Root cause

Computer-aided plant auditing made possible by successful university cooperation

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Disturbances and oscillations in production processes usually have a large effect on product quality, running costs and profitability because production and throughput may have to back away from their optimum settings to accommodate process variability. An international team from ABB and the Imperial College London/University College London's Centre for Process Systems Engineering has set out to significantly reduce the time spent on troubleshooting in processing plants so that operation and maintenance efforts are directed effectively.

Modern industrial process plants are utilizing recycle streams and heat integration in the drive towards efficiency. This mass and energy integration complicates the process control because variations can propagate through the plant in complex ways, often turning a single source of variation into a widely distributed disturbance. A propagated disturbance may affect key process variables such as feed, product and recycle flows, column temperature and product composition. It may upset just a single unit, for example a distillation column; it may be plant-wide if it affects a complete production process or even site-wide if utilities such as the steam system are involved. When there are many disrupted or oscillating measurements, finding the root cause of the disturbance is like looking for a needle in a haystack.

To solve the problem, ABB's Corporate Research Centers in Germany and Norway and the ABB Advanced Control Solutions Unit in Genoa, Italy, initiated a project with Imperial College/ University College London's (UCL) Centre for Process Systems Engineering (CPSE). The project aims at automatically detecting plant-wide disturbances and determining likely root causes so that these disturbances can be removed or dealt with by improved equipment, control schemes or tuning.

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In recent years researchers at the university have developed innovative methods based on advanced signal processing, spectral and nonlinear time series analysis for use in industrial process diagnosis. These methods are now being used as the core of a new ABB solution for computer-aided plant disturbance analysis based on online or historical plant data[1] 1. Extensive testing on industrial data has been successfully performed and some examples are presented later. A full-scale study of real-time plant data is currently underway where time trends simultaneously sampled every few seconds from hundreds of measurement points are analyzed so that plant-wide performance problems can be detected and diagnosed. The results of this study will be reported in future publications.

The main goal of the project is to develop a software application that identifies 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. This more focused approach eliminates the need for teams of control and maintenance staff to go round a plant systematically examining or testing every item of equipment. Instead, the maintenance effort is directed at the problem areas that are economically most relevant to the plant. Some key requirements for this methodology include:

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

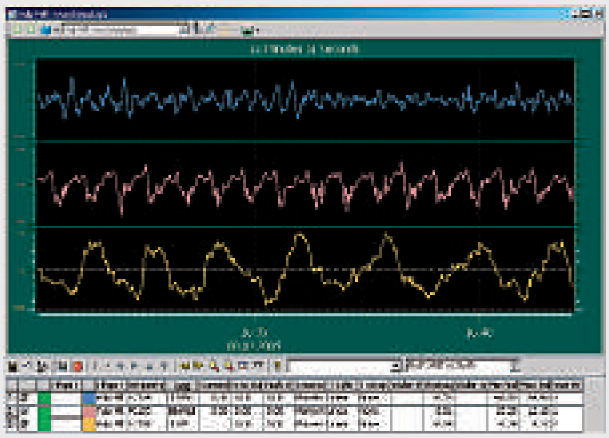
A powerful tool is one that not only automatically detects clusters of disturbed process variables (ie, measurements and control loop signals), but it

1 Complexity and quality requirements are increasing in modern plants to achieve world-class performance.

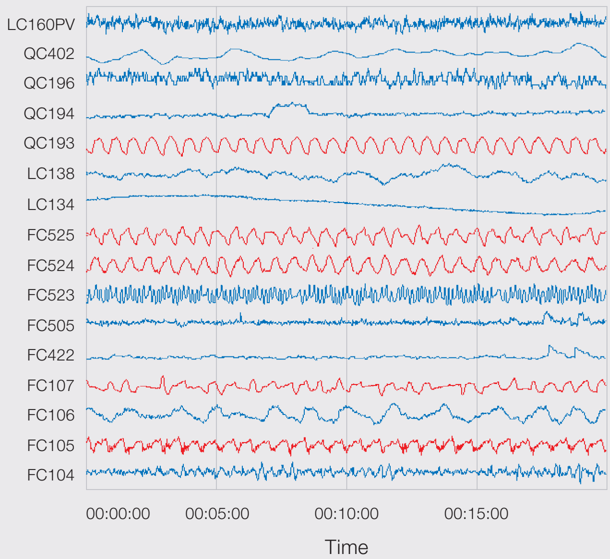
Footnote:
[1] In order to secure a head start for ABB using this innovative technology, the integrated computer-aided methodology has been filed as a patent

