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

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Abstract

This paper focuses on performance assessment of industrial controllers. Instead of using process or controller models, it is based on process data collected at regular time intervals. Data analysis includes a set of tests that are reviewed in the paper and implemented in a software system. A methodology based on the concept of the predictability of controller errors is also proposed for performance monitoring. It considers the time series of the error and verifies the existence of predictable patterns beyond the control horizon in each one of the controlled variables of the process. The result of the analysis is given as a performance index. Examples using industrial data from a refinery are provided.

Keywords: Process control; Controller performance; Loop monitoring; Performance benchmarking; Fault diagnosis

1. Introduction

The operation of modern process industries is based to a great extent in the use of a great number of control loops implementing a variety of control structures. Most of them are PID controllers and, more and more, advanced ones, such as MPC and real-time optimizers, are present on top of the regulation layer. Nevertheless, it is well known that loop behavior deteriorates with time. Process dynamic characteristics change along time and, if not properly maintained, a control loop will perform out of specifications after some time, which can lead to degraded process operation. In particular, problems with the regulation layer can cancel the benefits of advanced control systems and real-time optimization.

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 (Thornhill, Oettinger, & Fedenczuk, 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. One can roughly classify them as model or signal based, or deterministic and stochastic (Bezergianni & Georgakis, 2000). Signal based methods use only process measurements to test loop performance. Perhaps the best known of them is the Harris index (Desborough & Harris, 1992, 1993) based on the comparison of the actual controller variance to the ideal situation of a minimum variance controller. Thornhill et al. (1999), proposed the prediction of the error to determine the performance of a SISO controller. Ghraizi, Martínez, & de Prada (2003, 2004), Ghraizi et al. (2004), suggested 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.

In a different thinking line, Åström (1991) combined several classical loop performance measurements in order to perform

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qualitative and quantitative assessment of a SISO loops. Eriksson and Isaksson (1994) motivated by the fact that the Harris index was difficult to interpret and could not incorporate the effect of deterministic changes in the control loop, presented some alternative indices requiring exact models of both the process and its controller. Other methods have been proposed with the same aim, such as the one that compares closed loop variance with the open loop one (Bezergianni & Georgakis, 2000). A good recent survey of the topic can be found at Jelali (2006).

The main contribution of our work is based on the proposal of a procedure to obtain an index that allows the monitoring of the controller 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 off line to analyze some loops PIDs in a petrochemical plant, but it is also suitable for on-line implementation.

This paper focuses on a practical methodology for performing control loop monitoring. After Section 1, Section 2 explains the basis of the proposed monitoring index and Section 3 is devoted to the discussion of its tuning parameters. Section 4 describes a software tool for performing the analysis and review several test methods implemented on it, while Section 5 shows and discuss several examples of controller analysis using real data. Finally, Section 6 gives some conclusions.

2. Monitoring methodology

As mentioned above, several methods have been proposed for controller supervision. Having in mind the idea of monitoring on-line a large number of PID regulators, it seems reasonable to propose a methodology in which an index can be used for differentiating those loops which require further analysis from plant personnel from those that are performing "good enough". Then, other tests can be applied to the selected loops in order to diagnose the ultimate cause of the loop malfunctioning.

The Harris index is intended to be a measurement of the performance of the controller in relation to the best possible one. It is based on the fact that a minimum variance controller applied to a plant characterized by the model

$$A(q^{-1})y(t) = B(q^{-1})u(t-k) + C(q^{-1})\xi(t)$$

where $u(t)$ and $y(t)$ are the process input and output, k the process delay and $\xi(t)$ is a zero-mean white noise signal, gives a closed loop output such as:

$$y_{\mathrm{MV}} = \sigma D\xi(t)$$

with D is made up of the first k coefficients of C/A. As D can be identified from closed loop operating data, it is possible to estimate the lower limit of the output variance and construct an index comparing the present variance to the theoretical minimum one. Nevertheless, the knowledge of the process delay k is needed and, as mentioned above, the Harris index can be of limited use as a measurement of the actual performance of the loop. It measures how far a PID is from the best linear controller, but not directly how well the loop is behaving. So, for the purpose of controller plant supervision, one can think in a more informative performance measurement.

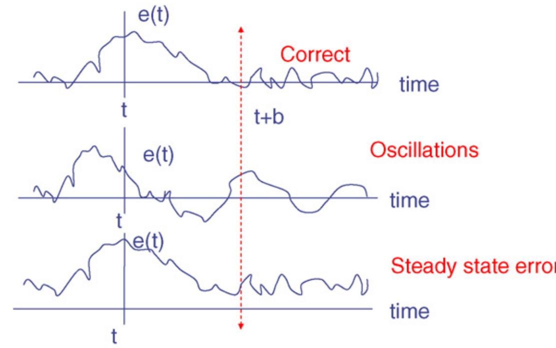

Fig. 1. Error patterns.

