

# CONTROL PERFORMANCE MONITORING: A DATA-DRIVEN APPROACH

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## Abstract

The paper aims at showing how process data and basic process understanding can be used to properly address, prioritize and solve some of the most challenging problems which have heavy impact on maintenance and control engineers' everyday operation.

While monitoring single control loop performances is a valuable procedure to quickly and efficiently spot suddenly arising faults and/or slowly developing degradation, it still misses the crucial feature to recognize, group and analyze similar patterns which might be the signature of a single major cause simultaneously affecting multiple loops.

The proposed methodology combines the bottom-up approach of single loop performance assessment with an innovative top-down procedure for plant-wide disturbance analysis. The combination of the two techniques, able to maximize plant asset utilization without requiring major investments, is achieved through the use of a specific, multi-technology software package, which is briefly introduced in the second section. The last section is devoted to a case study where the methodology has been applied to an actual petrochemical process.

## 1. INTRODUCTION

Control loop performance assessment is becoming increasingly popular at industrial process plants. This is due to the simultaneous presence of two stimulating factors:

1. An increased awareness of the impact that poorly performing loops have on plant profitability;
2. The vigorous advance in available technologies, mainly as result of the breaking ground research of Harris [1], who defined a metric, able to objectively measure control loop performance<sup>1</sup>

However, monitoring and restoring the operation of the complete set of controllers in a plant, is a pretty onerous business, regarding personnel commitment (and related cost). More specifically, such a requirement clashes both with the considerable reduction in staff experienced on the vast majority of production sites and with the shortage of people truly skilled in the field of control system tuning. The lower availability of time and resources inevitably leads to neglecting major aspects of process management, which nevertheless have an impact on the global economical bill. Part of this category is the maintenance requirements of regulating instruments and parts. Persistent temperature fluctuations caused by a valve in hysteresis or a badly tuned controller will have to be offset by the continuous use

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<sup>1</sup> In further works by Desborough and Harris ([2], [3]) the ratio of the best achievable variance to the actual variance of the controlled variable was identified as a fundamental performance index

of hot and/or cold fluids, the cost of which will accumulate in an insidious but not negligible way on the energy bill and consequently on variable production costs [4].

## 2. PROCESS DISTURBANCES

Process disturbances are unavoidable in the process industry. Due to physical and electrical coupling, these disturbances are usually distributed around the plant. This behavior increases in modern plants where recycle and tight integration, in combination with running the process closer to physical limits.

Disturbances are represented by variables that fluctuate and cause the process output of control loops to move from the desired operating value (setpoint). A disturbance could be a change in flow, temperature of the surroundings, pressure etc. Disturbances may be minimal or catastrophic, and cause production losses or, in serious cases, endanger human life.

Control practice is very much about diverting variability away from production-critical to non-critical variables. Typical examples of non-critical process areas are buffer tanks and plant inventories in general. Using storage tanks and process utilities as “process dampers” has been the main way to contain and reduce the effect of disturbances for many years. Unfortunately, modern industrial process plants have extensively and successfully exploited heat integration, recycles and recirculation streams to maximize energy efficiency and have drastically removed inventories because rightly identified as non-profitable capital and investment.

Disturbances can arise from problems related to several areas. A common classification allows identifying at least 5 different causes:

1. Process conditions
2. Constraint problem
3. Tuning problem
4. Excessive Process and measurement noise
5. Actuator problem, often valves

Although disturbances can be classified in different ways [5], in this paper we will rely on their trend signature to make a distinction between oscillating and non-oscillating ones.

### **Oscillating Disturbances**

Oscillations are the most prominent symptoms of deteriorated controller or process performance [6]. Several surveys have reported that an average of 30% of all loops may be oscillating in typical process plants, a value which seems almost constant through the major process industrial sectors (pulp & paper, utilities, refineries, etc.). The fact that some loops oscillate is often known to the operators. However, what is not known is the cause, and then which are the appropriate measures to be applied. As a result, oscillating loops tend to be accepted as an unavoidable problem and so neglected or be put in manual mode.

Oscillations origin can be either endogenous (i.e. coming from within the control loop) or exogenous, having their causes outside the control loop envelope. Among this latter are external variations in upstream units affecting feedrate or feed composition or temperatures, problems related to loop coupling, etc. Figure 1 shows the more common causes for endogenous causes.

Focusing on reducing variability on a univariate basis (SISO) can be misleading or even counterproductive, because of the risk of wasting resources in analyzing and modifying the operation of loops which are oscillating because of exogenous causes.

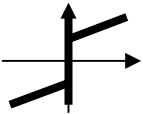
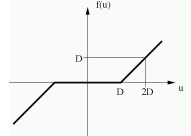
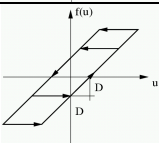
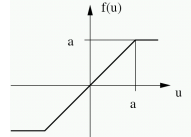
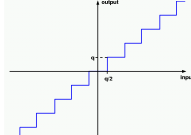
Cause	What is it?	Graphical Representation of static nonlinearity
<b>Stiction</b>	Property of an element such that its smooth movement in response to a varying input is preceded by a static part followed by a sudden jump.	
<b>Dead-band</b>	The range through which the input may be varied without initiating a response	
<b>Backlash</b>	The play or loose motion in an instrument due to the clearance existing between mechanically contacting parts. Lost motion after reversing direction.	
<b>Saturation</b>	The controller requires more action than the actuator is able to deliver. May lead to wind-up related problems if not taken into account.	
<b>Quantization</b>	The process of transforming a continuous signal into one of finite steps or levels, as in an A/D converter.	

