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Real-time Reconciliation and Optimization in large open pit coal mines

(RTRO-Coal)

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Real-time Reconciliation and Optimization in large open pit coal mines (RTRO-Coal)

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Directorate-General for Research and Innovation
Directorate D - Industrial Technologies
Unit D.4 — Coal and Steel
Contact Hervé Martin
E-mail RTD-PUBLICATIONS@ec.europa.eu

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B-1049 Brussels

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Real-time Reconciliation and Optimization in large open pit coal mines

(RTRO-Coal)

Dr M.W.N. Buxton

Delft University of Technology (TUDT)

Stevinweg 1, 2628 CN Delft, The Netherlands

Prof. Dr Jörg Benndorf, Dr Ralf Donner

TU Bergakademie Freiberg

Fuchsmühlenweg 9, 09599 Freiberg, Germany

Dr Wojciech Naworyta

Akademia Gorniczo-Hutnicza im. Stanislawa Staszica Krakow

A. Mickiwicza Av. 30, 30-059 Krakow, Poland

Mr O.M. Lohsträter, M. Lindig

Mitteldeutsche Braunkohlegesellschaft mbH

Glück-Auf-Straße 1, 06711 Zeitz, Germany

Mr H. Rosenberg, S. Asmus

RWE Power AG Essen

Stüttgenweg 2, 50935 Köln, Germany

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Final report

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1. Final summary

The project aim was to develop an integrated framework for Real-Time-Reconciliation and Optimization of the production process in large open pit coal mining operations. The focus was to integrate the different disciplines of

- operational monitoring using state-of-the art sensor based material characterization methods applied in coal mines,
- modelling of geological uncertainty,
- continuous mining system simulation for performance prediction under geological uncertainty,
- data assimilation for updating resource, in particular coal quality, models based on operational monitoring data and
- operations research for optimized decision support in short- and long-term mine planning

to one coherent closed-loop-concept (monitoring – updating of decision making models – optimization of production control). This framework allows to utilize data and information available along the production process in an integrated way to increase production efficiency and decrease environmental impact while maintaining a high quality of in-spec coal products. Main results per Work Package are summarized next.

WP 1

The aim of WP1 was to develop an innovative stochastic simulator of a continuous mining process from extraction to coal stockpiling and waste dumping. Taking into account all uncertainties associated with the process influencing factors, the simulator will predict the expected process behaviour, project efficiency and reliability to meet production targets for a given set of decision variables.

To achieve the objectives set for WP1, following tasks were performed.

<u>Task 1.1:</u> *Development of a theoretical approach for an innovative stochastic mining process simulation tool.*

Based on an in-depth review of the state-of-the-art of general system simulation approaches, available simulation software and recent applications of process simulation in the mineral resource extraction context, a conceptual model for a mining process simulator for continuous coal mining operations has been developed. This conceptual model integrates all boundary conditions and requirements defined in cooperation with the mining companies MIBRAG mbH and RWE AG for the two case studies Profen and Hambach mine. The conceptual model describes the objective function, typical key performance indicators of continuous mining operation, constraints and decision variables related to short-term mine planning and production control.

<u>Task 1.2:</u> *Definition of key performance indicators, efficiency measures and reliability measures of a continuous mining process and quantification of stochastic behaviour of the influencing factors.*

For the two case studies, a detailed problem specification has been defined. The first case study is the Profen mine of MIBRAG mbH, where the main focus is on coal quality management. The simulation tool to develop should be able to predict expected coal quality, delivered per train or day, and its uncertainty in prediction, given a short-term mine plan. Necessary input data in terms of system-design and parameters and also target variables have been defined. The focus of the second case study, the Hambach mine of RWE, is on waste materials management for stable dump design. The simulator is to be developed to evaluate system performance in terms of down time, which is due to the defined and constrained sequence of dumping different overburden types (wet and dry material) per waste spreader bench. Necessary input data in terms of system-design and parameters and also target variables have been defined.

<u>Task 1.3:</u> *Implementation of the simulation approach, testing and validating it in an historical and reconcilable mining environment.*

For both case studies, a full process simulator has been developed that meets requirements defined in Task 1.2. Using the Software Arena® from Rockwell, the process design of both case studies has been implemented. To mimic the stochastic behaviours, e.g. the downtime behaviour of equipment, an intensive operational data analysis has been conducted and stochastic model parameters inferred. For both cases a verification study has been carried out in a fully controllable environment.

Task 1.4: *Setting up the simulation process for a field testing period in a mining operation and validate it in an industrial process as preparation of Work Packages 3 and 5.*

For a given test period, both simulators have been implemented and tested against historical operational data. This implementation included the integration of a resource or material block model (WP3). For the MIBRAG test case, the ability to predict coal quality parameters has been benchmarked against true data, for the RWE case the daily performance per piece of digging equipment has been compared to operational monitoring data. A comparison showed that the simulator is able to predict the performance including an uncertainty range that realistically captures operational behaviour. With these result, the developed simulation tools are proven to be used as basis for simulation based optimization in WP5.

WP 2

The objective of WP2 was to develop a new and in the industrial environment of mining operations ground breaking statistical self-learning tool. It is founded on a comparison between model-based predictions with in-situ sensor measurements for different process KPI's and analyses the data to identify sources of differences and quantify its magnitude.

Task 2.1: *Development of the theoretical framework and the detailed algorithm for the self - learning data analysis tool based on statistical learning theory.*

Based on an in-depth literature review on statistical methods for integrating spatially and timely dense data into spatial models (here the resource model), it was found that methods of data assimilation could be a suitable choice. In particular, techniques related to the Kalman-Filter are an appealing choice for the problem, since they simultaneously integrate model based predictions and sensor measurements to sequentially update the underlying model. The method of the Ensemble-Kalman-Filter, which is originally designed in the context of system and control theory, was adapted and has been put in a geostatistical context. With this method, a flexible way has been developed to update resource models (in particular coal quality models) based on indirect sensor data observed in the downstream process. Also, the method is able to incorporate geological uncertainty and uncertainty in the sensing signal. With this result, early in the project, the previously separately planned WP2 and WP3 could be combined, since the task of data analysis and updating was developed in an integrated solution.

Task 2.2: *Implementation of the learning algorithm including testing and validation in a completely know and fully controllable environment.*

The method of the Ensemble-Kalman-Filter has been implemented in a Python–coding environment. Using the fully known environment of the Walker-Lake data set, the performance of the implementation was tested and the efficiency in updating was demonstrated. To test the plausibility of results, the method has been compared to a fully proven but computational less efficient method of a Partical Filter. Both methods, the Partical Filter and the Ensemble-Kalman Filter performed equally well.

Task 2.3: *Field test and proof of practicality and added value in a large scale industrial application in a continuous mining operation.*

For the RWE-case study, the algorithm developed within Task 2.2 has been operationally implemented. Several parameters of the algorithm, including ensemble size and localization strategy, have been calibrated. The method was applied to the Frimmersdorf seam in one of RWE's mine, where the quality of coal extracted by a single excavator on a single bench is measured by an online coal quality sensor (KOLA-system). Based on these measurements, the resource model and operational data of the digging sequence, the developed updating algorithm showed significant improvements in predicting the ash content. The prediction error decreases by 40 to 60%.

Task 2.4: *Setting up the learning algorithm for real-time application and develop interfaces to the Work Package 1.*

For the purpose of operational implementation, the interfaces between the algorithm and the operational data base in the mines has been defined and implemented. The interfaces contain of two list files. File one is the model based prediction at a sensor station and includes the original resource block model combined with material tracking data from operational records. The second file is the measurement file and contains sensor measurement values marked with a time stamp. With this setup a simple interface was defined, which supports the practical application of the method.

WP 3

Using the analysed differences between model based prediction and in-situ measurements during operational monitoring, the goal of WP3 is to extend the current industry resource modelling standard towards a "self-learning" short-term-mine planning model that integrates data and information relevant to optimized production control and meeting coal/overburden quality targets. It is developed to be updateable in a real-time manner.

Task 3.1: *Definition of basic requirements for an updateable short term planning model.*

For the case studies at MIBRAG and RWE, basic requirements and data necessary for the updating algorithm have been defined. Details include the geological background, mine system description, the resource block model including modelled attributes, available exploration data base and sensors for material characterization.

Task 3.2: *Extension of the framework of advanced geostatistical methods to integrate data of different source and data quality.*

The part of Task 3.2 associated with the updating algorithm has been performed together with Task 2.3. In the combined time of both tasks, the method has been coded and validated. The second part of Task 3.2 focused on a method for "self-learning" parameter of the resource model. With the availability of online data, new information about the spatial structural behaviour of critical coal attributes becomes available. The initial description of the structural behaviour in the geostatistical model by the means of a variogram or spatial covariance function is usually based solely on exploration data. The new, highly dense sensor data will provide improved insight into the spatial structure and allow to improve the inferred geostatistical model parameters of the model. Therefore, a method has been developed to conduct an automated inference for geostatistical model parameters, in particular the variogram parameters, when new data become available. The approach focused on practicability in application and the opportunity to integrate different types of data, namely direct and indirect. Further the approach has been developed aiming to improve inference of model parameters in the presence of strong trends, as often the case in lignite deposits.

Task 3.3: *Implementation and validation of the new geostatistical method in a fully known and completely controllable environment.*

With the implementation of Task 2.3 and 3.2, the algorithm has been undertaken a performance test. In a synthetic environment different parameters have been tested, including variability of the prior model and the sensor error. Also, the ability to update, when a blend of materials originating from two or more different excavators is measured, has been investigated. The latter one was performed in preparation of the operational implementation at the MIBRAG mine site. Using the criteria of the updating range and percentage reduction in prediction error, it could be shown that the algorithms also performs well in these cases. Overall it was concluded, that in a typical lignite environment with moderately varying coal quality parameters and well calibrated sensors (relative sensor measurement errors up to 10%) the updating method performs well.

Task 3.4: *Field testing and proof of industrial applicability in a large open pit mining operation.*

The updating method has been operationally implemented in the Profen mine of MIBRAG mbH. Next to this, a method simplification has been developed and implemented. A pre-requisite of the updating methodology is the availability of a set of realizations or ensemble members of the coal resource, generated by the use of conditional simulation in geostatistics. In mine sites, the skill set of performing these type of expert tasks in geostatistics, is not always given. With this background, a new and more simple method was developed to generate a set of realizations based on the available short-term resource model in the mine. In a black-box step, a stochastic fluctuation is added around this available model, capturing the spatial uncertainty. In a comparison of both approaches, the theoretically correct one based on a complete geostatistical simulation and the simpler approach, it was demonstrated that after few updating steps, both methods perform equally well. This is a major finding as it demonstrates that the results are robust against the prior resource model uncertainty. As a second aspects in the study, it was shown that the method is able to update the resource model in situations, when the material observed on the conveyor belt by a sensor is a blend of two or three excavators. By the large amount of timely dense sensor data, the method is able to discriminate material differences from different locations. With this test the operational implement-ability of the resource updating method has been proven.

WP 4

The goal of Work Package 4 was to adapt an uncertainty based long-term mine planning optimization algorithm from discontinuous planning in diffuse deposit styles to continuous mining operations in compact deposit styles. This new approach bases the optimization on simulated models of geology rather than on estimated models. This will ensure high probabilities of meeting production targets and a homogeneous coal quality delivery over the whole life of the mine while maximizing the monetary value in terms of Net present value (NPV). Results of WP4 will be combined with results originated in WP5 (short-term optimization) in an integrated short- and long-term optimization concept (WP6).

Task 4.1: *Application of recently developed simulation framework in a large coal deposit in Poland and validation of results in a completely known mining environment.*

A review of available methodology in conditional simulation in geostatistics and its application resulted in the choice of the Generalized Sequential Gaussian Simulation (GSGS) for being a suitable tool to generate equally likely simulated models of the coal seam geometry and coal quality parameters in lignite deposits. For the application and also for activities related to tasks 4.2 and 4.3, a coal field in Poland has been chosen, which is characterized by one coal seam, which is locally split into two sub-seams. For each of the sub-seams the coal quality parameters ash content, calorific value and sulphur content have been investigated. Based on the available data set and an explorative data analysis including an analysis of variographie, GSGS has been applied to generate 25 realizations of both, the geometry of the seams and sub-seams and also the spatial distribution of coal quality parameters within the seams. With this, a model capturing in-situ variability and spatial uncertainty is available for the subsequent optimization task.

Task 4.2: *Development of a new uncertainty based algorithm in long-term mine planning of large lignite deposits integrating the goals of meeting long-term production targets with a high probability and flexibility while maximizing the monetary value in terms of NPV.*

In a review of techniques of mathematical optimization applied to long-term mine planning, it was found that the technique of Stochastic Integer Programming (SIP) offers a suitable solution to incorporate modelled geological uncertainty into the long-term optimization task. Based on a documented approach in a discontinuous iron ore mine, an SIP-optimization formulation has been defined, which incorporates technical constraints of a continuous mining setting. The objective function maximizes the NPV of the operation reduced by expected penalties through deviations from production targets. The decision variables are the extraction period per long-term mining block. Constraints include typical long-term mining constraints and also a precedence constraint, which ensures a technical feasible annual progress relation between overlying cuts.

Task 4.3: *Validation of plausibility and demonstration of the applicability and economic benefit of the uncertainty mine planning optimization method in an application for life-of-the-mine planning of a large mining project.*

Based on the ultimate pit limit, designed benches, and the simulations from Task 4.1, a block model of the deposit has been prepared. The application of the optimization formulation from Task 4.2, which has been implemented using a CPLEX solver, resulted in a stochastic mine plan. Due to practical constraints and available data, the case study focuses on a particular long-term part of the deposit representing an approximately 5-year production period. Although this area does not represent the life-of-the-mine, as suggested in the initial task description, the demonstration of benefits in respect to the ability to meet production targets was performed without loss of generality. A comparison to a traditional optimizer, based on an estimated model, shows the benefit. Over a lifespan of 5 years, savings in the order of 10.000.000 Euro can be realized due to less frequent deviations from production targets. Also, due to improved coal quality streaming, it is expected that the desulfurization plant can be calibrated better and ecologic indicators improve.

WP 5

The goal of WP5 was to research on and develop a ground breaking real-time short-term mine planning optimization tool taking into account all updated information captured in short-term resource and process models from WP3. Optimization methods are designed to optimally decide on short-term mine process decisions to reliably meet production targets, increase process efficiency and manage energy efficiency.

Task 5.1: *Definition of a specific optimization formulation for short-term production scheduling of a continuous open pit mining process.*

For both case studies, the Hambach mine of RWE and the Profen mine of MIBRAG, a detailed problem specification has been formulated. For the Hambach mine, the aim is to optimize a material dispatching problem. The waste material is divided in wet and dry material, which has different geo-mechanical properties, which have to be taken into account in dump construction. With this background the dumping sequence of spreaders and the connections between excavators and spreaders, implemented at the central mass distribution point, are to be optimized. The optimization criterion is to maximize equipment uptime while obeying a stable dumping sequence. The Profen case study focuses on coal quality management. For different planning horizons, weekly and monthly, the schedule of the excavators and the extraction sequence is to be optimized aiming for a coal quality stream that meets production targets in terms of lower and upper coal quality bounds with a high statistical certainty. For both cases, Hambach and MIBRAG, a mathematical formulation of the problem has been defined including the objective function, decision variables, constraints and also necessary models as input.

Task 5.2: *Development of an innovative simulation-based optimization framework suited for short-term mine planning in continuous open pit mines.*

An in-depth literature review and analysis on techniques of mathematical optimization with respect to applicability to the problem defined in Task 5.1 has been conducted. Simulation based optimization has been found to provide a suitable general approach. Different methods of simulation based optimization have been evaluated in applicability. It was concluded that a hybrid approach using a combination of different methods would work best, as it would be able to balance out computational efficiency and drawbacks, such as local optimum traps. Further a concept for simulation based optimization was developed that uses the simulators developed in WP1. As a result, the framework's components, how they will interact, and what algorithms will be implemented for the different components is described in detail.

Task 5.3: *Implementation and validation of the simulation based optimization framework.*

For three defined problems an optimization solution has been developed:

- A hybrid simulated annealing – genetic algorithm approach has been developed for simulation based optimization of weekly job scheduling of excavators in the Profen mine.
- A stochastic integer programming solution has been defined for mid-range block sequencing in the Profen mine.
- A complex optimization solution has been developed for dump sequencing and dispatch decision for waste materials in the Hambach mine.

The implemented solutions have been verified and validated in a controllable environment. Plausibility has been tested in several presentations in front of mine production personnel.

Task 5.4: Field test in a large industrial application.

The developed methods have been operationally implemented, calibrated and applied. In particular, for the RWE case Hambach, all model parameters have been inferred from operational data and for a given period, the optimizer has been applied and compared to real operational data. In an evaluation of results within the planning and operational department of RWE, it was concluded the results are plausible and decisions suggested by the optimizer are trustworthy.

WP 6

The goal of WP6 was to integrate the five previous working packages to a framework and benchmark the results of the innovative real-time optimization approach against current industry practice. The framework will be utilized to support strategic decisions in long-term mine planning and exploration.

Task 6.1: *Operational implementation of the real-time reconciliation and optimization system developed.*

For the test case Profen mine of MIBRAG mbH, a complete closed-loop-system has been implemented. ICT-Interfaces between existing operational control and planning systems have been defined and implemented. For a defined period, the updating algorithm developed in WP 2 and 3 has been implemented for updating the coal quality parameter ash content in a short-term planning model. The updated model forms the basis for the developed short-term optimizers related to weekly job scheduling of major equipment and monthly extraction sequencing. With this implementation, a closed-loop-system is available that continuously updates the coal quality model based on production monitoring data and provides informed decision support for short-term coal quality control.