The performance-monitoring concept revolves around the idea of predictability of controller behavior beyond a chosen horizon b. If a control loop exhibits "good" performance, we expect that it will be able to cancel any disturbance entering the loop up to present time t, or follow a set point change correctly, after some sensible time interval b (expressed in terms of sampling periods). Then, it is suppose that, from $t+b$ on, the error cannot be distinguished from a random walk stochastic process so that it cannot be predicted adequately using information up to time instant t (see Fig. 1 for details). Nevertheless, over the control horizon b, the controller behavior is fully predictable since it corresponds to its own control policy built-in by design. By contrast, the error of a control loop exhibiting "incorrect" performance, after time instant $t+b$, will show patterns of behaviour (oscillations, steady error, etc.) that can be predicted using present and past measurements. 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 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 us denote by a scalar $e(t)$ the controller error,

$$e(t) = w(t) - y(t) \tag{1}$$

with $w(t)$ the controller set point, whereas $\hat{e}(t)$ stands for the prediction of such error based on past values of the controller error. 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:

$$r(t) = e(t) - \hat{e}(t) \tag{2}$$

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:

$$\hat{e}(t+b) = a_0 + a_1e(t) + a_2e(t-1) + a_3e(t-2) + \cdots + a_me(t-m+1) \tag{3}$$

where the time indices refer to sampling periods, m the model order and a_i are the unknown parameters. Several authors (Harris, 1989; Desborough & Harris, 1992; Ghraizi et al., 2003; Stanfelj, Marlin, & MacGregor, 1993) have discussed methods to estimate prediction models. In our case the parameters will be fitted upon data, using least-squares regression:

$$[a_0, a_1, \ldots, a_m]^{\mathrm{T}} = (X^{\mathrm{T}}X)^{-1}X^{\mathrm{T}}Y \tag{4}$$

where

$$X = \begin{bmatrix} 1 & e(1) & e(2) & \ldots & e(m) \\ 1 & e(2) & e(3) & \ldots & e(m+1) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & e(n-b-m+1) & \cdots & \ldots & e(n-b) \end{bmatrix} \tag{5}$$

$$Y = [\,e(m+b) \quad e(m+b+1) \quad \ldots \quad e(n)\,]^{\mathrm{T}} \tag{6}$$

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. More precisely, the PI index is defined as:

$$\mathrm{PI} = 1 - \frac{\sigma_r^2}{\sigma_e^2} \tag{7}$$

where σ_r^2 is the variance of the residuals $r(t)$ and σ_e^2 is the variance of the actual errors $e(t)$:

$$\hat{\sigma}_r^2 = \frac{1}{n-1}\sum_{i=1}^{n}(r(i)-\bar{r})^2 \tag{8}$$

$$\hat{\sigma}_e^2 = \frac{1}{n-1}\sum_{i=1}^{n}(e(i)-\bar{e})^2 \tag{9}$$

Both of them estimated from a set of n plant data. Similar calculations can be used to define a measure of the predictability of controller outputs. For a given interval of time, if a controller is performing well, so that it does not exhibit a predictable behavior beyond the control horizon, the variance of the residuals will be similar to the one of the errors, $\sigma_r^2 \approx \sigma_e^2$ giving rise to a near zero value of the PI index. As the controller behavior is more predictable, the residuals will decrease in amplitude so that σ_r^2 will decreases relative to σ_e^2, which in turn increases PI. For a controller exhibiting an easily predictable behavior (e.g., output saturation) $\sigma_r^2 \ll \sigma_e^2$, and PI = 1.

It is possible to define confidence intervals for sample estimations of the predictability index, which allow using control charts to detect excursions associated to loop malfunctions. It is known that, assuming independence, the expressions

$$\frac{(n-1)\hat{\sigma}_r^2}{\sigma_r^2} \quad \text{and} \quad \frac{(n-1)\hat{\sigma}_e^2}{\sigma_e^2} \tag{10}$$

where $\hat{\sigma}$ means the estimate of σ, follow a χ^2 distribution with $n-1$ degrees of freedom, so that its ratio will follow an F distribution with $n-1$, $n-1$ degrees of freedom. The estimate of the confidence interval is then carried out according to the following equation:

$$P\left(\frac{\hat{\sigma}_r^2}{\hat{\sigma}_e^2}F_{0.5\alpha,n-1}^{-1} \leq \frac{\sigma_r^2}{\sigma_e^2} \leq \frac{\hat{\sigma}_r^2}{\hat{\sigma}_e^2}F_{0.5\alpha,n-1}\right) = 1-\alpha \tag{11}$$

where $F_{1-a/2,n-1}$ is the F statistic, α the level of confidence, n and σ_r are, respectively, the size of the subset of data (group) and the variance of the residuals.

3. Parameter tuning

It is necessary to provide some guidelines on how the three parameters, m, n and b involved in the calculation of PI should be selected. As all of them are expressed in terms of a number of sampling time, the selection of the sampling rate should be considered too.

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 and, on any case, bigger than the control horizon b. Typical values are around 30–40. Too high a value for f creates problems of overfitting while a value too low will lead to poor extrapolation capabilities in the model all of which will affect the sample estimation of the PI index. m will also affect the computing time.

Parameter n is the size of the data sample and it should take into account the trade off between index variance and data homogeneity. A very small size of the data set increases the size of the confidence interval of the PI index but presents more sensibility to local changes in the loop performance, while a too big data set 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 set point of the loop remains constant, 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. Values of n around 1000 data samples provide a good compromise.