Figure 1

### Non-Oscillating Disturbances

Non-oscillating disturbances are characterized by the irregular presence of alterations in the normal time trend, which can appear as spikes or valleys, but can also sometimes look somehow similar to the time trends of oscillating disturbance. Common causes for non-oscillating disturbances can be often related to constraints or process problems and it is not uncommon to have the overlapping of both oscillating and non-oscillating effects. However, persistent non-oscillatory disturbances are generally characterized by their spectra, and this makes the frequency domain a potential candidate for non-oscillating disturbances detection.

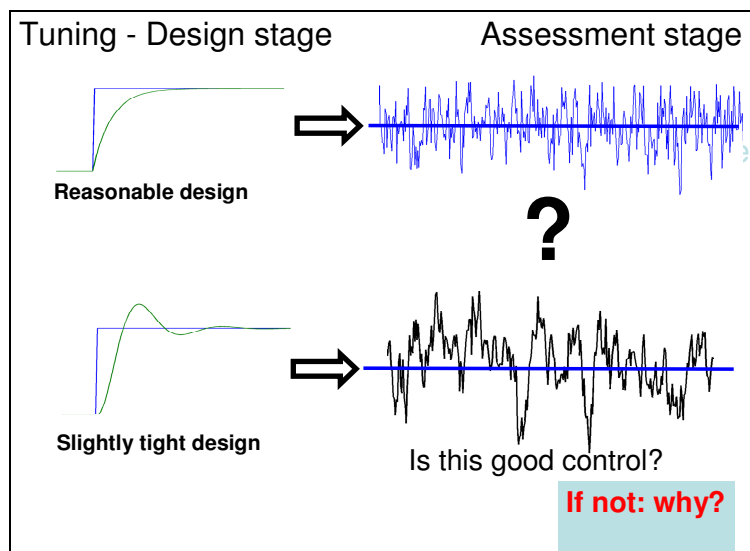
### 3. DESIGNING AN EFFECTIVE LOOP PERFORMANCE MONITORING TOOLKIT

The operational and logistical constraints seen in §1, dictates that, in order to be actually accepted by the industrial community, Control Loop Condition Monitoring (CLCM) must be inherently automatic, passive and non-invasive. The major requirement is that, only normal process data must be used for analysis: by passively listening to the process, a diagnosis has to be established.

This is far from being a simple task. In the design phase, the designer usually creates a controller that satisfies some given performance specifications. The situation is different for CLCM where no ad-hoc experiment is practically possible: Figure 2 compares two different tuning sets for the same loop. While it is easy to tell which is the best at the design stage, the same is not so easy just looking at historical trends.

Additionally to be effective, CLCM cannot be an infrequent task. Disturbances may appear in very different format and time scales, they can be periodic or irregular or even be related to some given shifts or operative configuration: loops can feature problems only under given conditions (transitions, low loads, etc.) which can verify only a few hours a day so it is important that monitoring and assessment is based on data collected on a continuous or semi-continuous base.

A further level of complexity comes from the nature and operation of modern process plants. Modern industrial process plants utilize recycle streams and heat integration in the drive towards efficiency. This mass and energy integration complicates process control because variations can propagate through the plant in complex ways, often turning a single source of variation into a widely distributed disturbance [7]. A propagated disturbance may affect key process variables such as feed, product and recycle flows, column temperature and product composition. It is therefore essential to determine if the, say, persisting oscillations of a given loop are due to exogenous or endogenous causes, so to properly direct maintenance efforts and resources.



**Figure 2 - Performance Assessment: Tuning vs. Auditing**

Combining loop auditing (bottom-up) and plant-wide disturbance analysis is crucial. While only a careful assessment of how the single loop is behaving can provide the needed level of details useful to identify and fix locally the problem, a comprehensive, global look is also needed. Methodologies are needed to analyze where the major variability comes from and where it can be increased.

Summarizing an effective and practical CLCM industrial tool should satisfy the following five major requirements:

1. Auditing procedures must be non-invasive;
2. Auditing should not be an off-line infrequent procedure;
3. Auditing results must be saved and made available to the user when needed
4. When abnormal conditions are detected, further detailed analysis should be possible both on a local and a global approach

#### **4. LOOP PERFORMANCE MANAGER DESCRIPTION**

Based on the requirements described in the previous paragraph, a new software package has been realized and made available to the industrial community. Optimize<sup>IT</sup> Loop

Performance Manager (since now indicated with the acronym LPM) is a process control maintenance tool for control engineers, instrument technicians and maintenance personnel, which has been designed to provide a bridge between the technologies developed in the academia and the existing, relevant needs in the industrial world [8]. Its mission is to ensure that control loops, and – consequently – the whole production process, operate at peak performance. The package has been structured in a modular way consisting of three software applications:

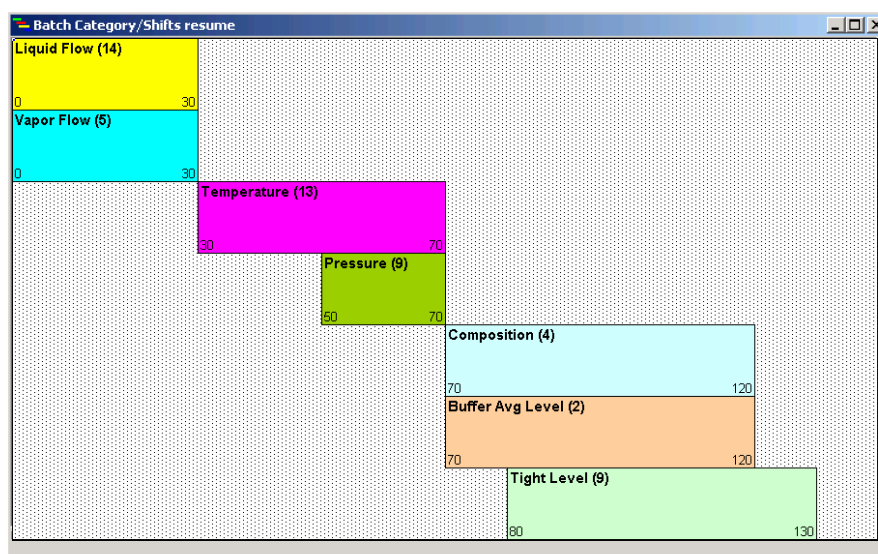
1. a tuning component used to improve control loop performance,
2. an auditing component used to monitor loop performance
3. an additional software component able to analyze simultaneously multiple loops detecting common behaviors and identifying possible root causes, thanks to innovative algorithms. For its capability to correlate causes and effects all over the whole process topology, the last methodology goes under the name of Plant-wide Disturbance Analysis (PDA).