Task 6.2: *Integration of the long-term and short-term planning approach as an iterative process to proactively study feasibility of short-term operations within the framework of the long term mine plan.*

An integrated long-term - short-term optimization algorithm has been developed and implemented using CPLEX. Based on results of WP4 and WP5, the optimizer balances out long-term optimality in terms of NPV with short-term losses due to constraints imposed by the long-term plan. For a defined period, the method has been applied and demonstrated to generate long-term plans, which are more robust with respect to short-term feasibility in execution.

Task 6.3: *Quantification of the value of additional information introduced in the planning model during the production phase and develops a top-down framework for integrating and optimizing short-and long-term exploration and data-gathering.*

A Value of additional Information (VoI) concept has been developed and implemented. In a case study, it was shown that the integration of operational online data leads to a fast convergence of blocks in the local neighbourhood of the current extraction face towards a significantly improved value. Applied to optimization task, it was shown that related to the task of weekly job scheduling of excavators, the additional value created is in the order of 10.000 Euro per week. For the task related to monthly sequencing, the impact is a magnitude larger and is up to 30.000 Euro per week. In conclusion, it is estimated that the utilization of production monitoring data by the means of real-time reconciliation and optimization has the potential to increase operational efficiency in the order of about €2Mio., alone for the case of short-term coal quality control for ash in a mine with 8 Mio. tons of production.

2. Scientific and technical description of the results

2.1 Introduction and Project Overview

A sustainable exploitation of coal deposits is a complex multi-objective task. On the one hand, the coal extracted from deposits has to meet tight customer specifications; mainly modern coal fired power plants. On the other hand, coal deposits can be rather complex and often involve multiple seams with multiple splits and diverse inherent coal-quality distributions. Customer requirements are usually tight in terms of upper and lower bounds of multiple coal quality parameters, such as calorific value, ash or sulphur, which have to be met on a train by train basis. The overburden covering the coal has to be excavated, transported and dumped in a sequence that guarantees safety and long-term stability of the waste dump. At the same time production management aims to maximize utilization and effective production rates of major mining equipment, minimize specific costs and contribute to the long-term mine plan.

Successful planning and operations management in coal extraction have to be based on a sound understanding of key features in the deposit. This knowledge is usually based on exploration data and typically captured in a digital 3D resource model. Exploration data are gathered in campaigns prior to operation, often undertaken years or decades ago. The sample spacing is designed to capture major features of the deposit with the anticipated level of accuracy, while there is often the mandate to reduce exploration expenditure. Although resource models are created using sophisticated geostatistical modelling techniques, such as different types of Kriging or conditional simulation, locally they can exhibit significant deviations from *in-situ* resource characteristics [1]. Short-term production scheduling is based on resource models and aims to define an extraction sequence that is aligned with the previously mentioned objectives. The scale of short-term production targets can be as small as a train load in the order of 1000t that is shipped to a power plant; such a scale is not supported by data gathered during exploration. Consequences can be unexpected deviations from production targets, which may have significant impacts on sustainable process indicators. Therefore, the understanding of short scale variability of coal characteristics is critical in order to control the operation and to meet production targets with a high level of reliability.

With recent developments in production monitoring over the past decade, online data capturing production performance provide an enormous alternative source of information. Literally a flood of data is available, captured in a high spatial and timely resolution. Sensor technology for detecting characteristics of raw materials on a conveyor belt has been proven in industrial applications in some mining operations. For example, Figure 1 shows a radiometric sensor on a coal-conveyor measuring ash-content online. Figure 2 compares laboratory analyses and sensor based measurements for coal ash content of train-car loads of approximately 100 t. The correlation coefficient of 0.93 suggests a high information content of sensor data. A second example is GPS data of equipment, measuring the exact extraction location. Implementations of such kind of systems are standard in continuous lignite mining. Examples are the RWE Power system "satellite-assisted excavator operation control-SABAS" [2] or online reconstructions of actual excavator cutting plains by MIBRAG [3]. Figure 3 illustrates results of such measurements, which provide direct information about actual excavated coal-waste boundaries.

Figure 1: Radiometric sensor measurement of coal in the Profen mine (photo of MIBRAG).

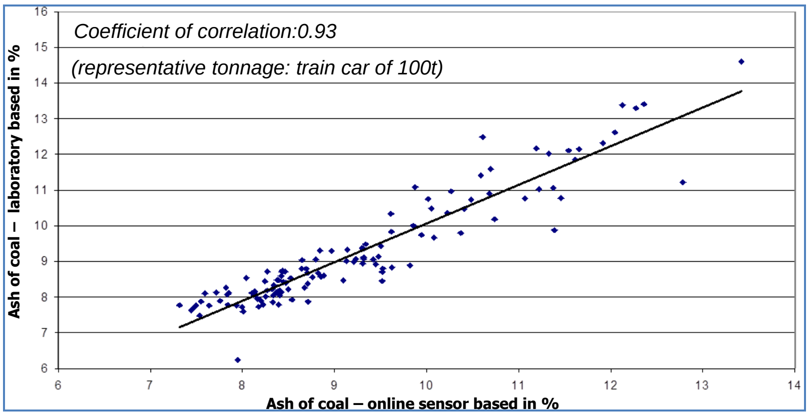

Figure 2: Correlation between sensor-based measurements and lab analysis of coal samples.

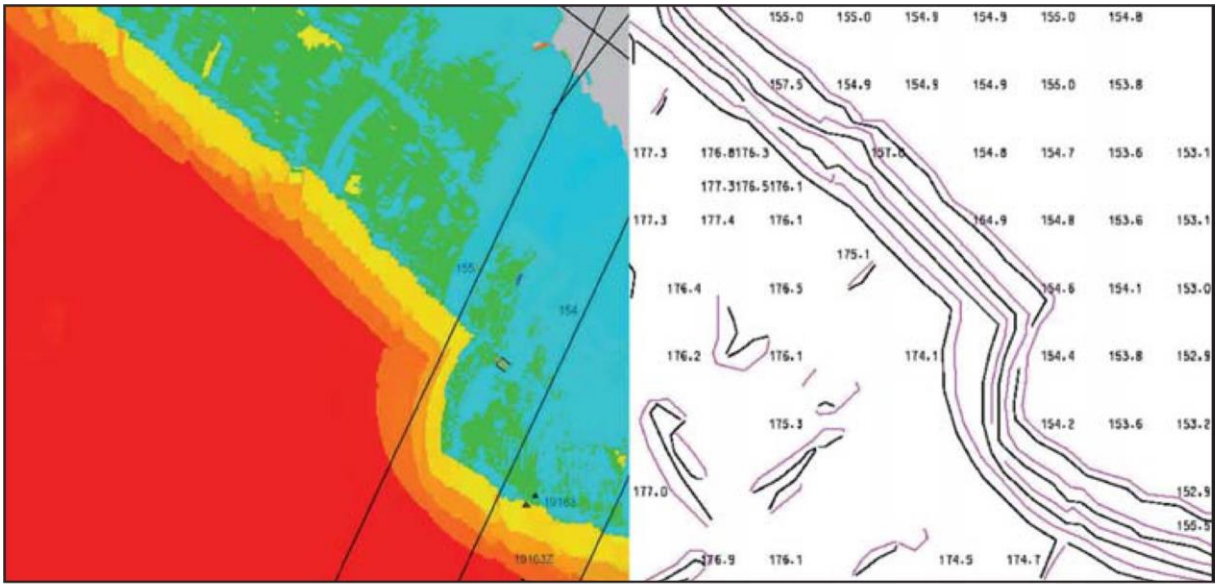

Figure 3: Online GPS-data of an excavator digging a coal seam (reproduced after [3]).

To date, sensor information is mainly utilized in feed forward loops applied for downstream process control, such as supporting dispatch decisions, material sorting or blending on stockpiles [4,5,6]. An immediate feedback of sensor information into the resource model and planning assumptions to continuously increase its certainty in prediction does not occur. Reconciliation exercises are often performed on a discontinuous basis and over a monthly to a yearly time span. However, the ability to immediately feed production monitoring data back suggests a significant potential for improvement an operational efficiency. With increased certainty in prediction of coal qualities or material characteristics of overburden blocks the frequency of misclassification and unfavourable dispatch decisions is expected to decrease. Buxton and Benndorf [7] quantified this value in the order of $5 Mio. per annum for an average sized operation.

RTRO-Coal is a multi-partner European RFCS-funded project, which aims to realize the previously mentioned potential. The abbreviation *RTRO-Coal stands for Real-Time-Reconciliation and Optimization of the production process in large open pit coal mining operations*. Utilizing ICT-based process monitoring, RTRO-Coal developed new methods in stochastic mine system simulation, intelligent process data analysis, back-propagation combined with real-time planning model updating and decision support under uncertain mining conditions. Applications are developed for short- and long-term planning of continuous coal mining operations. The applicability and the expected benefits of the frameworks will be assessed by the means of industrial scale field tests. Figure 4 summarizes the project work-flow.

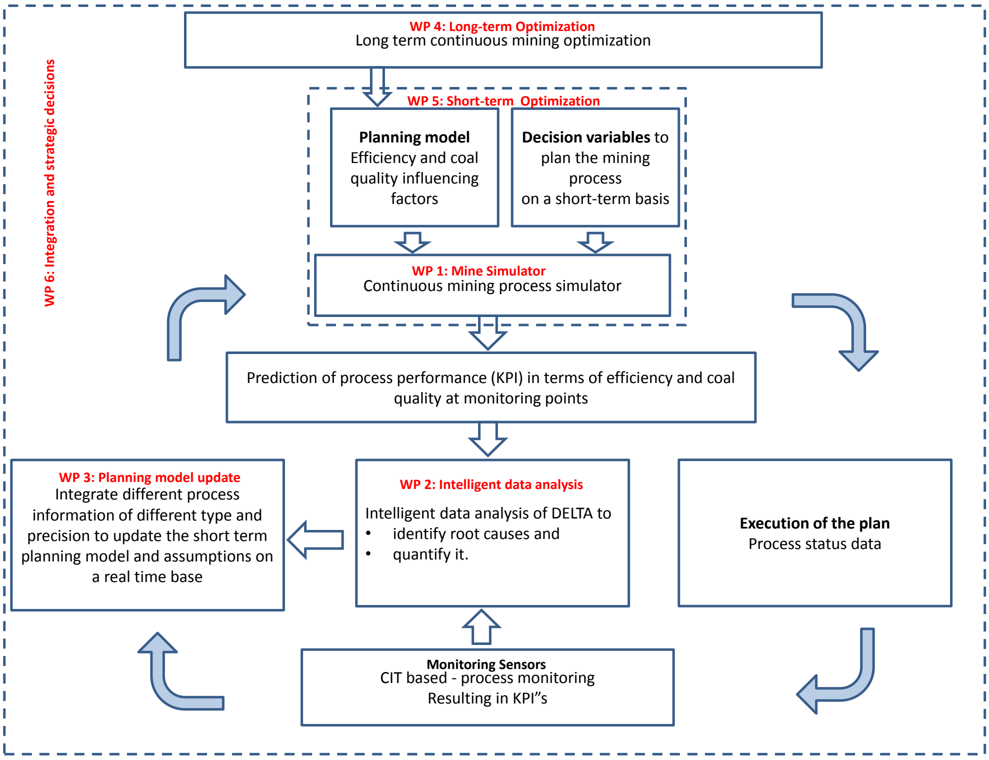

Figure 4: RTRO-Coal work-flow and Work Packages.

2.2 Objectives of the Project

The following overview provides the objectives per Work Package, which were aimed to be achieved during the complete project from 01/10/2013 to 30/09/2017.

The overall aim of RTRO-Coal is to develop an integrated framework for Real-Time- Reconciliation and Optimization (RTRO) of the production process in large open pit coal mining operations. The research was aimed to progress from the state-of-the-art and develop new methods in stochastic mine system simulation, intelligent data analysis, advanced geological modelling, quantifying geological uncertainty and process optimization. These developments would foster the utilization of all relevant ICT-based data and information available along the production process and integrate them in a real-time manner to optimize production of in-spec coal products as required in the subsequent value chain. With this aim, results are expected to have a significant impact towards the digitization in the mining industry.

The research activities focussed in the development of three main modules that include a stochastic mine simulator, a real-time planning model updating framework and a real-time optimization framework. These three parts were split into six distinct objectives:

- Development and field testing of a new mine process simulator for continuous mining operations from extraction to coal stockpiling and waste dumping. It shall capture different process influencing factors and its uncertainty, such as equipment efficiencies, geological uncertainties or uncertainties in demand (**content of WP 1**).
- Development and field testing of an innovative framework to update this simulator on a real-time basis utilizing process monitoring data by the means of intelligent learning algorithms. This requires the development of:
    - a statistical learning algorithm for intelligent process data analysis (**content of WP 2**) and
    - a geostatistical method to integrate all available data to real-time update the short-term planning model (**content of WP 3**).
- Development and field testing of a new reliability based optimization framework for continuous open pit mining operations including short-term production scheduling and integrated

short-and long-term mine planning optimization. In detail, three new algorithms have to be developed, tested and validated for

- long-term mine planning optimization under geological uncertainty (**content of WP 4**),
    - short-term production scheduling optimization (**content of WP 5**) and
    - integrated short- and long term mine planning (**content of WP 6**).

Details objectives per WP are provided next.

Work Package 1: Continuous Mining Process Simulator

The aim of WP1 is to develop an innovative stochastic simulator of a continuous mining process from extraction to coal stockpiling and waste dumping. Taking into account uncertainties associated with the process influencing factors, the simulator will predict the expected process behaviour, project efficiency and reliability to meet production targets for a given set of decision variables and its level of confidence.

Specific objectives include:

- the development of a theoretical approach for stochastic continuous mining process simulation taking into account uncertainty in process influencing factors,
- the definition of KPIs, efficiency and reliability measures characterizing a continuous mining process and quantification of the stochastic behaviour of these factors,
- the implementation of the simulation approach, testing and validating it in an historical and reconcilable mined-out environment and
- to set up the simulation process for a field test in a mining operation and validate results on an industrial scale.

Work Package 2: Intelligent Mine-Process Data Analysis

The aim of WP2 is to develop a new and in the industrial environment of mining operations ground breaking statistical self-learning tool. It is founded on a comparison between model-based predictions and in-situ sensor measurements for different process KPI's. It analyses data to identify sources of differences and quantifies its magnitude.

Specific objectives include:

- the development of a theoretical framework for a self-learning algorithm to analyse differences between the actual measured and the predicted expectations of KPIs at process monitoring stations. The framework accounts for uncertainty in model based prediction and precision of sensor measurements.
- the implementation of the framework, testing and validation in a completely known and fully controllable environment,
- field testing to proof its practicality and the value added in a large scale industrial application related to continuous mining operation and
- setting up the system for real-time application and develop interface to WP1 (continuous mine process simulation) and WP 3 (planning model update).

Work Package 3: Planning Model Update

The aim of WP3 is to extend the current industry standard towards a "self-learning" short-term-mine planning model that integrates data and information relevant to process efficiency, energy management and meeting coal/overburden quality targets. It is updated in a real-time manner utilizing relevant process information along the chain from exploration to beneficiation.

Specific objectives include:

- the definition of basic requirements for an updateable short-term planning model,
- research to extend the framework of advanced geostatistical methods to integrate data of different source and data quality (such as exploration, on line data, optical sensors) and data support to update the block-based prediction of geological attributes, quantify its uncertainty in prediction and map its spatial variability,
- implementation and validation of the new geostatistical method and evaluation of its practicality, computational efficiency and its precision in a fully known and completely controllable environment and
- a field test in an industrial applicability in a large open pit mining operation.

Work Package 4: Long-Term Planning Optimization

The aim of WP 4 is to adapt an uncertainty based long-term mine planning optimization algorithm from discontinuous planning in diffuse deposit styles to continuous mining operations in compact deposit styles. This new approach will base the optimization on simulated models of geology rather than on estimated models. This will ensure high probabilities of meeting production targets and a homogeneous coal quality delivery over the whole life of the mine while maximizing the monetary value in terms of Net Present Value (NPV).

Specific objectives include:

- the application of recent developments in computational efficient methods for conditional simulation to a coal deposit in Poland and validation of the simulated coal geometry and coal quality in a completely known mining environment,
- development of a new uncertainty based algorithm in long-term mine planning for large lignite deposits integrating the goals of meeting long-term production targets with a high probability and flexibility while maximizing the monetary value in terms of NPV and
- validation of the plausibility and field test to demonstrate the applicability and economic benefit of the uncertainty mine planning optimization method in an application for life-of-the-mine planning of a large mining project.

Work Package 5: Short-Term Planning Optimization

The aim of WP5 is to research on and develop a real-time short-term mine planning optimization tool taking into account all updated process efficiency, energy efficiency and coal quality influencing factors. It will be designed to optimally decide on short-term mine process decisions to reliably meet production targets, increase process efficiency and manage energy efficiency.

Specific objectives include:

- the definition of a specific optimization formulation for short-term planning of a continuous open pit mining process including decision variables, objective function, constraints and boundary conditions,
- research on and theoretical development of an innovative simulation based optimization framework suited for the defined problem,
- implementation and validation of the simulation based optimization framework and
- field test to demonstrate the value added and the practicability by defining the value of information and the gap to the current practice in a large scale industrial application.

