

Towards Mineral Beneficiation Process Chain Intensification

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Abstract: As a part of the H2020 SPIRE project, Intensified by Design (IbD®), mineral beneficiation process chain will be intensified in terms of more efficient usage of energy and raw materials. The work focuses on optimizing control of the grinding circuit, coarse flotation process, new solids measurements and soft-sensors, as well as adaptive dynamic mass balancing. All demonstrators are interconnected through plant-wide optimization. In this paper, the process intensification activities carried out at the mini-pilot scale mineral beneficiation plant are briefly described. The real-time adaptation strategy utilizing Differential Evolution for parameter estimation in a sliding window is presented. The initial results show a successful parameter estimation result even in a short time window.

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1. INTRODUCTION

In mineral beneficiation process, the target is to get highest possible recovery for the valuable material with minimum energy consumption and environmental impact. The factors hindering these objectives are typically related to challenges in characterization of processed material and process streams, large lag-times due to equipment; as well as time-varying and complex dynamics (Zhou, Chai, and Wang 2009). Process intensification (PI), a rapidly growing field of research and industrial development, can be understood as a development aiming to smaller, safer, sustainable and energy-efficient technology (Keil 2017). Whilst smaller equipment may not directly suit to the development in mineral processing, the other goals of PI are well related to the targets of mineral beneficiation. The particle size reduction by grinding consumes about 4% of world's energy, and about 50% of mine site energy (Jeswiet and Szekeres 2016). In the H2020 SPIRE project, Intensified by Design (IbD®) (Anon 2018), mineral beneficiation process will be intensified in terms of exploring approaches to avoid excess use and loss of energy. The mineral beneficiation process chain intensification incorporates the following four targets of development; 1) Grinding circuit optimizing control, 2) Coarse flotation, 3) New solids material measurements, and 4) Dynamic mass balancing and model adaptation. The demonstrations will focus on sulphidic ore types, but the methods for redesigning process flows, capacities, and product particle size are applicable in any base metals, ferrous, or industrial mineral beneficiation plants.

Overall, PI is achieved in terms of less energy input in grinding, higher plant throughput and increased grade and recovery. The improved process chain management and the

coarse flotation machine will allow using substantially less energy in upstream grinding process which in turn has environmental benefits. An improved efficiency by 10-30% and increased total recovery of valuable metals by 1-3% is pursued.

Part of the demonstration activities are carried out at the Oulu Mining School (OMS) mini-pilot scale mineral beneficiation plant. The mini-pilot includes minerals processing from ore crushing to mineral enrichment. It enables studies in wide range of research areas. The mini-pilot has a modular construction making its process layout reconfigurable to some extent. The adaptable process, with its updated instrumentation and automation system, makes OMS mini-pilot facility a suitable environment for the demonstrations in this study. The research environment and the demonstration activities are shortly described in the following Section. In Section 3, the model adaptation algorithm applied in dynamic mass balancing demonstrator is presented along with initial results. Finally, the interconnection of all demonstrators through plant-wide optimization, and therefore mineral beneficiation process chain intensification, is discussed in Section 4.

2. RESEARCH ENVIRONMENT AND DEMONSTRATIONS

The OMS mini-pilot facility was developed based on the beneficiation plant of Pyhäsalmi mine (Finland) with the scaling ratio of 1:5000. The mini-pilot grinding circuit uses a rod mill for pre-grinding and a ball mill for secondary grinding. Classification can be currently done with a screw classifier or a hydrocyclone. The grinding product is then led to a preconditioner which works as a buffer between grinding and flotation circuits.

The mini-pilot process intensification through control actions requires additional online information about the continuous process. Online control actions need information about the process state and the disturbances in the unit processes. Therefore, the process has been instrumented exhaustively. For instance, the grinding mills and the ore silo were equipped with strain gauge weight measurement sensors, ore feed rate measurement was implemented, and flow meters for the water feeds were added. In addition, the frequency regulators connected with varying motors provide power consumption, current and moment information for monitoring motor performance. Grinding mill slurry temperature can also be measured with pyrometers. These measurements offer additional information for grinding circuit monitoring and potential soft sensor applications to be tested in mini-pilot. In proportion, the instrumentation project covered also the flotation sections, but these details are out of scope of this presentation.