Parameter b represents also the prediction horizon for the time series model and should be equal to the time beyond which a controller performing “well” should have rejected a disturbance. It has been analysed by different authors like Harris (1989), Desborough and Harris (1992), Stanfelj et al. (1993), Harris, Bourdreau, MacGregor (1996) and Ghraizi et al. (2004). In our work, we have observed that b should be equal to the expected closed loop settling time, including any possible delay, independently of the type of the loop so that so it can reflect the necessary prediction characteristics in a control loop. A too short value of b will give good predictions of the error, that is, high values of the PI index, even if the loop has a good response because the error cannot fully not be cancelled in such this short period of time. By the contrary, a value of b too high will make more difficult to identify poorly performing loops and to compute predictions properly. Typical values of b are around 15.

Regarding the sampling interval t_m, it is necessary to avoid an excessive or slow sampling. Common rules for sampling time selection can be applied, such as obtaining 15–20 samples in the closed loop settling time. Nevertheless, having in mind that the application is not control, but supervision, slightly bigger sampling times are recommended, shortening computing times in this way. Of course the choice depends on the loop dynamics. Values of 5 s are recommended for fast loops such as pressure or flow, while others such as temperature can operate with 1 min. As mentioned above, all other parameters are affected by the choice of t_m. 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), so that poor error predictions can be expected. In the same way, low sampling times will lead to large number of data n or prediction horizon b, increasing computation times.

4. Analysis tools

In order to help performing plant loop monitoring, a Matlab Toolbox was developed which implements several tests and auxiliary functions. The main screen of the toolbox, called ACCI, can be seen in Fig. 2. The slide buttons on the upper left part allows selecting a batch of data and fixing the parameters t_m, m, n, b to carry out the monitoring method. The menus on the bottom left part are used to perform loop analysis using indexes such as the proposed PI, as well as other methods. The graphs shown in the screen correspond the different signals and the results of the analysis.

The proposed methodology for the analysis of a batch of data of size n, first analyses the type of loop in order to identify its desired dynamic behaviour and set accordingly the value of its parameters. Then, it uses the above-mentioned PI index for screening if the loop is exhibiting the desired behavior or it is a candidate to further analysis. Once a loop shows a high PI value, several other tests can be applied to it in order to confirm the problem and getting additional insight about it. These tests are linked to the type of loops and its objectives, and include the trend of PI values (to discriminate a punctual problem from a persistent one), percentage of time a manipulated variable is saturated, as well as other tests based on spectral analysis, correlations, etc. If the loop requires retuning, the Harris index can provide a good measurement of the margin for improvement and the impulse response of the error can give directions on how to retune the loop. Next, we will refer briefly to these tests:

The first one is the Harris index, will indicate how far the actual output variance is from the one provided by a minimum variance controller. For its computation an estimate of the process delay is required, which can be an added difficulty. A value of the Harris index close to one means that no improvements are expected from re-tuning the controller, while a value near to cero means that there is a wide margin for improvement.

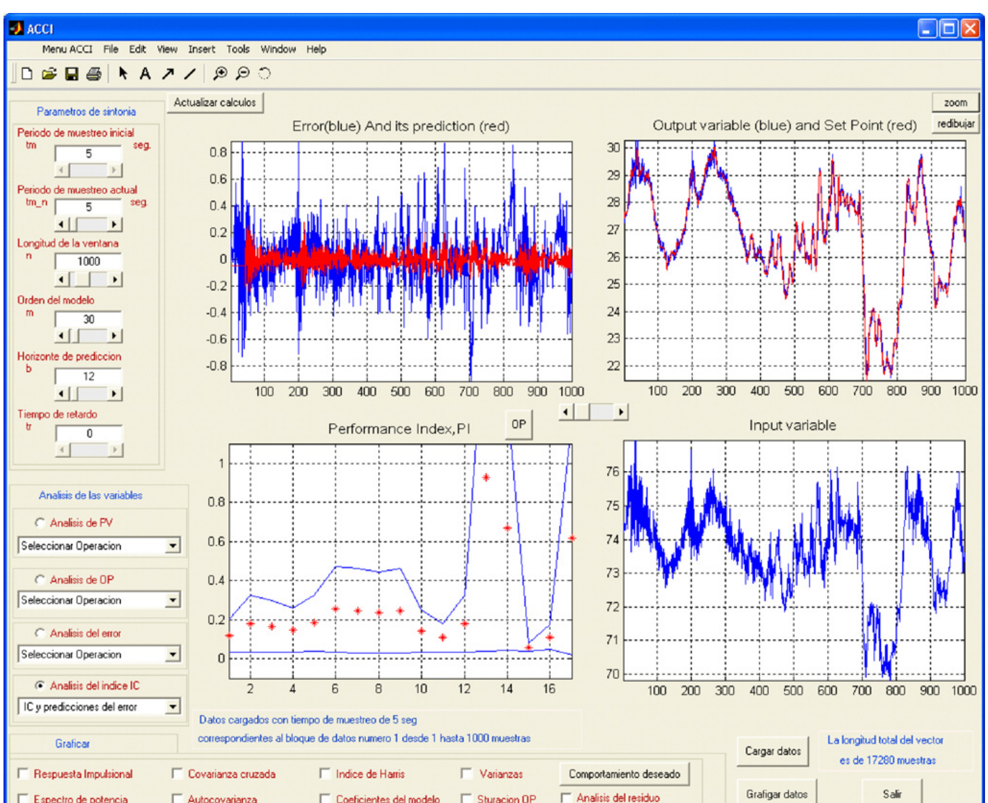

Fig. 2. Main screen of the monitoring Toolbox.