2 Time trends of selected measurements.

a) The recent history of a few measurements, typical of a DCS operator's panel.



b) High-density display of a distributed oscillation with the oscillating measurements highlighted.



should also characterize them, highlight plant-wide disturbances and indicate particular locations where the root cause of the disturbance may be.

Root-cause analysis in a pulp mill

A faulty valve in a pulp mill was causing plant-wide oscillations and it seemed the only way of telling which control loop had the faulty valve was to test each valve in turn. For simplicity, the methodology is illustrated using this example and a relatively small data set. The power of the procedure is even more apparent for large data sets. The analysis presented below requires preliminary data preprocessing and optional filtering, both of which are part of the tool but are not covered here.

2 shows time trends of selected measurements (hereafter referred to as "tags") displayed in the *low density* format typical of a DCS operator's display (2a) and in a *high density format* (used in the analysis tool) where the trends are normalized and stacked (2b). The low density format will not enable operators to detect wide-spread disturbances because the number of tags and the time resolution is simply too low. The oscillatory disturbance, however, is obvious in the high-density format and the cluster of oscillating measurements detected by the tool is highlighted in red. The root cause can be determined from this cluster and how this is done is explained in the following sections.

Disturbance detection for clustering time trends

The first step in the analysis is to detect time trend clusters that display similar periodically oscillating patterns. The oscillation detection is performed using advanced signal processing methods and in this context the *signals* are the time trends of the measurements.

Traditional oscillation detection methods look for zero crossings of the mean-centered signal. Noise, however, is a problem because it causes extra zero crossings which affect the accuracy of the method. A solution to this problem is described in [1].

With the new solution, oscillations are detected by looking for zero crossings of the signal's auto-covariance function. In fact, it is possible to detect multiple oscillations present in the same measurement. This is a significant improvement over previous methods which directly used time trends because:

- The auto-covariance function is less noisy than the time trend, making it easier to identify the zero crossings
- The method used to calculate the auto-covariance function means frequency domain filtering can be applied and selected frequency ranges are focused on.

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The cluster of time trends indicated in red in 2 is easily found using this approach. There is no restriction to the number of tags being analysed. Current investigations use several hundred tags which are readily analysed due to the efficient implementation of the underlying algorithms.

Spectral analysis for clustering time trends

Spectral analysis, another way of viewing the information contained in the measurements, shows what periodic features are present in the time trends. Frequency spectra are very useful in detecting distributed disturbances as:

- Spectral analysis can easily be applied to measurements from several process units or plant sections because power spectra are invariant to the phase lags caused by time delays.
- Even with a noisy time trend, spectral analysis gives clear results because the spectral content of the disturbance only occupies a narrow band of frequencies.
- Spectral analysis is insensitive to missing values and outliers because the transforms of such effects are spread thinly across all frequencies in the spectrum.

