Real-Time Mineral Resource Models-
Approaches for the Integration of online Production Data

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ABSTRACT:

The flow of information along the mining value chain from exploration through resource modelling, reserve estimation, mine planning, operations management and beneficiation occurs typically in a discontinuous fashion over long time spans. Due to the uncertain nature of the knowledge about the deposit and its inherent spatial distribution of grades, actual production figures in terms of produced ore grades and quality but as well production efficiency often deviate from expectations. To react to deviations, reconciliation exercises are performed to adjust mineral resource models and mine planning assumptions, however, often with a timely lag of weeks, months or even years.

With the development of modern Information and Communication Technology (ICT) over the last decade literally a flood of data and information about different aspects during the production process is available in a real-time manner. For example, sensor technology enables online characterization of geochemical, mineralogical and physical material characteristics on belt conveyors. The ability to exploit the value of this additional information and feed it back into resource models and planning assumptions will open up new opportunities to continuously control the decisions in a mining operation for an increased resource recovery and process efficiency. This change in paradigm from a discontinuous towards a near real-time reserve reconciliation and model updating calls for suitable modelling methodologies for real-time back propagation of newly available information into resource/reserve models.

The contribution introduces a new Kalman-Filter based approach for real-time updating of mineral resource models utilizing online sensor data. The theoretical description of the method is provided first followed by a demonstrative case study that investigates the performance for different data configurations and parameters and illustrates the value added.
Introduction

Successful planning and operations management in mineral resource extraction is based on a solid understanding about the spatial distribution of ore tonnage and grades in the deposit. The knowledge about the deposit is based on exploration data and typically captured in a digital 3D resource model. Exploration data are gathered in campaigns previous to operation, often undertaken decades ago. The sample spacing is designed to capture major features of the deposit with the anticipated level of accuracy, while minimizing costs. Although resource models are created using sophisticated geostatistical modelling techniques, such as different types of Kriging or conditional simulation (e.g. [1]), they can locally exhibit significant deviations from in-situ resource characteristics.

Short-term production scheduling in mining operations is based on the resource model and aims to define an extraction sequence that meets short-term production targets in terms of ore tonnage produced and associated grades or qualities. The scale of the short-term production targets can be as small as a train load in order of 1.000t that is shipped to the customer; a scale, which is not supported by data, gathered during exploration. The consequences can be unexpected deviations from production targets, which cause significant economic impacts. Therefore the understanding of short scale variability of ore characteristics is critical to control the operation and to meet production targets.

As demonstrated in various case studies (e.g. [2;3;4]), short scale variability and uncertainty in prediction can be modelled by conditional simulation and propagated through a transfer function to assess the expected performance of a short-term mine plan. Although this methodology enables to recognize the magnitude and frequency of potential deviation, it does not lead to an increase in knowledge, since no additional data are included in the decision making process.

With the recent developments in Information- and Communication technology (ICT) over the past decade, online data capturing of production performance has almost become standard. Literally a flood of data is available. For example, sensors for detecting characteristics of raw material on a conveyor belt are available and used in some operations. For example, documented studies refer to the application of specific sensor technologies such as Near Infra Red [5] or Dual Energy X-Ray Transmission [6]. The application of sensors provides a high density of information on a short scale with a reasonable precision. The example in Figure 1 compares lab analysis and sensor based measurements for a train load of approximately 100t. The correlation of 0.93 suggests a high information content of sensor data.

![Figure 1: Correlation between sensor-based measurements and lab analysis in coal samples.](image)

Coefficient of correlation: 0.93

(representative tonnage: train car of 100t)
To date sensor information are mainly utilized in feed forward loops applied for downstream process control, such as supporting dispatch decisions or blending on stock piles (e.g. [7;8]). A feedback of process information into the resource and planning assumptions to continuously increase its certainty in prediction does not occur. However, the ability to feed data back suggests a significant potential for improvement of operations efficiency. With an increased certainty of predicting grades for mining blocks the frequency of misclassification and unfavourable dispatch decisions is expected to decrease. Buxton and Benndorf [10] quantified this value in the order of $5 Mio. per annum in an average sized operation. A breakthrough towards a “self-learning mine” (Figure 2) utilizing all available data for real-time feedback control and process optimization requires a fast integration and processing of data, a back-propagation of process information into the models and a real-time decision support. A similar framework was recently developed in petroleum reservoir management [9] and demonstrated increased process efficiency in the order of 6% to 9%.

This contribution introduces a new and innovative framework for real-time reconciliation and optimization for extractable reserves in continuous mining operations. It consists of a closed-loop approach, which feeds back sensor-data into resource models and optimizes operational decisions to account for the gained information during production in real-time. First the concept is described and later demonstrated in an illustrative case study.