While addressing the reader to [9] for more details on the objective, model-based tuning procedure available in LPM, in the following some hints on how the loop auditing and the plant-wide disturbance analysis are executed in LPM are given.

### Loop Auditing Description

The Loop Auditing module is used to monitor control loops to insure that their performances do not degrade. It can detect loop problems early and provide diagnostic suggestions to solve them before more severe troubles may jeopardize profitable operation.

An embedded, configurable scheduler allows LPM to collect live data over a standard OPC connection at multiple, pre-defined times during each day. For each loop 4 signals are collected: (Process Variable, Setpoint, Control Output and Controller Mode). In § 3 it has been stressed that CLCM must be a continuous activity. On the other side trying to monitor – say – 200 loops continuously and simultaneously could result in overloading the DCS acquisition channels. The conflict has been solved by introducing the “loop category batch data acquisition” concept. Dividing the loops in categories allows scheduling the data collections in multiple periods (see Figure 3) which can be repeated in shifts (batches) over the single day. This seems a good trade-off between the opposite requirements of monitoring the loops over a significant portion of live data and not overloading the acquisition channel.



**Figure 3**

After completing data collection, the program calculates a group of 50 different performance indices and stores these in the auditing database. Three of them (% of time in auto mode, % of time in saturation, absolute mean error) are calculated in continuous mode (with sampling every minute for all loop types) as a statistic reference, while the remaining 47 are processed in batches (i.e. at the end of each data collection shift) and contain all the most significant details. With the addition of a proper knowledge base the indices are on their turn, used to compute diagnostic hypothesis (Figure 4).

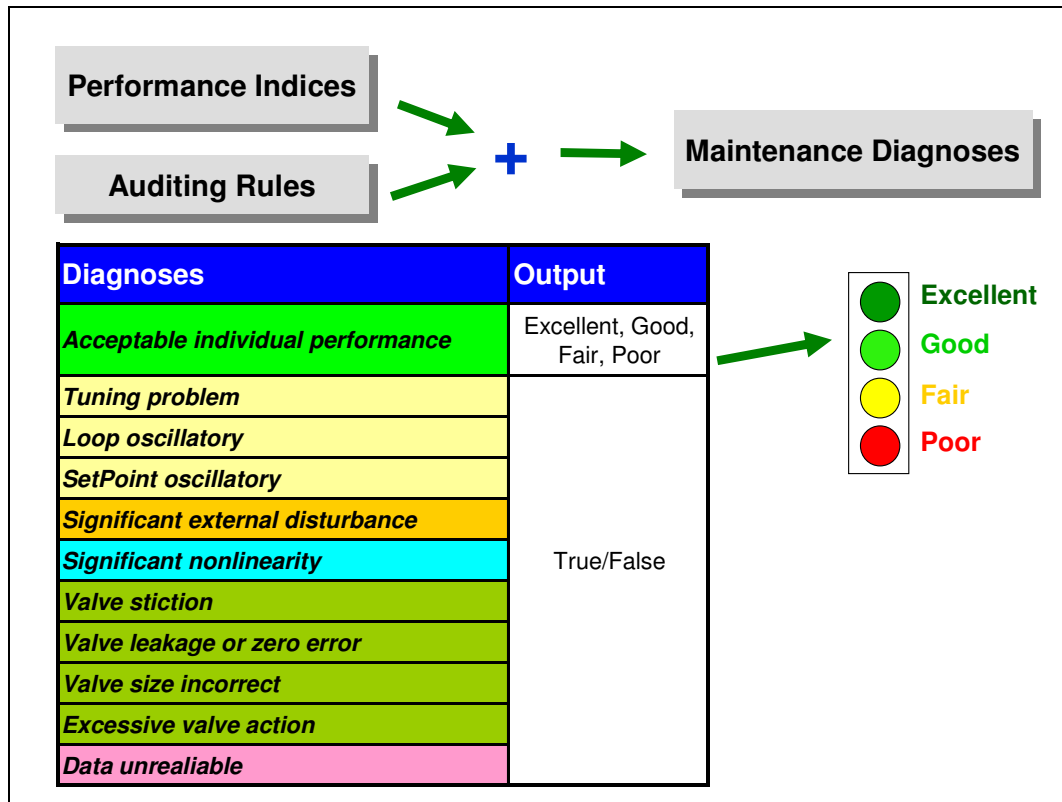
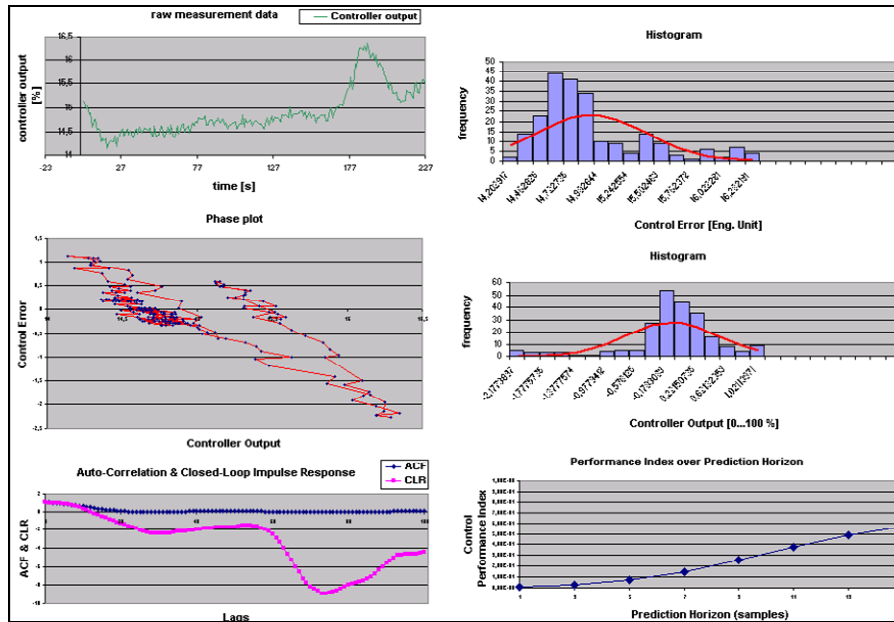