As a part of the instrumentation project, dynamic process simulation tools (Schneider Electric SimSci® Dynsim) and advanced process control software (Schneider Electric APC) will be implemented to the mini-pilot. Dynsim can be used in conjunction with APC for the data from the simultaneously running mini-pilot process. Dynsim has access to automation system data for online simulation purposes. Model identification can be performed in APC and fast simulation then run in Dynsim environment. Matlab will be used to support new control research in conjunction with SimSci® software. SimSci® APC will be later used to implement model predictive control (MPC) into mini-pilot process. Process response tests can be done with fully automated pseudo random binary sequence (PRBS). Dynamic simulation and MPC aid in the finding of the optimal control configuration for operating process energy efficiently without compromising product quality.

2.1 Coarse flotation machine

Currently, the particles need to be ground down to liberation size in grinding circuit in order to be able to recover them in the subsequent flotation circuit. At the same time, there are also coarse, liberated particles in the mass flow. Too coarse particles contribute to the loss of valuables to tailings and restrict the recovery of the process. On the other hand, further grinding would result into finer particles, but there is a risk of over-grinding that will also impair the flotation results – and lead to significant energy consumption increase in the grinding stage. Coarse flotation (flash flotation) is a technology allowing to recover larger particles already in the grinding phase and hence enabling decreased grinding energy consumption.

The custom build small-scale coarse flotation machine has been integrated into mini-pilot facility, where the machine can be operated within the grinding circuit or in an isolated circuit. The coarse flotation machine consists of cell with monitoring window and three probe orifices/valves aside. The machine is equipped with variable drive motor for the rotor. The motor set point, and therefore the rotor rotating speed can be adjusted from the automation system. The air

addition is performed with a manually regulated valve connecting the coarse flotation machine and the compressed air pipeline. The bottom valve position and the position of the conical top plate can be manually adjusted. The machine is equipped with three pressure sensors located in different heights around the middle of the cell.

Volume of the coarse flotation machine is 23 L. The machine was scaled to handle nominal slurry mass flowrate of 250 kg/h with solids content being 60-65% (applicable slurry density around 1.8 kg/L). The product flowrate from the top outlet depend on the flotation conditions and feed mineral properties. Most of the fed material is discharged from the bottom outlet and recycled to the process.

In coarse flotation tests in the mini-pilot, the grinding circuit can be operated in different intensities to produce different kind of feeds for the small scale coarse flotation machine. In particular, different feed slurry densities and particle size distributions have been tested. The outputs from the small scale coarse flotation machine tests will next be utilized in the development of a phenomenological model for the machine.

2.2 Grinding circuit optimizing control

Typically, the ore feed characteristics (mainly changes in hardness of gangue and floatability properties of minerals in ground material) are varying all the time, causing disturbances to the downstream processes. Additionally, if the grinding circuit is not well under control it will result in increased fine particle size fraction, which cannot be recovered in the down-stream flotation stages and causes problems in dewatering process.

Pre-requirements for optimized control are comprehensive measurements of the grinding circuit. Grinding mills have been instrumented e.g. with weight, rotating speed, and energy consumption measurements. Along with the known and new solids measurements, measured data can be further processed by soft sensors, which are developed in the project. For example, in case of ball and rod mills, the additional information about drum volumes occupied by ore and water enables the on-line estimation of slurry density. Furthermore, it will be studied if energy consumption at certain rotating speed could provide additional information of the processed raw material in the drum. One of the targets is to reduce energy consumption of the grinding circuit. This can be achieved by understanding the process state and feed ore quality better.

2.3 New solids measurements

The main reasons that prevent having the grinding circuit process in complete control are the lack of cost-effective and robust on-line measurements for characterizing the solid material within the grinding circuit.

