Real-Time Mining: Moving towards continuous process management in mineral resource extraction

J Benndorf¹, MWN Buxton², K Nienhaus³, L Rattmann⁴, A Korre⁵, A Soares⁶, A deJong⁷, N Jeannee⁸, P Graham⁹, D Buttgereit¹⁰, S Gehlen¹¹, F Eijtelkamp¹², H Mischo¹³, M Sandtke¹⁴, T Wilsnack¹⁵

1. Assistant Professor, Delft University of Technology, Geoscience and Engineering, Stevinweg 1, Delft, NL. Email: j.benndorf@tudelft.nl
2. Associate Professor, Delft University of Technology, Geoscience and Engineering, Stevinweg 1, Delft, NL. Email: M.W.N.Buxton@tudelft.nl
3. Professor, RWTH Aachen, Department of Mining Machines (IMR), Wuellnerstrasse 2, Aachen, Germany. Email: knienhaus@imr.rwth-aachen.de
4. Senior Lecturer, RWTH Aachen, Department of Mining Engineering (BBK1), Wuellnerstrasse 2, Aachen, Germany. Email: rattmann@bbk1.rwth-aachen.de
5. Reader, Imperial College, Department of Earth Science and Engineering, Royal School of Mines, London, SW7 2AZ, UK. Email: a.korre@imperial.ac.uk
6. Professor, Instituto Superior Technico, Centre for Natural Resources and the Environment (CERENA), Avenida Rovisco Pais 1, Lisboa, Portugal. Email: asoares@ist.utl.pt
7. Manager R&D, Nederlands Organisatie voor Toegepast Natuurwetenschappelijk Onderzoek-TNO, Schoenemakerstraat 97, Delft, NL. Email: a.de.jong@tno.nl
8. Chief Technology Officer, Geovariances, Avenue Franklin Roosevelt 46BIS, Avon, France. Email: jeannee@geovariances.com
9. Manager R&D, Dassault Systemes GEOVIA Ltd. Unit 6, Phoenix Business Park, Coalville, UK. Email: Peter.GRAHAM@3ds.com
10. Chief Technology Officer, XGraphic Ingenieurgesellschaft mbH, Aretzstraße 9, Aachen, Germany. Email: buttgereit@xgraphic.de
11. Senior Research Engineer, LSA-Laser Analytical Systems & Automation GmbH, Indeweg 82, Aachen, Germany. Email: christoph.gehlen@lsa-systems.de
12. Chief Executive Officer, SonicSampDrill BV, Ultimaat 8, Giesbeek, NL. Email: f.eijkelkamp@eijkelkamp.com
13. Professor, University of technology ‘Bergakademie’ Freiberg, Department of Underground Mining, Akademiestrasse 6, Freiberg, Germany. Email: helmut.mischo@mabb.tu-freiberg.de
14. Managing Director, Spectral Industries BV, Schoemakerstraat 97, Delft, NL. Email: msandtke@gmail.com
15. Managing Director, Ingenieurpartnerschaft für Bergbau, Wasser und Deponietechnik (IBeWa), Lessingstr. 46, Freiberg, Germany. Email: th.wilsnack@ibewa.de
ABSTRACT

The flow of information, and consequently the decision-making along the chain of mining from exploration to beneficiation, typically occurs in a discontinuous fashion over long timespans. In addition, due to the uncertain nature of the knowledge about deposits and the inherent spatial distribution of material characteristics, actual production performance often deviates from expectations. Reconciliation exercises to adjust mineral resource and reserve models and planning assumptions are performed with timely lags of weeks, months or even years.

The key concept of Real-Time Mining promotes the change in paradigm from discontinuous intermittent process monitoring to a continuous process and quality management system in the resource extraction process. The framework includes a real-time feedback control loop that rapidly links online data acquired during extraction at the mining face, during material handling and processing with a sequentially updatable resource model. This will allow near real-time optimization of decisions related to long-term planning, short-term sequencing and production control.

The proposed framework integrates the building blocks automated sensor based material characterization, online machine performance measurements, underground navigation and positioning, underground mining system simulation and optimization of planning decisions and updating techniques for resource/reserve models in a holistic manner.