Work Package 6: Integration and Strategic Decisions

The aim of WP6 is to integrate the five previous WPs to one coherent closed–loop-framework and benchmark the results of the innovative real-time optimization approach against current industry practice. The framework will be utilized to support strategic decisions in long-term mine planning and exploration.

Specific objectives include:

- the integration of all tools and interfaces developed within WP 1 to 5 to one coherent framework and set up a field test application in a large mine.
- the integration of the long-term (WP4) and short-term (WP5) planning approach as an iterative process to proactively study feasibility of short-term operations within the constraints of the long-term mine plan.
- the quantification of the benefit in terms of the value of additional information introduced in the planning model during the production phase and development of a top-down approach for optimizing short-and long-term exploration and data-gathering.

2.3 Results Obtained per Task

This section includes:

- comparison of initially planned activities and work accomplished,
- main results and
- a description of activities and discussion, highlighting innovations made

on a task by task basis.

The conclusions, indicating the achievements made within RTRO-Coal and a discussion on the exploitation and impact of the research results will follow in section 2.3 and 2.4.

Work Package 1: Continuous Mining Process Simulator

Task 1.1 (Lead TUDT with input from MIBRAG and RWE): Development of a theoretical approach for an innovative stochastic mining process simulation tool taking into account uncertainty in process influencing factors

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Continuous mining systems containing multiple excavators, producing multiple products of raw materials, are highly complex and exhibit strong interdependencies between constituents. A network of conveyor belts is used for transportation of the extracted materials to the different waste dumps or the coal stockpile. Techniques of stochastic process simulation, whether discrete, continuous or combined [8], provide a powerful tool for measuring performance indicators of complex systems. In the past few years there has been a large development in applications of process simulation in the mining industry. For example, Panagiotou [9] described the application of the simulation program SIMPTOL for opencast lignite mines that use bucket wheel excavators (BWEs), conveyors and stackers. The main objective was to select and match the equipment to fit material characteristics while meeting production requirements and mine profiles. Michalakopoulos *et al*. [10] presented the simulation model of an excavation system at a multi-level terrace mine using the GPSS/H simulation language. The principal model output variables are production and arrival rate at the transfer point of mineral and waste. Later on [11] utilized the Arena simulation software for the simulation of Kardia Field mine in Greece. The validation of results illustrates an acceptable match with the actual data. Fioroni *et al*. [12] used discrete tools for the simulation of the continuous behaviour of a conveyor belt network in a large steelmaking company. The authors proposed a modelling approach of the flow process, which uses portions of materials, which are treated as discrete entities in simulation modelling. The results demonstrated that this technique was valid and successful.
Summarizing findings in literature, stochastic process simulation is a potent method for measuring the KPIs in continuous mining systems. However, the investigation of impacts of geological uncertainty on the performance of continuous mining systems is still seen as a major gap. Within RTRO-Coal WP 1 a new stochastic based mine process simulator was developed focusing on the effects of geological uncertainty to predict mine process performance and reliability.

To account for geological uncertainty, RTRO-Coal combines the two simulation concepts, geostatistical simulation for capturing geological uncertainty and stochastic process simulation to predict the large continuous mining system's performance and reliability. Figure 5 shows the integrated simulation approach. As such it incorporates the timely and spatially varying nature of mining problems.

The output of the simulator is the set of values for each KPI. At this stage, penalties are applied when deviating from production targets. KPIs are summarized in an evaluation function, which results in a probability distribution when multiple replications are evaluated.

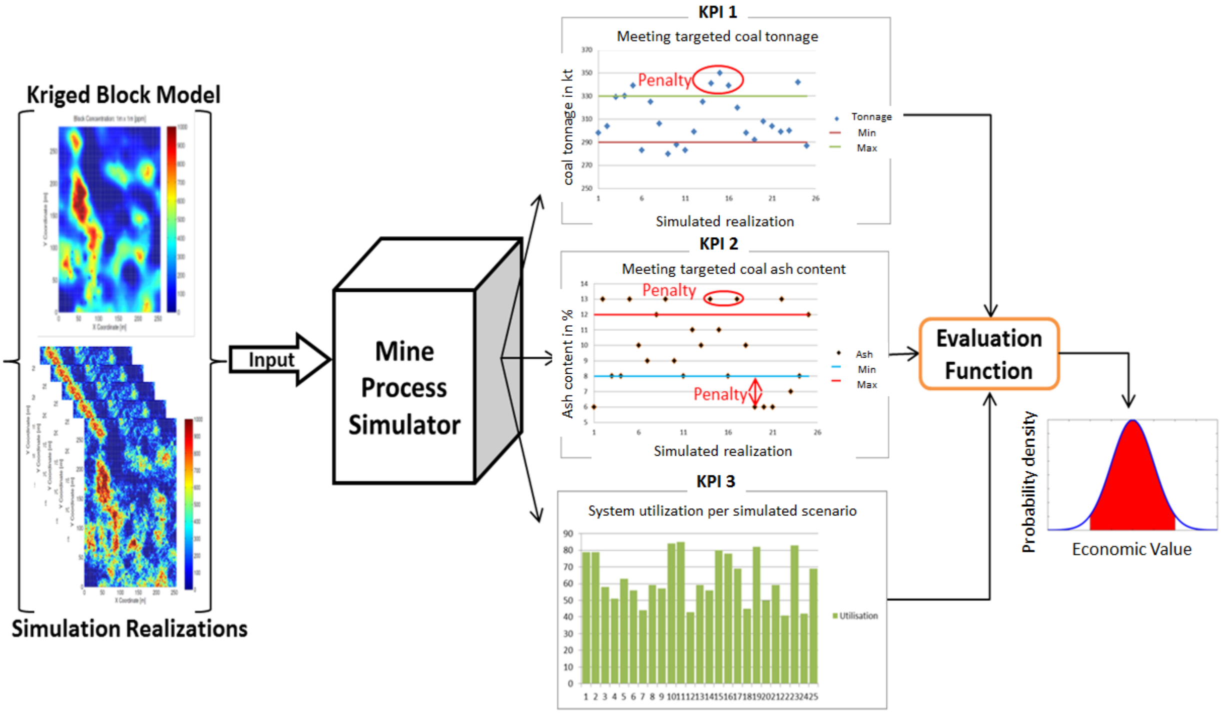


Figure 5: Integrated simulation approach (reproduced after [3]).

Next, a formalized description of the simulation approach is provided. After a declaration of sets and indexes used, the focus is on describing general KPI's for continuous surface mining, which will be used to evaluate different planning variants. Decision and control options for short-term mine planning and production control are explained. The link between KPIs and decisions made is complex and may not be explicitly described by an analytical relation, in particular when the interest is on uncertainty [35]. This link will be provided be a discrete event mining process simulation combined with geostatistical simulated deposit models.

Sets and Indices

In this section, a formal description of the simulation model, in particular KPIs, is presented. First, sets and indices are defined.

Sets

1- *N:* set of key performance indicators, *KPIs*
2- *T:* set of extraction periods
3- *MT*: set of types of materials
4- *Q*: set of critical coal quality parameters
5- *E:* set of excavators
6- *R:* set of simulation replications

Indices

1- $t \in T$: index of mining periods, $\{1, 2, 3, \ldots, T_{max}\}$;
2- $mt \in MT$: index of types of materials, $\{1, 2, 3, \ldots, MT_{max}\}$
3- $q \in Q$: index of coal quality parameters, $\{1, 2, 3, \ldots, Q_{max}\}$
4- $e \in E$: index for excavators, $\{1, 2, 3, \ldots, E_{max}\}$
5- $n \in N$: index for *KPIs*, $\{1, 2, \ldots, N_{max}\}$
6- $r \in R$: index of simulation replications $\{1, 2, \ldots, R_{max}\}$

Evaluation Function

The simulation approach is designed to quantify a value representing the level of achievements towards several defined targets. This value will subsequently be called evaluation function value. Since there are multiple objectives, a representative value can be obtained by summing up the weighted system Key Performance Indicators (KPIs), which are defined hereafter. The weights indicate the importance of the corresponding KPI and can be adjusted by the user as required.

$$J = \frac{1}{R_{\max}} \sum_{r \in R} \sum_{t \in T} \sum_{n \in N} c_{nt} \quad J_{nt}^{r}$$

In this Equation, J_{nt}^{r} is the merit of the n^{th} KPI at time t and replication r and c_{nt} represents the related weight. To incorporate the effect of stochastic components, the evaluation function is evaluated as a mean value over a set of replication R. Alternatively, a distribution of the evaluation function can be derived by calculating a histogram from values corresponding do different replications.

A different approach for evaluating a certain outcome of a simulation model run with respect to multiple KPIs is to use the pareto concept [36]. The outcome defines a pareto point in a N_{max} - dimensional space, which can be compared to other outcomes based on other decision variables by the means of a pareto frontier. This way of multi-objective evaluation can be of particular interest for finding better decision variables using simulation-based optimization. It is not further discussed but will be topic of future research.

Key Performance Indicators, KPIs

KPIs should be defined to measure process performance with respect to previously defined objectives or targets. Generally, for production control of continuous mining system, meeting the coal quality and quantity targets, compliance with the long-term plan, effective capacity, specific energy usage or utilization of the equipment can of interest. For the defined case studies, the focus is on three of these KPIs: meeting coal quality targets, coal quantity targets and utilization of equipment.

KPI Coal Quality:

Meeting quality specifications of coal is most critical in lignite extraction. To reach high efficiencies in the downstream processes, e.g. high efficiency in the power plant, multiple coal quality parameters have to be delivered within predefined ranges of targets. These coal quality parameters can include the calorific value, ash content, sulphur content, iron (Fe_2O_3) content in the ash or moisture of the coal. Deviating from these targets may result in costs. To evaluate a short-term mine plan with respect to coal quality, a penalty function is introduced quantifying this KPI, which associates a cost to deviations from upper or lower coal quality limit.

Next Equation defines the KPI related to penalties for deviating from minimum and maximum values of quality targets for different types of extracted materials. It sums up all deviations from production targets over all defined time periods t, for all coal products mt for a replication r.

$$J_{1t}^{r} = \sum_{mt \in MT} \Big[max\left(0, \left(CQ_t^{mt,r} - TQ_{max,t}^{mt}\right)\right) cd_{t,u}^{mt} + max\left(0, \left(TQ_{min,t}^{mt} - CQ_t^{mt,r}\right)\right) cd_{t,l}^{mt} \Big] CT_t^{mt,r}$$

$$for\ t = 1, \dots, T_{max}\ ,\ r = 1, \dots, R_{max}$$

where $CT_t^{mt,r}$ is the coal tonnage of product *mt* in tonnes, mined in period *t* and related to replication *r,* and $CQ_t^{q,mt,r}$ represents the coal quality parameter *q* of product *mt* in grade units, mined in period *t* and related to replication *r.* Both are evaluated by the simulator for each replication. The simulator provides the link between the set of chosen decision variables and the tonnage and quality produced by evaluating the whole extraction process mapped in the Discrete Event Simulation model.

$TQ_{t,\max}^{q,mt}$ and $TQ_{t,\min}^{q,mt}$ are maximum and minimum target values of coal quality parameter *q* of product *mt*, mined in period *t in grade units*, and $Cd_{q,u}^{mt,r}$ and $Cd_{q,l}^{mt,r}$ are costs related to deviations from upper and lower quality targets in €/(grade unit and tonne) for material type *mt* at time *t* and replication *r.* These parameters represent are defining the penalty function, which can be for example part of a contract between the mine and the customer.

KPI Coal Quantity:

Contractually defined quantities of coal to be delivered have to be ensured on a day by day basis. Even when having a stockpile as a buffer, on a day by day basis production targets should be met. For a given replication *r,* next equation quantifies deviations from coal quantity targets and is designed to evaluate if the quantity of different types of coal extracted in period *t* is within predefined ranges of targets. If not, penalties apply.

$$J_{2t}^{r} = \sum_{mt\ \in MT} \left[max\left(0, \left(CT_t^{mt,r} - TT_{max,t}^{mt}\right)\right) cd_{t,u}^{mt} + max\left(0, \left(TT_{min,t}^{mt} - CT_t^{mt,r}\right)\right) cd_{t,l}^{mt} \right] CT_t^{mt,r}$$

$$for\ t = 1, \dots, T_{max}\ ,\ r = 1, \dots, R_{max}$$

Where $CT_t^{mt,r}$ (tonnes) is coal tonnage related to replication *r*, ($TT_{t,\min}^{mt}$, $TT_{t,\max}^{mt}$ (tonnes)) are the minimum and maximum of target tonnage and ($Cd_{t,u}^{mt}$, $Cd_{t,l}^{mt}$ (€/tonne)) are the costs of deviation from the target tonnage for upper and lower values of material type *mt* at time *t* and replication *r.*

KPI Utilization:

A representative measure of the extraction system utilization can be derived from the utilization of excavators (Equation 4). This is because excavators are always located at the first point in the production chain and are not operating, when any subsequent element of the system is broken down. In a shift an excavator is scheduled to operate for a given time, typically 8h. The difference between actual producing time and scheduled time is caused by

- equipment movements and positioning (changing slices or blocks to extract),
- dispatching purposes, such as changing the destination at the mass distribution center or
- unscheduled breakdowns.

The first item is an operational requirement and may be estimated with a reasonable accuracy. The second item is directly linked to geological uncertainty and accounts for the fact, that different material has to be transported to different destinations. The dispatching action induces a delay since the conveyor configuration has to be changed. If we would know the geology perfectly, then this type of delay could be quantified with 100 % certainty prior to operation. The third item, unscheduled breakdowns, are related to uncertainty that is associated with operational behaviour of equipment.

$$J_{3t}^{r} = \sum_{e \in E} \left[1 - \left(T_{active}^{e,t,r} / T_{sched.}^{e,t}\right)\right]$$

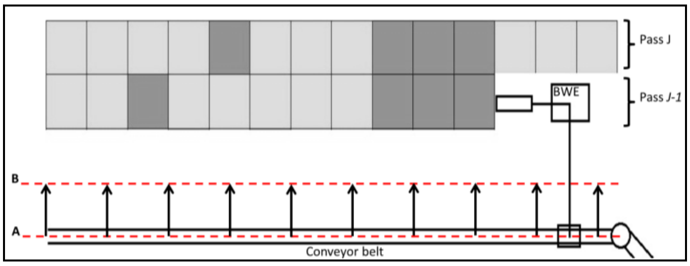
$$for\ t = 1, \dots, T_{max}\ ,\ r = 1, \dots, R_{max}$$

Where $T_{active}^{e,t,r}$ (hours) is the actual producing time, $T_{sched.}^{e,t}$ (hours) is the scheduled time. In this way, J_{3t}^{r} provides an average percentage deviation from scheduled operating time, considering all excavators. In case of different weighting of excavators due to different priority, a corresponding weighting factor could be introduced.

Constraints

Every mining operation faces a number of technical and physical constraints. For the presented approach these are taken care of in the Discrete Event Simulator and are not discussed in detail. However, with respect to the extraction sequence in continuous mining, one special constraint will be mentioned, which is an addition to the typical access constraints known from shovel-and-truck operations.

Using long stretched belt conveyors imposes an additional thought. The conveyor on a particular bench can only be moved to the next position, if all the blocks in one pass are mined out. The conveyor belt shifting constraint is schematically shown next.



Conveyor belt shifting constraint, the conveyor belt can only be shifted from position A to B if all blocks in pass *(j-1)* are mined.

Decision Variables

The decision variables are a set of quantities that the decision maker controls. These are implemented as input variables in the Discrete Event Simulation model and represent typical decisions on short-term planning and production control in a continuous surface mining operation. Some of the decision variables include:

- *extraction sequences*: sequence of extracting mining blocks for each excavator,
- *task schedules of excavators*: different alternatives for short-term plans or
- *planned extraction rate* of excavators in the different time spans.

Simulation model

The proposed simulation model for continuous mining systems is intended to reproduce the operation behaviour as expected in a realistic opencast scenario. The extraction and conveying processes of lignite and waste are emulated in a combined discrete-continuous stochastic manner. This gives the possibility to incorporate uncertainty associated with geological block model and recreate the deterministic and/or random occurrences of events such as operating stoppages because of unavailability of spreaders or conveyor belts, equipment failures, preventive and corrective maintenance activities.

The software selected to implement the simulation model is Rockwell ARENA 14.5, which allows closely reproducing the behavior of complex real systems with complicated decision logic. The software offers intuitive flowcharting support to the modeling, control over the flow of entities in the system, record custom statistics, user-defined expressions and interfacing with external databases and spreadsheets [8].

A more detailed description of the developed model is provided in RTRO-Coal Deliverable 1.1.

Task 1.2 (MIBRAG and RWE): Definition of KPIs, efficiency and reliability measures of a continuous mining process and quantification of stochastic behaviour of the influencing factors

Case MIBRAG: Production Efficiency and Coal Quality Management, Profen Mine Germany

The Profen Mine/ Schwerzau field serves as an industrial case study for developing the stochastic continuous mine system simulator. Key challenges of short-term mine planning and production control arise out of two main boundary conditions:

(1) production targets: three different coal types in predefined coal quality specifications need to be delivered on a day by day basis to different costumers and
(2) the geology of the Schwerzau field is complex, including multiple split seams with strongly varying seam geometry and spatial coal quality distribution.

