Resource Model Updating for Underground Mining Production Settings

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ABSTRACT:

This research is part of the European Union funded 'Real Time Mining' project, which aims to develop a new framework to reduce uncertainties during the extraction process in highly selective underground mining settings. A continuously self-updating resource/grade control model concept is presented and aims to improve the raw material quality control and process efficiency of any type of mining operation. Applications in underground mines include the improved control of different components of the mineralogy and geochemistry of the extracted ore utilizing available "big data" collected during production. The development of the methodology is based on two full scale case study, the copper-zinc mine Neves-Corvo in Portugal and Reiche-Zeche mine in Germany. These serve for both, for the definition of method requirements and also as a basis for defining a Virtual Asset Model (VAM), which serves for artificial sampling as benchmark for performance analysis. This contribution introduces to the updating concept, provides a brief description of the method, explains details of the test cases and demonstrates the value added by an illustrative case study.

1 Introduction

In mineral resource extraction a main goal is to meet production targets in terms of ore tonnage, mineral grades or other material properties. Mine plans and operational schedules are optimized to maximize mill throughput and metal recovery while maintaining a given cost level (Boisvert et al, 2013). Models of the spatial distribution of material properties in a deposit, such as the resource or grade control model, allow the forecast of expected raw material characteristics of the extracted ore, and are used as input for mine planning and operational decision making (Lessard et al, 2014; Boisvert, 2013). For optimal decision making, these models should consider the maximum amount of information available. This is especially the case in highly-complex deposits, where traditional exploration sampling and modelling approaches are only limited able to capture the variability and corresponding spatial uncertainty. Models with low variability understate the local variability in the estimates properties that should be considered in the design and operation of the mine and mill (Deutsch et al, 2016).

The development of cost efficient sensors for material characterisation during production monitoring, such as hyperspectral face images or sensors for material characterization on a belt conveyor, provides an additional source of information. More often than not, differences occur between model based predictions and data acquired during production monitoring due to model uncertainties. To incorporate this additional information, recently an approach has been developed to integrate operational sensor data in resource or grade control model utilizing inverse modelling (Benndorf, 2015). The implementation of this process was performed on an artificial test case considering a univariate attribute and investigating different extraction configurations and sensor precisions. In three full scale case studies (Wambeke and Benndorf, 2016; Yüksel et al, 2017; Wambeke and Benndorf, 2017) the approach has been proven in concept in an open pit environment for gold and coal deposits. These applications focus on the integration of ball mill data in a geometallurgical grade control model and coal quality data from online sensors in coal quality models. A key feature of the method is the ability to reconcile the production monitoring information obtained at different locations during the logistic extraction process from blended raw material originating from different areas of the mineral deposit at the same time step. The capability of these methods of assimilating direct and indirect information leads to significant improvements in mining block prediction in local areas close to this assimilated information.

This contribution extends the previous work, mainly performed in open pit mining, to cases in multi-variate underground mining settings using an ensemble sequential updating approach. Grade control models of the underground mine settings considered are geostatistically modelled using a conditional simulation approach, which are parametrized based on constraints imposed by the cut-and-fill mining method and resulting stope geometry. The extraction process considered is a discontinuous cycle that involves drilling, blasting, loading, scaling and supporting. During these steps control decisions have to be taken with respect to block evaluation (block classification), scheduling (short-term mine planning) and operational control. During the hauling, blending and other logistic decisions have to be taken. These decisions are based on information about the ore block or the raw material in the muck pile or on the conveyor belt. Typically, this information involves grades, mineralogy and processing related indicators such as a Ball Mill Working Index and relate to the average value of ae support on a smallest minable or during logistics manageable unit (SMU). Resource or grade control models are built to capture this information on different scales of interest. These are used to make model based predictions to simulate certain mine scheduling or operational decisions. During operational monitoring online sensors allow to acquire literally a flood of data about the ore, for example by the means of face imaging or scanning of material on the conveyor belt. Data may be indirect measurements on a different support, which generally can be related to the ore attribute by a non-linear relation (Tolosana-Delgado et al, 2013). To lift the full potential of utilizing this information for continuously updating grade control models, this problem is translated into assimilating non-linear observations against the spatial grade control model (Wambeke and Benndorf, 2017, Deutsch et al, 2016). Figure 1 summarizes the concept of the here developed sequential updating algorithm for underground mining.

