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Fault diagnosis and economic performance evaluation for a simulated base metal leaching operation

Johannes Jacobus Strydom, Jason John Miskin[1], John Themba McCoy, Lidia Auret*, Christie Dorfling

Department of Process Engineering, Stellenbosch University, Private Bag X1, Matieland 7602, South Africa

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ABSTRACT

A dynamic process model based on a base metal refinery including critical control layers has been developed. The critical control layers include sensors, actuators, regulatory controllers, alarm systems, safety interlocks and supervisory control. With the help of expert knowledge, a fault (abnormal event) library was incorporated into the dynamic model.

Fault diagnosis methods are used to detect and identify abnormal process conditions. With the use of the dynamic process model, fault detection and identification methods can be more rigorously and accurately evaluated for hydrometallurgical industry use.

An economic performance function is developed from expert knowledge. Once the fault diagnosis is complete, an economic impact analysis based on the fault diagnosis results is completed. A possible economic case for fault diagnosis is concluded from the results.

1. Introduction

1.1. Dynamic models and their application

Dynamic models are useful tools for optimizing processes or assessing possible process changes. These changes could be the possible implementation of advanced control or process monitoring. Operators can also be trained with dynamic models.

With the ongoing increase in computational resources, more complex models are developed in the metallurgical industry. Extensive research has been conducted on metal concentrator dynamic modelling. This includes SAG mills, ball mills, crushers, screens, cyclones and flotation cells (Karelovic et al., 2016; Alves dos Santos et al., 2014; Quist and Evertsson, 2016; Salazar et al., 2009; Salazar et al. 2010).

In the hydrometallurgical industry, leaching is a widely used process where some targeted metal is dissolved from the solid phase and then separated. These systems usually involve complex chemical reactions and are challenging to model and simulate given the constant changes in feed materials and constantly changing chemical interactions.

Not much work has been conducted towards the development of dynamic models for nickel and copper leaching. Faris et al. (1992) developed a nickel and copper acid leach model. The work illustrated the possible use of dynamic models for operator training.

A dynamic model was recently developed by Dorfling et al. (2013a,b) and updated by Miskin (2016). The model predicts the extent of leaching through simulation of 21 complex chemical reactions. The model includes various control layers, including sensor, actuators, regulatory control, supervisory control, alarms, and safety interlocks.

This work will describe the structure of the dynamic model developed by Dorfling et al. (2013a,b) and Miskin (2016), and how it was used for assessing fault diagnosis performance.

1.2. Process monitoring and fault diagnosis

In order to further improve process efficiencies, statistical methods to detect and identify faulty process conditions have received significant attention in several studies (Aldrich and Auret, 2014; Qin 2012; Groenewald et al., 2006; Lindner and Auret, 2015; Russell et al., 2000).

Different strategies for fault detection and fault identification can be used: plant-wide monitoring, where all measurements are considered simultaneously, and distributed monitoring, where tailor-made approaches for specific types of abnormal events are applied in subsystems of the process. Plant-wide monitoring has the benefit of a single, unified approach: fewer parameters to select and monitoring modules to maintain. However, plant-wide monitoring may suffer from

* Corresponding author.
E-mail address: lauret@sun.ac.za (L. Auret).

[1] Current address: Opti-Num Solutions, Northview, 57 Sixth Road, Hyde Park, Johannesburg 2196, South Africa.