**Fig.2: Closed Loop Concept in a continuous mining operation.**

### 2 Moving Towards Real-Time Reserve Management - The Closed Loop Concept

Figure 3 illustrates the closed-loop-concept for Real-Time Reserve Management (RTRM) and is defined by following steps.

1) Based on available exploration data a resource model is generated and reserves are assessed as basis for short-term mine planning. This model is referred to as prior model.

2) Short-term mine planning and operational decisions are optimized to meet production targets most efficiently.

3) Based on decisions made and utilizing the resource/reserve model, expected process efficiencies and material characteristics can be predicted model-based at different locations in the process.
4) When executing the mine plan, measurements about the process efficiency and material quality can be taken sensor-derived at different locations (e.g. Figure 2).

5) Differences between model-based prediction (Step 3) and actual measurements (Step 4) may have two different causes, a resource model error and a measurement error. Modern techniques of data assimilation are used to separate the influence of these two causes and update the prior resource/reserve model (Step 1) to obtain a posterior model.

6) Go back to step 2 and optimize short-term and operational decisions.

The proposed RTRM requires the development of two new key algorithms, a real-time feedback loop and simulation-based optimization for short-term production scheduling. The first algorithm is to be developed as a back-propagation of process information into the resource/reserve model. To account for different data from different sources with a different data quality, density and support, the currently used methods in geostatistical modeling and data fusion have to be extended. Different data, e.g. from exploration holes and lab analysis, online responses of sensors, GPS measurements of actually mined coal or geodetic survey data have to be integrated consistently to update the reserve model in a Bayesian fashion. The updated model will lead to possibly new decisions in short-term operation management such as production sequencing, digging capacity control or stockpile management. Due to the complexity of short-term production scheduling traditional models of optimization, such as Linear Programming (LP) or Mixed Integer Programming (MIP) will reach their limits. For the complex continuous mining process a new simulation-based optimizing algorithm is developed to make real-time decisions under uncertain conditions in an optimal way.

### 2.1 Real-Time Feed Back Loop for Reserve Model Updating

To solve the challenge of feeding back production data multiple solutions are possible. This contribution proposes the application of Kalman-Filter techniques, which are designed to estimate the system states, in our case the local grades at excavation locations, recursively on the basis of noisy input data. Kalman introduced 1960 a method in the context of system and control theory describing a recursive solution to estimate the state of a stochastic process $Z$ at time $t+1$ [11]. The

![Flow chart of Real-Time Reserve Management](image)
idea is to update the resource model, denoted with $Z^*(x)$ as a linear combination of the prior block
model $Z_0(x)$ and the difference between model based prediction and sensor based measurements $l$.

$$Z^*(x) = Z_0(x) + K (l - AZ_0(x))$$  \hspace{1cm} (1)

Matrix $A$ is a design matrix and captures the contribution of each reserve block per time interval to
the production observed at a sensor station. The term $AZ_0(x)$ represents the model-based prediction
and integrates the operative decisions (digging capacity and location at each time) in $A$ and the
resource/reserve model $Z_0(x)$. The objective is to determine the matrix $K$, which is the unknown
updating factor (Kalman-Gain) as a best linear and unbiased estimator. A detailed derivation is not
scope of this paper and the reader is referred to literature, such as [13]. It can be shown that

$$K = (A^T C_{zz} A + C_{ll})^{-1} A^T C_{zz}$$  \hspace{1cm} (2)

An interpretation of equation (2) reveals the integrative character of the Kalman-Filter. The first
term is the inverse of two error sources: (a) the model prediction error, represented by the
covariance matrix of the resource model $C_{zz}$, which is propagated through the mining system by the
design matrix $A$ and (b) the measurement error, represented by the covariance matrix of the sensor-
based measurement $C_{ll}$. The second term represents again the model-based prediction. A
comparison of potential magnitudes of the two error terms reveals that:

- if the model error is large and the measurement error small, the Kalman-gain $K$ tends
towards 1. The application to equation (1) shows that the full difference between model-based
prediction and sensor-based measurement is taken into account to update the resource/reserve
model.