A successful operation under these conditions requires a pin-pointed coal quality and quantity management and equipment scheduling. In addition, operational efficiency is required for a profit-able operation. Figure 6 shows the extraction system, which consist of six excavators and two spreaders as well as a coal stock-and-blending yard (coal bunker) connected to a train load. Due to design constraints, anticipated production targets and operational aspects, there exist large num-ber of interdependencies between single entities in the production system.

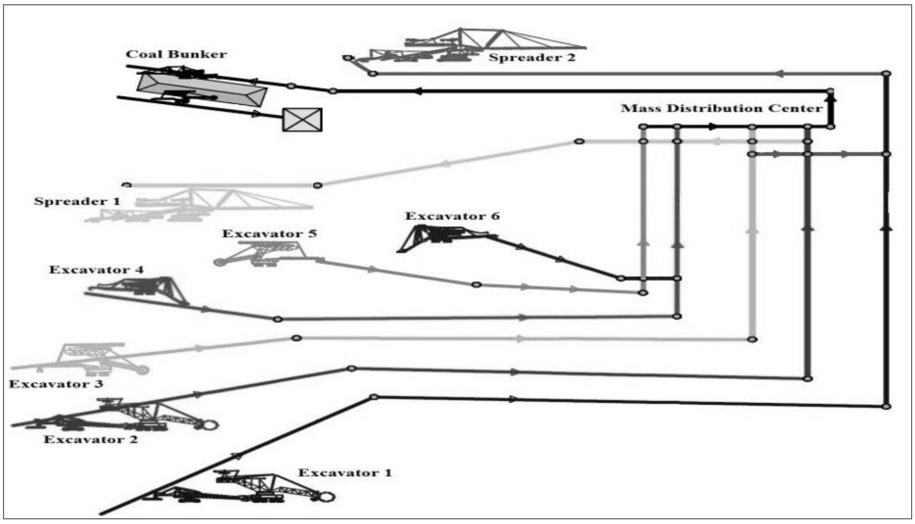


Figure 6: Schematic overview of the production system in the Schwerzau mining field, Profen mine.

The overall aim of the study was to develop a stochastic simulation method capturing most critical factors that influence the key performance indicators of the process.
In total six excavators have to be scheduled with the following operational details:

- Excavator 1 just extracts waste (sand, gravel, clay) and is connected to spreader 2.
- Excavator 2 is mostly producing waste and can send the materials to all defined desti-nations (coal bunker, spreader 1, 2).
- Excavator 3, 4, 5, 6 extract coal and waste and have access to spreader 1 and coal bunker.

A list of required data for building the MIBRAG simulation model is detailed in RTRO-Coal - Deliver-able 1.2a. It contains information on system description, data to infer a quantified description of capacity and down-time behaviour of main system elements, bench-, block- and slice geometries, geological data and also the currently used short-term resource block model. KPIs of interest: (pri-oritised by the interest of MIBRAG) include

1. coal quality produced,
2. coal tonnage produced,
3. compliance to long-term planning,
4. energy usage and
5. capacity of whole system.

Decision variable in daily/weekly planning include:

- extraction sequences of blocks for each excavator,
- task schedules, e.g. weekly excavator schedules

The following table summarizes KPIs, decision variables and major constraints.

Table 1: Summary of KPIs, decision variables and constraints for continuous mining operations.

Objective	Evaluation of aggregated KPIs of each simulation replication based on the pre-defined short-term planning targets.
KPIs	• J_1 - *Coal quality*: should be between defined lower and upper limit otherwise penalties apply. • J_2 - *Coal quantity*: should be between defined lower and upper limit otherwise penalties apply. • J_3 - *Utilisation*: average utilisation of the system can be concluded from the utilisation of excavators
Decision variables	• *Task schedules*: different alternatives for short-term plans of mine (daily/weekly/monthly). – focus of RTRO-Coal • *Extraction sequences*: sequence of extracting mining blocks for each excavator. – focus of RTRO-Coal • *Extraction rate* of excavators in the different time spans. – focus of RTRO-Coal • *Stockpile management*: sequence of stacking and reclaiming.
Constraints	• Each block can only be mined once. • A conveyor belt can only be moved further along, if all the blocks in the previous pass are mined out.

Case RWE: Overburden Management at Hambach Mine, Germany

The main focus related to the RWE case is in materials management. The term "material" is used in a sense of overburden management aiming to ensure stability of operational and dump slopes, and working floor and the spreader site [2]. The extraction of overburden is increasingly facing deficiencies in output due to difficult mining materials, so-called mixed soils (M2). These soils exhibit a high share of cohesive components and is difficult to drain. The fact that only a limited quantity of these unstable mixed soils can be placed in the waste dump results in downtimes and bottlenecks in the placement process on the dumping side. Figure 7 shows a comparison of M2 supply from the extraction site of the mine and placement options and capacity on the dumping site of the mine. To handle these quantities, pin-pointed and far-sighted operations management is required.

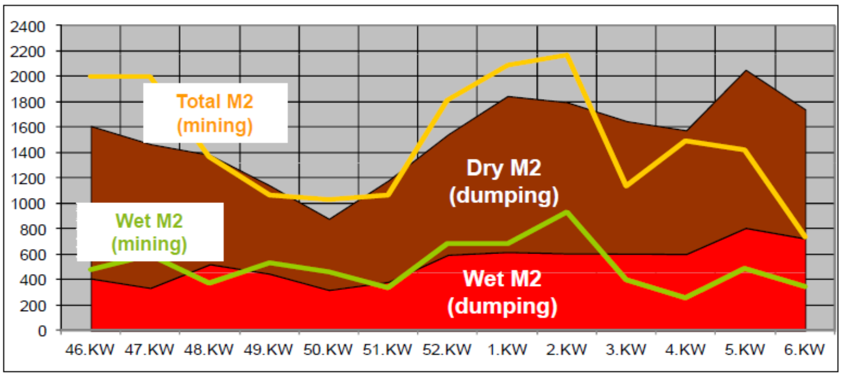


Figure 7: Comparison of M2 supply and placement options (reproduced after [6]).

Wet M2 material cannot be used for stable dump construction and needs to be filled in predefined polders constructed of dry material (Figure 8). Due to varying geology, the proportions of dry and wet material extracted by different excavators fluctuate strongly over time. Before dumping of wet material is possible, a polder or dam has to be prepared based on dry material. Depending on the current geological situation on the extraction side of the pit, these constraints may cause significant delays due to material management.

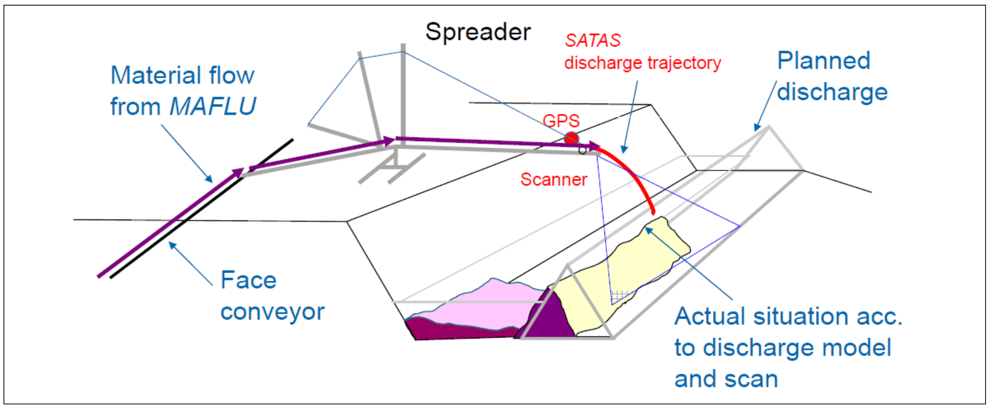


Figure 8: Waste Material management on a dump site (reproduced after [6]).

The aim of the RWE case is to optimize waste management to decrease downtimes/increase efficiency of excavators and spreaders while ensuring stable dump construction using a scheduling optimization approach.

A schematic view of the Hambach mine is shown in Figure 9. In total eight BWEs have to be scheduled to serve continuously seven spreaders with waste material and two bunkers with coal. Waste materials at the Hambach mine are categorized in three types of mixed soils, mixed soils type1 (M1), dry mixed Soils type2 (M2T) and wet mixed soils type2 (M2N). Each BWE excavates either lignite or waste in terrace cuts and transfers materials to the face conveyor belt, which carries it along the bench to the main conveyor belt. All excavated materials of the eight benches are distributed to their destinations at the mass distribution center. Based on a predefined daily schedule, waste is distributed to the seven spreaders for dumping, and lignite is forwarded to two coal-bunkers. Table 2 shows the technical specifications of the BWEs.

The mine operates 24 hours per day and seven days per week. Regular maintenance is carried out on weekly, monthly, and annually based schedules. During the regular maintenance or an unscheduled breakdown, the production process ceases on the bench.
Historical data show that next to scheduled maintenance, breakdowns of the equipment occur in a random manner. Due to the "in series" system configuration, equipment units feeding or are connected to the ceased equipment are blocked and set out of the operation while the maintenance is being done or the failure is being repaired. Furthermore, because of the multi-layer nature of the deposit, changes from one material type (e.g. M1) to another material type (e.g. M2N) or vice versa happens very frequently. Each time a material change takes place, the BWE stops excavating.
In summary, the system shows a stochastic behaviour that is based on the randomness of significant system constituents and operations. The combined effect of frequent changes in extracted materials and random equipment breakdowns, makes the prediction of the exact material flow rate at any given future time span as a major source of uncertainty.

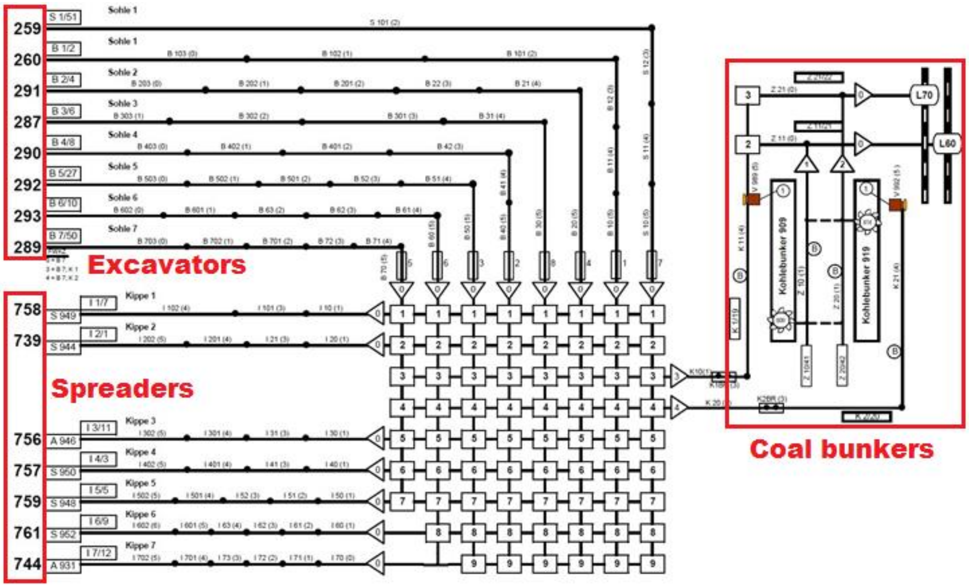


Figure 9: Schematic overview of the production system of the Hambach mine.

Table 2: Technichal specification of BWEs.

Bench	BWE model	Bucket capacity (m3)	Theoretical capacity (m3/h) *
S1	259	2.6	5700
B1	260	3.5	5700
B2	291	5.0	12500
B3	287	5.1	10400
B4	290	5.0	12500
B5	292	5.0	12500
B6	293	5.0	12500
B7	289	5.0	12500

A list of required data for building the RWE simulation model is detailed in Deliverable 1.2b. It contains information on system description, data to infer, a quantified description of capacity and down-time behaviour of main system elements, bench-, block- and slice geometries, geological data and also the currently used short-term resource block model.

Task 1.3 (Lead TUDT with input from MIBRAG and RWE): Implementation of the simulation approach, testing and validation in an historical and reconcilable mining environment

To analyse the performance of the proposed simulation formulation, a software implementation of the proposed simulator is investigated in a completely known and fully controllable environment. The objective of this investigation is to illustrate the effect of geological uncertainty on the performance of a complex continuous mining system. The well-known Walker Lake dataset in geostatistics is chosen as environment as it provides different sampling schemes and the exhaustive data set about a virtual deposit [14]. For the study conditionally simulated models were generated in order to quantify uncertainty associated with the geology. The technique of Sequential Gaussian Simulation [15] was used. This technique results in a set of equally probable scenarios (called realizations) of the deposit, which capture in-situ variability and uncertainty. The applicability to sedimentary multi-seam coal deposits was already demonstrated by Benndorf [15]. As a result, the real value block model (exhaustive *Walker Lake* dataset), an average type estimated block model using Ordinary Kriging for benchmarking and 20 conditionally simulated realizations of the deposit were available as different replications for building the simulation experiments.
The mining system implemented matches the MIBRAG configuration as described in Deliverable 1.2. The original dataset contains 93,600 mining blocks. For the purpose of adaptation to this problem, every 16 adjacent blocks are aggregated together to build up one mining block containing multiple slices. The volume of each mining block is 15,400 m^3. The block model is divided into six

equal areas and each area is assigned to one excavator; for simplification, two types of blocks exist, coal or waste block (Figure 10).

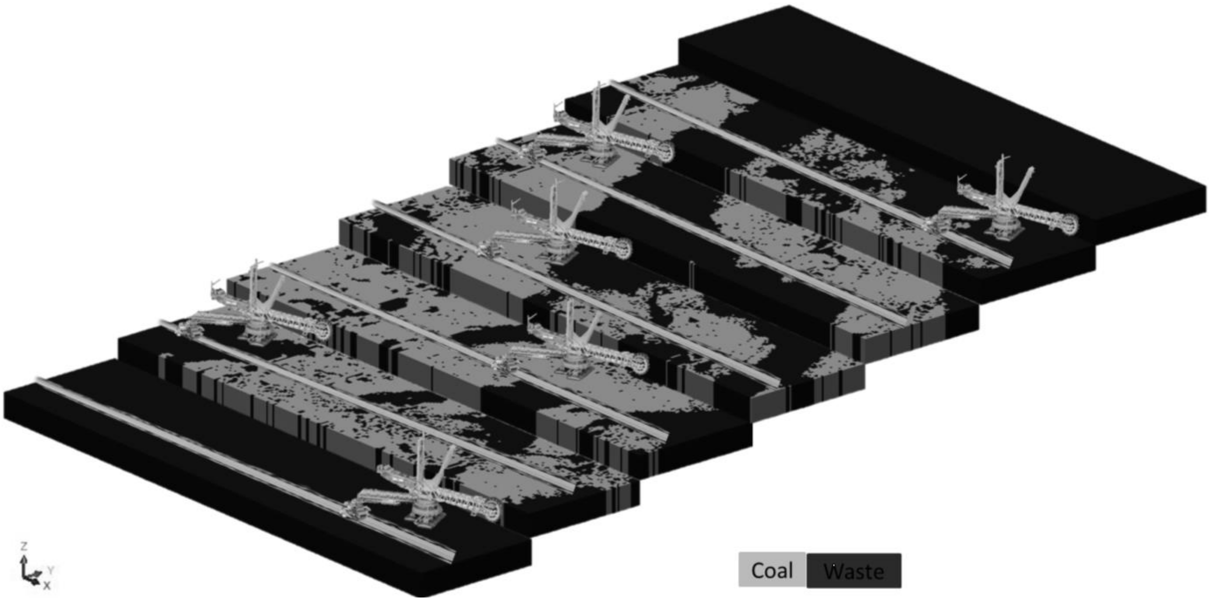


Figure 10: Reserve block model, assigned area for the excavators.

Table 3: System parameters used for the synthetic test case.

Type	Theoretical Capacity (loose m^3/h)	Scheduled Time $T_{scheduled}$ (h)
Excavator 1	4900	152
Excavator 2	4900	152
Excavator 3	3770	144
Excavator 4	1400	168
Excavator 5	3770	152
Excavator 6	740	152
Spreader 1	10,000	168
Spreader 2	10,000	168
Conveyor belts	6000	168

Table 4: Targets used in the synthetic test case.

Material Types		Targets		Penalties in per unit deviation	
Type	Density	Max	Min	Upper	Lower
Coal Quantity	1	322,700 t	316,000 t	1	1
Coal Quality		Ash content < 8.5%		1	

To illustrate the value of the integrated simulation approach for this report, KPI J1 is investigated, which is the ability to meet the coal quality target, in particular the ash content. The performance related to other KPIs is documented in Deliverable 1.3. Figure 11 shows the ash content for one week of coal production to be delivered by trains to power plants. Results reveal that predictions based on the estimated Kriging model (black line) and the reality (dark grey line) are not well correlated. Reasons for this effect are the smoothing effect and the introduction of a conditional bias. If based on predictions originating from estimated models control decisions are made, it cannot be guaranteed that these decisions will lead to optimal results. Contrary, considering the conditional simulation model, there are 20 realizations (light grey cloud) and the average of the realizations (doted red line). Comparing geostatistical simulation based predictions with the reality; the red line generally follows the true ash content well. Differences are in the expected range of deviations which are mapped by the shadow range (realization cloud).

