Importance of Auxiliary Systems for Process Fault Detection and Diagnosis

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Abstract—In industrial processes, fault detection and diagnosis is traditionally applied separately to process and equipment without relating the information on both systems. This paper shows the interaction during fault propagation between the process and its auxiliary systems, i.e. mechanical, electrical and utility systems. Evidence is given with an industrial case study. The relevance of this finding is demonstrated by showing the advantages of including information from electrical and mechanical data in a root cause diagnosis test.

I. INTRODUCTION

IT IS important to detect and diagnose faults in a system because a disturbed system operates inefficiently, risks sudden stoppage, and poses health and environmental hazards. Striking examples were the industrial accidents of Bhopal, Piper Alpha and the recent Gulf of Mexico oil spill. Hence, the application of fault detection and diagnosis practices has been common to processes, plant equipment, aircraft engines and actuators, and automotive equipment.

In the case of process plants, both process and equipment are monitored but the task is performed by two different departments; process performance is assessed by process or control engineers, while mechanical engineers are responsible for the equipment condition. The consequence of this division is that the relations between these interacting systems remain unexplored.

However, there have been several calls from industrial commentators [1-3] for the integration of process and machine health information. One argument is that a significant part of equipment wear and breakdown is related to the process conditions, for example, process pumps that may unintentionally run in cavitation conditions. One suggestion by [1] is the incorporation of the machine state into the control system to be part of the feedback to control loops. This way, the protection of the equipment could also be accounted for in the control actions.

The contributions of this paper are (i) to show that fault propagation in a plant involves both the process and its auxiliary systems, like mechanical, electrical and utility systems, and (ii) to demonstrate that fault diagnosis is

enhanced by taking account of the participation of these auxiliary systems. The paper shows examples where results are misleading if based only on process data.

The paper is structured as follows. First, academic research is reviewed to verify that to date the interaction between process and auxiliary systems in fault propagation has not been addressed, either in the context of process monitoring or machinery condition monitoring. In Section III an industrial case study is presented to demonstrate the existence of this system interaction. Finally, Section IV shows the relevance of this finding with a result from a root cause analysis method.

II. BACKGROUND AND CONTEXT

A. Fault Detection and Diagnosis in the context of Process Industries

In industrial processes unwanted deviations may affect variables such as temperature, pressure and flow rates which may adversely affect product quality, productivity, energy consumption and safety. Reasons for these disturbances include hydrodynamic instabilities, compressor trips, sensor faults, sticking control valves, and controller interaction [4]. Due to tight interlinking of process equipment, these disturbances usually propagate through the plant in complex ways and diagnosing the root cause is often a challenge.

The methods for fault detection and diagnosis (FDD) in the context of process systems have been reviewed in detail by Venkatasubramanian and co-workers [5-7]. The methods with greatest impact are data-driven [7-8] and are mainly supported by dimensionality reduction techniques like Principal Component Analysis [9] and Independent Component Analysis [10]. Recent work [11-12] has successfully integrated data-driven analysis with process knowledge without quantitative models of the process, by using an electronic process schematic to extract the causal information in an automated way. The use of quantitative model-based methods has, in fact, had little impact in process industries [5,7] due, in part, to the inherent nonlinear nature of chemical processes and the uncertainties of thermodynamic data [7-8].

Research in process FDD has been oriented to solve process-related challenges. Examples are the development of appropriate techniques for systems with multiple operating modes like batch processes [13], for nonlinear systems [14], and to cope with time-delayed correlations of data which result from disturbances being mainly carried by mass or heat flow [15].

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Likewise, the assessment of control loop performance is an active area of investigation in the context of process industries. This is because some of the most common sources of disturbances are control-related, such as poor controller tuning, control valve problems, sensors faults, and controller interaction [4]. These problems are aggravated by the fact that control loops are increasingly interconnected due to higher-integrated processes, which results in disturbances spreading across all process. Thus, a developing branch of research has been plant-wide detection and diagnosis, which was comprehensively reviewed in [4]. The main challenges addressed have been the identification process-wide of clusters of measurements having a similar faulty behaviour [16] and retracing the disturbance propagation path along these process measurements up to the root cause [17].

Despite the advances in plant-wide FDD, to date research has been limited to propagation of faults along process streams and the involvement of the auxiliary systems has not been considered. These auxiliary systems include plant machinery, like pumps, the electrical system and utilities, like compressed air and steam.

B. Fault Detection and Diagnosis in the context of Machine Condition Monitoring

Mechanical systems include, amongst others, electric motors, gear boxes, turbines, pumps, and compressors. Due to operational demands and even deficiencies in the original design, these machines may suffer from cracks, misalignment and looseness of their parts, fouling, insulation fails and fuse burn out. These faults usually manifest by changes in physical parameters like the vibration and acoustic levels, current, voltage, and lube oil composition [18]. For this reason, monitoring the behavior of mechanical systems is done to prevent machine breakdowns, which reduce production and safety, but also to schedule maintenance in a cost-effective manner and to create comprehensive logs of failures.