- if the model error is small and the measurement error large, the Kalman-gain $K$ tends
towards 0. The application to equation (1) indicates that the difference between model-based
prediction and sensor-based measurement is not taken into account to update the resource/reserve
model. The precision of the sensor is too low to add value to estimation of resources and reserves.
It is intuitive that with the integration of sensor-data in the resource/reserve model the prediction
uncertainty is decreasing. This is not only the case for reserve blocks, which are currently excavated
but as well for adjacent blocks to be excavated, which are spatially correlated. It can be shown that
the improvement in model prediction is quantified by

$$C_{zz}^* = C_{zz} - K A C_{zz}$$  \hspace{1cm} (3)

where $C_{zz}^*$ is the updated model covariance matrix, which is by definition smaller than the prior
model covariance matrix $C_{zz}$. The presented method is limited to normally distributed errors and
linear relationships in the design matrix $A$. These assumptions are not always valid in mineral
resource extraction, as grades may not be distributed normally and reserve estimation include non-
linear elements, such as cut-off grades, losses and dilutions. Expression (3) would not be valid. The
so called Ensemble Kalman-Filter [12] offers a solution, which is founded upon the Monte-Carlo
concept (Figure 4). Based on an ensemble of possible scenarios of the resource model, which
capture the uncertainty and variability in estimation, the application of equation (1) to each of the
ensemble members leads to updated scenarios. A statistical evaluation of the updated models leads
to an empirical representation of the new model error $C_{zz}^*$. The Ensemble members can be
generated using commonly applied techniques of conditional simulation in geostatistics (e.g. [1; 2]).
2.2 **Simulation based Optimization for Short-term and Operative Decisions**

Methods of mathematical programming, such as Dynamic Programming or Mixed Integer Programming, are well acknowledged in the field of mine planning optimization [e.g. 14]. Recent research was successfully performed to integrate geological uncertainty [15;16] leading to an increased NPV by 24% while reducing the risk of not meeting production targets. Jewbaly [17] firstly introduced a short-term production scheduling optimization based on geological uncertainty and proves its benefit in the Australian gold mining industry.

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 optimization during design and operation of processes [18;19;20]. Simulation based optimization 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 computational large systems, such as continuous mining operations.

The simulation of mining systems is well established and supported by modern software products [e.g. 21;22]. Simulation based optimization is based on the perturbation of decision variables and the mapping of the corresponding objective value, which is derived from system simulation. Utilizing the Response Surface Method the objective value can be mapped as a function of decision variables, even if not all possible combinations are tested. The efficient exploration of combinations of decision variables can be supported by stochastic gradient decent methods. The maximum of the resulting response surface of the objective values leads to optimal decision variables.
An Illustrative Example

The subsequent example aims to investigate the performance of the proposed updating methodology for different mining system configurations and sensor precisions. It represents an artificial test case, which is built around the well-known and fully understood Walker Lake data set. The data set (Figure 5) is interpreted as quality parameter of a coal deposit, e.g. as calorific value. It is sampled irregularly at a spacing corresponding to an average of two reserve block lengths. 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 2t/m³ one mining block represents a tonnage of 5120t. 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 5) was used as prior model.

Without loss of generality the artificial block model shall be mined applying a continuous mining system equivalent to Figure 2, which contains of multiple bucket-wheel excavators positioned at separate benches. Figure 5 shows the extraction sequence for the case of two excavators. Different digging rates were applied: Excavator one mines at a rate of 500t/h and excavator two at 1000t/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.

The combined material flow 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 250 t 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%.

### 3.1 Evaluation Measures

The performance of the proposed Kalman-Filter approach will be evaluated using two measures. The first measure is the mean square difference or mean square error (MSE) related to the true block value. Here, the difference between estimated block value \( z^*(x) \) 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

\[ MSE = \frac{1}{N} \sum_{i=1}^{N} (z^*(x_i) - z(x_i))^2 \]  

As second measure the theoretical block variance \( BV \) is used, which can be calculated using equation (1) for the Kalman-Filter and (2) for the Ensemble Kalman Filter.

### 3.2 Results and discussion

To evaluate the performance for different system configurations and different sensor precisions, following cases were investigated:

- operating only one excavator using KF
- operating simultaneously two excavators using KF and EnKF
- operating simultaneously three excavators using KF

Table 1 summarizes the parameter used in this experiment. In order to guarantee linear independency of rows in the production matrix \( A \), a cyclic component was added to the extraction rates in the cases two and three excavators. This cyclic behavior is typical for continuous mining equipment can be observed in practice.

<table>
<thead>
<tr>
<th>Case</th>
<th>Extraction rate</th>
<th>Extraction mode</th>
<th>Sensor Precision</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>One excavator</td>
<td>( E_1 ): 500t/h</td>
<td>constant</td>
<td>1%, 5%, 10%</td>
<td>KF</td>
</tr>
<tr>
<td>Two excavators</td>
<td>( E_1 ): 500t/h ( E_2 ): 1000t/h</td>
<td>cyclic</td>
<td>1%, 5%, 10%</td>
<td>KF and EnKF</td>
</tr>
<tr>
<td>Three excavators</td>
<td>( E_1 ): 500t/h ( E_2 ): 1000t/h ( E_3 ): 2000t/h</td>
<td>cyclic</td>
<td>1%, 5%, 10%</td>
<td>KF</td>
</tr>
</tbody>
</table>

Table 1: Equipment parameter and model approach used.