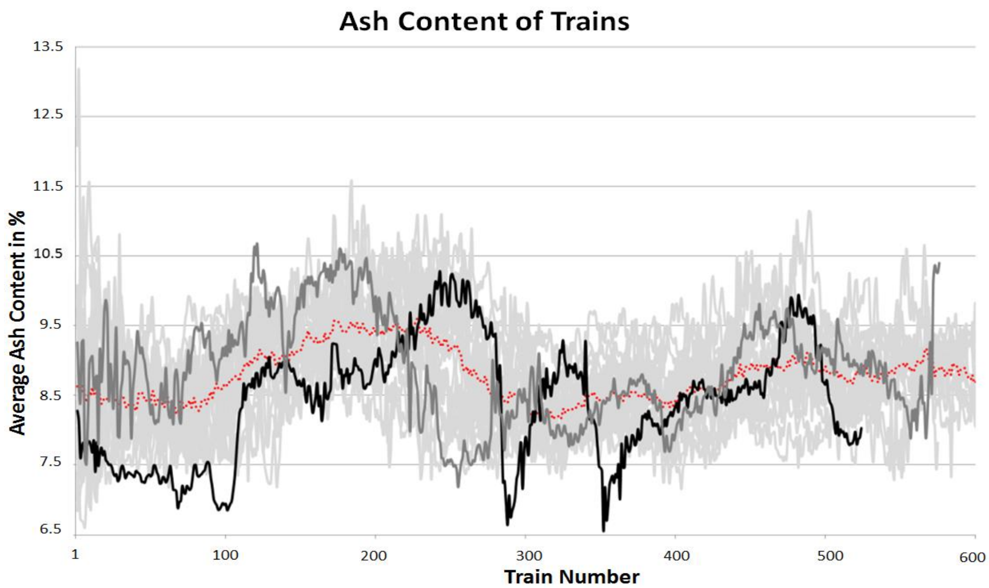


Figure 11: The average ash content in the delivered trains.

The previous example illustrates that the integrated simulation approach is a valid and powerful tool to explore the effect of geological uncertainty on the expected performance of complex continuous mining systems. It provides a valuable tool to the mine planning engineer to foresee critical situations affecting the continuous and reliable supply of raw material.

Task 1.4 (Lead TUDT with input from MIBRAG and RWE): Setting up the simulation process for a field testing period in a mining operation and validate it in an industrial process as preparation of Work Packages 3 and 5

In Task 1.4, both case studies have been implemented as a process simulator taking into account all historical data from operations. This included the definition of a conceptual model and also the definition of attributes of single elements, such as the break-down behaviour of equipment. For the subsequent use of simulation models in WP3 and WP5, these have to be validated with the aim to determine, whether a simulation model is an accurate representation of the system. The timing and relationships of validation and verification are shown in Figure 12.

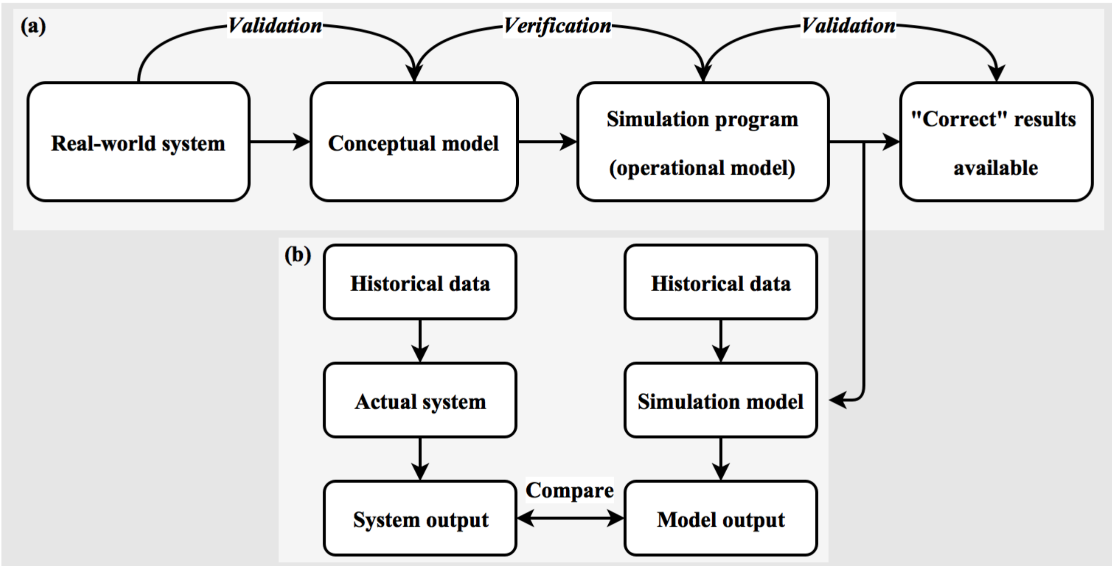


Figure 12: Modelling and simulation process (reproduced after [1]).

The predicted values of the simulator aim to quantify realistic expectations of the values of the actual system. Task 1.4 of WP1 is related to the final step of the simulation model building process. The methodology behind this task is presented in the rectangle b in Figure 11. All modelled KPIs are compared against the reality (actual system). Following evaluation measures have been defined for the purpose of this validation: bias, average deviation, and relative error.

- The **bias** refers to the tendency of the simulator to over- or under-estimate the value of a population parameter. The bias can be defined as the sum of differences between all predicted and actual KPI-values over all *n* predicted time intervals:

$$BIAS = \sum_{n} (KPI_{simulated} - KPI_{actual})$$

- The **average deviation** is one of several indices of precision. Here, it is defined as the mean absolute deviation between all predicted and actual KPI-values over all *n* predicted time intervals:

$$AVERAGE\ DEVIATION = \frac{1}{n} \sum_{n} |KPI_{simulated} - KPI_{actual}|$$

- The **average relative error per day** is derived from the absolute error (average deviation) divided by the magnitude of the actual value. Within this WP it is defined as:

$$AVERAGE\ RELATIVE\ ERROR = \frac{1}{n} \sum_{n} \frac{|KPI_{simulated} - KPI_{actual}|}{KPI_{actual}}$$

Validation Case MIBRAG

Three months (92 days) of production data (from 18.06.2014 until 17.09.2014) were used to set up an industrial scale simulation run. For this time frame the following production data were available: extracted amount of coal/waste, coal quality parameters sensed on conveyor belt 62, equipment downtimes. Given these data, modelled KPIs were validated against actual system outputs. Based on geodetic surveying campaigns of the mine, the three-month time frame was divided into three individual months (Figure 13):

- July: 18.06.2014 till 18.07.2014 (31 days)
- August: 18.07.2014 till 13.08.2014 (26 days)
- September: 13.08.2014 till 17.09.2014 (35 days)

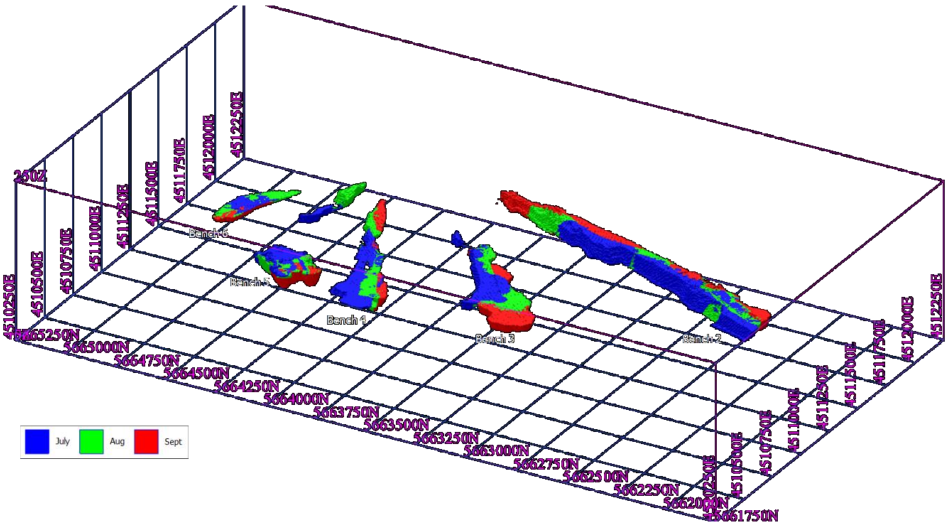


Figure 13: Mining areas corresponding to each of the three months per bench.

To evaluate the representatively of simulation results, a set of numerical experiments was designed. The strategy for designing experiments follows three major objectives. The first objective is to show that the simulation model reproduces observed data of the real system, when historic deterministic input is provided. The second objective is to evaluate the representatively of the stochastic component 'breakdown behaviour' (utilization KPI). The third objective is to quantify the effect of geological uncertainty and reconcile its results against measured KPIs observed in reality. With these objectives, experiments are set up as follows:

- *Experiment 1 - run the simulation model without stochastic components:* The input reserve block model is derived from historically actual measured data and all parameters, such as working schedule, failures, and excavation rates are taken as historically performed and are deterministic values.
- *Experiment 2 - Run the simulation model with stochastic component 'breakdown behaviour':* The reserve block model is kept like in Experiment 1 and represents reality. In this experiment, theoretical distribution models for predicting unplanned downtime of equipment are added to the model as stochastic components.
- *Experiment 3 - Run the simulation model with stochastic component 'breakdown behaviour' and 'reserve model':* This experiment is designed for the quantification of geological uncertainty. The stochastic input 'resource model' is added to the simulation model. In total, there are 27 different reserve block models (different possible values for ash content):
    - An estimated model (ash content), which is provided by MIBRAG
    - An estimated model (ash content) that is created by TU Delft
    - 25 possible realizations of spatial distribution of ash content based on conditional simulation (taken from WP2).

For this report the last experiment was chosen to be presented. Details on experiments 1 and 2 are presented in Deliverable 1.4. The third experiment is the most comprehensive test. Table 4 presents the summary of total production for month July. The difference between actual and prediction are 15.63% for coal and 1.32% for waste. The sum of the production of coal and waste shows the difference of less than 3% which is an acceptable deviation. This order of deviation between coal tonnage prediction and actual can be evaluated as satisfactory. In industry practices for resource classification (e.g. [16]) a deviation of 15% over a three months' period is acceptable for the category measured resources. Still, it has to be concluded that the ability to predict ROM coal tonnage is the major uncertainty factor in simulation prediction of MIBRAG's system. This is mainly due to the complex geological conditions. As a result, the resolution of the block model was agreed to be on a block scale instead of a finer slice scale.

Figure 14 summarizes the validation results of the ash content for the month of July. The blue dash-line shows the ash value of actual production measured by the RGI sensor on conveyor 62. The red dashed-line shows ash values of TU Delft's estimated model and red dot-dash-line shows ash values predicted by MIBRAGs estimated model. The range of uncertainty is illustrated by a dark shadow cloud in the graph and is derived from the conditionally simulated models. Given the exploration data, the TU Delft estimated model performs well. Deviations from the model fall mostly into the shaded uncertainty range. With a confidence level of 68% some days, where the actual falls outside the range, are reasonable. An additional contributing to the uncertainty in predicting ash is the uncertainty in geology, which may lead in practice to different blending scenarios during production than predicted by the simulator. The MIBRAG model on this local scale seems to underestimate the ash-content. Given that the ash content is predicted on a day by day basis and the coal from multiple days is further homogenized in a blending bed, simulation results appear to be realistic and represent the current geological situation in the Schwerzau mine.

Table 5: Summary of total production of month July.

	Model data	Real data	Difference (%)	Bias	Average deviation per day	Average relative error per Day (%)
Coal (10^3 t)	653.77	774.85	-15.63	-121.09	10.90	49.22
Waste (10^3 m^3)	2088.58	2061.17	1.32	27.41	14.01	23.22
Total volume (10^3 m^3)	2657.08	2734.96	-2.84	-77.88	12.26	15.90

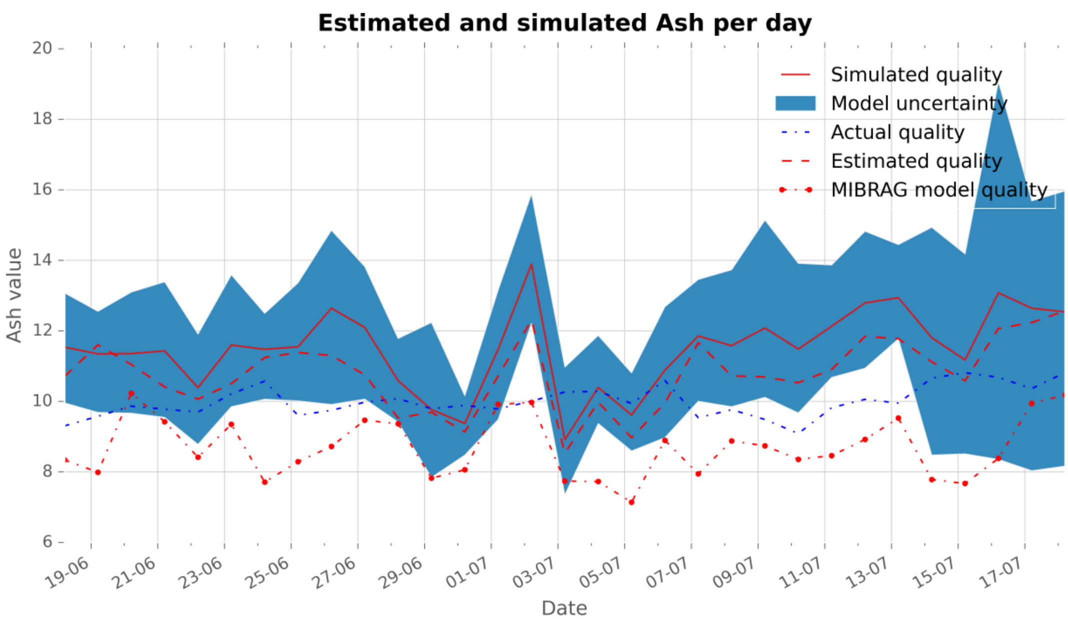


Figure 14: Daily ash values per day for month July.

Results show that definded targets are achieved and the simulation model is verified and validatied against the reality (historical data). An uncertainty in monthly prediction of coal tonnage of approximately +/- 15% originates mainly due to geological uncertainty and is in an acceptable range for measuered resources (e.g. [16]). During the validation study some aspects and potential for improvement in data capturing were identified and recommendations have been given to MIBRAG (Deliverable 1.4). Based on results of this study it has been decided that the smallest model resulution is one mining block (set up of an excavator). A more detailed division in mining slices per block is not sensible, mainly due to uncertainty in predicting geological attributes.

Validation Case RWE

A time horizon of three months (from 01.01.2015 until 31.03.2015) was chosen to set up the simulation run. For this time frame all production data (three working shifts per day an 8 hours) were provided by RWE, including extracted amount of coal/waste (different type of waste materials) and all downtimes data. The experimental set up was chosen similar to the MIBRAG case. Since the main focus at RWE is on waste (geological uncertainty is less significant than in the MIBRAG case) experiment 3 was not performed.

The summary and statistical meassures of the total production of month January are presented in Table 6. The maximum difference in the production of coal is to 2.9%. Considering the whole operation, a difference of 1.2% is seen for this month. The average deviation per working shift is about 31 Tm^3 corresponding to about 0.13% The total shift-based production and also for different material types at the Hambach mine for month January are shown in Figure 15 and Figure 16. The differences between simulation based prediction and actual production for the historic case are judged to be neglectable. The validation for RWE is successful.

Table 6: Summary of the total production of the month January in the Hambach mine, Exp. 2.

Material Type	**Simulated (m^3)**	**Actual (m^3)**	**Difference (%)**	**Bias (m^3)**	**Average deviation per shift (m^3)**	**Average relative error per day (%)**
M1 (10^3 m^3)	10,557	10,656	-0.93	-99	28	0.26
M2T (10^3 m^3)	4,257	4,290	-0.77	-33	15	0.35
M2N (10^3 m^3)	4,257	4,290	-0.77	-33	15	0.34
FOKI (10^3 m^3)	33	33	0.00	0	0.4	1.24
KIES (10^3 m^3)	16	16	0.00	0	0.3	1.57
Coal (10^3 t)	4,060	4,183	-2.94	-123	9	0.22
Total volume (10^3 m^3)	23,181	23,469	-1.23	-288	31	0.13

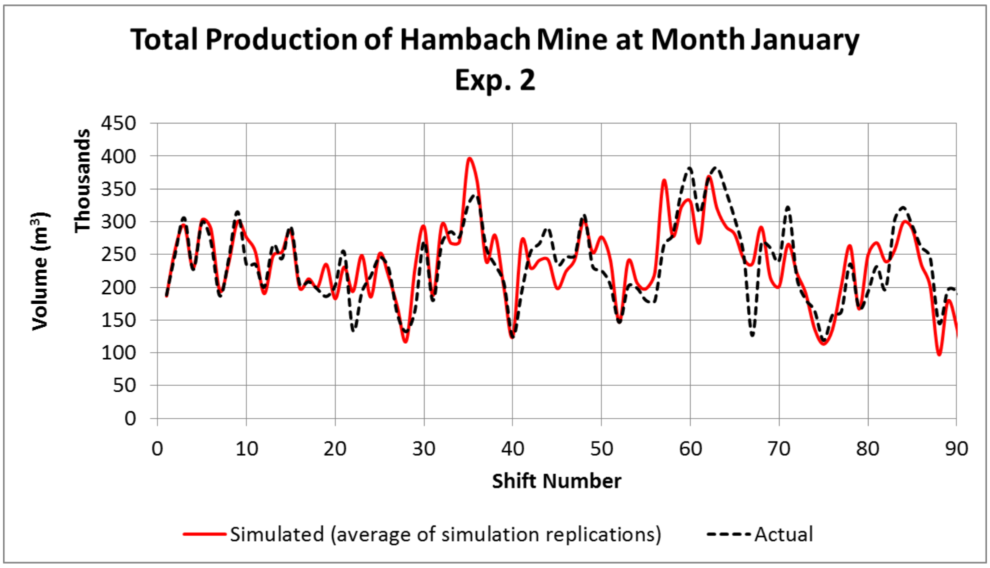


Figure 15: The total shift-based production of Hambach mine in month January, Exp. 2.