Within the IbD project, number of measurements techniques has been tested in the mini-pilot. A Raman spectrometer (Kaiser RamanRXN1) has been used with an immersion

probe in the coarse flotation machine utilizing the tailored sample orifices of the machine. A camera-based prototype for particle tracking has been installed next to the coarse flotation machine, so that it images the slurry through the window on the wall of the machine. The applicability of Raman spectroscopy for in-line mineral concentration analysis will be assessed after the demonstration. If successful, Raman spectroscopy offers a direct way to measure the mineral concentration in-line. This measurement can potentially be used in the control of mineral beneficiation, which would then have an effect to economic, energetic and environmental performance of the plant. The particle tracking prototype produces information about the direction and velocity of particles in the slurry, and possibly also about the movement and size of the bubbles. This information can be graphically presented as a vector field, and the velocity and angle distribution of the particles can be calculated. The information will be compared to the results of phenomenological model of the coarse flotation machine. Hence, the particle tracking results can be used to validate the modelling results, and to select some model parameters.

2.4 Dynamic mass balancing and model adaptation

In addition to on-line measurements, utilizing indirect measurements to provide information about unmeasured variables would allow to monitor the state of the system and facilitate better usage of resources through a plant-wide decision support system (DSS). DSS can assist operators for example in choosing the best control alternative to optimize the plant's performance by simulating the effects of the different actions on process outputs.

Mass balancing is a common practice in pre-processing metallurgical data, for example, prior to calculating the recoveries of beneficiation processes. In mass balancing, or in other terms data reconciliation, the basic idea is to maintain the unit balances: everything that goes into a unit must come out. The process measurement data can consist of flow rates, elemental or mineral assays, size fraction analyses and solids percentage measurements. Data reconciliation algorithms utilize known process and measurement variations, namely standard deviations. They will assist the computation algorithm, and determine whether each measurement should be adjusted to hold the mass balance over all the process units in the plant. Calculations are typically based on flowsheet models. In IbD-project, the flowsheet based mass balancing scheme has been further developed and packaged as an on-line calculation routine that is based on Outotec's Advanced Control Tools (ACT[®]) and HSC[®] Chemistry Software.

The aforementioned mass balancing routine is based on simple flowsheet model, i.e. on the knowledge on how the equipment in the plant are connected with each other. Another, and more demanding option, is to build a full-fledged dynamic simulation model of the process. This would require much more detailed information on process parameters and material properties, for example. In turn, the model can accurately describe the process state, for which the model was calibrated. In order to run such a dynamic

simulation model with reliable results in changing process conditions, the model needs to be continuously updated with the measured data from the real process. This can be accomplished with a sophisticated adaptation algorithm that will compare the state of the flowsheet model to the state of the real process and manipulate certain simulator parameters based on the observed differences. An online model adaptation algorithm presented in the next Section will be tested within this demonstration.

3. MODEL ADAPTATION

Adaptation is here related to automatically maintaining the model performance over time. After the identification stage and the model deployment, modelling error and prediction uncertainty are likely to increase due to future changes in the modelled process. Specifically, the need for model adaptation may origin from changes in input variable distribution or due to a concept drift – a permanent change in a dependency between input and output variables. A change may occur suddenly, occasionally, or by incremental drifting. Reasons for the changes in data distribution are numerous, ranging from a sensor fouling to reconfiguration of the sub-process(es). The process may also naturally exhibit time variant and/or non-linear behavior. In practice, the changes may cause adaptation needs either to model dynamics or to model parameters, and thus to the variable dependencies in a model structure. To cope with the adaptation requirements, several different strategies can be distinguished; 1) Continuous or periodical parameter identification, 2) Re-configuration of the identified model structure, 3) Multiple models, 4) Adaptation mechanism in a model structure, and 5) External or disturbance model for adaptation.

The above-mentioned adaptation strategies are applicable individually or as a combination with each other. The first two strategies include a change detection method to classify if there is a need for the adaptation. Typically, the detection is based on monitoring the evolution of the modelling error by statistical methods. If a notable change is observed, parameters of the models are updated. Tuning of the parameters may proceed recursively or in time windows. For this task, most of the discussed parameter identification algorithms are suitable in their recursive or initial form. The parameters can be replaced also from an existing lookup-table, if the detection result is properly quantified and includes information for the parameter scheduling.

A bias or time dependent properties in model residuals may indicate the need for model structure re-configuration, namely existence of the concept drift. This requires at least partial repetition of the model structure identification procedure. Some case examples on adaptation mechanisms and their applications are shown in Table 1.