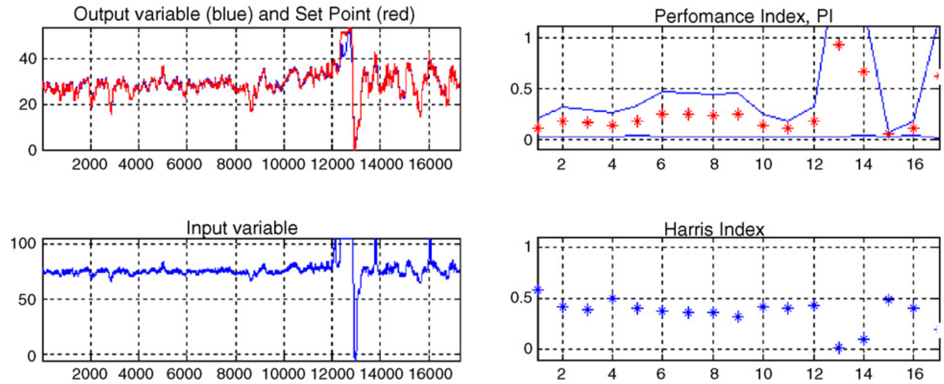

Fig. 3. Set point and controlled and manipulated variables, PI and Harris indexes.

Nevertheless, a value close to one does not means that the controller is performing well, but a bad behavior can come from other sources, for instance input signal saturation, not necessarily from bad tuning.

Spectral analysis of the error and control signals gives further information on the controller functioning. As it is known, it provides the frequency content of a signal. High values of the spectrum of the error signal at low frequencies mean that poor tracking of the set point takes place. In the same way unacceptable fast changes in the control signal will be reflected in significant values of the high frequency components of its spectrum. More interesting is to compare the same range of frequencies in the different signals, set point, controlled and manipulated variables and error signal to see which signals are powered or attenuated so that responsibilities on possible oscillations can be assigned to the controller or external disturbances. Also, similar frequency peaks in different loops can indicate the source of external disturbances or couplings between them.

Autocorrelation coefficients of the error for different values of the index k indicates how much the error at time $t+k$ depends on the error at time t. In full agreement with the ideas behind the PI index, after b samples, in a well functioning loop the error should be independent of the previous errors, so that the autocorrelation coefficient should drop to zero for $k>b$. In the same way, oscillations in the graph will indicate over-tuning, while a slow drop will indicate too loose a tuning (Biao, Shah, Badmus, & Vishnubhotla, 2000) (Shah, Patwardhan, & Huang, 2001).

Cross correlation can be used to check dependencies between several variables. In particular, ideally, in a well tuned loop the error should not depend after some time on the manipulated variable (but the manipulated variable would depend on the error). Also, prediction error residuals should not depend on the error, which could be check using its cross covariance.

Finally, the impulse response computed from an AR model of the error can be used to obtain dynamic characteristics of this signal, which provide and additional information about settling times, delays, oscillating behaviour, etc. and can be useful for deciding how to retune the loop if necessary. As before, oscillations in the graph will indicate over-tuning, while a slow decline of the coefficients will indicate too loose a tuning.

5. Industrial data analysis

In order to test the proposed methodology, several analysis were performed with the ACCI toolbox using data from a wide set of different loops taken from a petrochemical plant. In particular we will present here two cases from different types of loops.

5.1. A flow control loop

In Fig. 3 (left) one can observe 17 batches of 1000 data each of a flow loop operating as the internal loop of a cascade so that its set point is changing continuously. It behaves correctly most of the times, so that it is difficult to distinguish the controlled variable, named output variable or process variable (PV), from the set point (SP) in the upper left graph, being the manipulated variable, named input variable, control variable or Output to Process (OP), the one shown in the bottom left graph. Nevertheless, its performance deteriorates at the 13*th* batch (after data 12,000), because the new operating point has saturated the control signal (bottom left). The performance index PI is represented on the upper right graph. At the beginning, it does not have high values what indicates that the loop is performing well and the error has little predictability, as shown in the right hand side. But in the 13*th* batch of data, the manipulated variable saturates and the PI almost is equal to one. For the computation of the PI index, the parameters were chosen according to the nature of the loop: $t_m = 5$ s, $b = 12$, $m = 30$.

Fig. 4 shows this information in more detail. Referring to the upper graph, it corresponds to the controlled variable and its set point in a time interval around sample 9600, where the loop is working correctly, while the values of the error and its predictions for this range are shown in middle graph. Notice that the prediction error model fails to predict future errors as expected. On the contrary, as shown in the lower graph, which displays also the error and its predictions for a range belonging to the 13*th* batch where the controller does not work properly, the error can be predicted easily this time, which corresponds to a high PI. Once the process returns to its normal state, the error, and the index take small values again. In Fig. 3 bottom right, the Harris index is displayed for the shake of comparison:

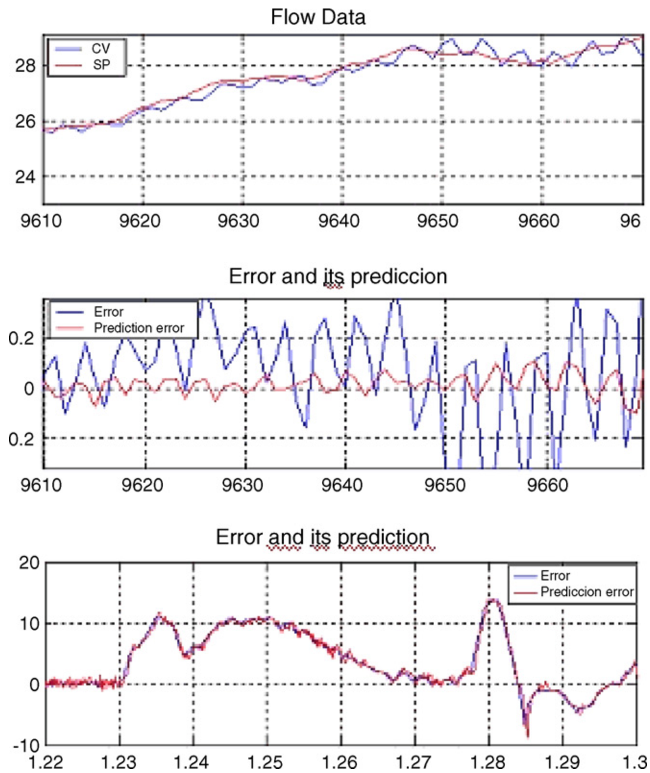

Fig. 4. Flow Data with their errors and PI.

the values around 0.4 from most of the samples did not give a clear indication of good behaviour, but provides information that a margin for improvement does exist in the controller. At the same time, it shows also the abnormal behaviour at the 13*th* batch, obviously not due to bad tuning.

From a different point of view, the power spectrum of the controlled variable (PV), manipulated variable (OP), set point (SP) and error signal, represented in Fig. 5 for data batches 1st and 13th displays the different behaviours of the loop: on the left graphs, the error (graph d) has no low frequency components, indicating good set point following. Also, the low frequency range of the controlled and manipulated variables (graphs a–c) allows to infer that changes in the output are due to set point changes and not to the behavior of the controller, but around the frequency 0.05 the action of the controller seems to be responsible of the output oscillations, notice that they do not appear in the right hand side graphs. On the contrary, in these graphs, the error (graph h) shows low frequency components, that are steady errors, and we can infer that the saturation of the controller is responsible of the bad behaviour because it suppresses the normal action of the controller.

Similar analysis can be performed using correlation functions as in Fig. 6 where the autocorrelation coefficient of the error is displayed for the previous two data batches, showing the contrast between them. On the left, the error, after b samples, does not depends on its previous values, but shows some oscilla-

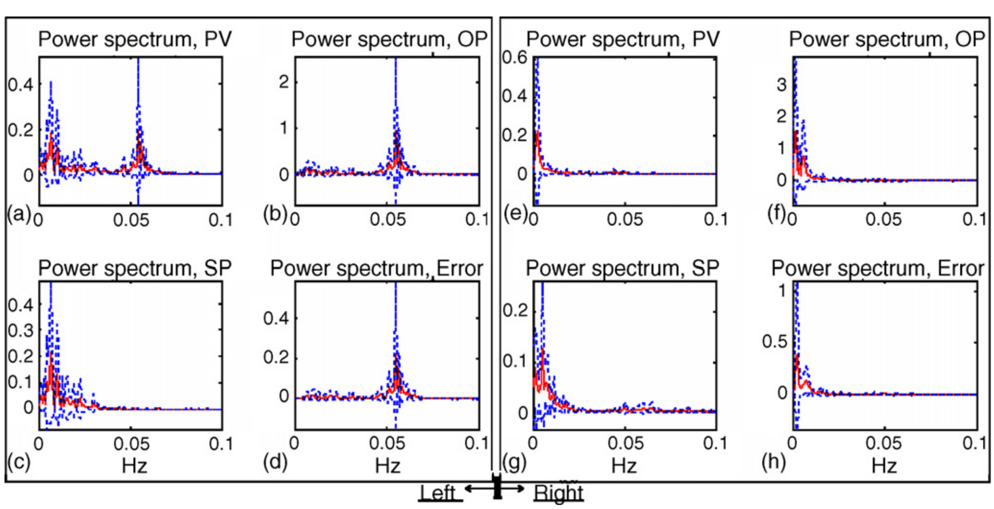

Fig. 5. Power spectrum of the PV, OP, SP and error in batches 1st and 13th.

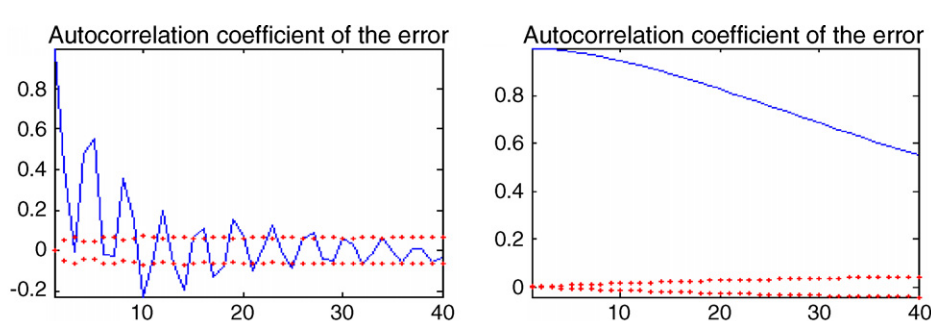

Fig. 6. Autocorrelation coefficient of the error.