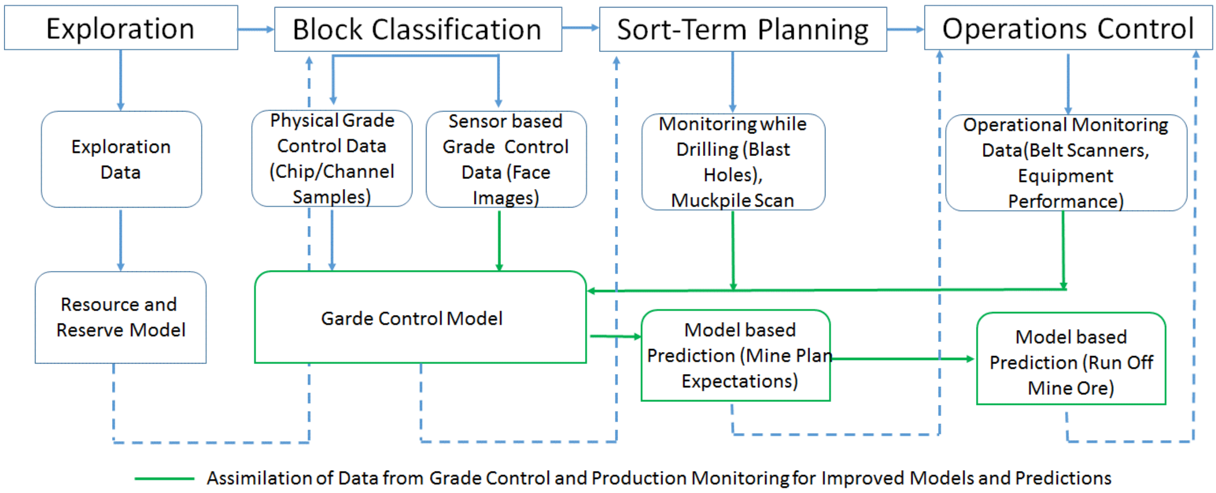


Figure 1: Data and information flow for grade control model updating for underground mining settings.

This paper first presents a description of the method developed for updating a grade control model. Second, the test case is presented, which serves as basis for deriving practical requirements for theoretical development and also as benchmark for performance evaluation, the Reiche Zeche Mine. A Virtual Asset Model (VAM) has been generated, serving as exhaustive data set. The model has been developed in collaboration between Geovariances and TU Freiberg within the European Real Time Mining Project funded by Horizon 2020.

2 A Brief Description of the Model Updating Algorithm:

Tis chapter provides a brief, however, non-complete description of the algorithm. A detailed description will be provided in the special issue “Geomathematics for Real-Time Mining” of Mathematical Geosciences.

The integration of data observed during the mining production process is achieved by using an inverse modelling approach (Tarantola, 2005). The inverse problem aims to determine the unknown model parameters by making use of the observed state data (Zhou et al, 2014). In the present case the models to be updated are generated by geostatistical techniques. The model parameters are ore attributes at each location X, which are described by a regionalised random variable $Z(X)$. A set of random variables at different locations is summarized in a random field $\boldsymbol{Z(X)}$, which is under the assumption of a normal distribution fully described by its first two order moments, which are the mean vector and the spatial covariance.