The methods to process and interpret the condition data for FDD have been reviewed in detail by Jardine and co-workers [19]. In terms of data processing for feature extraction, active areas of investigation have been the development of the wavelet transform to cope with non-stationary time trends [20] and the extension of dimensionality reduction techniques to nonlinear systems by the use of kernel functions [21]. The interpretation of the extracted features has been mainly addressed with pattern recognition techniques, which match meaningful features in the measured data with patterns that characterize the different machine faults. In particular, research has been focused on neural networks [22], for their ability to model nonlinear systems, and statistical clustering with Support Vector Machines [23], to optimise the boundary curve between fault clusters.

To date, the focus of machinery FDD has been on the individual asset and has not included the behaviour of the

system where the machine is located, despite the fact that this system may be itself the cause for the faults. Also, no work has been reported on comparing the behaviour of different machines placed in the same system. The reason to do so would be to recognize when similar faulty behaviours spread system-wide.

C. Fault Detection and Diagnosis of Plant Utilities

Plant utilities provide services essential to the efficient operation of a plant. Examples include cooling water, steam, fuel gas and compressed air. These systems are physically separate from the main process but any disturbance affecting the utility generation and distribution, such as faults in boilers, gas turbines, pumps and flow metering, has an impact on the economy and safety of the whole plant.

The methods for the detection and diagnosis of faults in these auxiliary systems are identical to those used in the diagnostics of process and machinery; however emphasis has been given to model-based methods. Particular examples are the use of particle filtering for predicting the fault probability distribution in a heat exchanger [24] and modeling steam systems consisting of boilers, feed-water and distribution systems for performance studies [25].

Traditionally, FDD in plant utilities is focused on the condition of the equipments responsible for the utility generation and distribution, without studying the effects of the faults plant-wide [26-27]. Recently though, [28] acknowledged a malfunctioning utility as a cause for plant-wide disturbances and estimated its economical effects. Despite this advance, research is still missing on disturbance-crossing between the main process and the plant utilities and the role of the utility systems as means of plant-wide fault propagation.

III. INDUSTRIAL CASE STUDY

A. Data set and motivations for analysis

This section analyses a set of data and process schematics from a real gas processing plant. The process can be classified as large-scale since more than 7500 measurement tags and around 350 drawings were available. The time trends provided were sampled at 30 s intervals for 31 days of operation, adding up to more than 89000 samples per tag. Included in this data set are measurements from the mechanical, electrical and utility systems in addition to the measurements from process streams.

The dimension of the data set and the information on auxiliary systems were the reasons to choose this case study for an exploratory analysis in search of examples supporting the existence of system-crossing disturbances, i.e., disturbances which propagate between the process and the mechanical, electrical and utility systems.

B. Example 1: Disturbance-crossing from cooling utility

In Fig. 1 four examples are presented which reveal the

Fig. 1. Examples of disturbances crossing from the incoming utility stream ($T_{u,in}$) to the effluent process stream ($T_{p,out}$).

propagation of disturbances from the cooling utility to process streams through a heat exchanger.

Each of these examples plots a disturbed cooling medium temperature, measured at the inlet of a heat exchanger ($T_{u,in}$), and the temperature time trends of the process streams before and after interacting with the utility ($T_{p,in}$ and $T_{p,out}$).

As may be observed, the abnormal episodes which were affecting the cooling utility manifested in the effluent process stream. However, before entering the heat exchanger, this process stream was free of those particular disturbances. For instance, in Fig. 1 a), the feature with several sharp spikes between hours 3 and 4 is not present in

$T_{p,in}$ but can be seen in $T_{u,in}$ and $T_{p,out}$.

Utilities are used by control engineers to divert variability from the process. However, these examples reveal that utilities may themselves act as sources of disturbances, a fact which exposes the need to integrate this auxiliary system in process fault detection activities.

C. Example 2: Disturbance-crossing via mechanical system

Fig. 2 shows an integrated schematic of the gas recompression area and the mechanical and electrical devices associated with the compressors.

Fig. 2. Integrated schematics of the process and mechanical components for the gas recompression area of industrial case study.

Selected measurement points are represented in the figure: (i) on the process streams, representative pressure and temperature tags before and after compression; (ii) on the electro-mechanical system, measurements of speed, current, power and vibration; and (iii) measurements from the speed control loop.

In Fig. 3, 4-day snapshots of these three sets of measurements are shown together. The reason is to show the significant similarity between them. In particular, one can see a series of abnormal features in the form of sharp transient spikes and large oscillations which are distributed across the majority of the variables. This fact suggests that the process streams and the auxiliary systems interact during fault propagation.

Fig. 3. Time trends of process, control, electrical and mechanical measurements in Gas Recompression area of industrial case study.