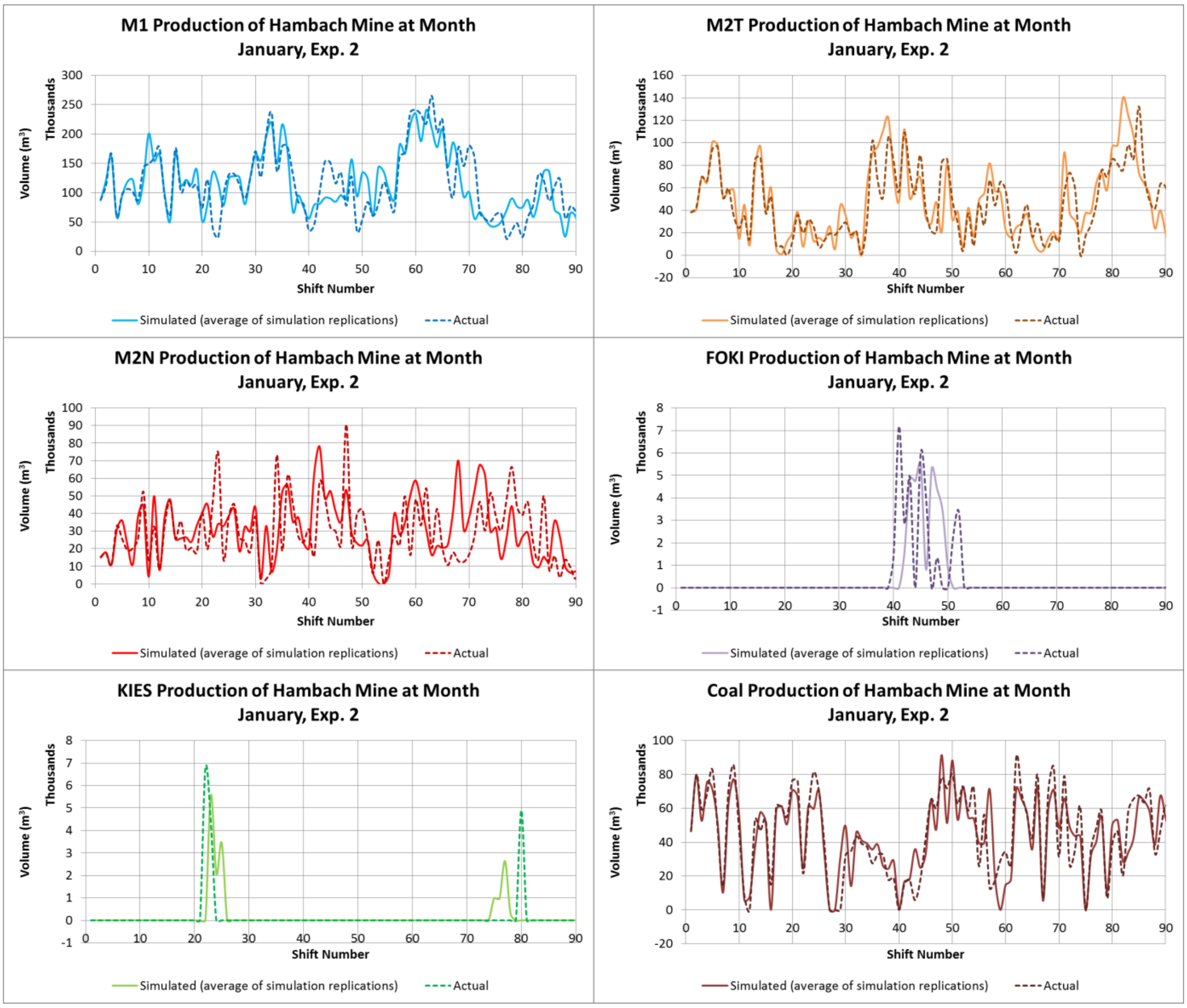


Figure 16: The shift-based production of different materials of Hambach mine in month January, Exp. 2.

Work Package 2: Intelligent Mine-Process-Data Analysis

Task 2.1: Development of a theoretical framework and a detailed algorithm for the self –learning data analysis tool based on statistical learning theory

In lignite mining, similar to other branches of mining, the initial step prior to mining activities is creating a resource model based on exploration data, usually drill hole data. In order to produce a valuable representation of the coal seam geometry and quality attributes of the seam, traditionally geostatistical interpolation methods are used. Based on this resource model, a long- and short-term production plan is created and mining activities will be executed according to this plan. In case of discovering unexpected waste intrusions in the coal seam during production, the short-term model has to be adjusted. The current practice, using off-line sample analysis and modelling techniques, this may take days or sometimes even weeks. Using online sensor techniques for coal quality characterisation in combination with rapid resource model updating, a faster reaction to the unexpected deviations can be implemented in operation leading to increased production efficiency. This concept was initially proposed by Benndorf [17] as a closed-loop-framework. Figure 17 illustrates this conceptual workflow that integrates online-sensor data into the resource model, as soon as they are obtained.

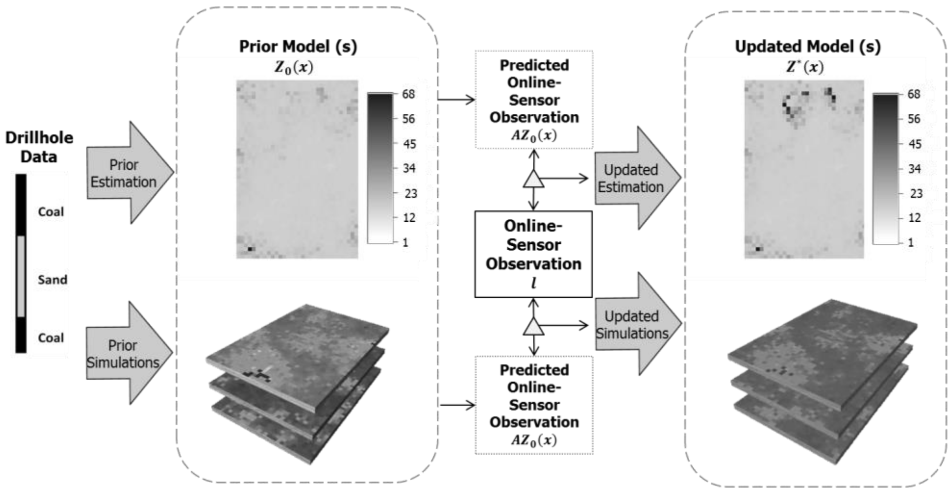


Figure 17: An overview of the resource model updating concept.

The framework developed within Task 2.1 focuses on the identification and quantification of the differences between the resource model based predictions and online sensor measurements. The main challenge lies in the ability to comprehend the source of the difference and feed the gained knowledge back to the resource model. Solving this challenge results in a resource model that is continuously updated as soon as sensor measurements become available.

Different parametric and non-parametric methods of statistical learning theory were investigated with respect to applicability for resource model updating, including

- Bayesian updating (parametric),
- modern data assimilation methods such as Kalman Filter, Ensemble Kalman Filter and Normal-Score Ensemble Kalman Filter (parametric),
- black-box approached machine learning methods such as Artificial Neural Networks and Support Vector Machines (non – parametric)

The analysis of methods showed that the of the Normal-Score Ensemble Kalman Filter (N-Score EnKF) offers the most comprehensive framework to analyse differences between model based predictions and observations and as well to update the resource model at the same time. It is able to handle non-Gaussian data, as commonly found in coal quality parameters (ash, sulphur, calorific value) and as well non-linear relationships between observations and coal quality parameters. Table 7 is summarizing the comparison between methods and is given below.

Note that the ability of the N-Score EnKF to analyse differences and update the model combines tasks initially distributed over two Work Packages (WP2 – Data Analysis and WP3 – Resource Model Updating). Still, it is a more comprehensive framework. Data analysis and the updating tasks have to be both implemented, tested and evaluated. The scheduled resources allocated for working hours within the tasks remained therefore unchanged.

Table 7: Summary of applicability of data assimilation and machine learning techniques for resource model updating.

Data Assimilation Methods			Machine Learning Methods	
Kalman Filter (KF)	**Ensemble Kalman Filter (EnKF)**	**Normal-Score Ensemble Kalman Filter (NS-EnKF)**	**Artificial Neural Networks (ANN)**	**Support Vector Machines (SVM)**
Applicable for linear systems Assumes Gaussian data Requires very expensive storage and computation	Applicable for non-linear systems Assumes Gaussian data Same update eq.s of KF except the K gain is calculated from the error cov.s provided by ensembles	Applicable for non-linear systems Do not assume Gaussian data Same algorithm with EnKF except NS transformation	Applicable for non-linear systems Black box approach Difficult to implement and interpret	Applicable for non-linear systems Black box approach Difficult to implement and interpret

Following tasks have been worked on in strong collaboration:

- Task 2.1 and Task 3.2a,
- Task 2.2 and Task 3.3 and
- Task 2.3 and Task 3.4.

The description of progress within this reports focuses on the main results which can be assigned to individual tasks. Following the formal description of the method is summarized.

Let $\boldsymbol{Z}(\boldsymbol{x})$ be the vector representing the state of a spatial stochastic process modelling the spatial distribution, where $\boldsymbol{Z}$ refers to local coal properties such as the local ash content at excavation locations $\boldsymbol{x}$. The updated resource model $\boldsymbol{Z}^*(\boldsymbol{x})$ is a linear combination of the prior resource model $\boldsymbol{Z}_0(\boldsymbol{x})$ and a weighted difference between model based prediction and sensor based measurements $\boldsymbol{l}$

$$\boldsymbol{Z}^*(\boldsymbol{x}) = \boldsymbol{Z}_0(\boldsymbol{x}) + \boldsymbol{K}(\boldsymbol{l} - \boldsymbol{A}\boldsymbol{Z}_0(\boldsymbol{x}))$$

Matrix $\boldsymbol{A}$ represents the production sequence, so the term $\boldsymbol{A}\ \boldsymbol{Z}_0(\boldsymbol{x})$ represents the model based prediction on measurement location based on the prior block model. The Kalman gain, $\boldsymbol{K}$**,** calculates a weighting factor based on the prediction and measurement error covariances. The Kalman gain matrix indicates the reliability of the measurements, to decide "how much to change the prior model by given a measurement" and can be derived from a minimum variance estimate, which leads the Kalman Filter (KF) to provide an optimal solution by minimising the cost function.

$$\boldsymbol{K} = (\boldsymbol{A}^T\boldsymbol{C}_{zz}\boldsymbol{A} + \boldsymbol{C}_{ll})^{-1}\boldsymbol{A}^T\boldsymbol{C}_{zz}$$

The Kalman gain $\boldsymbol{K}$ can be calculated according to the above stated equation. As mentioned above, it contains two different error sources, $\boldsymbol{C}_{zz}$, the model prediction error and $\boldsymbol{C}_{ll}$, the measurement error. The model prediction error can be represented by the variance - covariance matrix of the prior resource model, which is propagated through the lignite mining process by the production sequence matrix $\boldsymbol{A}$**.** The measurement error is the covariance matrix of the sensor-based measurement. The updated model error or model precision can be derived by calculating the posterior covariance matrix $\boldsymbol{C}_{zz}^*$ (after updating) and results in

$$\boldsymbol{C}_{zz}^* = (\boldsymbol{I} - \boldsymbol{K}\boldsymbol{A})\boldsymbol{C}_{zz}$$

Above equations indicates a decrease of the uncertainty of the resource model blocks, not only for the currently excavated ones but also for the adjacent blocks which are spatially correlated [18]. Figure 18 illustrates an overview of the KF based resource model updating concept

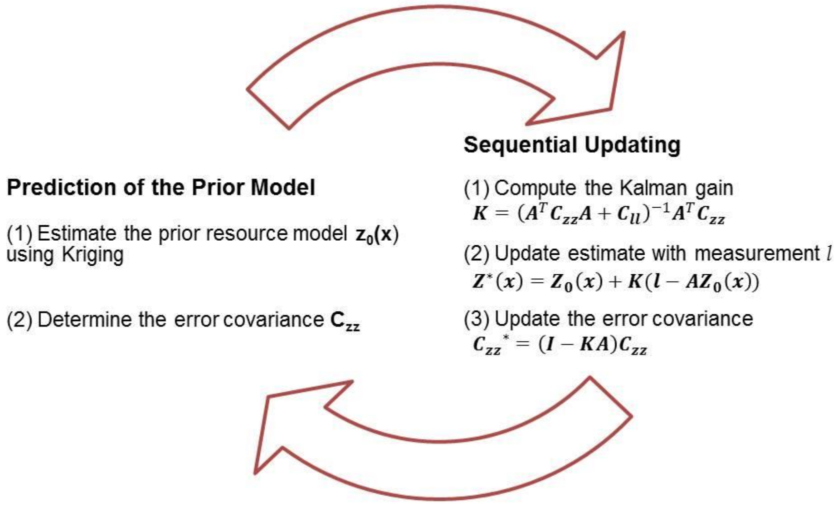


Figure 18: An overview of the KF based resource model updating concept.

The KF offers a large potential in improving the resource recovery by combining online data with the resource model and consequently decreasing its uncertainty. Yet, there are different challenges to solve in order to comprehend the source of the difference between sensor measurement and the resource model, and feed the gained knowledge back to the resource model. The main challenges to solve are the size of the estimated resource model (in the order of multiple millions of grid nodes), non-Gaussian behaviour of data, the different support of observations and resource model blocks and a possible non-linear relationship between the observations and model attributes.

The (EnKF) provides a comprehensive solution for large-scale applications when explicit storage and manipulation of the covariance matrix is impossible or not feasible [19]. Moreover, EnKF is able to deal with the non-linear systems. The developed EnKF framework uses SGS in order to create the ensemble of realizations, also called prior ensemble $\boldsymbol{Z_0(x)^e}$, where e=1,…,N is the number of the corresponding realization/ensemble member. Next, the algorithm continues recursively using the following recurrence relations,

$$\boldsymbol{Z}^*(\boldsymbol{x})^e = \boldsymbol{Z_0}(\boldsymbol{x})^e + \boldsymbol{K}^e(\boldsymbol{l}^e - \boldsymbol{A}\boldsymbol{Z_0}(\boldsymbol{x})^e) \ .$$

$$\boldsymbol{K}^e = (\boldsymbol{A}^T \boldsymbol{C_{zz}}^e \boldsymbol{A} + \boldsymbol{C_{ll}}^e)^{-1} \boldsymbol{A}^T \boldsymbol{C_{zz}}^e$$

$$\boldsymbol{C_{zz}}^{*e} = \overline{(\boldsymbol{Z}(\boldsymbol{x})^e - \overline{\boldsymbol{Z}(\boldsymbol{x})^e})(\boldsymbol{Z}(\boldsymbol{x})^e - \overline{\boldsymbol{Z}(\boldsymbol{x})^e})^T}$$

where $\boldsymbol{Z(x)^e}$ and $\boldsymbol{l^e}$ respectively consist of an ensemble of block models and the measurements. $\boldsymbol{C_{zz}^{*e}}$ refers to the updated error covariance of the resource model, where the overbar denotes the expected values of the ensembles. The covariance matrices represent the whole ensemble and the Kalman gain $\boldsymbol{K^e}$ is derived from these.

To deal with the non-Gaussianity of the data, a new approach NS-EnKF is proposed by Zhou [20] which transforms the original state vector into a new vector that is univariate Gaussian at all times. Gaussianity is achieved by applying a normal-score transformation to each variable for all locations and all time steps, prior to performing the updating step in EnKF.

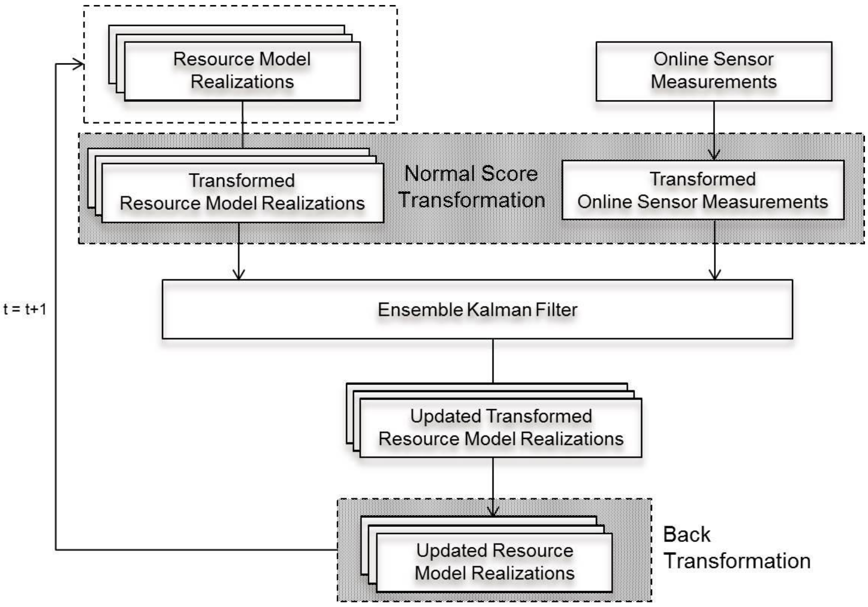


Figure 19: Flow chart of the NS-EnKF based approach, (modified from [20]).