The idea behind the updating procedure is to solve the inverse problem related to following equation:

$$\boldsymbol{Z}(\boldsymbol{X}) = \boldsymbol{A}^{-1}(\boldsymbol{d})$$

where the term $\boldsymbol{A}^{-1}(d)$is the inverse of the forward model. This maps the attributes $\boldsymbol{Z}(\boldsymbol{X})$ from a spatial support onto the observations $d$on a timely support. The operator $\boldsymbol{A}$ links the spatially modelled attributes $\boldsymbol{Z}(\boldsymbol{X})$ with the observations **d** and provides a forward observation model. This model can be non-linear, mainly due to the change of support and possibel non-linear relations between modelled block value and observation. This non-lineraity is the main reason why ensemble sequential updating methods are preferred for updating grade control models. In (Benndorf, 2015), a first attempt is documented to translate the concepts of sequential updating from systems and control theory to mineral resource extraction. The introduced concept was based on the Kalman Filter approach with an observational matrix $\boldsymbol{A}_t$.The sequential updating procedure is expressed by the updated state estimate:

$$\boldsymbol{Z}(\boldsymbol{X})_t = \boldsymbol{Z}(\boldsymbol{X})_{t-1} + \boldsymbol{W}(\boldsymbol{d_t} - \boldsymbol{A}_t\boldsymbol{Z}(\boldsymbol{X})_{t-1})$$

where the difference between the model-based predictions $\boldsymbol{A}_t\boldsymbol{Z}(\boldsymbol{X})_{t-1}$ and the observations $(\boldsymbol{d}_t)$ gives the innovator term of the equation. $\boldsymbol{Z}(\boldsymbol{X})_t$is a vector of the spatial attribute after t updates. This is a vector state variable of dimension N, where N is the number of mining clocks considered. The matrix of weights $(\boldsymbol{W}_t)$ is of size $MxM$and balances out the accuracy of new observations obtained with the prior information (Wikle, 2007). This weighting factor is expressed as:

$$\boldsymbol{W}_t = \boldsymbol{C}_{t-1,zz}\boldsymbol{A}^T(\boldsymbol{A}_t\boldsymbol{C}_{t-1,zz}\boldsymbol{A}_t^T + \boldsymbol{R})^{-1}$$

where the term $\boldsymbol{C}_{t;zz}$is the covariance matrix of MxNsize and the $\boldsymbol{A}_t$of size NxM is the observation operator, which expresses the change of support of the observations as a a non-linear operator. The term $\boldsymbol{R}$is the error matrix associated with the device accuracy.

The computation of the prior error covariance $(\boldsymbol{C}_{t-1;zz})$ may by expensive in computational terms. However, the second part of the equation implemented as Ensemble-Kalman Filte (see Wambeke and Benndorf 2017) to estimate the forecast error covariance $\boldsymbol{C}_{t-1;zd}$and the observation error covariance $\boldsymbol{C}_{t-1,dd}$, it is shown to be more flexible and efficient in computational terms.

As Benndorf (2015) discussed, the sequential updating is optimal when all variables involved are Gaussians and the forward observational model ($\boldsymbol{A}$) is linear. This reason introduces for most data sets the necessity to map data to a Gaussian space prior updating. The most common transformations are quantile matching based. For instance, normal score transformation and anamorphosis (Riovoirard, 1984). Both methods differ on the back transformation. In the normal score transformation, variables are transformed separately while in Anamorphosis transformation, is done by a Hermite series approach joining several variables. The practical aspect is that the normal score transformation do not satisfy the non-stationarity assumptions and after certain updates it does not represent the local updated conditions. For that reason, the Gaussian Anamorphosis functions are used (Beal et al., 2010; Simon and Bertino, 2009).

The algorithm presented here is able to assimilate on-line sensor data provided during the mining production process to the grade control model. The algorithm can deal with different aspect such as the simultaneous integration of information from different localization. The forward simulator model reflects the support of the observational error that is present on the support of the information.

