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# Mineral processing plant data reconciliation including mineral mass balance constraints

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ABSTRACT

The operation of mineral processing units or plants is related to the mineral composition of the ore. However, unit performances are usually characterized in terms of metal content or recovery as this data is easier to be obtained rather than the mineral content. This paper presents a data reconciliation method that combines material balancing calculations and mineral stoichiometric information to estimate balanced mineral composition, chemical assays and flow rates in various streams of a mineral processing plant. The advantage of this method is evaluated by comparing the variance of the reconciled variables from this method to those obtained from usual data reconciliation methods. The estimated mineral composition leads to improved process performance evaluation.

## 1. Introduction

The ore that is feeding a concentrator is made of minerals that condition the energy requirements for the ore comminution and the performance of the subsequent separation circuit. Indeed, a change in the mineral composition of the ore may affect grinding mill throughput as well as the recovery or grade of the economical products. Despite this recognized relationships, the mineral composition of the ore is seldom measured or estimated to provide regular information for plant performance evaluation. Some methods such as QEM-SCAN are available to measure the concentration of the minerals in the ore samples (Lamberg, 2007; Whiten, 2008), but such an approach is too time demanding and expensive to be applied on a daily basis for plant monitoring. Therefore, plant operators usually evaluate the plant performance using chemical assays of metals or elements that are readily measured from ore samples.

Samples of the streams of mineral processing plants are collected on a daily basis to be assayed for the strategic elements. The measurements are reconciled to produce coherent data based on the material conservation concept (Hodouin et al., 2010). Then the reconciled data is applied to characterize the day to day operation of the plant in terms of grade and recovery of the valuable metals. However, such diagnosis is only partial as elements can be transported by different minerals that respond differently to the concentration process. A possible way to detect a problem resulting from the change in the mineral composition of the ore requires determining the concentrations of the various minerals in the ore and in the produced salable concentrates. Since measuring the mineral content of the ore could be a demanding task, one should consider estimating this data from the daily chemical assays of the samples collected on the main streams of the circuit. Some authors have already investigated the problem. Whiten (Whiten, 2008) described a method to estimate the minerals content of an ore sample. Lamberg and Vianna (2006) proposed a method to do a sequential mineral reconstruction followed by a material balance. Few authors take account for the mass conservation of the reconstructed minerals content (Subramanian et al., 2016). These authors consider the overall problem of material balance reconciliation and mineral content reconstruction and apply their method to batch and semi-batch processes. They also suggest a method to simultaneously carry out the mineral composition estimation and to balance all the species content so that mass conservation is verified for the overall processing circuit.

The objectives of this study are: (1) to propose a more efficient data reconciliation calculation algorithm for large size data set based on a hierarchical structure allowing an analytical solution for the ore mineral and/or chemical composition; (2) to apply the method to a simulated complex sulfide Pb-Zn-Cu-Ag ore flotation plant; (3) to compare the reconciled process variables and performance indices reliability of the proposed method to the conventional ones that do not make use of the mineral stoichiometric constraints.

The paper consists of four sections. The first section presents the formulation of the data reconciliation and mineral reconstruction problem involving flow rates, chemical elements and mineral composition measurements. The second section proposes a method that simultaneously estimates the mineral composition from the chemical assays

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**Nomenclature**

*Variables and functions*

| | |
|---|---|
| $a$ | Number of measured elements ($1 \le a \le n$) |
| $\underset{z}{\operatorname{argmin}}\, g(z)$ | Value of $z$ which minimizes the function of $g(z)$ |
| $A$, $B$, $C$ | Intermediate calculation matrices |
| $F$ | Vector of solids flow rates $F_j$ |
| $f$ | Relative flow rates vector |
| $\mathbf{f}$ | Diagonal matrix of relative flow rates |
| $\mathscr{F}$ | Block diagonal matrix of the relative flow rates |
| $f^*$ | Vector of independent relative solids flow rates |
| $E$ | ($n \times 1$) vector of $e$ values required to express the stoichiometry when using $Y^-$ |
| $I$ | Number of available information pieces or identity matrix depending on the context |
| $J()$ | Maximum likelihood criterion |
| $\ell$ | Number of plant streams |
| $\mathscr{L}$ | Lagrange associated to a constrained LQ problem |
| $m$ | Number of selected ore minerals |
| $M$ | Network matrix |
| $\mathscr{M}$ | Block diagonal matrix of $M$ repeated $n$ times or of different $M_k$ matrices |
| $n$ | Number of selected ore chemical elements |
| $p$ | Number of nodes in the plant |
| $q$ | Number of measured mineral mass fractions ($0 \le q \le m$) |
| $V$ | Variance-covariance matrix |
| $x$ | Generic notation for any element mass fraction $x_{ij}$ |
| $X$ | Vector of $x$ values |
| $y, y^-$ | Generic notation for any mineral mass fraction $y_{kj}$ |
| $Y$ | Vector of $y$ values |
| $Y^-$ | Vector of $m$-1 mineral mass fractions |
| $Z$ | Total number of variables to be estimated |