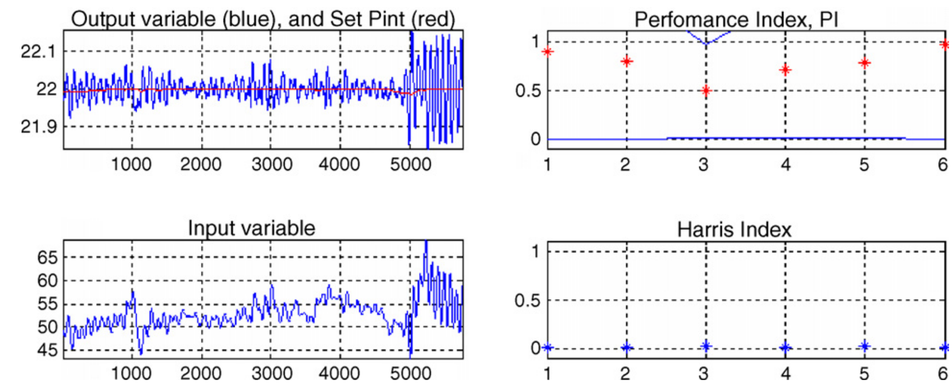

Fig. 7. Data set and PI and Harris indexes.

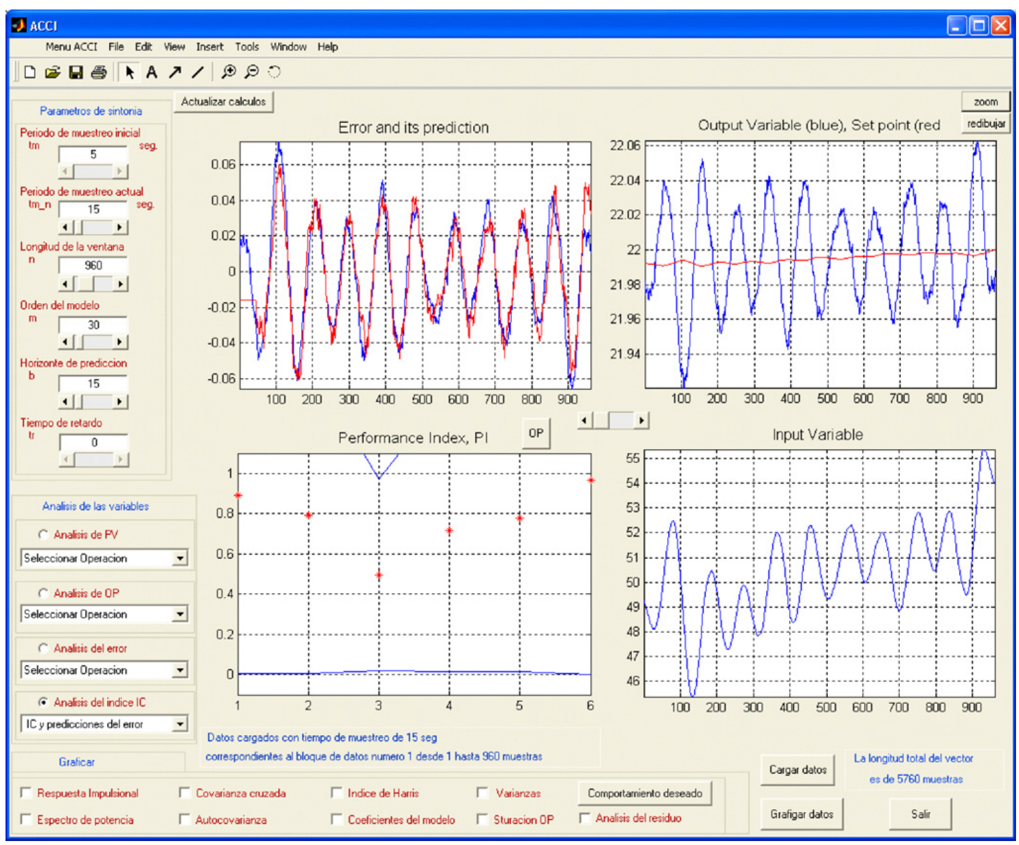

Fig. 8. A pressure control loop.

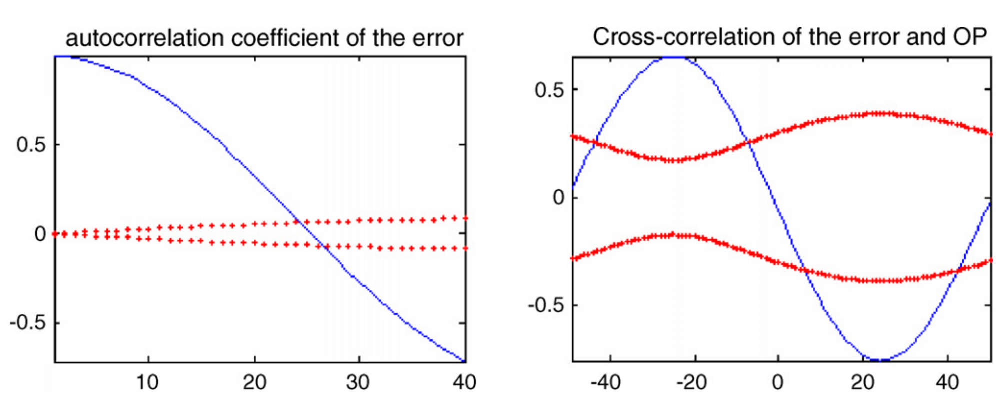

Fig. 9. Autocorrelation of the error and cross-correlation of the error and OP.

tory behaviour. On the right a clear dependence is shown, which corresponds to high values of the PI index.