3 Test Case Description

The aim of this section is to provide information for a comprehensive understanding of the test case, at which the mathematical framework will be implemented. The test case serves mainly three purposes in the Real-Time Mining project. First, it provides a near-operational environment for understanding of requirements and deriving specifications for the methods developed. Secondly the case provides a comprehensive data set. For this purpose, based on available data, the VAM have been created. This is a conditional simulation of ore geometry and key ore properties on a high spatial resolution. It serves for both, generation of data sets and as benchmark for performance evaluation of the updating algorithm. Next to the Reiche Zeche case, which is the case discussed here, a VAM has also been defined for the Neves Corvo case. Both cases have been developed by TU Freiberg and TU Delft in cooperation with Geovariances. The software used to simulate has been Isatis®. It is envisaged, that during the course of the Real-Time Mining project, the VAM from the Reiche Zeche mine, including exploration and grade control data sets, will be openly shared with the scientific community. This is to make this 3D “playground” accessible for method testing.

3.1 Test Case Reiche Zeche Mine

The Reiche-Zeche mine is located in Freiberg (Germany). This is a polymetallic sulphide deposit defined within a continuous vein that was formed by different hydrothermal mineralization events. Resulting requirements are that model mas to present both, a strongly varying geometry of the vein., and the spatially varying mineral content within the vein. The vein has a general decline 50 degrees, which is represented by a trend plain. Around there are undulations, which cause variations in the vein thickness from some centimetres to approximately 1,4m.

The main data set that has been used to generate the VAM of mineralogical content consists in 114 samples distributed along 3 different drifts. The samples have been taken in one-meter step separation and analysed in laboratory. The minerals present in the samples are: Arsenopyrite (A), Galena (Z), Pyrit (P), Bornite (B), Dolomite (D), Quartz (Q) and Gneis (Gn).

The name of the sample area is Wilhelm Nord. The name of the orebody is named Wilhelm Stehender. It is exploited in the second level of the mine in around 150 meters depth. The elevation of the area is around 282.6m asl (above sea level). The vein has a dip of around 50 ENE-WSW with a thickness from 0 to 1.4 meters. For the data analysis the main minerals to model have been defined. These are Arsenopyrite (As), Galena (Gl), Pyrite (Py) and Sphalerite (Sph). The remaining minerals are of no-techno economic significance and have been clustered as waste. A continuous solid domain has been created within the volume of the vein. This is possible due to the nature of the deposit. After obtaining the model that will represent our fully known reality, a sampling algorithm has simulated the exploration information that will be used to create the simulations. Figure 2 shows a section and a front view of the deposit models and the distribution of sphalerite.