3.1 Adaptation example

The adaptation algorithm is presented in Fig.1. Fundamentally, the adaptation is a parameter estimation problem in a sliding window. The optimization method applied here is Differential Evolution (DE) with window size

as the adjustable parameter and root mean squared error between the measured process output and simulated output as an objective function. An example illustrating the performance of the selected adaptation strategy is given; Assume a dynamic process, whose behavior can be described with an ARMAX structure, given in (1) and the optimal control signal can be determined as (2).

$$y(k) = 0.5218 - a \cdot y(k-5) + b \cdot u(k-5) + c \cdot v(k-5) - v(k) \quad (1)$$

$$u(k) = (a - c) / b \cdot y(k-5) \quad (2)$$

In (1) and (2), $y(k)$ is the process output at time instant k , a , b and c are model coefficients, u is the exogenous (process) input, and v is the random noise component (from uniform distribution between 0.9 and 0.99).

Table 1. Examples of selected model adaptation methods and related applications.

Reference	Keywords	Description
Soft Sensor Model Maintenance: A Case Study in Industrial Processes (Chen et al. 2015)	Soft sensors, Inferential sensors, Kalman filter, Model mismatch index, PLS	Presents an index to monitor prediction performance/update need of a model that is then updated by partial least squared (PLS) regression. Claimed as an online update method.
A practical multiple model adaptive strategy for single-loop MPC (Dougherty and Cooper 2003)	Model predictive control (MPC), Dynamic matrix control, Adaptive control, Multiple models	An adaptation mechanism based on scheduling multiple models according to current/estimated process state.
A Survey on Concept Drift Adaptation (Gama et al. 2014)	concept drift, change detection, adaptive learning	A review on model adaptation by machine learning community.
LPV models: Identification for gain scheduling control (Bamieh and Giarré 2001)	Gain scheduling control, identification for nonlinear systems, LPV models	Linear Parameter Varying (LPV) adaptation mechanism for model updating, an example.
Review of adaptation mechanisms for data-driven soft sensors (Kadlec, Grbić, and Gabrys 2011)	Adaptation, Incremental learning, Online prediction, Process monitoring	Several adaptation mechanisms for (data-driven) models discussed. Adaptation of monitoring metrics, adaptive and online data-preprocessing methods.
Ship stabilization control using an adaptive input disturbance predictor (Liu et al. 2010)	-	A case example on using an input disturbance model in combination with a process model as an adaptation mechanism. In this approach, a disturbance model is adapted instead of a process model.
Development of adaptive modeling techniques to describe the temperature-dependent kinetics of biotechnological processes (Rivera et al. 2007)	Bioreactors, Modeling, Optimization, Parameter estimation, Temperature effect, Artificial intelligence	An example of a hybrid modelling approach, where a Neural Network (NN) is applied to model kinetic behavior of a bioprocess together a mechanistic model. Adaptation mechanism is based on minimization of modelling error by re-estimating parameters of the NN-model if needed.
An Approach for Physical Model Adaptation based on transient Measurements (Schirmacher et al. 2009)	Engine modelling, Statistical modelling, Physical modelling, Parameter identification	Presents a methodology to adapt a physical model to measurement data applying a statistical correction model that is first identified with a controller minimizing the modelling error. Later, the controller is not needed as the identified statistical model describing the functional relation between process state and a parameter to be tuned in the physical model is applied.
On Parameter Design for Predictive Control with Adaptive Disturbance Model (Wang, Zhao, and Xu 2012)	Model predictive control, Adaptive disturbance model, Disturbance rejection, Parameter design	In this approach, a disturbance model is adapted instead of a process model. It is then a modelling methodology, where the disturbance model is applied to model the unmodeled portion due to uncertainty existing in the process model output.
Fuzzy modelling of carbon dioxide in a burning process (Ruusunen and Leiviskä 2004)	Adaptive systems, Efficiency, Optimisation, Energy, Soft sensing	A multiple model approach to adaptation, bases on monitoring the current process state and utilizing this knowledge as a parameter for scheduling the local pre-identified models and their combinations.

Now, assume that the behavior of the above process need to be estimated from past process measurements and control signals with a following ARX model presented in (3):

$$\hat{y}(k) = -\xi_1 \cdot y(k-5) + \xi_2 \cdot u(k-5) + \hat{v}(k) \quad (3)$$

where ξ_1 and ξ_2 are the model parameters to be identified. The identification was done with the adaptation strategy presented above (DE), and with a stochastic approximator (SA, using Delta learning rule and recursive estimation).