The contribution introduces to the Real-Time Mining concept and the building blocks and will provide a review the state-of-the-art. Technological readiness of necessary building blocks is assessed and critical gaps for further technology development are identified. The value added is illustrated by means of a selected case study.
INTRODUCTION

With the depletion of known and established mineral reserves, the decrease in head grades and the continuing demand of mineral raw materials by the modern society, future exploitation will move towards extraction of deposits under geologically more complex conditions. Complex deposits are characterized by a low continuity in grade and high irregularity in the geometry of the ore boundaries. As a result a profitable exploitation of the deposit becomes a lot more challenging. To be able to better utilize such unconventional mineral resources of the future, smart autonomous mining systems are needed, which integrate local exploration of spatially varying material characteristics in-situ and have the ability to follow and extract the pay zones in the ore body while optimizing the sustainable value of extraction (e.g. European Commission, 2010). The main barriers to overcome for the successful economic exploitation are:

- effective grade control which will maximize resource potential along the whole value chain,
- minimization of handling zero-value material introduced by dilution, thus
- reducing unnecessary expenditure of energy and financial resources and
- management and control of the geological uncertainty due to limited information available,

thus optimising resource utilisation. The current state-of-the-art in mineral resource management is a discontinuous intermittent process along the mining value chain (Figure 1 upper part). It starts with collection of exploration data, e.g. drill holes, followed by the development of a 3D spatial resource model, generated using sophisticated geostatistical modelling techniques. The resource model is used to specify the extractable reserves. Due to data scarcity, it is associated with a significant level of uncertainty. Notwithstanding this uncertainty, mine planning decisions are made, expected performance is predicted and the plan is executed. A comparison between model based predictions and actual performance typically occurs at the end of the production process, when ore grades and tonnages are determined for materials shipped to the customers. At this stage, deviations from production targets are noted; however, the opportunity for corrective action is no longer available. From data gathering to the final reconciliation, often months or even years may have passed.

FIG 1 – Moving from discontinuous process to a real-time continuous closed-loop process.

In April 2015 the multi-partner and multi-national European Commission funded R&D project Real-Time Mining was launched. The key concept of Real-Time Mining research promotes the change in paradigm from...
discontinuous intermittent process monitoring and control to a continuous closed-loop process management system (Figure 1 lower part). The development of such an integrated framework in the context of mineral resource management is novel and involves significant scientific challenges as it has to integrate multiple distinct scientific disciplines into one coherent process monitoring and optimisation framework. Main building blocks of Real-Time Mining are

- underground equipment positioning,
- sensor-based material characterization,
- sensor-based machine control monitoring,
- methods of spatial grade prediction using geostatistical approaches and rapid updating and
- optimization of short-term planning.

The main objective is to develop an innovative technical solution for resource-efficient and optimal high precision/selective mining in geologically complex settings. This will integrate the different components of autonomous positioning of mining equipment, spatially-referenced real-time sensor-based monitoring, extraction planning model updating together with decision and machine control optimization. The near autonomous system will enable access for exploration and exploitation in small deposits and difficult locations by selecting suitable equipment feasible in ruggedized and extreme conditions.

This contribution will introduce a closed loop framework for Real-Time Mining. First the concept and necessary building blocks are outlined followed by a review of the state-of-the-art. The focus in the review is on the identification of necessary progress in research and technology development to develop a so far conceptual framework (technology readiness level TRL 3-5) to an industrial proven concept (technology readiness level TRL 7-9). Over the next four years Real-Time Mining anticipates to close these gaps. An illustrative case study at the end highlights some selected aspects and demonstrates the potential value added.

THE REAL-TIME MINING CONCEPT AND BUILDING BLOCKS

Typical deposits in the context of geological complexity consist of some of the following attributes

- geologically structurally irregular, e.g. dismembered, deformed, narrow veins, steep geometries (typical for tin or tungsten veins, lead-zinc, gold, chromite, rare earth deposits),
- high spatial variability of grades and presence of deleterious elements, e.g. arsenic, cadmium,
- highly diffuse grade boundaries (typical for rare earth deposits, massive sulphide hosted copper deposits),
- clusters of low tonnage deposits or occurrences (typical for tungsten deposits).

The extraction of these raw materials is generally done by surface mining and underground mining methods based on depth of occurrence of the ore. Common to both mining methods is the necessity to sequentially complete the following process steps

- define and understand the ore body during exploration,
- estimate the resource potential (resource modelling)
- develop a long-term extraction plan (mine planning),
- develop a short-term sequence of extraction tasks (extraction sequencing)
- optimize operational control to produce material, including blending and dispatch decisions which accords with predefined specifications.

The amount of information available from traditional exploration is increasingly inadequate in more complex geological settings. The resolution of the data and the ability to interpolate in-between data is insufficient to generate the required knowledge about the deposit in order to provide real-time control of the extraction process within the limits set by principles of sustainable mining. In conventional mining applications this process is currently intermittent and discontinuous since it relies on physical sample collection and subsequent analysis in an external laboratory.