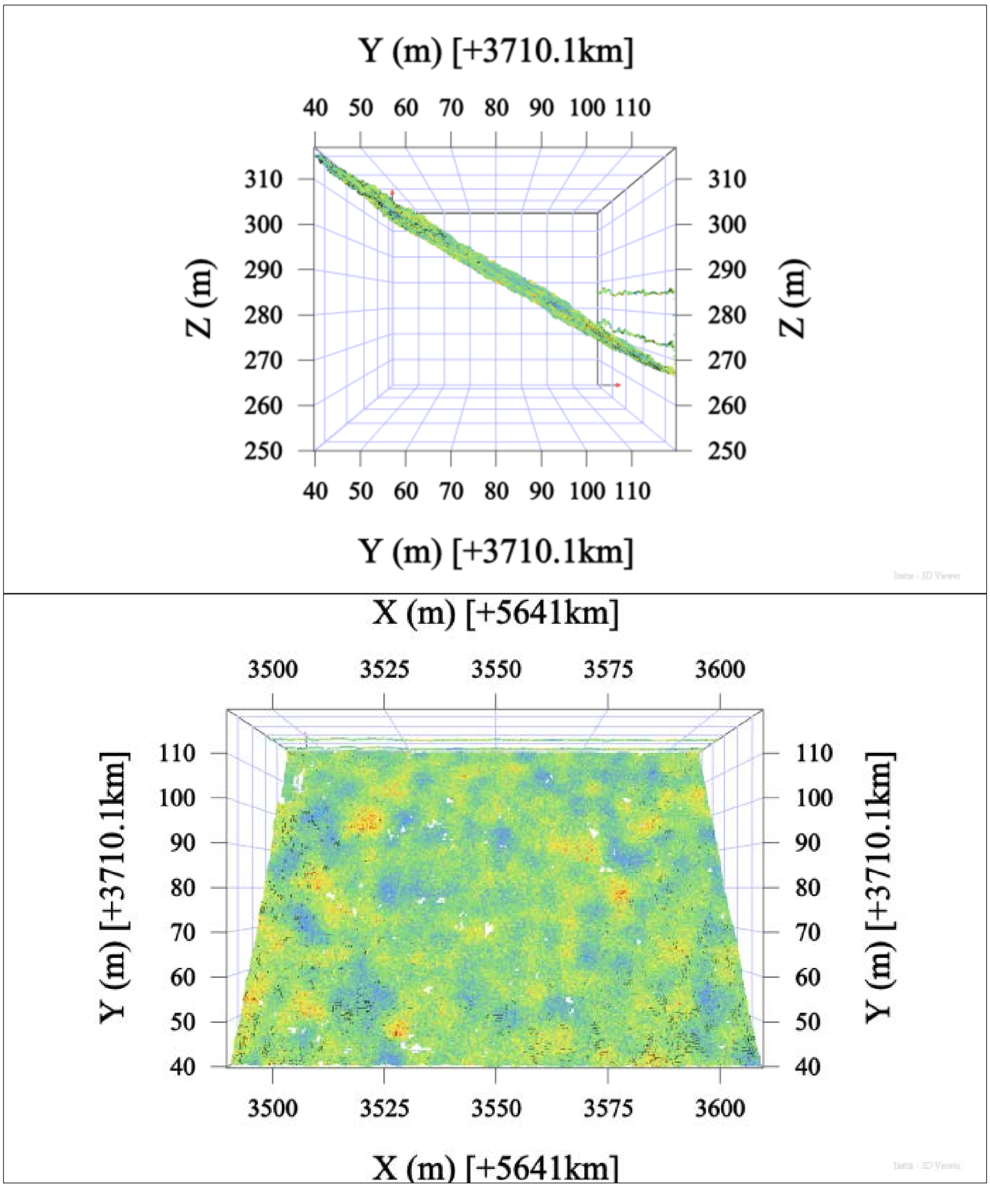


Figure 2: VAM Reiche Zeche, spatial distribution of sphalerite.

3.2 Test Case Neves Corvo Mine

The Neves and Corvo massive sulphide deposits are part of the Iberian Belt. In this study two different orebodies are considered. The Neves orebody has a maximum thickness of 55 m and measures 700 m by 1200 m. It consists of massive pyrite and cupriferous massive sulphides with low copper and zinc contents. The information obtained from Neves orebody consist of 1986 Exploration samples and 16967 production samples. The Corvo orebody has a maximum thickness of 95 m and measures 1100m by 600 m. It is composed by vertically staked lenses of massive cupriferous ores having a lens of barren pyrite and large massive lenses of cassiterite. The data set of

Corvo consists of 394 exploration samples and 19322 chip samples. The variables of grade that has been used correspond to the elements of arsenic (As), cupper (Cu) and Zinc (Zn).

Neves and Corvo orebodies have been built for a single domain used this solid as the estimation zone. The primary variables of interest remained As (ppm), Cu (%) and Zn (%). The size of panel is 20x20x8 m3 and the size of selective mining units is 4x4x4 m^3.

For this case study, the two orebodies Neves and Corvo have been simulated within given geological domains. In total 1,986 sample data for the Neves and 394 sample data for the Corvo orebody based on exploration drill holes are available. In addition, grade control data from already mined out areas have been integrated to support the model. Figure 3 shows the drill hole collars and available chip samples for the Neves orebody.