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Nomenclature

A	number of retained principal components
ANOVA	analysis of variance
BMR	base metal refinery
C_j	squared prediction error contribution for variable j, averaged over all samples
$\widetilde{C}_{jj}$	diagonal element j of residual subspace matrix
$C_{i,j}^{HT}$	Hotelling's T^2 contribution for variable j from sample i
$C_{i,j}^{SPE}$	squared prediction error contribution for variable j from sample i
D	density
$\mathbf{D}$	matrix used in calculation of Hotelling's T^2 reconstruction based contribution
DD	detection delay
EPF	economic performance function
f_i	fraction of PGM element i lost to copper cathodes
F	Flow rate
F_i	PGM element i inlet flow rate to copper electrowinning circuit
F_{is}	PGM element i normal operating conditions flow rate to copper electrowinning circuit
FAR	false alarm rate
L	level
LSD	least significant difference
m	total number of measured variables
MAR	missing alarm rate
n	total number of samples
NOC	normal operating conditions
P	pressure
P_i	PGM price for element i
$\widetilde{\boldsymbol{P}}$	unretained principal components
$\mathbf{P_A}$	retained principal components
$\mathbf{P_{A,j}}$	vector of weights associated with variable j in the retained principal component matrix
PCA	principal component analysis
PGM	platinum group metal
RBC	reconstruction based contribution
RBC_j^{HT}	Hotelling's T^2 reconstruction based contribution for variable j
RBC_j^{SPE}	squared prediction error reconstruction based contribution for variable j
SPE	squared prediction error
T	temperature
$\mathbf{T}$	score matrix
$\mathbf{T_i}$	score vector for sample i
$\mathbf{T_{TEST}}$	score matrix for unseen data
T^2	Hotelling's T^2 statistic
TAR	true alarm rate
$\mathbf{x}$	vector for a single sample of m measured variables
$\mathbf{X}$	scaled measurement matrix
$\hat{\boldsymbol{X}}$	reconstructed scaled measurement matrix
$\mathbf{X_{TEST}}$	unseen scaled measurement matrix
$X_{i,j}$	scaled value for sample i and variable j
$\hat{X}_{(i,j)}$	reconstructed scaled value for sample i and variable j
δ_i	vector of length m, with all elements zero, except the ith element is one
$\boldsymbol{\lambda_A}$	first A eigenvalues
μ	mean
σ	standard deviation

poor fault identification performance: the inability to accurately determine the location and type of abnormal event. Distributed monitoring has the benefit of improved fault identification, but requires more parameters to select and modules to maintain. Tailor-made approaches may also miss new types of abnormal events, not designed for.

Plant-wide monitoring has received much attention in literature. Yin et al. (2012) compared a selection of latent variable methods (such as principal component analysis, Fisher discriminant analysis, partial least squares, and independent component analysis) and variants thereof for plant-wide monitoring, as applied to the simulated Tennessee Eastman process benchmark problem. Li et al. (2016) developed a new fault identification approach using dynamic principal component analysis and causality metrics (e.g. Granger causality and transfer entropy), also applied to the simulated Tennessee Eastman process benchmark problem. Rato and Reis (2013) also use dynamic principal component analysis, but incorporating decorrelated residuals to counter autocorrelation present in the Tennessee Eastman benchmark. Yu et al. (2015) consider joint probability functions and Gaussian copula for fault detection and identification (also on the Tennessee Eastman problem).

Distributed monitoring typically involves designing fault detection techniques for specific valve faults (e.g. Horch (1999) considers valve stiction; Ling et al. (2007) investigate backlash, deadband, leakage and blocking) or other control loop faults (Bauer et al. (2016) present an excellent survey on control loop monitoring; Chen and Howell (2000) describe self-validating control systems).

In this work, principal component analysis (PCA) in a plant-wide monitoring approach is used. PCA is the most common fault detection technique, requiring few parameters and design choices, and being able to detect unknown abnormal events that would sufficiently upset normal operating conditions. In PCA monitoring, faults are often identified using contribution plots with reconstruction based contributions, which were recently introduced by Qin and Alcala (2009).

1.3. Economic performance

Typically, monitoring performance is summarized in terms of false alarm rates, missing alarm rates, and detection delays, and rarely assessed in terms of economic performance (Olivier and Craig, 2017, Bin Shams, 2010).

One approach to assessing economic performance for control systems (Bauer and Craig, 2008) may be adapted for use in monitoring systems: the economic performance function. The aim of an economic performance function is to evaluate the possible economic benefit of a change to a process. Economic performance estimation techniques have also not kept up with the changes in advanced process controllers (Bauer and Craig, 2008). Economic performance functions are typically used to assess regulatory control performance, and may not capture the additional benefit of improved uptime and safety.

Another approach to assessing economic performance for monitoring systems is to estimate the economic impact of shut downs on the process, before and after monitoring system implementation (see Nochur et al., 2001). This approach is challenging, since detailed information on maintenance management is required.

1.4. Contributions of this work

This paper aims to assess the possible benefits of process monitoring on a copper-nickel pressure leaching system. The complex dynamic model is used to generated realistic process data. PCA is trained on simulated normal operating conditions data, and applied to simulated fault data Faults are identified with contribution plots. The value of the early fault detection and identification is then evaluated with specific economic performance functions.

The methods used in this paper are selected based on a philosophy of rigorous evaluation of fault diagnosis techniques. Rigour is introduced in three ways: firstly, by creating the most realistic test

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