The Real-Time Mining approach will progress towards an innovative self-learning extraction process. It will provide a real-time process feedback control loop linking online data acquired during extraction at the mining
face and during material handling for rapidly updatable resource model associated with real-time optimization of long-term planning, short-term sequencing and production control decisions. Figure 2 summarizes the integrated concept of the project and the interaction between necessary building blocks (BB). A similar approach to Real-Time Mining has been recently developed in the context of hydrocarbon extraction and demonstrated a reduced extraction cost and associated increase in resource efficiency of 6% -9% (e.g. Jansen et al, 2009).

The Real-Time Mining concept follows the general closed-loop approach and can be applied to general mining settings, open pit and underground. It builds on a (near) real-time interaction between the mining machine and extraction process, resource and mine planning models and decisions to be made on a short-term scale. During the mining process, online production data will be obtained which can be geo-referenced based on localization- and material tracking systems. Utilizing these data and relating them to material properties offers the ability to update resource/grade control models used for short-term decision making and production control. Decisions within the latter can be optimized using sophisticated optimization tools.

Following building blocks are integrated in the RTM system:

**BB1:** For a quantifiable impact monitoring of all measures developed within RTM, a set of sustainability and industrial viability indicators is needed. These focus on all aspects of sustainability including safety, environmental and social impact, economic impact as well as industrial viability. The indicators will provide the foundation for defining the required data parameters, the evaluation criteria and optimization targets and are directly related to both, local geological properties and the raw material extraction system.

**BB2:** The spatial context of all data acquired has to be determined in order to fully exploit the value of sensor data gathered during production. BB2 will provide and integrate demonstrated technologies for underground positioning (UP). These technologies have to be applicable to the physical conditions expected in small scale mining applications, including case specific required level of precision.

**BB3:** Understanding relevant geological material parameter to monitor and classify, BB3 will provide ruggedized and modular combinations of sensor technologies applicable for real-time material characterization in small scale mining environments. The intention is to characterize grades and geo-metallurgical attributes such as textures, mineralogy and hardness. This application requires the development of a multi-variate statistical interpretation rule to relate combination of sensor signal with raw material properties and an appropriate sampling strategy to account for the sampling medium, material variability and required levels of precision. The sensor data will be spatially constrained using the data from BB2 and integrated into a consistent data base.
**BB4:** Sensor concepts acquiring real-time machine performance data provide additional information related to material characteristics, such as specific energy usage, pull up or pull down pressure. Depending on the rock strength and rock hardness RTM considers two scenarios of extraction: A) Extraction by drilling and blasting with subsequent loading/hauling and B) Extraction by rock cutting coupled with continuous hauling. Examples of machines considered are shown in Figure 3.

![A1) Underground Drilling (Results used in grade control) A2) Sonic Drilling Innovative application: grade control B) Rock Cutting No grade control](image)

**FIG 3 – Examples of mining machines considered within Real-Time Mining (RTM).**

**BB5:** Computational efficient methods for integrating enormous data sets have to be advanced for integrating sensor information with different formats into a single consistent spatial database. Visualization tools will be developed for supporting real-time operation control and decision making, resulting in a virtual operation control cockpit. This will also integrate results from the updated resource model (BB6) and optimized mine plan (BB7).

**BB6:** provides a geostatistical framework allowing for a rapid and sequential update of the short-term resource/reserve model utilizing highly dense sensor based data generated from online material characterization (BB3) and machine performance (BB4). To predict the performance along the whole value chain, attributes of the spatial model to be updated including economic, extractability and processing relevant attributes of the raw material as well as attributes affecting safety and environment as defined in BB1. Results will be used as input for optimizing the extraction process in BB7.

**BB7:** provides rapid and real-time optimization methods in the context of long-term mine development, short-term sequencing, production control and auxiliary processes. Utilizing real-time updated models about the spatial distribution of ore from BB6, it is expected to lift a huge potential in improving efficiency-related to selective extraction and resource recovery, eliminating waste in an early stage of the process chain, more effective dispatch decisions, blasting design or local rock support strategies. To close the loop, BB7 will feed back information to BB5 as virtual operation control cockpit.