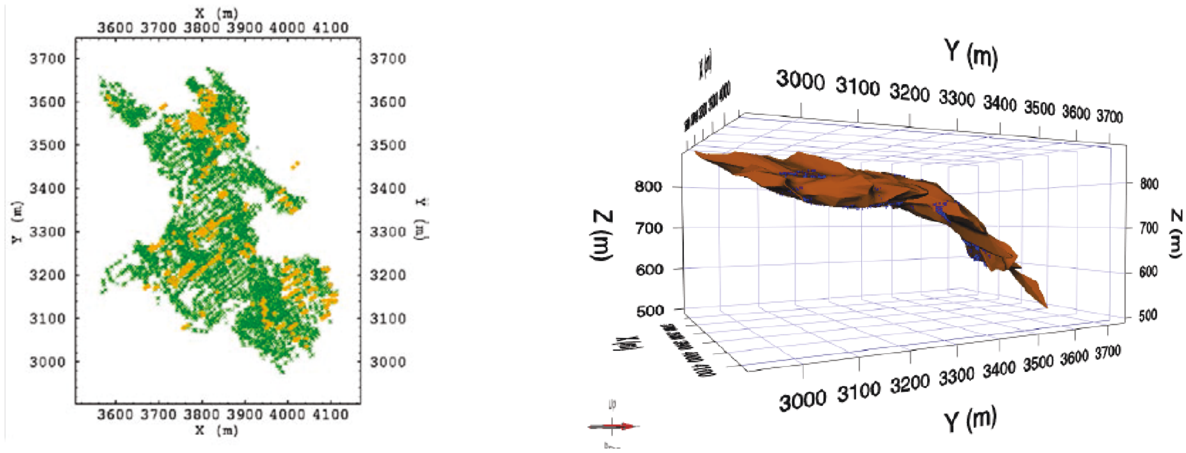


Figure 3: Neves ore body- drill hole collars (left) and chip samples (right).

The simulation approach has been conducted in following steps:

12. Transformation of raw variables (Cu and Zn) into their Gaussian equivalent through Gaussian Anamorphosis for the exploration and production assays;
- Calculation of experimental covariances and cross-covariances on the Gaussian transforms;
- Sample Co-Kriging from Gaussian exploration and production assays;
- SMU Kriging from the Gaussian exploration assays and the Gaussian pseudo exploration values at production data location of the main variables with a variance of measurement error;
- Turning bands simulations (100 realizations) with variance of measurement error from Gaussian variables kriged (produced by cokriging in the item 3) and with a local mean (produced by kriging in the item 4) has been applied.

Note that for the integration of grade control data, Kriging with a variance of measurement error has been used to account for the different data quality of exploration and production data. The study has been performed using the software isatis® (Geovariances, 2016) As a result, 100 equally likely representations of the Cu and Zn grade distribution within the two orebodies are available for further use in the optimization step (**Figure 4**).

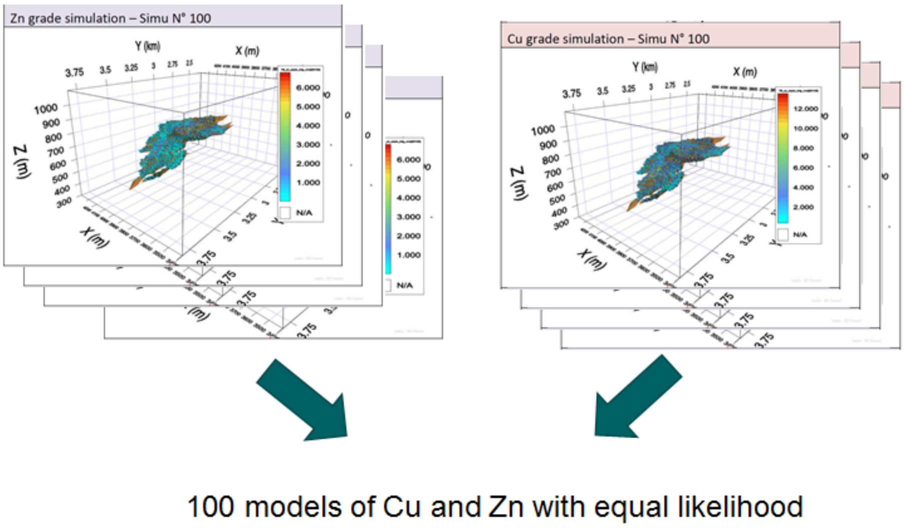


Figure 4: Result of the conditional simulation.