5.2. Other case studies

Moving now to a different kind of control loops, we will show how the plain observation of the graphs trends is not sufficient to asses correctly the state of the loop.

First, a pressure loop also placed as the internal loop of a cascade, will be considered, but this time with very smooth movements of the set point. The whole set of $n = 960$ data, PV plus SP and OP can be seen on the left hand side of Fig. 7 with the PI and Harris indices on the right. In this case six batches of data with $t_m = 15$ s, $b = 12$, $m = 30$, were used. The PI index indicates a bad behaviour, with a small improvement in batch 3, even if the absolute value of the error is small, which is corroborated by the oscillatory behaviour after sample 5000. The Harris index is in accordance with this diagnosis, indicating a performance far away from the minimum variance one and, so, a wide range for improvement does exist.

Fig. 8 shows the Acci Toolbox screen with a zoom over the first batch of data. The set point and controlled variable are displayed on the upper right and the manipulated variable in the bottom right, with the error and its predictions on the upper left. It is worth noting the good predictions of the error, as well as the oscillations of the output around the set point originated by a too active control which explains the high value of the PI.

Fig. 9 provides information from the point of view of the correlation functions. On the left, the autocorrelation coefficient

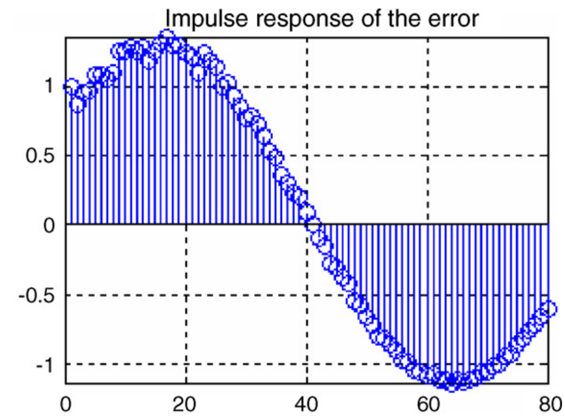

Fig. 10. Impulse response of the error.

of the error shows a big dependence of the error on its past values for delays bigger than b, confirming the bad performance of the loop. On the right, the error also shows a noticeable dependence of the error with the manipulated variable, which should not appear in a well performing loop, where the errors, after some time, should be the result of the stochastic disturbances entering the loop.

From the model error used to compute the Harris index, it is possible to obtain the impulse response of the error. This is displayed in Fig. 10, and shows a long settling time as well as oscillations due to overtuning, probably due an integral time too short, in line with the previous analysis.

Finally, we will present other pressure control loop. In the left part of Fig. 11, we can observe some batches of data and their