Figure 4 illustrates the concept for a general underground mining setting. Based on a prior resource model the extraction sequence at different loading points is planned and a model based prediction can be performed for monitoring/sensor stations. Sensors will measure the actual properties of the raw material within a certain precision. The difference between model based prediction and sensor based measurements will be fed back into the resource model resulting in an updated or posterior resource model. Based on the new information available mine planning decisions and production control strategies can be revised and adjusted to most current information.
STATE OF THE ART, IDENTIFIED GAPS AND PROGRESS

With the aim of developing a proved concept ready for industrial market entry after four years of Real-Time Mining, a thorough analysis of the state-of-the-art for the several building blocks was performed. To map the state-of-the-art to the level of applicability in a mining environment, the Technology Readiness Level scale of the European Commission was adapted. Figure 5 summarizes the current state-of-the-art and the required progress to achieve Real-Time Mining goal.

The main need for scientific and technological development was identified for three building blocks

- sensor combinations for material characterization in high throughput and ruggedized mining conditions,
- comprehensive geostatistical feedback-framework for rapid resource model updating,
- rapid optimization techniques for short-term planning and production control.

Following sub-sections outline concepts and recent developments within these identified fields, which will be matured for industrial application within RTM.

Sensors for Material Characterization

Real-time sensor-derived data are required to identify and discriminate material properties such as texture, mineralogy, geochemistry and physical properties at the mining phase. Specific sensor techniques that have the potential to be used to satisfy these requirements include Laser Induced Breakdown Spectroscopy- LIBS (e.g. Death et al, 2008), Visible Near Infra-Red - VisNIR, Short Wave Infra-Red - SWIR imaging (e.g. Harris et al, 2010) for determining textures and mineralogy, X-Ray Fluorescence - XRF for geochemistry and thermal, Mid Wave Infra Red – MWIR or Long Wave Infra-Red –LWIR (e.g. Shimoni et al, 2007) for assessing rock forming minerals. Imaging techniques are required for size, volume and shape determination. These will contribute towards mass and density determination. Infra red (VisNir, SWIR, LWIR), XRF, RAMAN and LIBS methods require no pre-preparation of sample.

FIG 5 – Evaluation of Technology Readiness Levels of Building Blocks within RTM.

The main need for scientific and technological development was identified for three building blocks

- sensor combinations for material characterization in high throughput and ruggedized mining conditions,
- comprehensive geostatistical feedback-framework for rapid resource model updating,
- rapid optimization techniques for short-term planning and production control.

Following sub-sections outline concepts and recent developments within these identified fields, which will be matured for industrial application within RTM.

Sensors for Material Characterization

Real-time sensor-derived data are required to identify and discriminate material properties such as texture, mineralogy, geochemistry and physical properties at the mining phase. Specific sensor techniques that have the potential to be used to satisfy these requirements include Laser Induced Breakdown Spectroscopy- LIBS (e.g. Death et al, 2008), Visible Near Infra-Red - VisNIR, Short Wave Infra-Red - SWIR imaging (e.g. Harris et al, 2010) for determining textures and mineralogy, X-Ray Fluorescence - XRF for geochemistry and thermal, Mid Wave Infra Red – MWIR or Long Wave Infra-Red –LWIR (e.g. Shimoni et al, 2007) for assessing rock forming minerals. Imaging techniques are required for size, volume and shape determination. These will contribute towards mass and density determination. Infra red (VisNir, SWIR, LWIR), XRF, RAMAN and LIBS methods require no pre-preparation of sample.
**Infrared Spectral Techniques**

Infrared spectral techniques are used to determine mineralogical parameters for geological material. The infrared is divided into:

- **VisNir** (wavelength range 0.4 to 0.7 µm), which identifies clays and iron.
- **SWIR** (wavelength range 0.7 to 2.6 µm). The short wave infrared (SWIR) is an important range for providing mineral identification for hydroxyl, water and carbonate bearing minerals.
- **MWIR** (wavelength range 3 to 5 µm). No commercial system for mineral identification is available.
- **LWIR** (wavelength range 6 to 14 µm). The long wave infrared (LWIR) is one of the most important regions for mineralogy as silicates can be identified in these wavelength ranges. Applications for mineral detection are known but implementation of systems is limited due to immature instrumentation development. Technical solutions are emerging in terms of instrumentation and application.
- **Currently test hyperspectral imaging systems are available for the MWIR and the LWIR.**

Specific SWIR applications have involved the real-time assessment of materials on conveyor belts during the material handling (Goetz *et al.*, 2009). Technologies such as the CSIRO HyLogger suite have been developed to provide voluminous and automated data capture. These systems capture infrared data from drill core or chip samples. Other systems have been developed for on-belt monitoring (i.e. ASD systems). These all provide an important impetus in driving the technology development forward through commercial entities. Hyperspectral imaging systems for logging of drill cores have been developed such as the sisuRock system by Spectral Imaging Ltd. (SPECIM) in Finland. At this stage it is not possible to image rock materials across the full infrared wavelength range (from approximately 400nm to approximately 1mm) with a single spectrometer.

