

## Performance monitoring of industrial controllers based on the predictability of controller behavior

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### Abstract

This study focuses on performance assessment of industrial controllers. A methodology based on the concept of the predictability of controller errors is proposed for performance monitoring. The proposed approach is based on evaluating controller behaviour by analysing the time series of its error and to verify the existence predictable patterns beyond the control horizon in each one of the controlled variables of the process. To favour its implementation in a plant information system a performance index is proposed. For effectiveness of the monitoring algorithm, proper selection of some tuning parameters depending on the type of loop (temperature, level, pressure, etc.) is discussed. Examples using industrial data from a refinery are provided.

**Keywords:** Process control, controller performance, loop monitoring, performance benchmarking, fault diagnosis.

### 1. Introduction

With the increasing complexity of control structures and the sheer number of controllers in modern process plants, the automation of performance monitoring tasks is a key issue to grasp the benefits of advanced control systems and real-time optimization (Thornhill, et al., 1999). In process plants there are thousands of control loops whose performance demands continuous supervision. Human personnel simply cannot have the budget of attention to handle this overwhelming task which renders many loops to remain open or providing a service much below the required standards. Abnormal operation of control loops can make a significant impact not only in the economy but also in the safety of the process. During the last decade several monitoring techniques have been developed. Desborough and Harris (1992, 1993) focusing on the comparison of the actual controller variance to ideal of a minimum variance controller. Thornhill, et al., (1999), proposed the prediction of the error to determine the performance of a SISO controller. Ghraizi, et al., (2004), suggest a practical index for performance monitoring of a control loop based

on the analysis of the predictability of the error time series emphasizing proper selection of the control horizon using engineering judgment. The contribution of our work is based on the proposal of a procedure to obtain an index that allows the controller monitoring in closed loop and to evaluate its performance using predictions to detect the existence of predictable patterns in the time series of the error associated to each one of the controlled variables of the process. The method was applied to analyze off line some loops of PIDs in a petrochemical plant.

## 2. Monitoring methodology

The performance-monitoring concept revolves around the idea of predictability of controller behavior beyond a chosen control horizon. Assuming the control 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 (see Fig. 1 for details). 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. Over the control horizon, the controller behavior is fully predictable since it corresponds to its own control policy built-in by design.

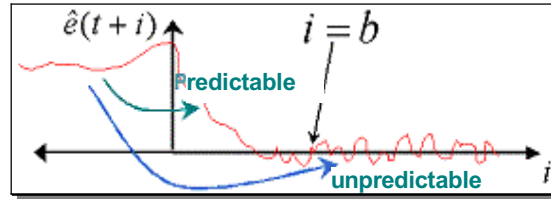


Figure 1: presentation of the prediction of the error.

It is worth discussing first the meaning of the control horizon  $b$  for a regulatory control task. Whatever the internal workings (PID, Predictive, etc.) of a controller, the value of  $b$  represents a sound engineering decision that takes into account among other things process dynamics, type of service and acceptable control energy. Let's denote by a scalar  $e(t)$  the controller error whereas  $\hat{e}(t)$  stands for the prediction of such error based on past values of the controller error, and possibly, control actions generated by the controller. The difference between the actual and predicted controller errors is the residue  $r(t)$  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:

$$\hat{e}(t+b) = a_0 + a_1 e(t) + a_2 e(t-1) + a_3 e(t-2) + \dots + a_m e(t-m+1) \quad (1)$$

Where  $m$  is the model order and  $a_i$  are the parameters to be fitted upon data using for example least-square regression. The *Predictability Index (PI)* 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,

$$PI = 1 - \frac{\sigma_r^2}{mse} \quad (2)$$

Where,  $\sigma_r^2$  is the residue variance and  $mse$  is the mean square error. 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,  $\sigma_r^2 \approx mse$  gives rising to a near zero value of  $PI$ . As the controller behavior is more predictable  $mse$  increases relative to  $\sigma_r^2$ , which in turn increases  $PI$ . For a controller exhibiting an easily predictable behavior (e.g., output saturation)  $\sigma_r^2 \ll mse(t)$  and  $PI=1$ . It is possible to define confidence intervals for sample estimations 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:

$$T = t_{1-\alpha/2, n-1} \sqrt{\frac{\sigma_r^2}{n}} \quad (3)$$

Where  $t_{1-\alpha/2, n-1}$  is the Student statistic,  $\alpha$  is the level of confidence,  $n$  and  $\sigma_r$  are, respectively, the size of the group of the data and the variance of the noise.

### 3. Parameter tuning

It is necessary to provide some guidelines on how some parameters involved in the calculation of  $PI$  should be selected. Parameter  $m$ , represents the order of the regression model. This parameter should have a value that is big enough to capture the characteristics of the time series of the error to reflect the predictable components in the model. As a rule of thumb,  $m$  should have a value slightly bigger than the loop settling time. Too high a value for  $m$  creates problems of overfitting and poor extrapolation capabilities in the model, which will affect the sample estimation of the  $PI$  index.