4 Application Reiche Zeche Mine

During a three field campaign related to blasts of mining blocks (Figure 5), complete data sets have been taken including images (RGB, hyperspectral, thermal, IR), and point data. These data are processed in Work Package 4 of The Real Time Mining and deliver information for a subsequent mining block, mainly additional information about proportions of minerals.

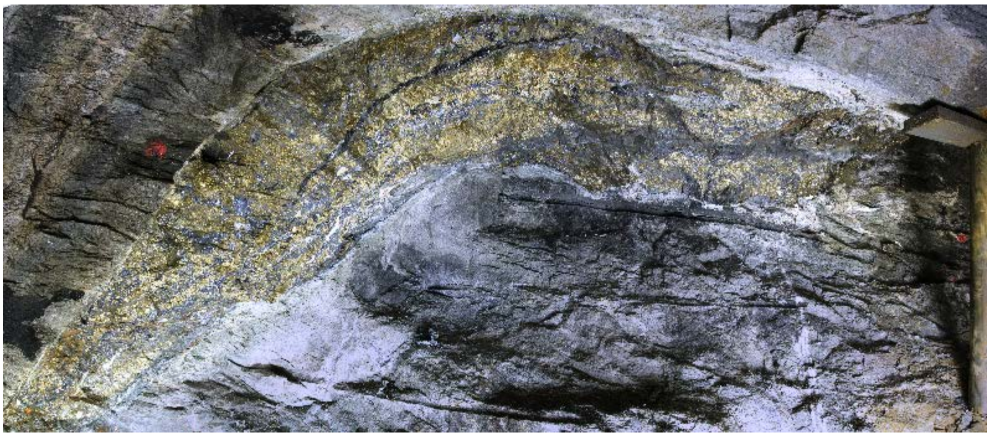
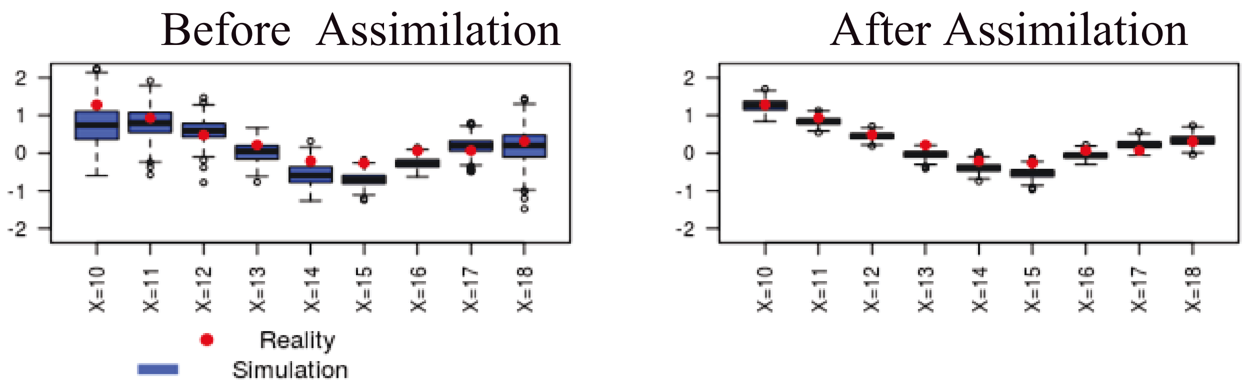


Figure 5: Face after blast in Reiche Zeche Mine, (Photo Hans Jürgen Burkhardt, July 2017).

A new algorithmic approach developed was coded and applied to sequentially integrate these data in a prior grade control model (see section 3.1) to continuously improve prediction of mineral content for the next mining blocks. Validation investigation using the synthetic environment provided by the VAM of the Reiche Zeche Mine show promising results.