The NS-EnKF approach follows the same steps as the standard EnKF, except the NS-EnKF has additional pre- and post-processing steps. Local grades at grid nodes will be normal score transformed before application of the EnKF, and once the update is complete, the normal score transformed data will be transformed back (Figure 19).

Task 2.2: Implementation of the learning algorithm including testing and validation in a completely know and fully controllable environment.

The subsequent example aims to investigate the performance of the proposed updating methodology. Here, an artificial test case is presented, which is built around the well-known and fully understood Walker Lake data set [14]. The data set (Figure 20) is interpreted as a quality parameter of a coal deposit, e.g., as ash content or CV, and is integrated in a typical mine topography. It is sampled irregularly at a spacing corresponding to an average of two reserve block lengths. The blocks were defined with a dimension of 16 m × 16 m × 10 m. The block-variogram is given with a spherical structure, range 50 m, nugget effect 0.4 and sill 0.6.

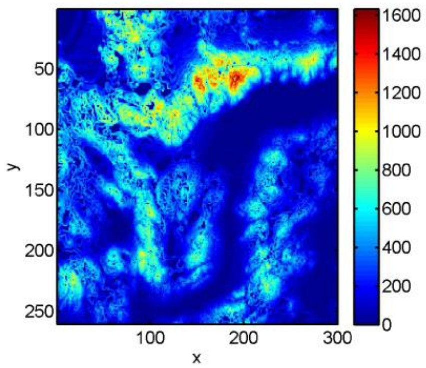


Figure 20: Walker lake data set.

Taking into account an assumed density of 2 t/m^3, one mining block represents a tonnage of approximately 5.120 t. Ordinary Kriging was used to generate a resource block model and the prior error covariance matrix, Generalized Sequential Gaussian Simulation (GSGS) 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 21) was used as the prior model.

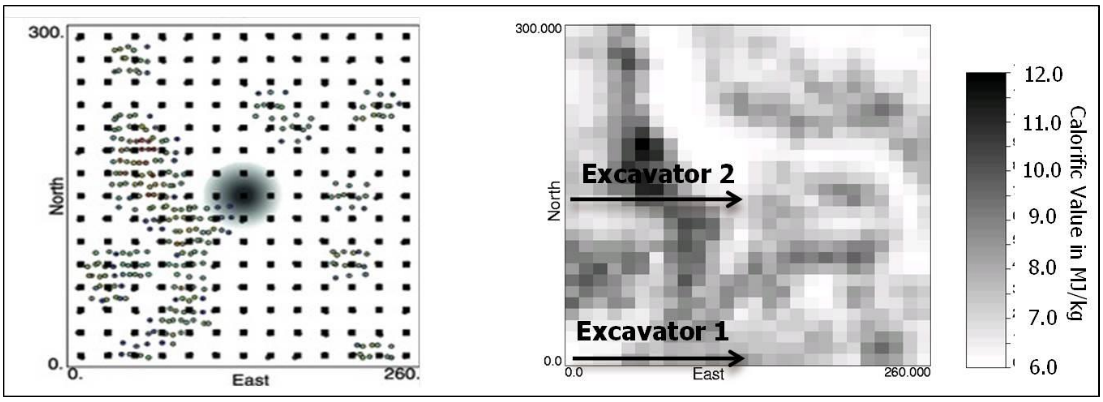


Figure 21: Prior model for updating based on Walker Lake data.

The artificial block model will be mined applying a continuous mining system, which initially consists of two bucket-wheel excavators positioned at separate benches. Different digging rates per excavator were applied. 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 combined material flow of two excavators is scanned online 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 min moving average (corresponding to about 250 t of 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 250 t to the mining block support of 5120 t 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 updating approach is evaluated using the mean square difference or mean square error (MSE) related to the true block value. Here, the difference between estimated block value $\boldsymbol{Z}^*(\boldsymbol{x})$ and real block value $\boldsymbol{Z}(\boldsymbol{x})$ from the exhaustive data set is compared. The MSE is an empirical error measure and can be calculated according to

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

Figure 22 shows the MSE for different sensor precisions compared to the prior case for blocks,

- which are already mined (mined blocks),
- which are one block distant and will be mined during next working shift, day or week (adjacent blocks) and
- which are two blocks distant and will be mined in the near future (indirect blocks).

The upper row shows results from the Kalman-Filter, the lower row shows results obtained by the Ensemble Kalman Filter.

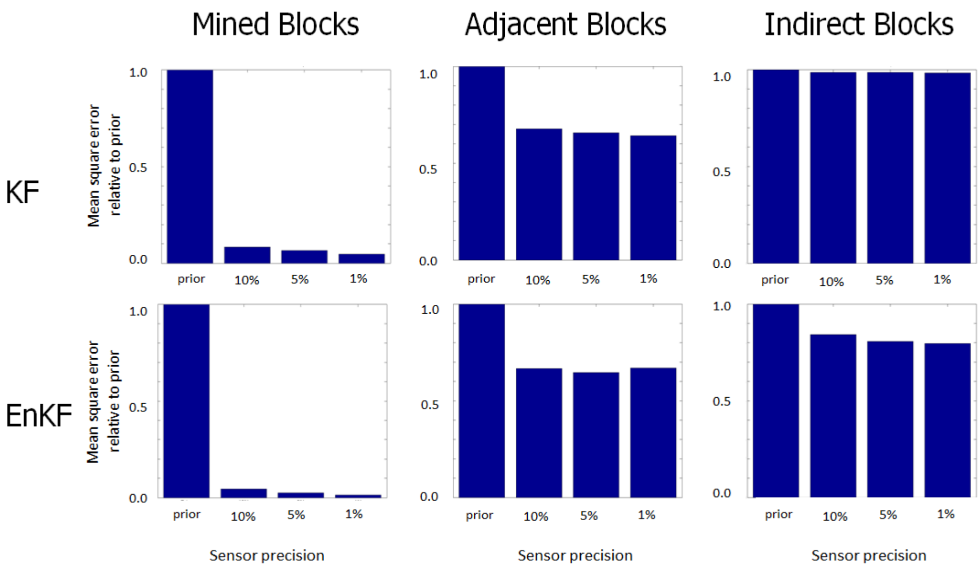


Figure 22: Evaluation of the results for resource model updating using the Kalman-Filter (KF) and the Ensemble Kalman-Filter (EnKF).

Figure 22 demonstrates 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, the following observations can be made:

- For mined blocks, the uncertainty almost vanishes. This is expected because blocks are mined. Residual uncertainties remain due to the sensor precision and the ability to track back the differences to its origin.
- 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 spatial correlation between two adjacent blocks.
- Blocks in the second next row are still updated. Due to the larger distance and the corresponding smaller spatial correlation, the effect is less obvious compared to directly adjacent blocks, however, still significant.

With this methodology an updating framework is presented that allows for a sequential integration of production data to continuously improve the resource model. In the next research stage of RTRO-Coal, the validated concept is applied to a full scale 3D resource model and implemented in a direct mining environment.

Task 2.3: Field test and proof of practicality and added value in a large scale industrial application in a continuous mining operation.

Note, a detailed description of cases and problem specification is provided under Task 3.1.

Task 2.3 provides a field test performed at the Garzweiler mine, RWE. The description of the case specific details is provided under WP3, Task 3.1.

The algorithm requires two sets of data for each run:

- The first data set contains a collection of the resource model realizations. A collection of predicted measurements is obtained by applying the observation model (mining sequence) to each block model realization.
- The second data set consists of a collection of actual sensor measurements which are characteristics for the blocks in a specific neighbourhood. The following will illustrate the creation of those data sets.

The geological model of the 6C Frimmersdorf seam was created in a 32x32x1 meter block model (Figure 23). The roof and the floor of the seam are provided from RWE and referred to as the LAVA model.

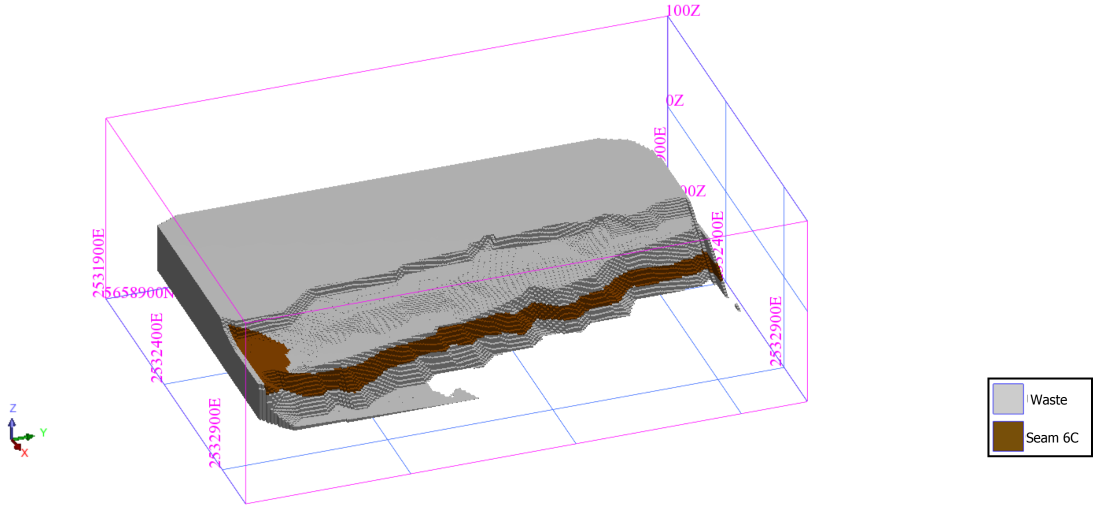


Figure 23: RWE Geological model.

The coal quality model for case RWE has the same dimensions and captures the spatial distribution of the wet ash content in percentages. Twenty-five simulated and one estimation models are created with geostatistical methods, based on the provided drill hole data. The simulated and estimated ash values are integrated into previously defined 6C Frimmersdorf seam geometry. Figure 24 illustrates the 25th simulated realisation as an example.

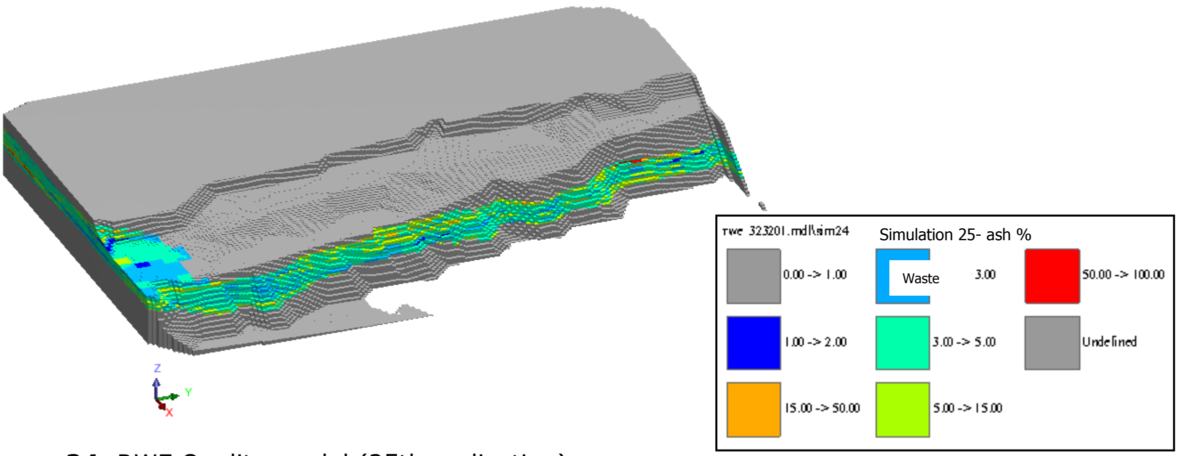


Figure 24: RWE Quality model (25th realization).

Predicted measurements are obtained by averaging the simulated ash values from each simulation set, which falls into the defined production block boundaries. The online RGI sensor measurement data and KOLA data are provided for the time corresponding to extraction. In order to determine the location of the received RGI and KOLA data, in other words to track back where the measured material comes from, the GPS data is matched with the measurement data based on the given timecodes.

A study bench, which produced for 15 days, is defined by considering all the available data (derived from topography, RGI, GPS and production data). Later, the study bench is divided into so-called "production blocks". This was necessary to reproduce the excavated production blocks. The horizontal divisions (or production slices) are based on the movements of the excavator during production, recorded by GPS data. The vertical divisions are based on the changes in the Z coordinates in the GPS data. In the end, the defined production bench is divided into 28 blocks and 5 slices, which gives 140 production blocks. Once the study bench is divided both in vertical and horizontal, the production blocks are now ready to be updated.

The defined study bench is divided into blocks and their respective related block ID numbers are given in Figure 25. As a start the 2nd slice of block number 1 is chosen to be updated, based on the KOLA measurements taken from that block. The series of updating experiments will continue until the 10th block. The update range is defined based on the variogram of the data as 450m in X and

Y direction and 2.5m in Z direction. The range of expected improvements is marked as the circled area.

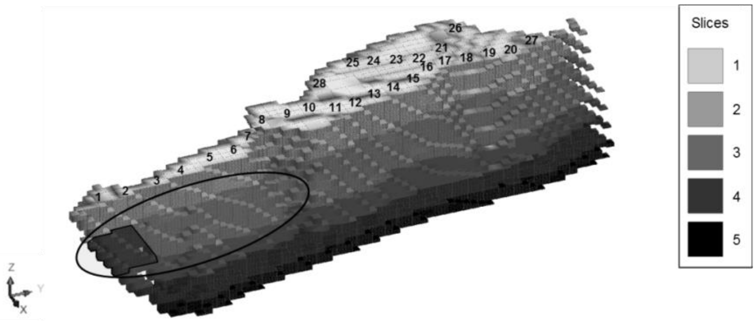


Figure 25: Production blocks.

Following the results of the previously defined experiment are presented. The added value of this application will also be discussed.

The first experiment uses the KOLA measurement, received from the 1st block's production, in order to update the neighbourhood blocks of the 1st block. Figure 26 illustrates the first experiment, where prior, posterior and measurement values are given. The averaged ash values from the prior simulation are represented with triangles and the related KOLA measurement values are given square marks. The light grey cloud of updated simulations covers the model uncertainty, while the long dashed line represents the average of the simulations. The vertical red line indicates which block's KOLA data has been used for that experiment.

Figures 27 and 29 presents results of similar experiments, except the base of the update is moving forward from 1st block till the 9th block, as if the production moves. In each graph, the mined out area is indicated with an arrow. Among results of 7 experiments, only four of them (1st, 2nd, 4th and 7th) are presented here since they adequately represent the rest.

It can be seen from the Figure 26 that the average of the prior simulations dramatically underestimates the actual KOLA measurements. This happens because the prior simulations are created based on the coal samples in the drill holes, while the KOLA measurements measure higher ash values due to the sand intrusions in the coal seam. Integrating the KOLA measurement of the 1st block updates the first nine blocks to some higher values. As expected, the update effect decreases while moving away from Block 1.

Already from the second experiment (updating the ash values based on the measurement of the Block 2), the KOLA data is well covered by the range of uncertainty in the updated neighbourhood. While the integrated measurement number increases (experiment 2, 3, …, 7) it is observed that the uncertainty in the near neighbourhood gets slightly smaller and more of the actual KOLA measurements are captured by this uncertainty range.

The improvements from the very initial averaged prior simulation to the most recent updated simulations are clearly observable

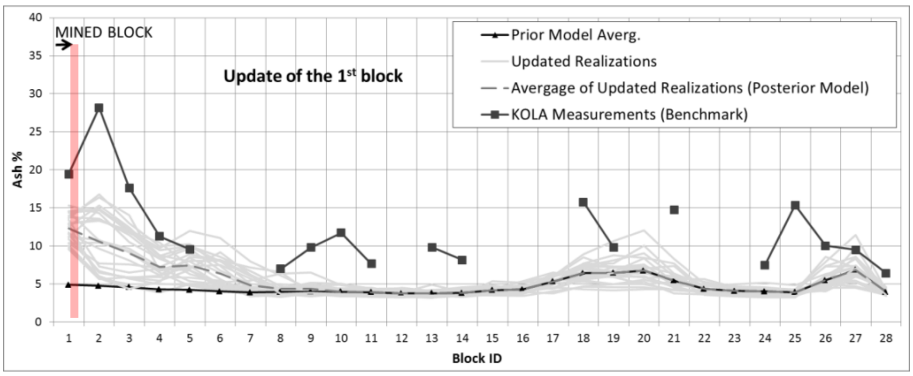


Figure 26: Experiment 1 - Updating: 2nd slice of the 1st block.