Figure 4

LPM loop auditing not only indicates the best and worst performing loops in a plant section, but it also gives detailed analyses on how to remove identified problems.

The reporting function generates weekly and monthly report files in Microsoft Excel format that can be configured by the user. These contain information of a quantitative (the values of the calculated indices) and qualitative nature. The latter relate to diagnostic hypotheses processed on the basis of tests performed on the performance indices themselves. Examples of the provided diagnostic indices are reported in Figure 4). Sometimes it is possible to meet loops whose operation is actually complex and worth of more in depth investigation. In this case the user can mark the troublesome loops with a special flag which enables the creation of the so-called “detailed report”. An example of it is given in

Figure 5, where it is possible to appreciate the wealthy amount of information (both in time and frequency domain) provided.



**Figure 5 – Detailed Report**

The auditing procedure placed at disposal by LPM is distinguished by a number of very interesting characteristics:

- Calculation of numerous indices: literature often emphasises how the detection of faults and malfunctions during control is only possible by the combined analysis of diverse indices [10];
- Conversion into a small number of clear diagnostic suggestions, the values of numerous indices often relating to statistic-operational aspects that are not uninteresting;
- Strengthening of the diagnostic results by explicit overall categorising of loops. Apart from anything else, this permits defining a hierarchy among the loops requiring attention, on the basis of their actual requirements;
- Continuity as regards monitoring on diverse time horizons. Entrusting to random samplings can easily completely falsify the evaluation of the state of health of loops operating, for instance, in very variable conditions.

An additional utility allows monitoring the background applications providing information and diagnostics on the operation of the LPM Auditing routines, while an LPM Web Client permits accessing and even configuring LPM reports and tuning logs from remote locations. The obvious advantage is that the maintenance engineer can monitor system health directly from his desk.

### **PDA description**

As pointed out above, in modern production facilities where energy and material recycles contribute to the propagation of disturbances throughout the whole plant, an abnormal condition in a single control loop can affect many others with the final outcome of auditing reports flooded by poor results. The localization of the root cause can be really troublesome requiring such a high level of effort and commitment that it may remain unsolved for days or even weeks, during which production lingers at sub-optimal or even degraded levels.

The Plant-wide Disturbance Analysis (PDA) module in Loop Performance Manager software enables the process or maintenance engineer to quickly analyze plant-wide problems in his facility, identifying unwanted plant behavior and its root causes so that operational and maintenance efforts are directed effectively.

A plant-wide approach means the behavior of the whole plant is observed using process measurements from routine operation. A simple offline data batch with some hundred samples is sufficient to allow the world-class algorithms included in the software to:

- Detect the presence of one or more periodic oscillations indicated by a regular pattern in the measurements.
- Detect non-periodic disturbances and plant upsets.
- Determine the location of the various oscillations/disturbances in the plant and their most likely root causes.

To achieve the above goals, PDA exploits cutting-edge, latest generation algorithms developed jointly by Imperial College London/University College London's Center for Process Systems Engineering and ABB Research Centers ([11], [12], [13] and [14]). Although based on very sophisticated technology, PDA is structured in such a way that interactions is quite simple and straightforward thanks to a specially designed wizard which filters out all the mathematical complexity without sacrificing accuracy and effectiveness.

PDA is designed to be run off-line on a collection of records each one containing up to several hundreds of process variables. As outlined in Figure 6, it is based on 6 main steps:

1. Data Import
2. Data Pre-processing
3. Data Filtering
4. Cluster Selection
5. Root-cause Analysis
6. Report Generation

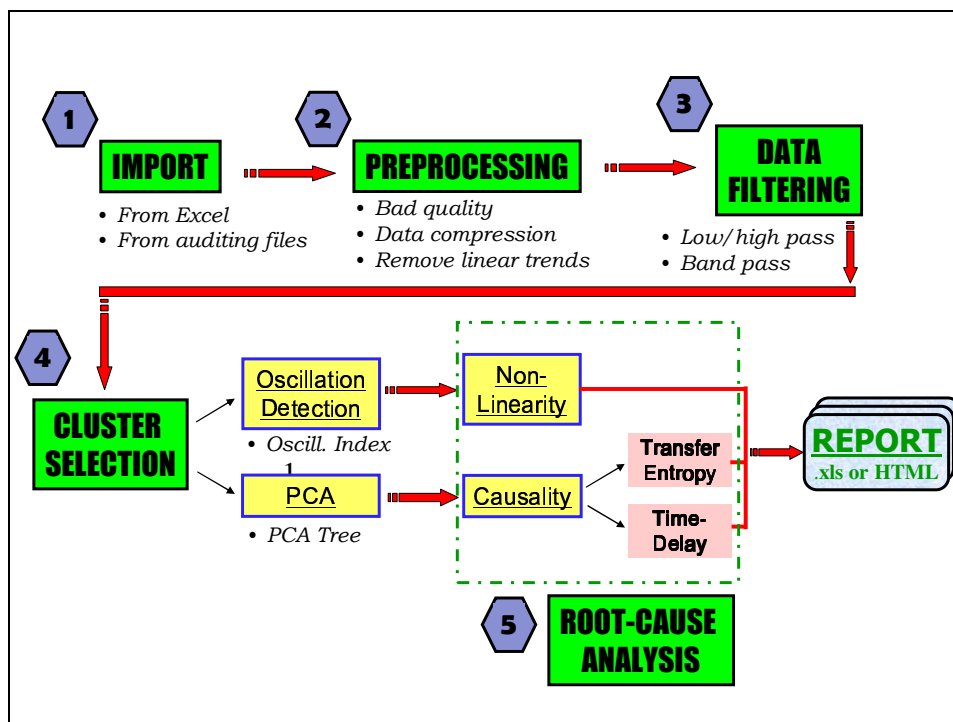


Figure 6

Special interest is in step 4 and 5, where different methods and algorithms are exploited to classify oscillating and non-oscillating disturbances (following the taxonomy introduced in §2) and then to identify the related root cause. More details about these steps are given in the next section.

## **Oscillating Loops**

### **a) Oscillation Detection**

The oscillation detection tool implemented in the application is based on the techniques described in [11] which determine the regularity of the zero crossings of the autocovariance functions (ACF). The ACF of an oscillating signal is itself oscillatory with the same period as the oscillation in the time trend. The benefit the ACF for oscillation detection is that the impact of noise is reduced because white noise has an ACF that is theoretically zero for lags greater than zero. The pattern of zero crossings of the ACF therefore reveals the presence of an oscillation more clearly than the zero crossings of the time trend.

The zero crossings of a periodic oscillation should be regularly spaced and therefore the intervals between the zero crossings are all about the same. Since there are two zero crossings per cycle of oscillation the period of oscillation  $T_p$  is twice the mean value of the intervals. If the time trend is not oscillating regularly then the zero crossings of the ACF happen at random times, and the intervals between the zero crossings are not all the same. The standard deviation of the intervals gives an indication of the regularity of the oscillation. An oscillation is considered to be regular if the standard deviation of the period is less than one third of the mean value,  $T_p$ .

A clustering algorithm then determines which tags belong to the same group of oscillations. The details of the algorithm are in [11].

### **b) Non-linearity Diagnosis**

A common cause of oscillation is the presence of non-linearity such as a valve dead-band which sets up a limit cycle in a control loop. Non-linearity is strongest close to the root cause because the mechanical low-pass filtering effects of process plant remove non-linearity as the disturbance propagates. The basis of the diagnostic method is an index for non-linearity<sup>2</sup> that grows stronger closer to the source [13].

The non-linearity test determines whether a time series could plausibly be the output of a linear system driven by Gaussian white noise, or whether its properties can only be explained as the output of non-linearity.

In PDA all the calculations and algorithm parameters such as the dimension of the phase space are selected automatically based upon the period of oscillation. The user has the opportunity to select the number of surrogates that will be used to make the reference distribution and also choose how much of the data set to analyze. About 12 to 15 cycles of oscillation are enough to assess the degree of non-linearity.

## **Non-Oscillating Loops**

Given the complexity of the task (and sometimes possible ambiguities in the results), LPM provides two causality analysis methods which should be jointly assessed.

### **a) Spectral PCA**

Spectral principal component analysis is used for the analysis of the spectral signatures of disturbed measurements [12]. Spectral PCA is insensitive to the time delays

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<sup>2</sup> Non-linearity may be inferred from the presence of a periodic but non-sinusoidal limit cycle having harmonics at multiples of the fundamental frequency.

caused by plant dynamics and thus offers benefits over time-domain PCA. In spectral PCA, signals having the same frequency components appear as clusters regardless of their time delays. If  $\mathbf{X}$  is a matrix with the spectra of the process measurements as its rows, PCA approximates  $\mathbf{X}$  as a sum over basis functions  $\mathbf{w}_i$ :

$$\mathbf{X} = \sum_i \mathbf{t}_i \cdot \mathbf{w}_i + \mathbf{E}$$

Row vectors  $\mathbf{w}_i$  are spectrum-like functions. Column vectors  $\mathbf{t}_i$  are known as scores.  $\mathbf{E}$  is the variation in  $\mathbf{X}$  that is unaccounted for by the model. Spectral PCA maps each spectrum in  $\mathbf{X}$  to a single point. Groups of similar spectra can thus be detected because their coordinates in the score plot are similar.

### b) Causality Analysis

#### *i) Transfer entropy*

This statistical method evaluates the predictability of a variable from another variable based on probability density functions (PDF). The causality measure used to quantify the extent of the influence of a variable X on another variable Y is derived from transfer entropy  $T(X|Y)$ . The latter is itself derived from entropy which is a measure of uncertainty of a random variable summing a weighed logarithm of the PDF [15]. Transfer entropy is calculated from joint PDF of two variables which provides a measure for the dependencies between those variables. The causality measure  $t(X,Y)$  is derived by comparing the influence of X on Y with the influence of Y on X:

$$t(X,Y) = T(X|Y) - T(Y|X)$$

Thus, large values of  $t(X,Y)$  indicate a strong causality from X to Y.