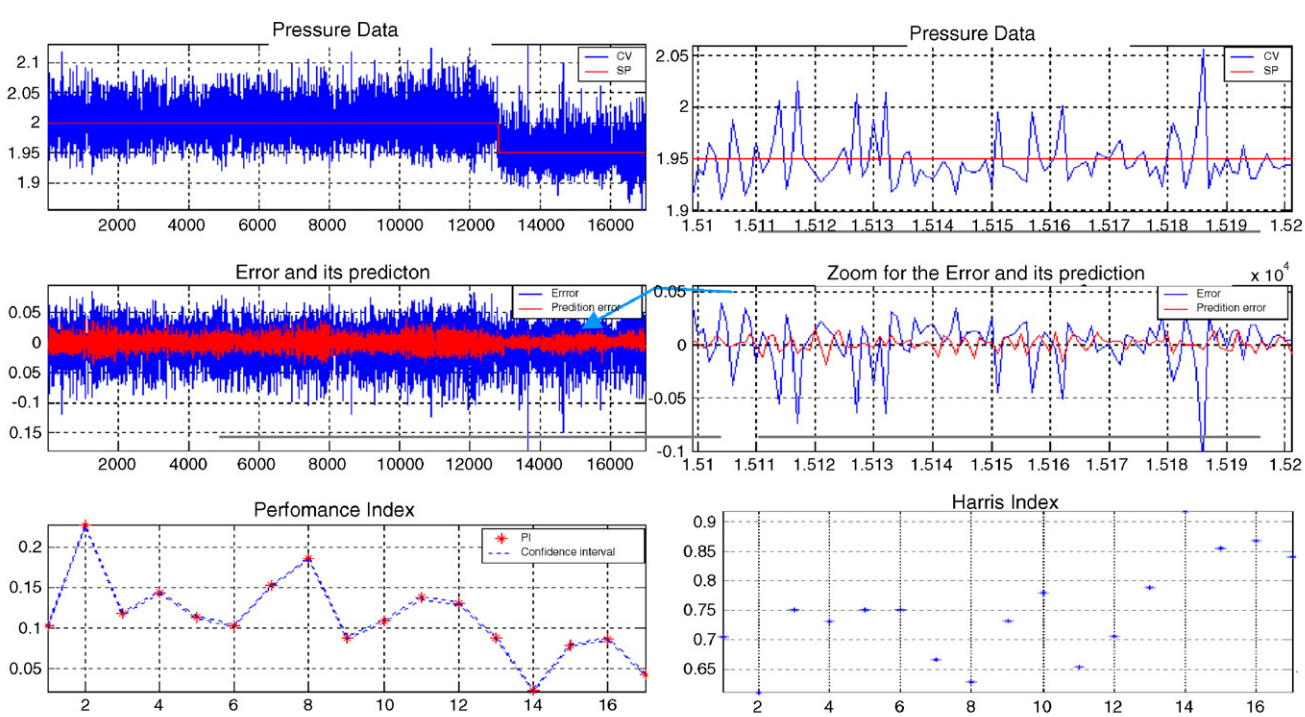

Fig. 11. Pressure data with their errors and PI.

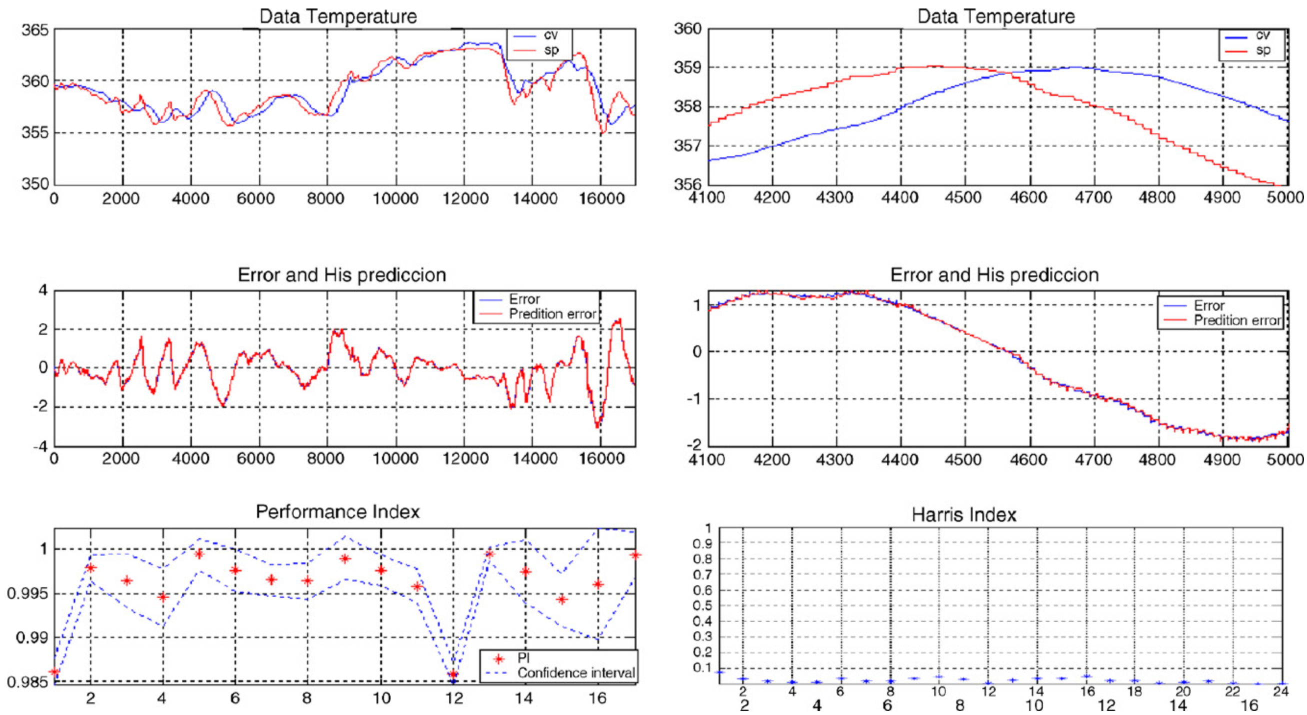

Fig. 12. Temperature data with their errors and PI.

analyses, while in the right part of the graph 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 middle of the graph. Finally, in the lower one, the values of the performance indices PI and Harris are displayed. Even if the pressure data on the left could suggest a too strong tuning and an oscillatory loop, the low value of the PI index indicate good performance, which is supported by the Harris index, which indicates small margin for improvement, as well as by the zoom of the PV and SP on the upper right graph and the prediction errors in the middle right graph.

The parameters were adjusted to the nature of the loop. In this way, we choose $t_m = 5$ s, $b = 12$ (number of samples), $m = 30$. For level ones $t_m = 60$ s, $b = 30$, $m = 30$, (in this case $n = 720$), for pressure $t_m = 5$ s, $b = 5$, $m = 30$, and for temperature $t_m = 60$ s, $b = 15$, $m = 30$.

Finally, Fig. 12 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 as expected. In addition, the Harris index is consistent with this result.

6. Conclusions

This paper presents results showing a promising way of analysing the performance of industrial controllers using a time series of the control loop 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 several industrial plant data sets showing that it can be a good tool for detecting bad loop behaviour.

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