**LIBS**

LIBS can be used for the analysis of solid, liquid and gaseous samples. An analysis can be performed in a few tenths of µs simultaneously for all chemical elements whose spectral lines lie in the detected spectral range of the spectrometer. Using modern data acquisition electronics, up to 1000 LIBS measurements per second are possible (e.g. Bette *et al.*, 2005).

Commercially available portable LIBS systems can be used for industrial material analysis, prospecting and mining environmental monitoring. The reduced size of all the components (especially laser-system and spectrometer) in a portable system limits the analytical-performance, resulting in only a small number of detectable elements at high detection limits. Expert knowledge is required to obtain usable results.

**Mineral characterisation using Raman**

This technique is well established (e.g. [http://rruff.info/](http://rruff.info/) documents Raman spectra of minerals). However, because Raman spectroscopy is a molecular technique, it is seldom used to characterise whole rocks such as those extracted during mining. With respect to Raman spectroscopy instrumentation, commercially available state-of-the art handheld instrumentation (e.g. BaySpec sold by: [http://www.rigakuraman.com/](http://www.rigakuraman.com/)) or Thermo Scientific ([http://www.ahurascientific.com/material-verification/products/truscan/](http://www.ahurascientific.com/material-verification/products/truscan/)) are designed for a non-mineralogical task, e.g. pharmaceutical. Although the hardware may be suitable to whole rock samples from mines, the software is not suited for the application. Issues regarding resolution and optical quality in complex poly-mineralogical applications are not resolved.

**The combination of Raman and LIBS**

This combination is attractive for remote mineralogical characterisation and has been increasingly studied by NASA and ESA for lunar and Mars exploration (Sharma *et al.*, 2003; Escudero-Sanz *et al.*, 2008). If the combination of Raman and LIBS can be applied to map the Martian surface, then it will definitely be applicable on Earth. An example of this is the analysis of sulphur-containing minerals. For this, LIBS showed high sensitivity in detecting cations and trace elements but was less sensitive in detecting anionic species. This gap was filled by Raman, which can identify the anion groups in the crystals and crystal forms from Raman active lattice modes (Sharma et al, 2007).

There is a gap between the highly portable systems designed for Mars, which are excessively expensive and highly overspecified for applications in a terrestrial industrial scenario and the current state-of-the-art bulky systems that combine Raman and LIBS for use in the laboratory environment. A portable combined Raman
and LIBS system does not currently exist but is clearly required for practical measurements in a field or operational environment.

**Progress beyond the state-of-the-art**

For all sensor types, imaging techniques may be required for size, volume and shape determination. These will contribute towards mass and density determination. Sensor resolution and the ability to discriminate differ for each of the different sensor types. Different sensor types generate different data outputs in terms of response, precision, accuracy and format. One specific sensor cannot satisfy all requirements. The maturity in terms of degree of development and definition of applications differs. Raman and LWIR have not yet been applied to large scale industrial process.

There is no current application that integrates combinations of these sensors for comprehensive material characterisation and discrimination in a highly variable and high throughput environment. In particular methods for defining sensor combinations and the relation to material characteristics are lacking. Methods for defining micro- and meso sampling schemes in order to obtain information that meet requirements of a given precision are also lacking. RTM will go beyond state-of-the-art by developing a modular, transportable multi – sensor ruggedized platform that permits combinations of infra-red (SWIR, LWIR), Raman and LIBS sensors suitable for operation in a mining environment.

**Sensors for Machine Performance**

**Rock cutting application**

Machine performance parameters that are measured during extraction are cutting force and energy consumption of the machine. These can be used to identify specific energy demand and the nature of the material being cut. Currently, there is no proven measuring system on cutting drums for mining equipment. Machine performance parameters are of major interest, since they provide information about the extraction process as well as information about the cutting tools currently in the face during the measurement (online). The process parameters measured during cutting directly show the influence of the machine parameters and the corresponding mineral properties during cutting. The cutting force contains information about rock breakage mechanisms and, hence, can be used to optimize the extraction process (Entacher et al, 2012). Currently, the cutting force is only measured on TBM machines. On other cutting machines, linear and conical cutting picks are used. Here, the cutting force is not measured, but estimated (Goktan and Gunes, 2005).