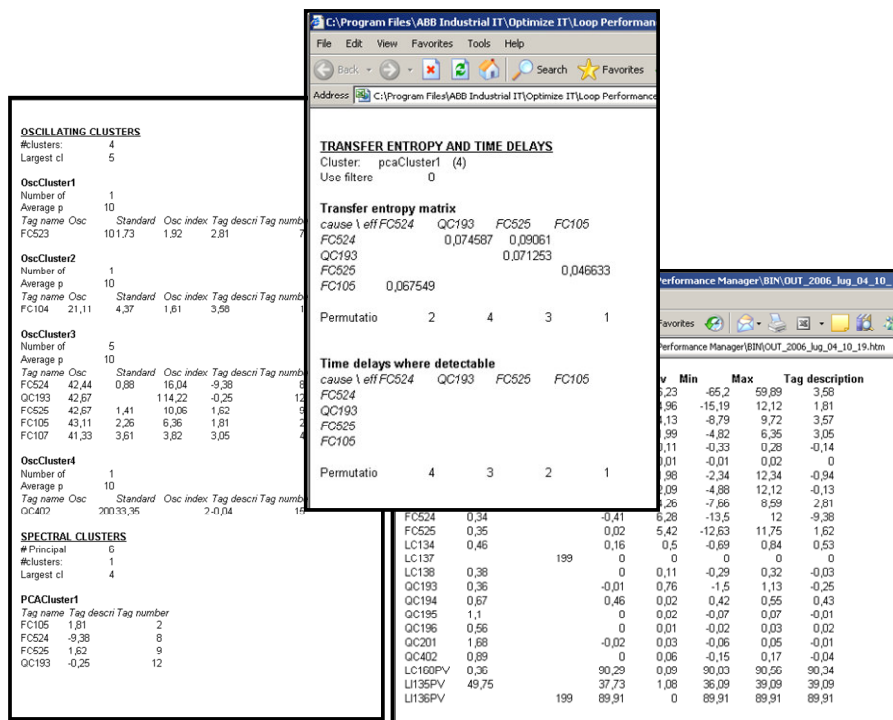
#### *ii) Time delay analysis:*

The second method implemented in PDA for causality analysis is based on the Cross-Correlation Function (CCF). It determines causal relationships between measurements from the presence of time delay between them. The underlying principle of the method is that when the disturbance propagates through the plant the disturbance can often be observed at a number of process variables with a time lag. The knowledge of the exact time lag hints towards the root cause by arguing that the variable closer to the root cause will show the disturbance before a variable further away. The CCF measures the similarity between signals at different time points and is therefore adequate to measure the time lag. The CCF of two time series delayed in time has a maximum value at the time delay that is equal to the dead time.

The difference between the two methods for causality analysis is that the Causality matrix based on transfer entropy is more sensitive. It can find a causal relationship even when there is no measurable time delay because it detects other effects such as smoothing of the time trend that occur as a disturbance propagates from its source.

### PDA Report

All the information related to the PDA analysis can finally be saved in pre-defined reports (available both in .xls and HTML formats) so to maintain a kind of historical collection of all the problems identified and solved at the plant. In several tabs each report includes all the statistics and the results about the related investigation