Parameter  $n$ , is the size of the data sample and it should to take into account the trade off between index variance and data homogeneity. A very small size of the data set gives rise to big variance in the index distribution, while a too big data set is mixes heterogeneous data, which may mask a lot of important information. Since index calculation uses the error of controller and not the controlled variables, it is not necessary that the loop remains in the same set point, but it is important that the characteristics of the loop are the same throughout (Ghraizi, et al., 2003), such that, sensors, valves, control algorithms should not be altered by calibration or tuning.

Regarding the sampling interval  $tm$ , is necessary to avoid an excessive or insufficient sampling. If the data are frequently sampled, the impulse response of the closed loop is not established inside the  $m$  samples. With low frequency sampling, the impulse response is only established inside a few samples and the important loop characteristics are not captured between the samples (Thornhill, et al., 1999; Stanfelj, et al, 1993).

Parameter  $b$  represents the control horizon, which coincides with the prediction horizon for the time series model. It has been analysed by different authors like Harris, (1989), Desborough, and Harris, (1992), Harris, et al., (1996), Stanfelj, et al., (1993). In our work, we have observed that  $b$  should be equal to the loop settling time, independently

of the type of the loop so that so it can reflect the necessary prediction characteristics in a control loop.

#### 4. Industrial data analysis

In order to test the index, several analysis were performed with a Toolbox implementing several monitoring functions. The length of the batches considered was  $n=1000$  samples of real plant data. The following graphs show the analysis of different loops taken from a petrochemical plant. The parameters were adjusted to the nature of the loops. In this way, we choose  $tm=5$  sec.,  $b=15$  (number of samples),  $m=30$  for flow control loops. For level ones  $tm=60$ sec,  $b=30$ ,  $m=30$ , (in this case  $n=720$ ), for pressure  $tm=5$  sec.,  $b=5$ ,  $m=30$ , and for temperature  $tm=60$ sec.,  $b=15$ ,  $m=30$ . In the left part of all the graphs, we can observe the batches of data and their analyses, while in the right part we can see a zoom of a certain area of them to visualize some details. The upper graph corresponds to the controlled variable and its set point, while the values of the error and its predictions are in the graph in the middle. Finally, in the lower one, the values of the performance index  $PI$  are displayed.

In figure 2 one can observe 17 batches of 1000 data of a flow loop which performance deteriorates at the 13<sup>th</sup> batch, due to a perturbation that has affected the process. The performance index at the beginning doesn't have high values what indicates that the error has little predictability, as shown in the right hand side, but when the perturbation appears, the manipulated variable saturates and the  $PI$  almost is equal to one. Notice the bottom right hand side graph showing that the error can be predicted easily this time. Once the process returns to its normal state, the error, and the index takes a small value again.

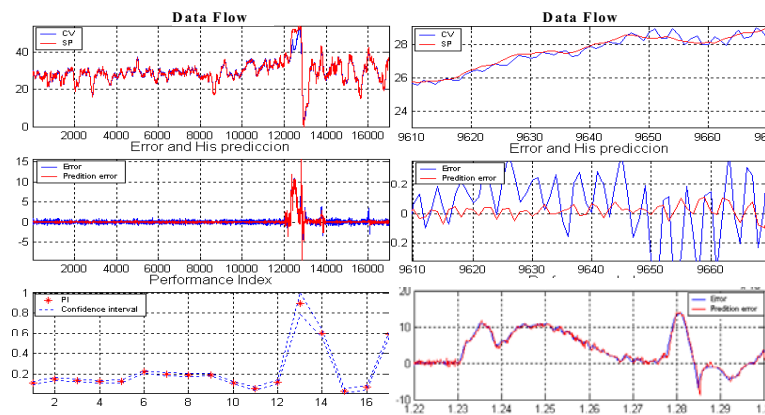


Figure 2: Data flow with their errors and  $PI$ .

In figure 3 one can observe results from a level loop where a change in the behaviour takes place after  $t=1000$  proximately. At the beginning, the  $PI$  has a small value but when the change takes place,  $PI$  increases reflecting the predictability of the error. By the contrary, the Harris index, shown in the bottom right hand side graph, does not performs equally well remaining in a low value which means bad tuning, not taking into account the special characteristics of an average level control.

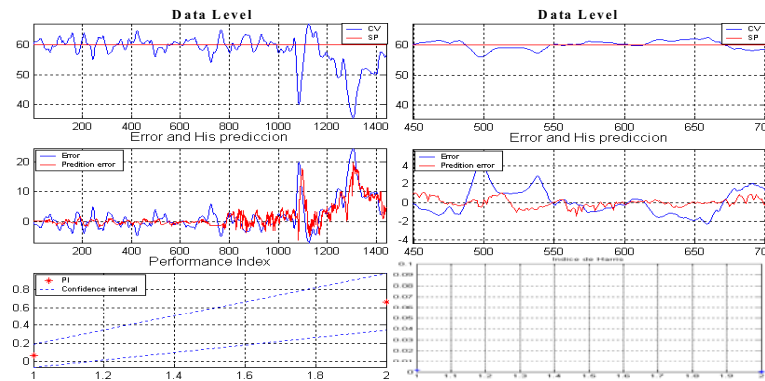


Figure 3: Data level with their errors and PI.