*Indices*

| | |
|---|---|
| $_x$ | Index for a matrix related to chemical elements |
| $_y$ | Index for a matrix related to mineral phases |
| $_f$ | Index for a matrix related to flow rates |
| $_i$ | Index for chemical elements |
| $_j$ | Index for plant streams |
| $_k$ | Index for minerals |
| $_r$ | Lower index indicating either the removed mineral in the conservation constraint or the reference flow rate |
| $^m$ | Upper index indicating measurement values of any measured variable |
| $\hat{}$ | Accentuation for an estimated or reconciled value of any variable |
| $^-$ | Upper index for any mineral content in a set of $m$-1 minerals |

*Greek symbols*

| | |
|---|---|
| $\alpha, \beta$ | Matrices used for expressing the network flow rates from the independent ones |
| $\lambda$ | Lagrange multiplier |
| $\varphi$ | Matrix containing the mass fraction coefficients corresponding to the chemical stoichiometry of the minerals |
| $\phi$ | ($n\ell \times m\ell$) block matrix that is obtained through the repetition of $\varphi$ |
| $\theta$ | Matrix pointing at the measured variables |
| $\psi$ | Modified $\varphi$ matrix for completeness constraint for minerals |
| $\Psi$ | Block matrix of $\psi$ |

*Acronyms*

| | |
|---|---|
| DR1, DR2, DR3 | Data reconciliation procedure using respectively raw data, balanced data and including mineral constraints |
| LQ | Optimization of a quadratic function under linear constraints |
| ML | Maximum Likelihood estimation method |
| NLP | Non-linear programming for optimization of a function under non-linear constraints |
| RSTDV | Relative standard deviation |

and balances this data with the estimated flow rates in the streams of a circuit. The third section describes the simulated mineral processing plant (a complex sulfides flotation plant) and the related data used to test the method. The fourth section discusses the data reconciliation results and compares the reliability of the variable estimates and metal recoveries to the reliability of those obtained through two other sub-optimal methods.

## 2. Formulation of the data reconciliation problem

A data reconciliation problem of a single process or a plant is usually defined as a statistical procedure that allows the estimation of measured and unmeasured process variables submitted to physico-chemical constraints. Usually the main considered constraints are the laws of mass and energy conservation. In the most frequent cases, one considers the total mass conservation of one phase and of the chemical species it is composed of, thus leading to a set of bilinear constraints (Hodouin and Everell, 1980). However the problem might also consider various phases, and various levels of the phase properties, i.e. temperature, chemical or physical properties, size-wise chemical composition, etc…, therefore leading to non-bilinear conservation constraints (Hodouin and Vaz Coelho, 1987; Bazin et al., 2003; Bellec et al., 2007). It is often considered that the measurement errors follow Gaussian distribution and the constraints are deterministic. The method applied in all such cases, where random uncertainties are present, is based on the maximum likelihood (ML) principle. In the present study the problem is limited to the following assumptions:

- The plant is assumed to operate in permanent regime (steady-state reconciliation).
- The plant is a $p$ nodes and $\ell$ streams (index $j = 1$ to $\ell$) network.
- The flowing material is the ore solid phase characterized by its $F$ flow rate vector of the $F_j$'s.
- Two ore properties are considered: the chemical composition $x_{ij}$ (mass fraction of element or component $i$ on stream $j$, $i = 1$ to $n$) and the mineral composition $y_{kj}$ (mass fraction of mineral $k$ on stream $j$, $k = 1$ to $m$).
- The mineral compositions are known through a stoichiometric matrix $\varphi$ ($n \times m$) as detailed in Section 2.1.
- The measurements are unbiased and their random errors follow Gaussian distribution without error correlation between the three measurement levels (flow rates, chemical elements and mineral mass fractions), but allowing error correlation within each of the three levels.
- All the selected process variables are estimable.
- The variable estimation problem is redundant, a necessary condition being that there are more measurements and non-redundant constraints than process variables to be estimated.
- The addition of the mineral stoichiometric compositions and possibly measured mass fractions add redundancy to the overall