Cause and effect relations between these variables could be inferred from the time trends and the process schematic. These relations are better understood focusing on the large oscillating feature which appears between days 1.5 and 3.

First, one can see from Fig. 2 that the control of the compressors speed is dependent on two pressure measurements at the entrance of this area (PC1 and PC2). The time series associated with these pressure controllers are shown in Fig. 3 for the controllers inputs (PC1_X and PC2_X in the section labelled "Process") and outputs (PC1_Y and PC2_Y in the section labelled "Control"). In these plots, one can see that the large oscillating feature from days 1.5 to 3 has opposing phases in the inputs and outputs, which is

explained with control theory as a response of the control system to the oscillating disturbance in the process.

Due to this control response, counter-disturbances were transmitted to the speed of the shaft, which then propagated throughout the vibration signals of the mechanical system and also to the electrical system. This finding confirms the existence of fault propagation from the process to the mechanical and electrical systems.

Evidence of fault propagation in the opposite direction, i.e. from the mechanical to the process system, could also be found in this example. From Fig. 3 it can be seen that the temperature measurements before both compressors (tags T1 and T3) did not present the oscillating disturbance, whereas after compression (tags T2 and T4) these oscillations appeared and had the same phase as the oscillations affecting the mechanical and electrical systems. The reason for the influence of the compressor operation over the temperature is the transfer of heat energy to the gas happening as a result of the work performed by the compressor. In this case, this influence acted as a means of fault propagation from the mechanical system to the process.

IV. RELEVANCE OF SYSTEM-CROSSING DISTURBANCES

The case studies presented in section III demonstrated that a process and its auxiliary systems are not independent regarding fault propagation. To show the importance of this interaction, the following section presents a result obtained with another example from the previous case study. This result demonstrates that root cause analysis is enhanced by taking into account the participation of these auxiliary systems.

A. Role of mechanical system in fault propagation mechanism

Fig. 4 a) shows the process schematic of the gas expansion-recompression area from the industrial case study presented in section III. In this area, the majority of the signals from the process, mechanical and electrical systems were affected by a common oscillating disturbance, which can be identified in Fig. 4 b) as a clear peak in the spectra of these tags.

The question needing an answer was to locate the origin of the oscillating disturbance, which was done using a well-established non-linearity test¹ available in the Plant Disturbance Analyser tool (PDA) by ABB, Genova, Italy [29]. The test computes how nonlinear a time series is using surrogate data analysis [30] and points the root cause and propagation path based on the assumption that non-linearity decreases when moving away from the root cause. This assumption, tested in [30] and elsewhere, is justified with the mechanical filtering exerted by the plant.

¹A non-linear time series is one in which the current value has a non-linear dependence on previous values. It is a characteristic of a time series produced by a non-linear system.

Fig. 4. Gas expansion-recompression area from industrial case study: (a) process schematics; (b) spectra of measurements affected by common oscillating disturbance.

The result yielded with the PDA tool showed T5 (temperature after the compressor), T2 and T4 (temperatures after the heat exchanger) to be, in that order, the tags with the highest nonlinearity. Interpretation of the non-linearity result required process knowledge and reasoning from first principles. Consideration of the direction of process flow showed:

- The compressor should be operating well because it is able to generate a flat output (P4) from a disturbed input (P3) (see Fig. 5).
- The oscillation must have originated in or near the heat exchanger, located at the left side of Fig 4. This is because there was a significant increase in non-linearity from the feed temperatures T1 and T3 to the effluent temperatures T4 and T2 (Fig. 6).
- T3 was oscillating because it derived from T2 after two separation stages and a compression process. However there is no sign of nonlinearity which means it was far downstream from the root cause.
- T5 is downstream from T4 and is expected to be oscillating; however, its nonlinearity is higher than that of T4, which is an unexpected result.

The unexpected result illustrates the need to consider the interaction between the process and the mechanical system. Doing so, one can understand that the oscillating disturbance crossed from the process to the compressor due to the speed control, which is based on the conditions in the second separator, and that the ensuing operating state of the compressor influenced back the process temperature. As a result, the nonlinearity in T5 was increased due to the combination of the original disturbance in T4 with the collateral disturbance propagated via the compressor.

Fig. 5. Pressure before (P3) and after compression (P4), with visible reduction of oscillating behavior.

Fig. 6. Time trends of process temperatures showing the increase in nonlinearity through the heat exchanger (T1 to T2 and T3 to T4) and through the compressor (T4 to T5).

V. CONCLUSION

In this paper, an industrial case study was presented to demonstrate the existence of system-crossing faults, i.e. faults which propagate between the process and the mechanical, electrical and utility systems. Also addressed were the absence of academic work in this area and the fact that results from process monitoring tools may require

careful interpretation due to the existence of these types of disturbances.

These findings motivate further work towards the development of a new automated tool, fit for fault detection and diagnosis in the presence of system-crossing faults.

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