**Progress beyond the state-of-the-art rock cutting:** RTM will use sensor information to gain an authoritative forecast of the characteristic values and predict the cutting force of conical and linear cutting tools (e.g. Sahoo, 2012). This information will be used for material identification to update the mineral deposit model.

**Drilling application**

In addition to the performance of rock cutting tools, the measurement of the real-time performance of drills offers a potential for online material characterization. Drilling is a key technology during blast-hole drilling and grade control. Real-Time-Mining intends to use and apply the innovative sonic drilling technology (SONIC, 2014). Sonic drilling in hard formations uses a combination of vibration with rotation. The use of rock drill bits will allow cutting of the material. In order to keep the temperature of the drill bit down and lift the cuttings foam injection is the best solution. A prototype sonic drill was developed by Sonic Samp Drill ® allowing the online measurement of Position of trolley to measure depth of drill string [m], Verticality X & Y [°], Rotation of clockwise pressure [Bar], Pull down pressure [Bar], Pull up pressure [Bar], Sonic pressure [Bar], Water pressure [Bar], Rotation Speed [Bar], Sonic frequency [Hz], Slurry volume [l/m], Accelerometer and G-force [/10 m/s²].

**Progress beyond the state-of-the-art sonic drilling:** It is likely that all the online captured data contain information about rock mass characteristics, such as UCS, breakage mechanisms and, hence, can be used to optimize the extraction process. At present there is no statistically rigorous method to relate this data to rock characteristics. RTM aims to develop the statistical regression methodology.

**Rapid Updating of Resource and Reserve Models**

The feedback of online sensor data into the resource model offers huge potential for improvement of operational management, however it is a scientifically challenging task. Data are of different data density,
sources (different sensors and exploration data) and associated uncertainties, which have to be consistently integrated in a computational efficient way. Sensors may be applied to material streams originating from multiple different sources, e.g. mining regions. Smart Tags® can be used for material tracking. To solve this challenge, RTM aims to develop a method for rapid and sequential resource model update (geometry of lithotypes and grade distributions, including deleterious elements). A very attractive approach, derived from system and control theory, is the application of Kalman-Filter (KF) techniques (e.g. Kalman, 1960; Evensen, 2003). These techniques are designed to re-estimate the unknown state parameters of a system (in this case the spatial distribution of grades and lithotypes) recursively on streams of noisy input data related to the system parameters (sensor data). Applications of Kalman-Filter approaches in a geo-scientific context can be found in reservoir engineering in the context of history matching and smart well concepts (e.g. Jansen et al., 2009; Hu et al., 2012; Heidari et al., 2011), in hydrogeology and geosciences (Wackernagel and Bertino, 2004) and others. In a mineral resource extraction application, especially for updating resource/reserve models based on online data, the application of these techniques was recently proposed for the very first time. A initial numerical investigation by Benndorf (Benndorf, 2014) in a simple 2D case using an exhaustively known dataset showed that both methods, KF and Ensemble KF (EnKF), improve the resource model significantly. Even when the sensed material comes from multiple different sources and the sensor precision is low, the filter improves the prediction of future mining blocks significantly by decreasing the true mean square error. Figure 6 shows the empirical mean square error between true block grades and re-estimated for different relative errors of the sensor and for different distances of mining blocks from the samples taken.

**FIG 6 – Example: results for resource model updating**

Progress beyond the state-of-the-art: RTM aims to develop, implement and test a novel geostatistical framework allowing for a rapid and sequential update of the short-term resource/reserve model. It will utilize the difference between model based prediction (prior model) and sensor data to generate a updated model (posterior model) utilizing Kalman-Filter-techniques. Specifically, the ability of EnKF methods to linearize and forward predict complex non-Gaussian relations, such as those usually encountered when dealing with grades or material characteristics aiming to provide reliable resource/reserve estimates as input to mine planning, will significantly reduce uncertainty.