The following figures show a stope, which has already partially been mined. Data from synthetic sensor data have been continuously integrated for updating the occurrence or proportion a mineral of interest. These data were designed to mimic the data obtained during the field campaign. First figure illustrate 9 blocks assimilated on the fourth stope assimilated. The second figure illustrates that the estimation lower decreases significantly, not only in the mined out area, but also in mining blocks, which will be mined during the next mining pass.



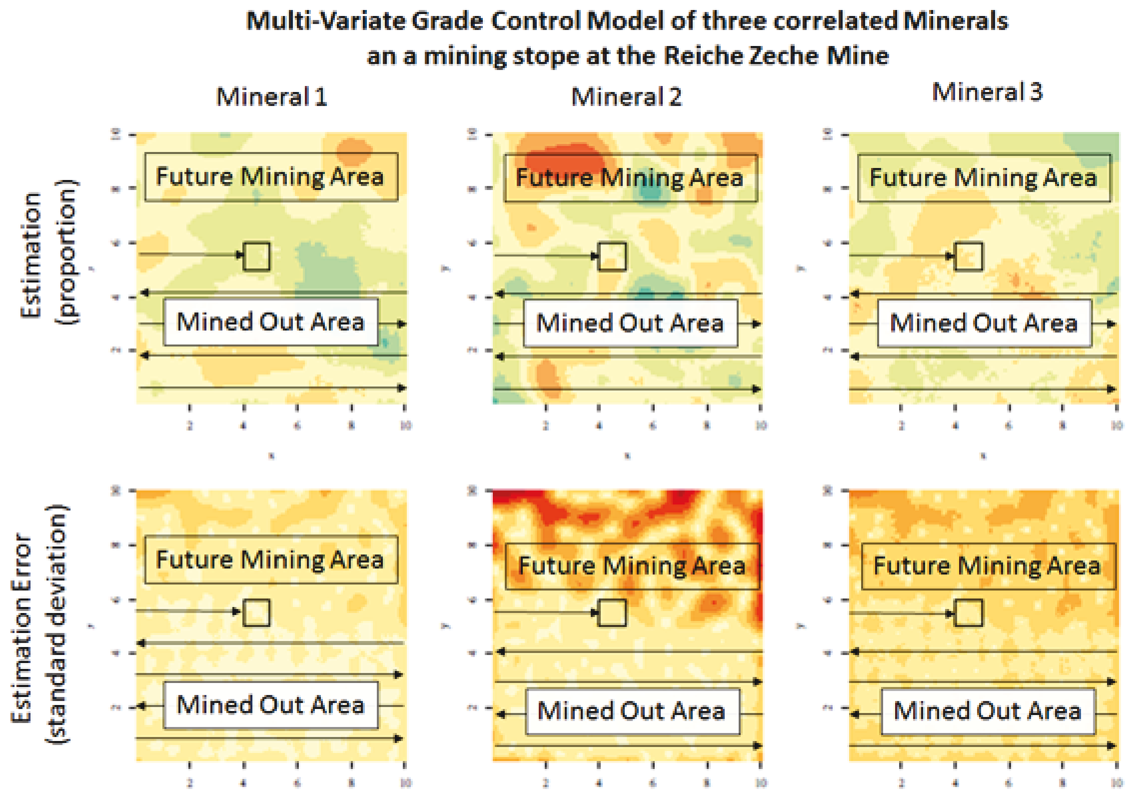


Figure 6 & 7: Sequential updating of mining blocks with a single stope in Reiche Zeche mine.

The newly updated mining bocks will provide a better estimate and forecast for production. In a scenario, where different mining stopes are operated simultaneously, the daily or weekly blending strategy can be adjusted accordingly.

5 CONCLUSIONS

A new approach for utilizing on-line data from production monitoring related to material characteristics for sequential grade control model updating has been presented. Due to its implementation using the ensemble sequential updating approach, it is very flexible. This refers to the fact, that it can deal with non-linear relations and with change of support. Also, the forward operator can be flexibly choosing according to the needs in the application. It can be a simulator, numerical or analytical expressions or even actual material tracking data. This makes this approach very attractive for operational implementation, as it can be linked to existing operational monitoring systems.

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