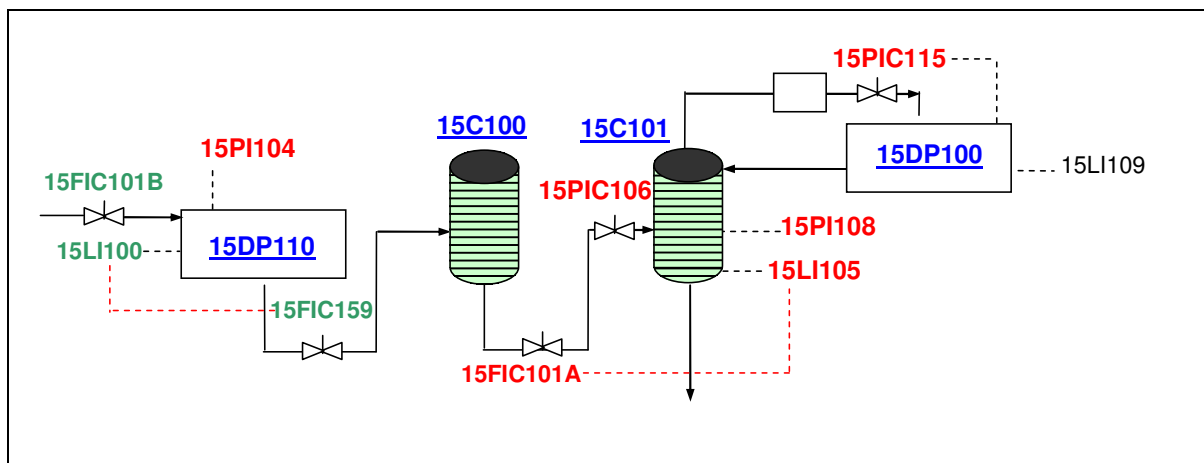


Figure 8

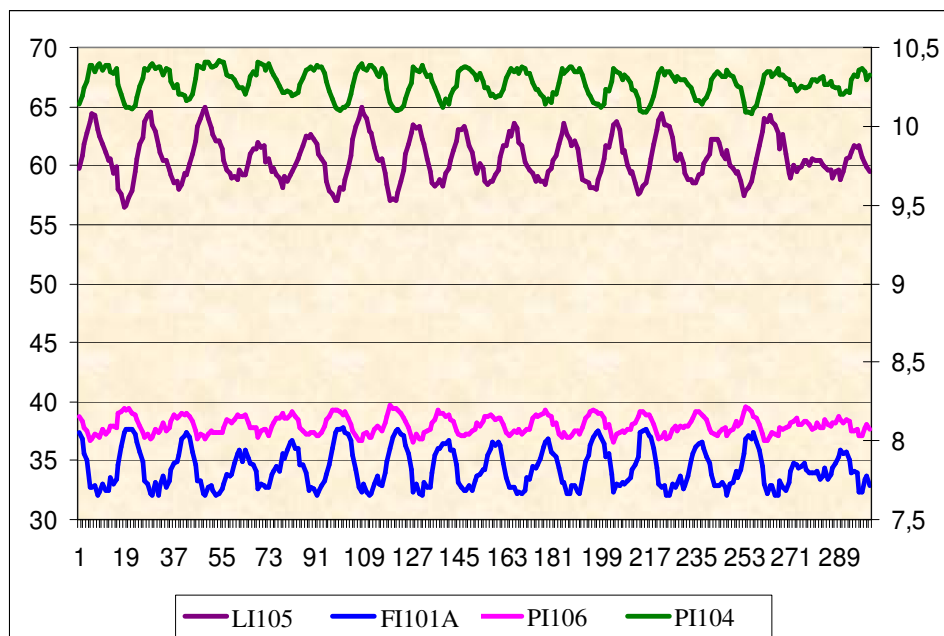
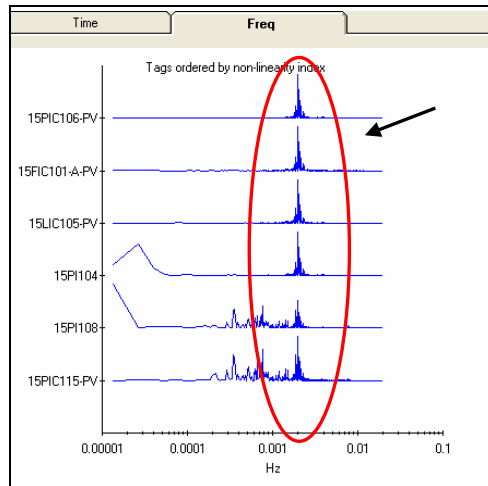


Figure 9

Cluster #3 is driven by pressure and flowrate upstream Column C101 which affects bottom level 15LIC105 and on column pressure measurements 15PI104, 15PI108 e 15PIC115. Cluster #7 is referred to Column C100 and shows the links between 15FIC101B with level 15LI100 and flowrate 15FI159, which are clearly interacting. These interactions are evident looking at the variable time trends as shown in Figure 9, where a zoom on a small time interval reveals the presence of a common disturbance almost constant in amplitude and frequency.

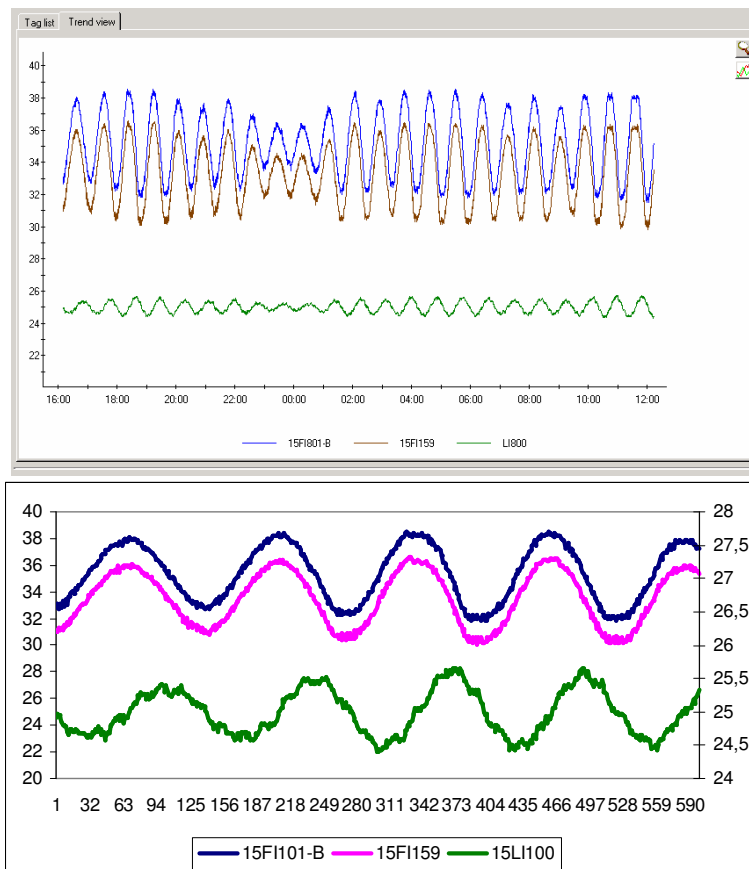
Moving to the Cluster Frequency Plot the analysis results, become self-evident and almost impossible to miss, as shown in Figure 10



**Figure 10**

It should be noted that just picking-up the presence of the cluster (out of over 500 variables and related time trends!) and detecting the presence of the disturbance may require days or weeks of analysis to an expert engineer while it is just a matter of minutes with a toolkit like PDA.

A similar analysis can be done on Cluster #7: Figure 11 shows the time trends of the 3 variables together with an enlargement to better catch dynamic details:



**Figure 11**

The tool provides also information which is useful to justify the algorithm results and to provide further process understanding. Figure 12 shows the Oscillation Index Charts for the two clusters under investigation. The Oscillation Index Chart plots the Oscillation Period (in seconds) against the Oscillation Index<sup>3</sup> for each loop, with the vertical bar of the cross marker proportional to the standard deviation of the period. The shorter the bar the more stable and persistent is the oscillation. This visualization tool provides concise and useful insight about the main dynamic features of the related process variables. It is clear for example why the algorithm has identified as a single group the collection of the seven loops belonging to Cluster #3: their oscillating period is very similar (see Figure 12). The same holds true for Cluster #7, even if we can notice that the loops belonging to it have a much higher oscillation period (around 55 minutes against the about 8 minutes of cluster 3).