Real Time Optimization for Short-term Planning and Production Control

The updated model will lead to possibly new decisions in short-term operation management such as production sequencing, digging capacity control or stock-pile management. Mine planning and production control optimization under geological uncertainty is a non-linear and computational expensive mathematical optimization problem. A discrete extraction period (typical problems vary between 5 to 20 periods) has to be assigned to each mining block, section or single blast (which can be in the order of $10^6$ to $10^7$) subject to constraints imposed by multiple partly competing production targets as well as physical, safety, environmental and economic related boundary conditions. Methods of mathematical programming, such as Dynamic Programming or Mixed Integer Programming, are well acknowledged in the field of mine planning optimisation (e.g. Ramazan and Dimitrakopoulos, 2004). Recent research was successfully performed to integrate geological uncertainty (e.g. Dimitrakopoulos and Ramazan, 2009; Benndorf and Dimitrakopoulos 2013) leading to an increase of 24% in NPV while reducing the risk of not achieving production targets. Jewbaly (in Jewbaly and Dimitrakopoulos, 2009) introduced a short-term production scheduling optimisation based on geological uncertainty and updateable models and demonstrates the benefit in the Australian gold mining industry. The previous mentioned applications are small or moderate in size. Short-term production scheduling in large mining operations represents a problem, which is typically complex and involves many interdependencies. These are difficult to model in a closed form.
Most of the mathematical programming approaches are limited by the amount of decision variables, as applications become large and suffer from reduced computational efficiency. In leading manufacturing process industries, such as aerospace, chemical industry or petroleum engineering, the simulation approach is applied to support making expensive decisions and optimisation during design and operation of processes (e.g. Young Jung et al, 2004; Schulze-Riegert and Shawket, 2007; Subramaniam and Gosavi, 2007). Simulation based optimisation methods, such as Response Surface Methods or Learning Automata Search, have been proven to result in near optimal solutions for decision problems and are especially applicable for scheduling complex and computationally large systems (Gosavi, 2003), such as continuous mining operations. The concept of simulation based optimisation is shown in Figure 7. Using general system simulation techniques the objective value \( J \) of a complex objective function can be evaluated for a given set of decision variables. The optimisation part, such as response surface methods in combination with gradient descent methods will explore the space of decision variables to obtain a near to optimal set of these.

**FIG 7- Simulation based Optimization within RTM.**

Stochastic process simulation, whether discrete, continuous or combined (Kelton and Law, 2000), provides a powerful tool for measuring performance indicators summarised in an objective function of complex systems. In essence the simulator assesses a complex objective function \( J \). Hall (2000) presented the requirement for successful simulation modelling, advantages and disadvantages of simulation as well as pitfalls for mining related application in two case studies. The results showed that simulation can be a powerful tool for the mining engineer. When used in proper applications it is able to provide insights into complex system behaviour. (Baafi and Ateepour, 1996 ) and (Askari-Nasab et al., 2012,) used discrete event simulation to investigate a truck-shovel system of discontinuous open pit mines. The process simulation method is used to optimise the truck fleet size for the system. For short-term mine planning (Soleymani Shishvan and Benndorf, 2014) presented for the first time a simulation based approach for continuous mining applications integrating geological uncertainty. The objective is to evaluate the performance in terms of producing the target quantity and quality in a large open pit coal operation and assess the efficiency for alternative production schedules. Different sets of decision variables are tested, including a shift schedule, block sequencing and defined production rates. Results demonstrated the stochastic approach provides the mine planning engineer with a valuable tool to foresee critical situations affecting the continuous supply of raw material to the customers and system performance. Comparing the outcome of different sets of decisions provides a tool for improved decision making. Salama et al. (2013) used a combination of discrete event simulation and Mixed Integer Programming (MIP) as a tool to improve decision making in underground mining. The proposed method uses the simulation approach to evaluate the operating costs of a set of different haulage system scenarios and obtained the cash flows for input into the MIP model.

**Progress beyond the state-of-the-art:** further work is required to extend current applications to continuous production control variables such as effective digging rates and include the short-term sequencing problem in the optimisation phase. For real-time decision support and short-term operation control simulation based optimization in mineral resource extraction is not known. Real-time data, which describe system parameters and boundary conditions will allow development of real-time optimization methods for decision making for short-term extraction scheduling, production control, dispatch and blending management. Due to the complexity of the problem and the required rapid optimization, methods will be built upon the simulation based optimization paradigm.
**ILLUSTRATIVE EXAMPLE DEMONSTRATING THE VALUE ADDED**

The subsequent example aims to exemplarily investigate the performance of one of the RTM building blocks, the proposed resource model updating methodology. Although this specific example is related to previous work developed for large surface mining operations, the basic principle is similar to the one applied in RTM. Here, an artificial test case is presented, which is built around the well-known and fully understood Walker Lake data set (Isaaks and Srivastava, 1989). The data set (Figure 8) is interpreted as quality parameter of a coal deposit, e.g. as calorific value. The deposit is sampled irregularly at a spacing corresponding to an average of two reserve block length. The blocks were defined with a dimension of 16m x 16m x 10m. The block –variogram is given with a spherical structure, range 50m, nugget effect 0.4 and sill 0.6.