In Fig.2, the process behavior is presented. The process output reaches a steady-state ($y \approx -11$) until an abrupt change in the process is detected at $k=480$. This change is simulated by adjusting the parameter a value from 1.0 to 1.1. In Fig.3, it can be seen that the DE adaptation strategy can rapidly update the estimation model and find a new level for parameter ξ_1 . In Fig.3, also the noise estimate is presented, showing only slightly increasing fluctuations for the DE after the abrupt process change. From Fig.3, it can also be seen that the SA fails in this exercise as it cannot adapt the parameter, but instead increases the noise estimate drastically. Hence, the DE adaptation strategy seem to offer a better performance for adaptation problems typically seen in industrial processes.

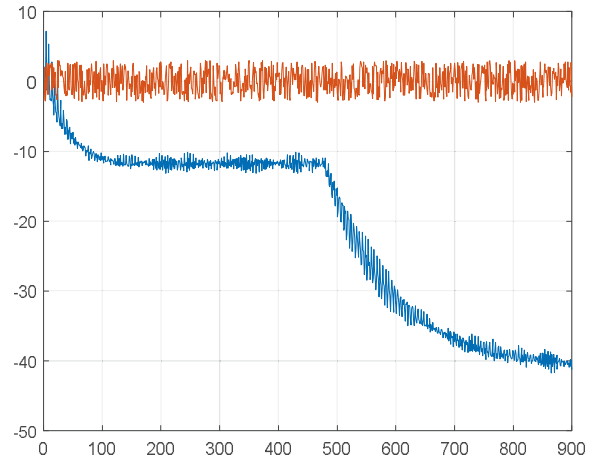


Fig. 2. Simulated dynamic process behavior. The blue line is the process output and the orange line is the optimal control signal.

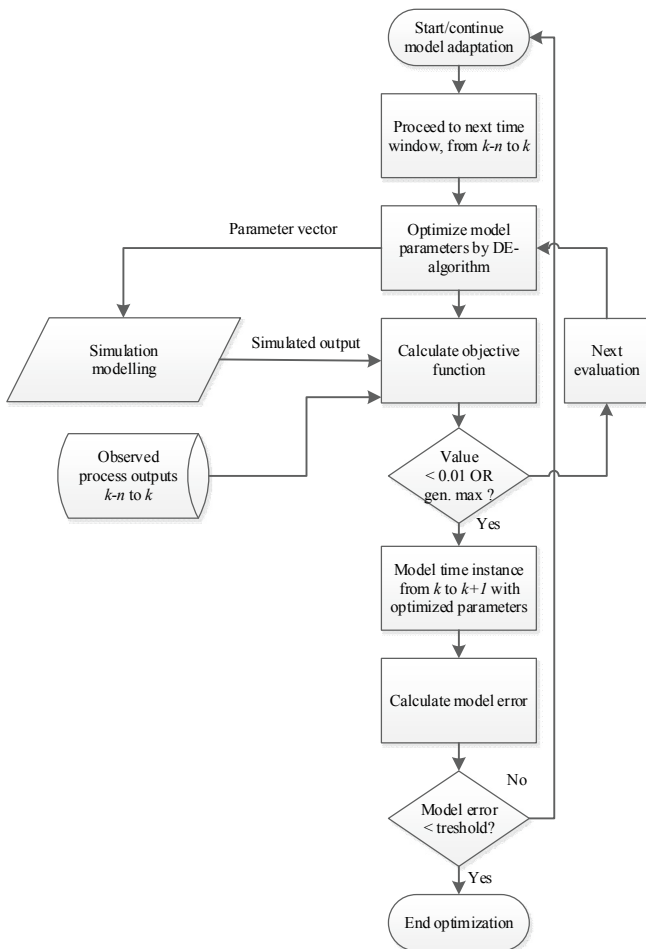


Fig. 1. Adaptation algorithm for online parameter identification.

