained are given in Fig 14 through Fig. 15 In Fig. 16, the actual T1 is compared to the predictions made using the linear model which reflects the drastic change in the close-loop reactor dynamics in the new scenario. Also, there is an increase in the process settling time compared to a well-tuned DMC.

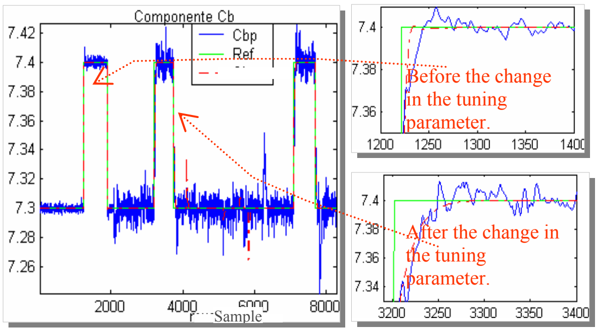

Fig. 15: Inadequate DMC tuning effects for controlling Cb

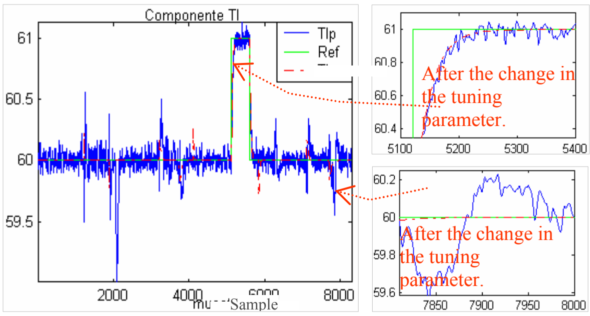

Fig. 16: Inadequate DMC tuning effects for controlling T1

In Fig. 16 and Fig. 17 the actual cost function J_{real} and the performance index IC_{Cont} are shown. The ill-tuning of DMC is clearly reflected in both cases.

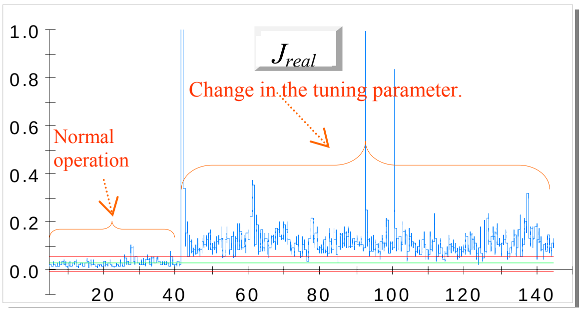

Fig. 17: Cost Index J_{real}.

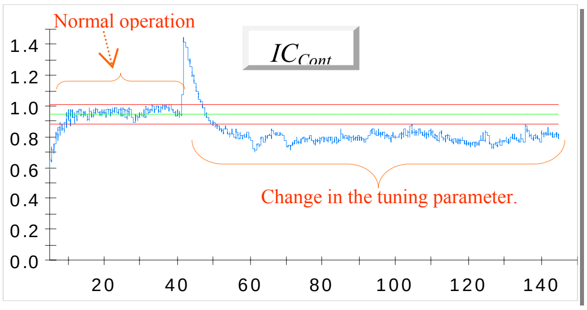

Fig. 18: Performance index IC_{pCont}.

In Fig. 18 the predictability index IC_{mv} is shown the ill-tuning of DMC, and we can also perceive it bad behavior seeing the increase in the confidence interval.

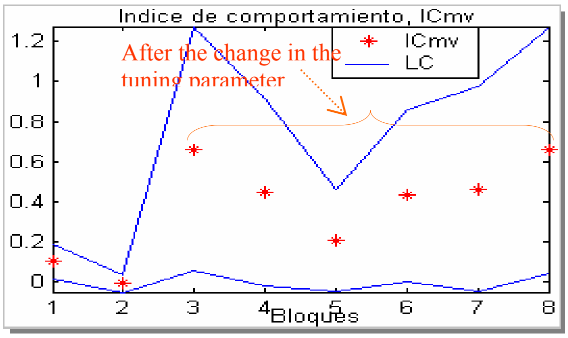

Fig. 19: Performance degradation detected using the performance index based on predictability

4. CONCLUDING REMARKS

Simple tools for performance monitoring of MPC have been presented using in a case the predictability of error and in the other case internal cost functions which can be integrated in a controller performance index. A case study, a chemical reactor controlled by a DMC has been used to illustrate the proposed concepts and methodology. Abnormal operating conditions resulting from a significant change in process dynamics and inadequate tuning help illustrate the discriminatory capability of performance indices and their corresponding confidence charts.

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