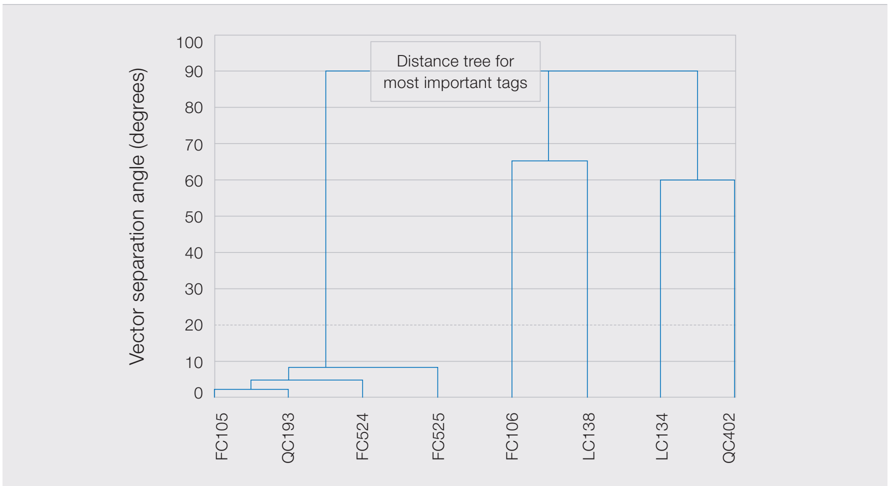
From the high-density spectral plot shown in 3b it is possible to see measurements with similar spectra. The oscillating cluster detected by the automated spectral clustering method is highlighted in red. Rapid and automated clustering of tags with similar spectra is of great value in a large scale study. The method implemented in the tool is based on spectral principal component analysis [2].

A powerful way of presenting the spectral clusters is by means of a hierarchical tree 3a. The vertical axis is a measure of the amount of mismatch between the signal spectra. Measurements whose spectra are similar to one another are clustered together on the end of a long branch, while those that are different appear on other branches. For instance, the five spectra marked in red in 3b are very similar whereas the rest have little in common. As well as creating the spectra and automatically detecting the spectral clusters, the tool gives an advanced user the opportunity to interact and experiment with the settings of the analysis.

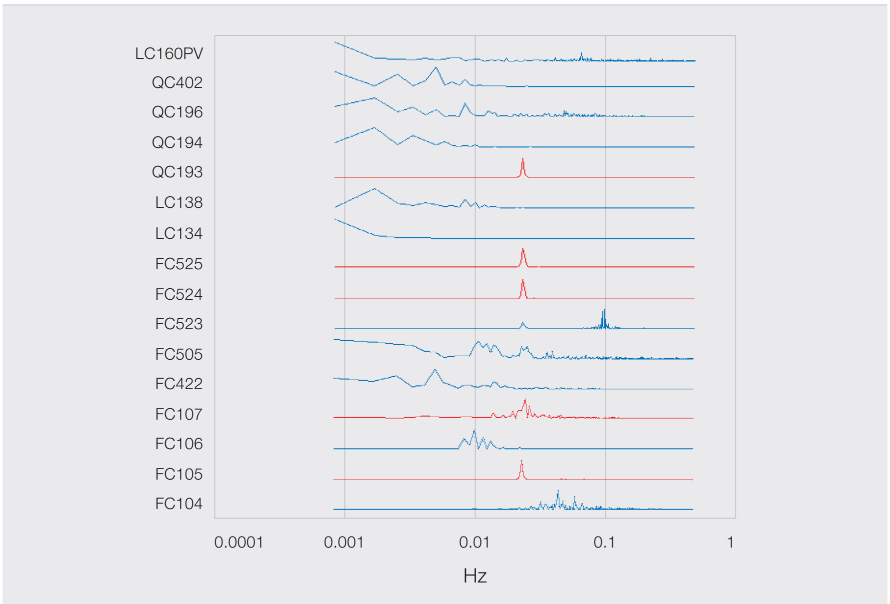
Spectral clustering is reliable for time trends that exhibit non-periodic features as long as their spectra are similar. In oil and gas applications, for example, the effects of non-periodic slugging flow are known to propagate widely throughout the platform.

3 High density plots.

a) The distance tree for the most important power spectra.



b) The power spectra of the pulp mill time trends.



Finding the likely root cause for disturbance clusters

A faulty control valve with non-linear characteristics (such as dead band and excessive static friction [3]) is one of the major causes of disturbance in chemical processes. The limit cycles caused by placing control valves in a feedback control loop can propagate widely. For this reason, the team has initially focused on the diagnosis of non-linear root causes. The methods developed for identifying sticking control valves as a problem source are also able to locate other non-linear based faults such as periodic foaming in a distillation column and slugging flows in pipelines.