Figure 4 displays data from a cascade loop in which a temperature output is following a changing set point very slowly with a significant steady error. In this case, the *PI* has high values all the time, and in the extended graph of the right is seen that the error is completely predictable. In addition, the Harris index is consistent with this result.

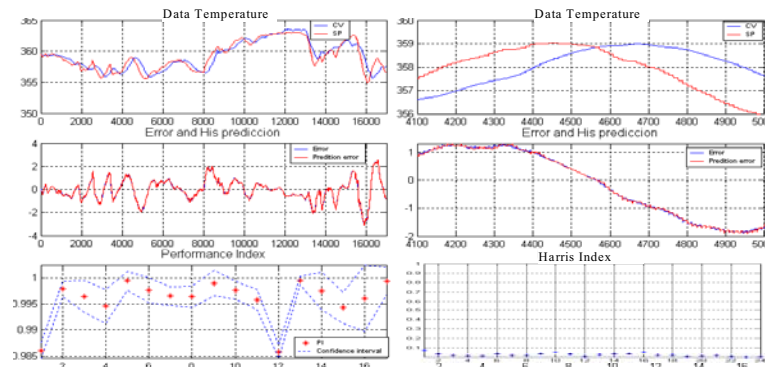


Figure 4: Data temperature with their errors and PI.

Finally, graph 5 shows the data of a pressure loop performing well. In this case, the error is not predictable and the values of *PI* are always low. Also, the Harris index is high but shows a higher variability than the *PI*.

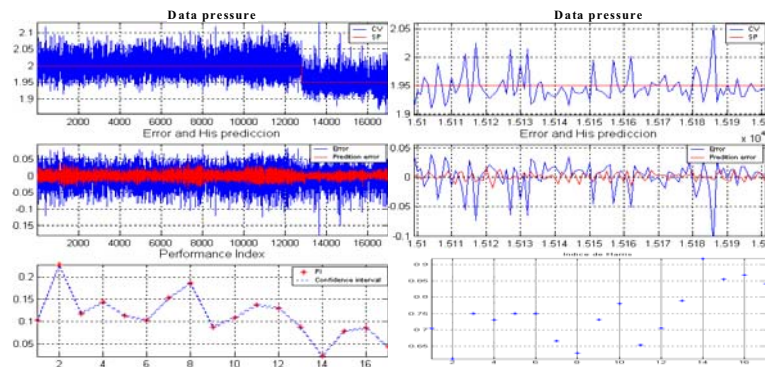


Figure 5: Data flow with their errors and PI.

Figure 6 shows the main window of the developed Toolbox, which allows not only perform analyses of a control loop using the index IP, but also other analyses based on cross-correlation, power spectrum, impulse response, Harris index, etc., that can be used to confirm or perform a deeper analysis in order to detect the possible cause of the controller's bad operation.

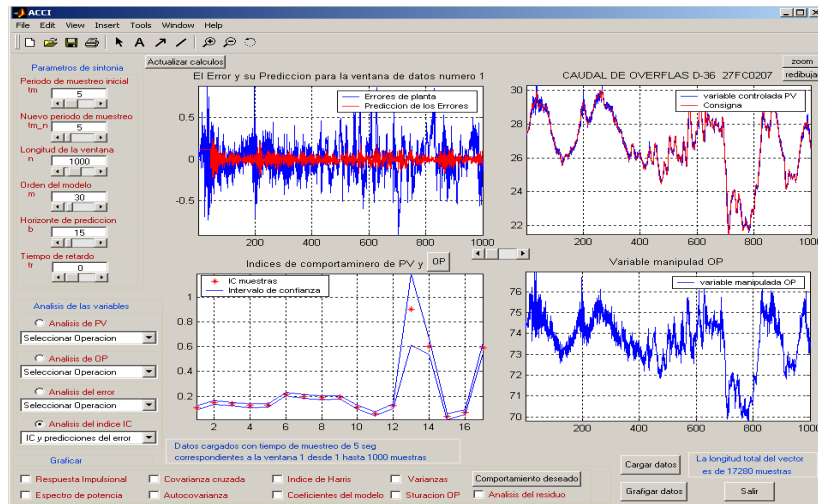


Figure 6: Data flow with their errors and PI.

## 5. Conclusions

This paper presents results showing a promising way of analysing the performance of industrial controllers using a time series of the error to detect the existence of predictable patterns. An index was computed to achieve this analysis evaluating the residuals between the controller's error and its prediction and some rules have been proposed to adjust the parameters of the method. Finally, it was applied to plant data showing a good behaviour.

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