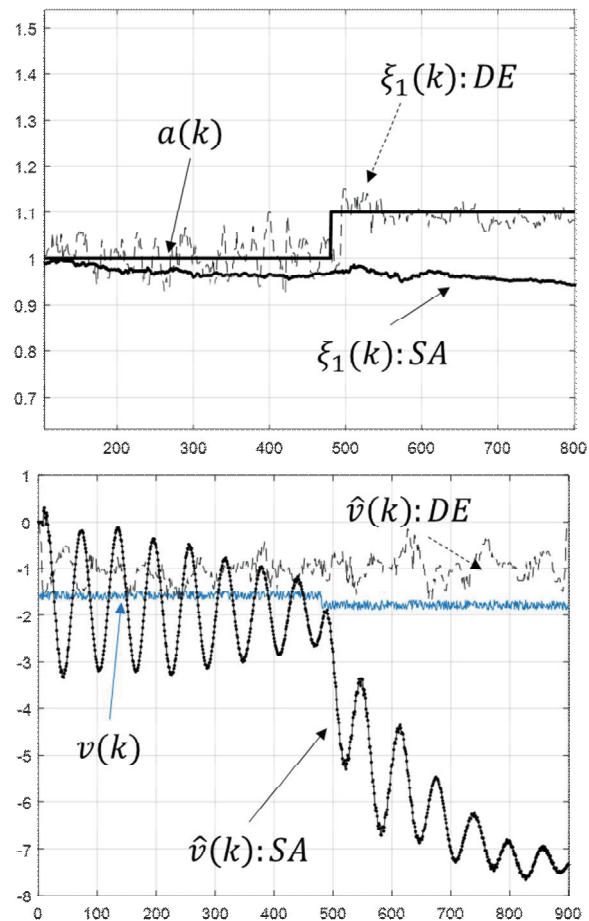


Fig. 3. Parameter estimation result (on top) and noise estimation result (on bottom) for the two adaptation algorithms.

3.2 Adaptation of dynamic simulation model

The test environment for the adaptation involves a process simulator in an external software, adaptation algorithm was

run in Matlab environment, and Outotec's Advanced Control Tools (ACT®) software was handling the data communication. Initially, the measured process outputs are also simulated and given in spreadsheet format for the adaptation algorithm.

The simulated process comprises a flotation flowsheet with four kinetic parameters to be adapted. The adaptation utilizes nine real-time simulation outputs and a pre-defined parameter space for the kinetic parameters, given in Table 2. In the initial tests, the applied time window for the adaptation was only four seconds after a process change that had triggered the adaptation. The DE parameters applied were the following; population size 40, number of generations 100, crossover factor 0.8, gain factor 0.8. The initial adaptation results presented in Table 2 show a convergence towards global optimum even with this very short time window. Hence, adaptation can be performed frequently and the highest adaptation frequency is mainly dependent on available computational power and the related software components. Naturally, the final adaptation frequency is chosen based on the process dynamics and/or the detected error between the model and process measurements.

Table 2. Parameter search space and adaptation result.

Parameter	1	2	3	4
Lower limit	1.4	0.1	0.005	0.0001
Upper limit	3.4	0.5	0.45	0.01
Real value	2.0	0.3	0.02	0.001
Adapted	2.0	0.3499	0.021	0.001

4. DISCUSSION AND CONCLUSION

Mineral beneficiation processes hold significant potential for energy and chemical savings. In this paper, the process intensification activities carried out OMS mini-pilot scale mineral beneficiation plant are briefly described. The continuous mini-pilot environment is equipped with modern modelling and control software and state-of-the-art instrumentation. The work focuses on optimizing control of the grinding circuit, coarse flotation process, new solids measurements and soft-sensors, as well as adaptive dynamic simulation. All demonstrators are interconnected through plant-wide optimization.

The adaptive simulation presented makes possible to track the changes in the process real-time and can be used as a soft sensor for variables that are difficult or expensive to measure including e.g. the raw material variations. The initial results show that in a short time window the parameters could be estimated accurately and the algorithm is likely to meet the soft sensor requirements regarding to relative modelling error.

Future work will focus on industrial implementation on the optimizing control employing the new solids measurements, fine tuning the software architecture for the dynamic mass balancing and model adaptation, and developing a phenomenological model for the coarse flotation machine.

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