A nonlinear time trend [4] cannot be described as the output of a linear system driven by white noise. It is characterized by phase coherence and, if it is oscillatory, by the presence of harmonics. An example of such a signal is one with a square wave pattern. A process plant typically acts as a low-pass filter, meaning a measurement close to a non-linear source has more non-linearity than a measurement some distance away. In other words, the square pattern is smoothed as it propagates through the plant, and this behavior is utilized to identify candidate problem areas.

One way of detecting non-linearity is by visually inspecting the time trends and spectra. However, this is a manual procedure which is unreliable, intricate and prone to error. The novel concept in the current approach is a nonlinearity assessment that is strongest at the source of the nonlinearity. In that way, the oscillation at the root of the problem can be distinguished from propagated secondary oscillations. The "assessment index" is large for the periodic but non-sinusoidal oscillating time trends that are typical of the output of a control loop with a limit cycle caused by nonlinearity.

In a non-linear assessment, the predictability of each time trend is compared with a set of constructed time trends that have the same power spectrum but random phases. A nonlinear time trend will have a high predictability when compared to the constructed time trends, whereas this difference will be small for a linear time trend [4].

The evaluation of the non-linearity index in the example reveals that the tag QC193 is in fact the root cause. It is not easy to spot the most non-linear time trend manually in 2 and 3, even with this small amount of data.

The described methodology is indeed quite powerful – especially when applied to large-scale problems – in that it can significantly reduce the number of man-hours spent pursuing the wrong root causes. Of course it will never replace human know-how, but a data-driven, computer-aided methodology as described here is, without doubt, an invaluable support tool.

The university collaboration

Before the project got underway, most of the basic research had already been completed and tested in real world applications. One of the biggest challenges at the beginning, however, was the transfer of algorithms developed in academia into a complete software application prototype. The prototype for plant-wide disturbance analysis is now finished and will be productized as a part of ABB's tool for control loop tuning and auditing: Optimize^{IT} Loop Performance Manager [5].

Transforming academic research results into a commercial product is a challenging task, as is the transformation of basic research code into a stable and understandable tool for different users. First of all, the underlying algorithms have to be customized by choosing robust and optimized parameters. Secondly, the work flow has to be adapted to be efficient, easy and complete. And finally, extensive tests are required to ensure the tool usuability in a larger number of applications.

A multidisciplinary project team has successfully ensured these robust and optimized innovative methods can now be applied to new plant data. In fact, a prototype is currently operational. The methods can be used for: the automatic detection of data compression; the automated choice of filter cut-off thresholds; and the selection of optimizing parameters for nonlinearity assessment. The data from each new case are automatically adjusted to match the recommendations. All the user has to do is select the disturbance from which the root cause can be identified.

Exploring the future

The successful collaboration between ABB and the Imperial College London/University College London's CPSE will continue so that new ideas can be exploited and transformed into innovative functionality.

One such idea focuses on exploiting electronically available topology information about plant equipment and its connectivity, such as piping and instrument diagrams, and signal and control diagrams. The exploitation of process knowledge combined with the non-linearity assessment methodology described previously will improve the diagnosis step even further, especially in cases where there is more than one suspect.

While non-linear problems, such as sticking valves, are common, there can be other root causes. A challenge for the future is to extend the root cause diagnosis tools. For instance, control loop interaction can arise when two controllers have a shared mass and/or energy store, eg, pressure and level controllers may compete for control of a reactor. Structural disturbances caused by coordinated transfers of mass and/or energy between different process units are becoming more prevalent as the industry moves towards increasingly integrated processes. Most process control engineers will be familiar with such examples.

The project team from UCL/Imperial College and ABB brought together people with quite different skills and positions: professors, a postdoctoral researcher, students, industrial scientists, software developers, product managers and people from industrial business areas. In this diverse field of expertise and expectations, the collaboration has been very smooth and efficient. It is a perfect example of a fruitful and successful project between industry and university.

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