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Monitoring of a simulated milling circuit: Fault diagnosis and economic impact

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ABSTRACT

The early detection and root cause identification of abnormal events in industrial processes is important, to allow for timely corrective actions, ensuring continued economic operation. This paper investigates the application of statistical fault detection methods, in conjunction with process topology data-driven techniques for root cause analysis, to a simulated milling circuit. Two faults (faulty particle size analyser and rapid mill liner wear) were simulated, and the statistical monitoring techniques tested. Fault detection proved accurate, and variables closely associated with the faults were identified by the root cause analysis. The need to further formalise the selection of data for process topology generation for root cause analysis was highlighted. The milling circuit simulation and fault data has been made available as a resource for future research. Economic performance factors were developed to quantify the impact of the faults and motivate for fault detection and diagnosis.

1. Introduction

The challenge of detecting and diagnosing faults in increasingly complex industrial processes (such as the minerals industry) has received significant attention in the literature, with the focus being on data-based methods (Ding et al., 2015; Ding, 2014; Groenewald et al., 2006; Groenewald and Aldrich, 2015; Kadlec et al., 2009; Li et al., 2016; Lindner and Auret, 2015; Yang and Xiao, 2012), rather than first-principles process modelling (Agrawal et al., 2015; Guerrero et al., 2016; Légaré et al., 2016; Salazar et al., 2014; Tidriri et al., 2016; Venkatasubramanian et al., 2003a, 2003b). Here, fault detection is defined as the indication at a specific time point that a faulty condition has started occurring, or is continuing to occur. Fault diagnosis is defined here as the indication of which measured process variables are most associated with the faulty condition (also referred to as fault identification in the literature), and the subsequent classification of process variables as either symptoms or causes of the faulty condition (also referred to as root cause analysis in the literature). The goal of detecting and diagnosing faults is to reduce or prevent faulty operating conditions and ensure continued economical operation.

Principal Component Analysis (PCA) and related methods (including nonlinear and dynamic versions of PCA) are commonly used for fault detection in the process industry (Aldrich and Auret, 2013; Chioua et al., 2016; McClure and Gopaluni, 2015; Qin, 2012). Contribution-based methods are often used in conjunction with PCA-based monitoring to identify faults (Miller et al., 1998); methods include complete, partial, diagonal, reconstruction-based and relative contributions (Alcala and Qin, 2011, 2009).

Fault diagnosis is cited as being possible by means of causality methods, which attempt to extract causal relationships between variables in the form of process topologies (Lindner and Auret, 2014; Maurya et al., 2003a, 2003b) either purely from historical data (Bauer et al., 2007; Bauer and Thornhill, 2008; de la Fuente et al., 2004; Lindner and Auret, 2014) or by making use of process knowledge (Groenewald and Aldrich, 2015; Landman and Jämsä-Jounela, 2016).

Despite the accepted economic benefits of process control in general (Bauer and Craig, 2008; Bouffard, 2015; le Roux et al., 2016; Wei and Craig, 2009) and fault detection specifically (Bin Shams et al., 2011), relatively little work has been done to illustrate the economic impact of correctly detecting and identifying faults. Extensive domain knowledge, and significant effort, can be required to develop economic performance factors, which relate process variables to economic performance. The benefit is the continuous prediction of economic performance, and the use of this prediction to assess test runs, plant modifications, control schemes, or even decide whether to shut down a plant following a fault (Olivier and Craig, 2017).

Whether detecting and diagnosing faults or assessing economic performance, any proposed method must be demonstrated or evaluated on a data set. While real operating data provides the most realistic test of any method, the "ground truth" is often missing: for example, the actual root cause of a fault may not be known. Simulated data is used in many studies, as diverse conditions can be simulated without the risk of