OscCluster3			OscCluster7		
Number of tags:	6		Number of tags:	3	
Average period:	486,1083		Average period:	3275,927	
Tag name	Osc. Period	Standard Dev.	Tag name	Osc. Period	Standard Dev.
15LIC105-PV	500	n.a.	15LI100	3277,78	26,35
15PIC106-PV	494,44	16,67	15FI159	3272,22	26,35
15FIC101-A-PV	494,44	16,67	15FI101-B	3277,78	36,32
15PI104	483,33	103,08			
15PIC115-PV	483,33	127,48			
15PI108	461,11	145,3			

Table 1

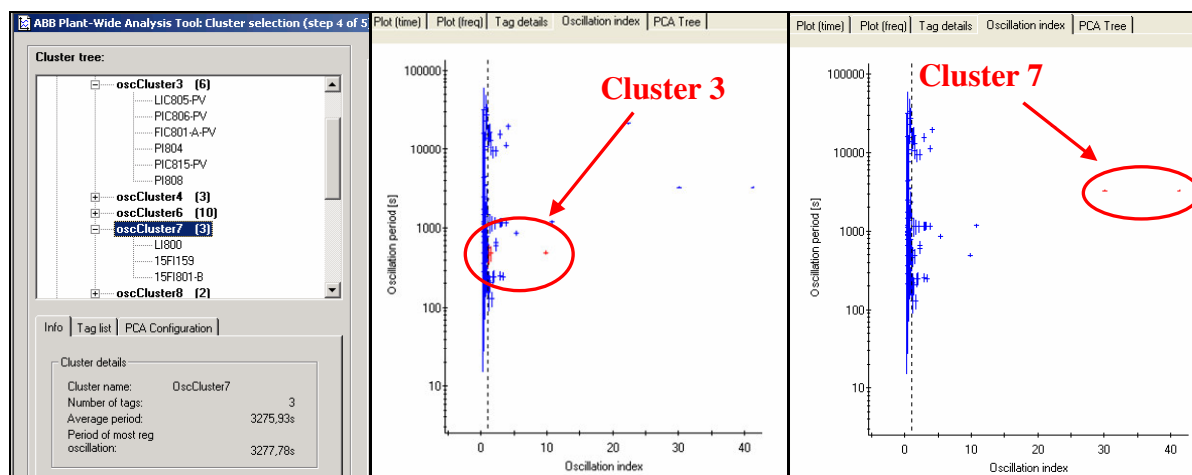
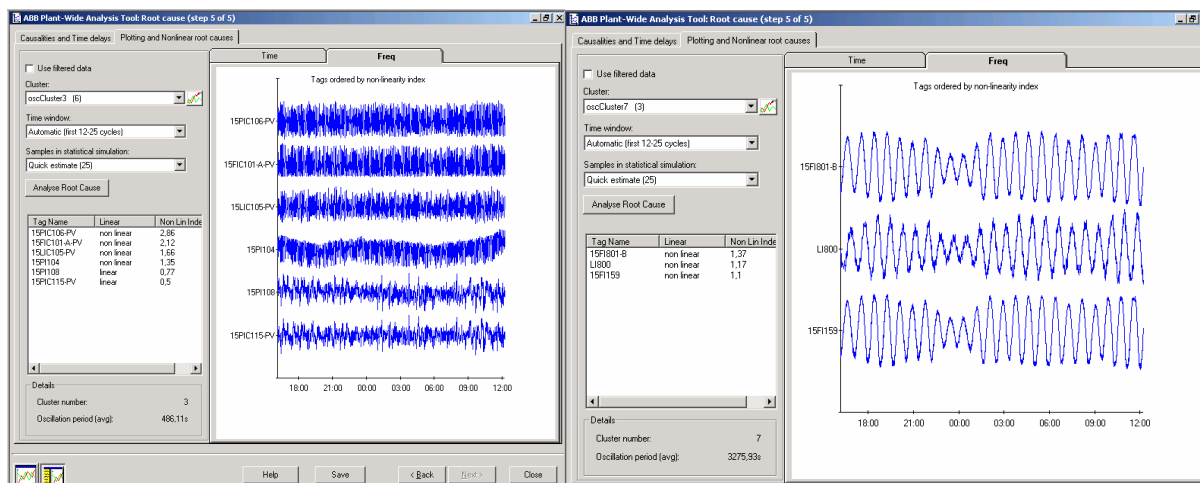


Figure 12

<sup>3</sup> Oscillation Index (OI) is a relative measure for indicating how oscillatory the control loop is. The higher the oscillation index is, the worse the situation is.



**Figure 13**

From a quick analysis of Figure 12 it is also possible to note that on average the oscillation indices of Cluster #7 have higher values than the ones of Cluster #3, this meaning that have a more regular oscillating behavior: the visual inspection of Figure 13, showing the time trends of the two clusters clearly confirms the numerical assessment.

Once the clusters have been detected, it is time to look for the root-cause. As described in §4 for oscillating loops the root-cause identification is based on the non-linearity index. Table 2 shows the non-linearity indices for the loops belonging to Clusters #3 and #7, from which results clearly that loop 15PIC106 is the candidate root-cause for Cluster #3 and loop 15FIC101A is the candidate for cluster #7.

<i>Cluster</i>	<i>Tag</i>	<i>Linear/Non linear</i>	<i>Non linearity index</i>
3	15PIC106-PV	non linear	2.86
3	15FIC101A-PV	non linear	2.12
3	15LIC105-PV	non linear	1.66
3	15PI104	non linear	1.35
3	15PI108	Linear	0.77
3	15PIC115-PV	Linear	0.5
7	15FIC101	non linear	1.37
7	15LI100	non linear	1.17
7	15FI159	non linear	1.1

**Table 2**

As described above, the process with its inventories acts as a low-pass filter which “cleans” the signal as it moves around the process: multiple harmonics, due to the presence of non-linearities are progressively damped and eventually removed and the oscillation becomes more regular. The highest is the non-linearity of the signal, the highest the probability of being the actual “disturbance originator”.

A good proof came examining datasets collected some weeks later, after a re-tuning effort spent on loops 15PIC106, 15FIC101A and 15FIC101: both cluster 3 and cluster 7 disappeared from the “radar screens” of the PDA analysis: simply the problems were removed acting only on the real source of the disturbance.

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