Taking into account an assumed density of 2 t/m$^3$ one mining block represents a tonnage of 5.120t. Ordinary Kriging was used to generate a resource block model and the prior error covariance matrix, Generalized Sequential Gaussian Simulation was used to derive the realizations or ensemble members for the EnKF application. For simplicity, no dilution and losses were applied resulting in the reserve model being equal to the resource model. The resulting block model (Figure 8) was used as prior model.

![FIG 8 - Resource Block Model used for the case study.](image)

Without loss of generality the artificial block model shall be mined applying a continuous mining system, which contains initially of two bucket-wheel excavators positioned at separate benches. Different digging rates were applied: Excavator one mines at a rate of 500t/h and excavator two at 1,000t/h. The material is discharged on belt-conveyors positioned on the benches, which are combined to one material flow at the central mass distribution point. The belt speed is assumed to be constant at 6m/s. For deeper insights in continuous mine system simulation for short-term planning and decision control under geological uncertainty, the reader is referred to (Soleymani-Shishvan and Benndorf, 2014).

The combined material flow of both excavators is scanned by a sensor positioned above a central conveyor feeding the stock- and blending yard. Since no real sensor data are available, virtual sensor data were generated. The artificial sensor data represent a 10 minute moving average (corresponding to about 250t production) and are composed of three components. Component one is the true block grade taken from the exhaustively known data set. Component two captures the volume variance relationship and corrects the smaller sensor-measurement support of 250t to the mining block support of 5120t by adding the corresponding dispersion variance. The third component mimics the precision of the sensor. For this case study the relative sensor error is varied between 1%, 5% and 10%.

The performance of the proposed Kalman-Filter approach will be evaluated using the mean square difference or mean square error (MSE) related to the true block value. Here, the difference between estimated block value $z^{t+1}(x)$ and real block value $z(x)$ from the exhaustive data set is compared. The MSE is an empirical error measure and can be calculated according to

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (z^{t+1}(x_i) - z(x_i))^2$$  \hspace{1cm} (4).

Figure 6 shows the MSE for different sensor precisions compared to the prior case for blocks,

- which are already mined,
• which are one block distant and will be mined next working shift, day or week and
• which are two blocks distant and will be mined in near future.

Figure 6 demonstrates clearly the ability of the presented Kalman-Filter based approach to decrease the uncertainty of predicting block values by updating based on sensor data. Considering the MSE, following observations can be made:

• For mined blocks, the uncertainty almost vanishes. Residual uncertainties remain due to the sensor precision.
• Adjacent blocks are updated resulting in a significant improvement compared to the prior model. For high precision sensors this improvement leads to an about 40% decrease of the MSE. This improvement is due to the positive covariance between two adjacent blocks. In addition, the sensor clearly influences the result.
• Blocks in the second next row are still updated. Due to the larger distance and the corresponding smaller covariance, the effect is less obvious compared to directly adjacent blocks, however, still significant.

The differences in block model are shown in Figure 9. It shows the prior model based on exploration data, the newly updated model and the differences between both models. Clearly the model is updated.

With this framework an efficient method is available to integrate production data with exploration data for a continuous updating of the resource model.

![Comparison between block models: prior model, updated model and difference.](image)

**CONCLUSIONS**

Online sensor measurements on production and machine performance and also material characteristics during the production process provide a huge amount of detailed information about the deposit in addition to exploration and grade control data. So far most of this information is used in forward decision loops. The ability to incorporate these data, derived during the production process, into resource/reserve models and a subsequent optimization of short-term planning and production control decisions promises a large potential for improvement in efficiency in any type of mining operation.

With the variety of geostatistical sequential resource model updating techniques a set of tools is available, which lead to an improved prediction of critical attributes in the resource/reserve model. However, additional scientific and technological development is necessary to further mature a set of techniques for industrial scale applications. A more general framework is necessary linking different scientific fields of underground positioning and material tracking, sensor technologies for material characterization and machine performance monitoring, data management and visualization techniques, geostatistical modelling and optimization of mine planning decisions. It is the aim of Real-Time Mining to further enhance and integrate these building blocks and demonstrate the holistic concept in selected industrial case studies in Europe.
With the ability of improved grade control and material characterization optimized decisions can reduce or even eliminate zero value material from the logistic chain as early as during extraction. Also, the in-situ recovery will be improved leading to increased resource utilization. The resulting more selective and precise mining process is expected to be especially applicable in geologically complex settings and may support economic viability of extracting these deposits. In a sense of sustainability these technical developments today will provide improved access to deposits and enable future generations to extract deposits, which are nowadays underutilized.

ACKNOWLEDGEMENTS

The Real-Time Mining project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 641989.

REFERENCES