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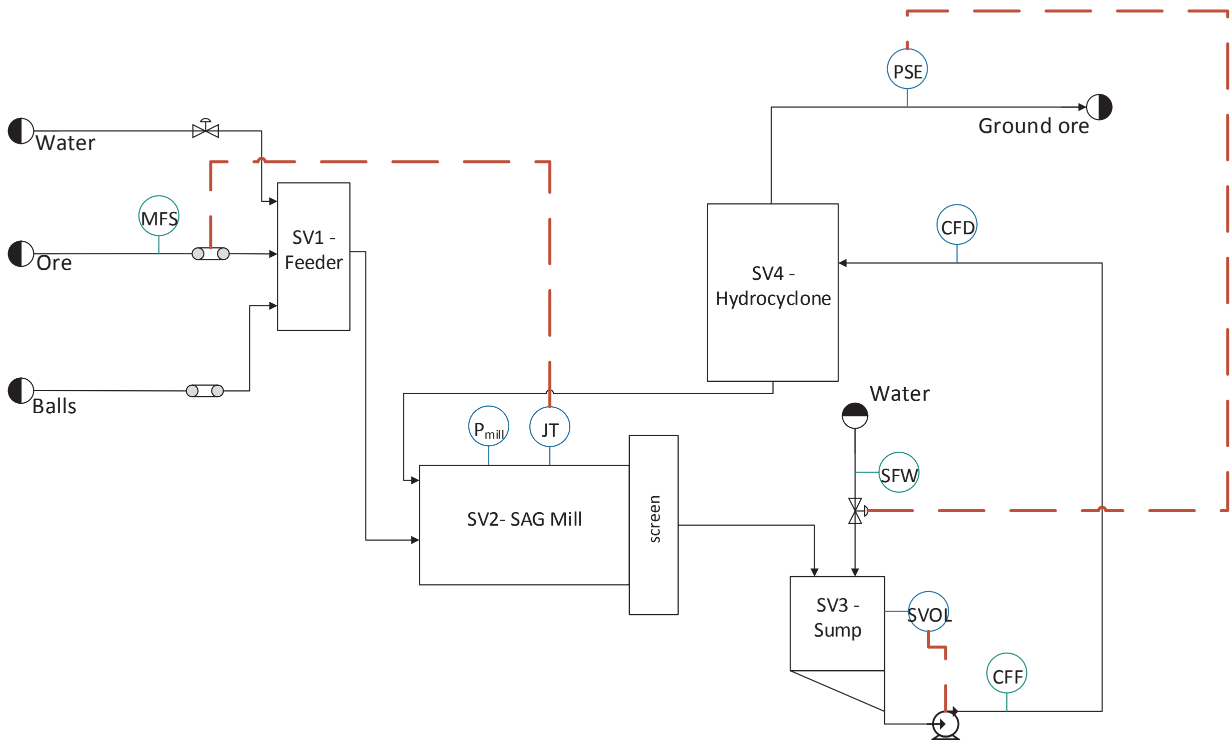

Fig. 1. Mill circuit model with control loops.

safety or financial impact. However, the simulations generating this data should be as realistic as possible, in order to provide the level of complexity and challenge required to test any proposed method, and demonstrate real-world applicability.

This paper describes the application of data-based fault detection and diagnosis techniques to a validated dynamic model of a run-of-mine milling circuit (Coetzee et al., 2010; le Roux et al., 2013), and illustrates the impact on economic performance of faulty or abnormal operation.

The proposed approach is suggested in general for more robust assessment of the actual benefit of abnormal event detection and root cause analysis in industrial processes. The dynamic simulation and simulated data are available online to promote further analysis and comparative studies.

The paper is structured as follows: Section 2 describes the milling circuit model, and the economic performance criteria that were used, and provides an overview of the data-based process monitoring approach which was applied. Section 3 shows and discusses the results of the process monitoring and fault diagnosis, and Section 4 provides conclusions and ideas for future work.

2. Methods

2.1. *Dynamic mill circuit simulation with process disturbances and abnormal events*

A dynamic model of a run-of-mine mill circuit has been developed to demonstrate the potential economic impact of fault detection and diagnosis. The mill circuit model and its control system is briefly described here, as well as the nature of input excitation (in the form of disturbances) to the model, the generation of normal operating conditions data and fault data. The model, which can be run in MATLAB and Simulink, has been made available as supplementary material for future research. For further details, see the Supplementary Material section of this paper.

A dynamic model (rather than industrial data) provides a well-defined data set to test the monitoring methods described below; the selected dynamic model is based on actual operations, however, and so it provides a level of complexity that ensures that the monitoring approach is rigorously tested.

2.1.1. *Mill circuit model and control*

The run-of-mine grinding mill circuit model presented by le Roux et al. (2013) is considered. This simulation is based on the model found in (Coetzee et al., 2010). This is a reduced complexity nonlinear model, consisting of four defined system volumes (SV) connected as shown in Fig. 1. The system volumes are the feeder, semi-autogenous mill, sump, and hydrocyclone. The feeder is a superficial SV that exists to separate the feed to the mill circuit into the five states used in the model. Fresh feed ore, water and steel balls are added to the mill from the feeder along with underflow from the hydrocyclone. The milled ore then exits the mill and enters the sump where water is added to modify the thickness of the slurry. Lastly, a pump transports the slurry to the hydrocyclone for classification.

The variable abbreviations used in Fig. 1 are described in Table 1.

The mill circuit model was built and tested in MATLAB R2014a, R2016a and R2017a and Simulink, using the ODE45 numerical integration method.

A control system for the circuit, consisting of single loop PI controllers with input filters and output saturation (see Table 2), was implemented. The output saturation and controlled variable setpoints are based on the data presented in le Roux et al. (2013).

Control loop pairings were determined based on previous investigations into this system (Craig et al., 1992). Control loop tunings were based on Proportional-Integral controllers with the form in Eqs. (1) and (2), and using the Ciancone correlations described in Marlin (2000).

$$MV(t) = MV(0) + K_c(E(t) + \frac{1}{T_I}\int_0^t E(t')dt') \tag{1}$$

$$E(t) = SP(t) - CV(t) \tag{2}$$

The three control loops which were implemented were:

– The sump volume (SVOL) is controlled by manipulating the cyclone