Figure 6 to 8 summarize the results for applying the Kalman-Filter to the cases A, B and C. Figure 9 shows the results the Ensemble Kalman Filter applied to case B. Each figure shows both measures, the MSE and \( BV \), which are separately calculated for already mined blocks, blocks directly adjacent to the mined blocks and blocks, which are two block-lengths away from mined blocks.

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. This is expected because in case of one excavator the sensor measurements can be unambiguously tracked back to the source block. 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 comparison between the empirical error measure MSE and the theoretical error measure \( BV \) reveals that the theoretical error measure reflects very realistically the true error. Observed \( BV \)'s are
quantitatively very similar to the MSE. Slight differences occur and are mainly due to the limited amount of blocks tested.

Figure 7 and 8 show the increased difficulty of the filter to track back the differences between the sensor measurements and model based predictions for combined material flow to the source blocks. The MSE and BV for mined blocks do not vanish completely; the remaining uncertainty can be interpreted as the limit of the filter for this special application. It is expected, that with increased sensor sampling, for example every 2 or 5 minutes instead of 10 minutes, the performance can be improved. Nevertheless, there is still a significant improvement in prediction for directly adjacent blocks and the next row of blocks. Again, MSE and BV behave similarly. Differences are again due to local anomalies of grades in the tested blocks and locally varying sample data configuration (figure 5).

Figure 9 shows the example of the EnKF applied to case B. Results are very similar to the Figure 7 and demonstrate the validity of using the EnKF. Due to the limited problem size, observations concerning computational efficiency cannot be regarded as representative.

Results demonstrate a significant level of improvement by incorporating sensor data, in this case about 15% to 40% relative compared to solely relying on exploration data. This improvement could be interpreted as magnitude of frequency reduction of being out of spec for delivery coal to customers. The significant positive economic impact is obvious.

![Figure 6: Performance of the KF for updating the resource model in case A.](image)
Figure 7: Performance of the KF for updating the resource model in case B.

Figure 8: Performance of the KF for updating the resource model in case C.
Conclusions, Value of RTRM and Future Outlook

The ability to incorporate online sensor data, derived during the production process, into resource/reserve models and a subsequent near real-time optimization of short-term or operational decision variables promises a large potential of efficiency improvement in any type of mining operation. This is especially the case, when the variability of grades or quality parameters inherent in the deposit is medium to large. The economic effect of such a RTRM and mining process control can be quantified by a profit function $J$, which was adapted from [24].

$$
\Delta J = J(\mathbf{u}_{\text{prior}}, d = 0) - J(\mathbf{u}_{\text{prior}}, d = d_i) + J(\mathbf{u}_{\text{prior}}, d = d_i) - J(\mathbf{u}_{\text{opt}}, d = d_i) + J(\mathbf{u}_{\text{opt}}, d = d_i) - J(\mathbf{u}_{\text{posterior}}, d = d_i)
$$

(5)

The first term is the loss due to difference $d_i$ between actual and anticipated production targets that is realized if the decision variables $\mathbf{u}_{\text{prior}}$ were fixed at their nominal values based on the prior resource/reserve model. The second term represents the effect of an optimal adaptation of the decision variables $\mathbf{u}_{\text{opt}}$ to the real conditions, and the third term is the difference of the optimal compensation of the difference and the compensation which is achieved $u_{\text{posterior}}$ by the chosen feedback and represents the residual uncertainty. This equation offers the means to evaluate, if real-time optimization makes sense. If the first term in (5) is much larger (in absolute value) than the second one, or if all terms are relatively small, then a variation of the decision variables offers no advantage. This can be the case at highly varying grades, where an adaptation to real-time data corresponds to the adaptation of noise. Real-time control aims to decrease the third term and should be designed at a timely resolution to decrease this difference to an anticipated level.

Future research has to be undertaken to validate the RTRM framework at large field tests. In particular limits of the feedback algorithms in terms of convergence as function of system complexity and available data density require further investigation. In addition to grades or quality parameters as well efficiency and recovery influencing parameters can be integrated in the reserve model, e.g. by using GPS sensors and energy consumption recordings at excavators. This will require efficient data fusion algorithms.
With an implemented framework further questions can be answered, such as: “What is an efficient monitoring network for the system?” or “Which implications do the knowledge gained have on the long-term planning and necessary level of exploration?” In particular the last question is interesting as it investigates the utilization of additional sensor data for mine planning and suggests that the level of “traditional” exploration may be decreased in future. New exploration strategies for a “self-learning-mine” have to be developed that incorporate the time-effect of available information and maximize the use of it.

At the University of Technology in Delft, the Netherlands, current research projects are aiming in the maturation of this framework.

5 References