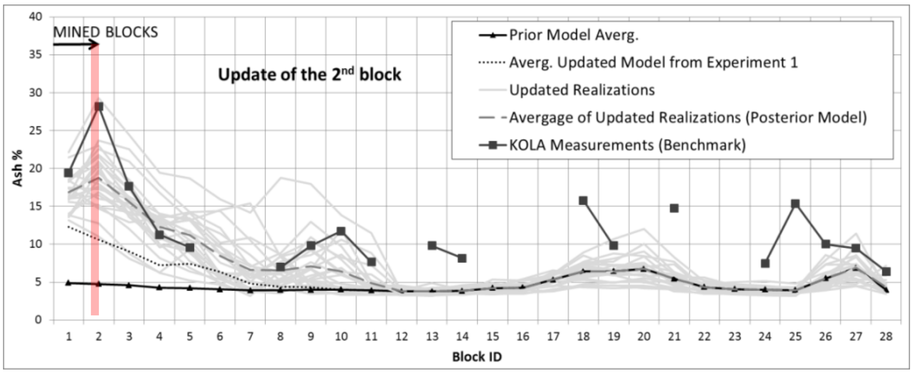


Figure 27: Experiment 2 - Updating: 2nd slice of the 2nd block.

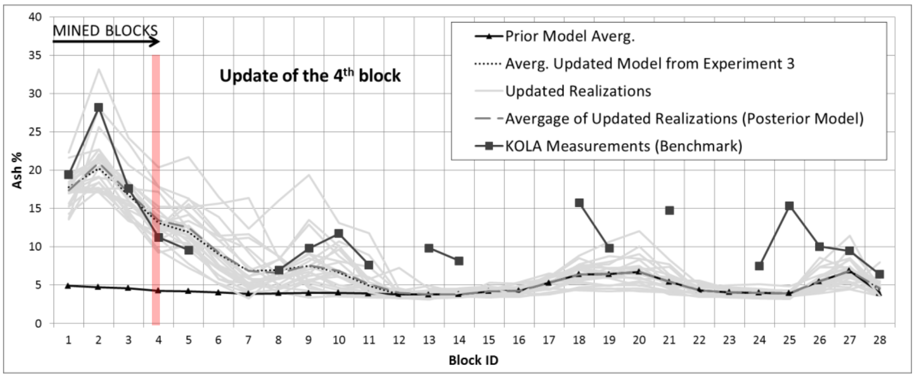


Figure 28: Experiment 4 - Updating: 2nd slice of the 4th block.

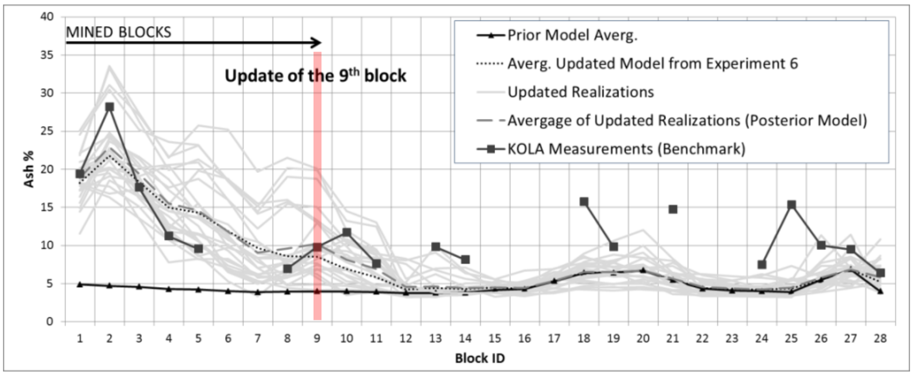


Figure 29: Experiment 7 - Updating: 2nd slice of the 9th block.

The presented experiment demonstrated a resource model updating case study in a large open pit mining operation using the actual measurements, the so called KOLA data. The results have shown that the developed updating algorithm works well in a real-3D case.

Figure 30 gives the calculated Mean Square Error (MSE) values for each performed experiment. Since this is a real case, the real block values are unknown. For this reason, the MSE compares the difference between estimated block value $Z^*(\mathbf{x})$ and measured KOLA value $(\mathbf{v})$. Once more, they are calculated relative to the prior averaged simulation. Figure 30 clearly indicates the improvements. The biggest improvement is observed on the first experiment, where the MSE value drops to 0.33 from 0.64. For the next experiments, the update is slightly smaller, yet observable. MSE values drop from 0.33 to 0.27 during the experiments between 2 and 7. This indicates in the order of 70% improvement while integrating online measurement data into the resource model.

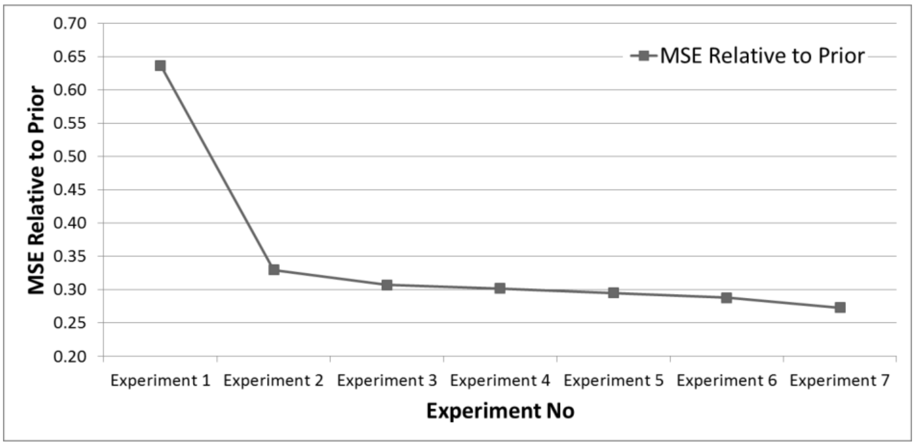


Figure 30: MSE Graph for performed experiments.

Task 2.4: Setting up the learning algorithm for real-time application and develop interfaces to the Work Package 1 (continuous mine process simulation) and Work Package 3 (planning model update).

To define the necessary interfaces, Figure 31 shows schematically the resource model updating framework. The concept required as first input a prior resource model realised by a set of geostatistically simulated deposit models. The second input consists of a collection of the predicted sensor measurements that are obtained by applying the production sequence to the prior resource model. The third data set consists of the actual online-sensor measurement values, which are collected during lignite production. Once all of the input data are provided into the real-time updating framework, the updated posterior resource model will be obtained.

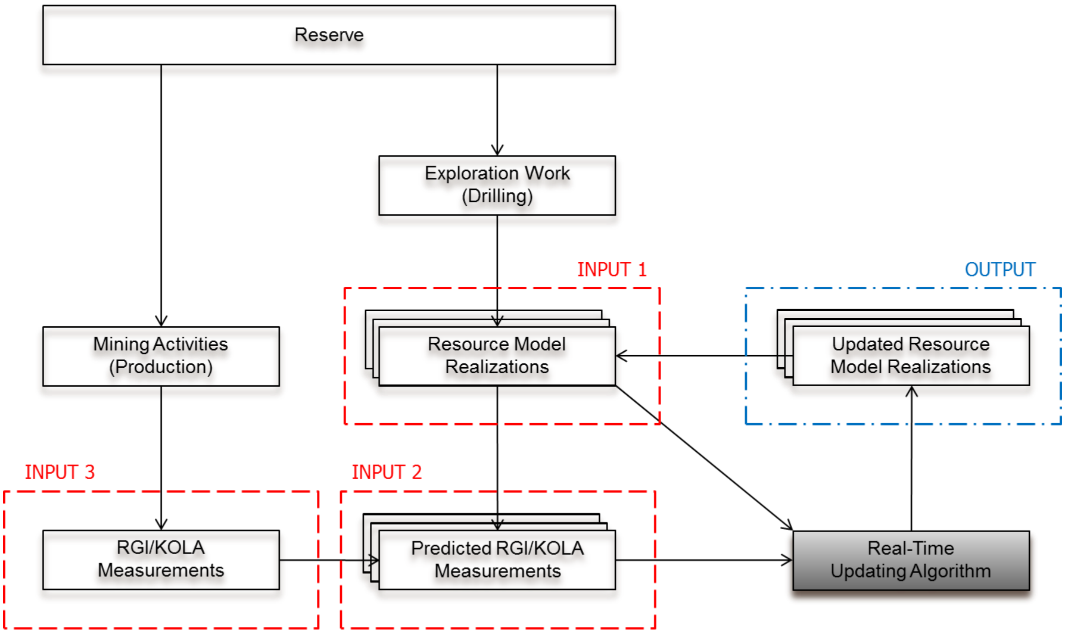


Figure 31: Overview of the real time resource model updating concept.

Interface 1 - Prior resource model:

The first data set required to apply the resource model updating framework is a collection of the resource model realizations, also called the prior model. In order to apply the introduced Ensemble Kalman-Filter Solution, a set of geostatistically simulated resource models is necessary. However, this requires some expert knowledge. Due to missing expertise skills, these models may in general not be available in an operational context. For these reasons, in order to apply the updating framework in practical and operational mining environment, a more robust and simplified application has been developed. The proposed simplification obtains the required prior model realizations by adding fluctuations around the company's short-term mining model. This short-term model is created by the mining engineers, based on applying the defined block geometries (Figure 32) on the company's estimated block model. In this way, each block will have an estimated ash value. Figure 33 compares both of the prior model generation processes.

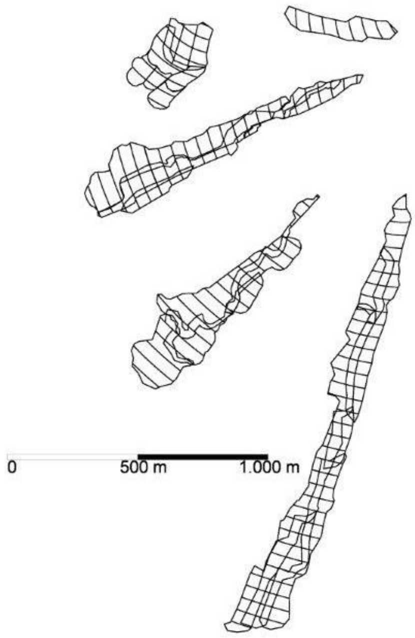


Figure 32: Planned block geometries in the production benches.

In order to create the required realisations in the prior model based on short-term model, the following strategy is employed:

- Short-term block model values are generally available in operations for each block and they deliver the prior estimation of block attributes (E-type estimate).
- A conditional simulation is applied to production block geometry. For this application, the previously calculated block scaled variogram model is used. Drill hole locations with "zero ash content" are used as the reference point while running the simulations around a zero mean. This can be done as an add-on, implemented in a "black-box", so the end-user is not affected.
- After this, simulated data on the production blocks refer to the uncertainty and they will be added on prior estimations of block attributes.
- The short-term model based on the simulations is now ready to be imported into the algorithm as the first main component (prior model).
- The updated resource model (posterior model) will be split in a mean part, which will be written back to update the short-term block model. The uncertainty related part will be written back in the ensemble part.

The process can easily be automated by using a previously calculated variogram model and some interfaces. In this way, there will be no requirement for an additional complex process of creating conditional simulations since they are not part of the daily work flow. Figure 33 compares the theoretical correct way (Based on Drill-hole Data) and the simplified application (Based on Short-Term Plan).

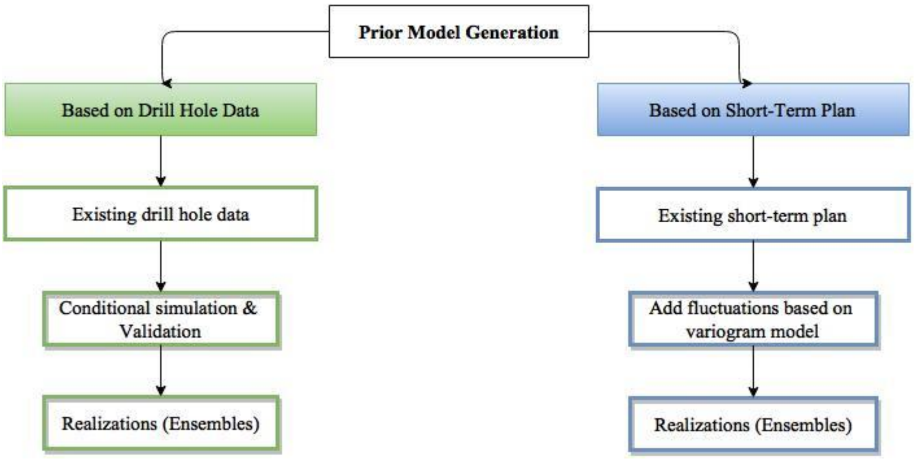


Figure 33: Flow chart of prior model generation.

The resulting interface for Input in WP1 and the updating framework a table containing the columns Block ID, block coordinates (X,Y,Z), block size (X,Y,Z), prior ash content estimation, prior simulations. This can be implemented as an Excel-Sheet.

BLOCK ID	X	Y	Z	size(X)	size(Y)	size(Z)	Estimation	Sim1	Sim2	Sim3	....	Sim24	Sim25

Interface 2 and 3: Predicted and actual measurement values:

In order to automate the updating process, the derivation of predicted measurements, production data have to be linked to the prior resource models. This can be achieved by creating a material tracking system, where the GPS-location of each excavator is linked with the material tracking systems and the actual sensor measurements and the laboratory analysis.

The interface is given in Figure 34 with the headings of the table. These data are the time stamp, RGI data (mass & ash content), laboratory analysis (mass & ash content), excavator production information (X,Y,Z coordinates of the excavator and the produced coal volume). These data can be extracted from operational systems and will be provided by MIBRAG as an online file.

TIME STAMP	RGI Data		Lab Analysis		Exc 309				Exc 351				Exc 1511				Exc 1541				Exc 1553				Exc 1580			
	mass	ash	mass	ash	X	Y	Z	Volumen K	X	Y	Z	Volumen K	X	Y	Z	Volumen K	X	Y	Z	Volumen K	X	Y	Z	Volumen K	X	Y	Z	Volumen K

Figure 34: Interface 2 and 3 - Predicted and actual measurement values.

With both input tables, the updating algorithm can be performed and set up in the actual operational environment. The system has been set up in the Profen mine of MIBRAG mbH and will be further evaluated in WP6.

More details can be found in RTRO-Coal Deliverable 2.4.

Work Package 3: Planning Model Update

Task 3.1: Definition of basic requirements for an updateable short term planning model.

Case MIBRAG

The main goal in the MIBRAG case Profen mine is to improve the accuracy of the resource model utilizing the online sensor data. The focus is primarily on the ash content of multiple seams, which is analysed online (Figure 35) on a central belt conveyor leading to the coal stock- and blending yard (conveyor 62). Additional data to be integrated are laboratory analysis data from coal- trains delivered to the costumers. These will be available with a delay of approximately 3 days. Using the exploration database of MIBRAG, a prior model of the target area was generated using estimation and spatial simulation methods. The prior model and sensor measurements form the input for the developed algorithm, which sequentially updates the resource model, called posterior model, leading to a sequentially update-able planning model using the most recent data.

For the test case, the target area is defined by MIBRAG as an already mined out area of 24.7km^2 (easting 4.509.620-4.514.300m, northing 5.661.453-5.666.700m) in 2014 (Figure 36).

Figure 35: Radiometric sensor measurement from Profen mine.

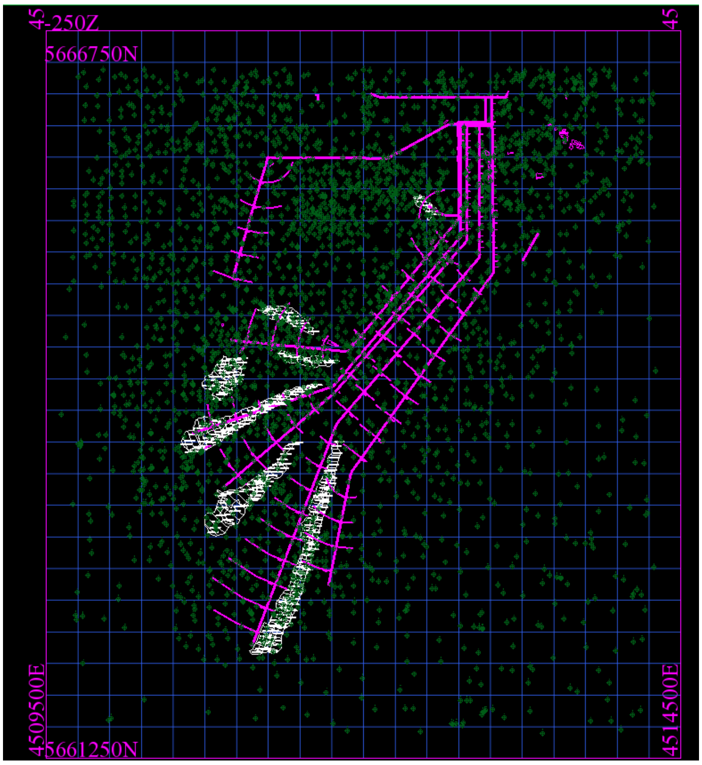


Figure 36: Benches, belt system and 3116 drill holes on the study area of Case MIBRAG.

Data required for the validation of the algorithm were defined and include:

- Drill core data with attributes coal quality (ash content) and material type.
- Available geological model, both geology and quality for the test area.
- Short-term block model (block ID, bench, cut & block, coordinates, block dimensions).
- Production data of excavators. For each excavator the extraction sequence needs to be reproduced.
- Operation data, including belt scales, material tracking, breakdown and scheduled maintenance.
- Measurement data (online measurement data, laboratory data for coal qualities of coal-trains delivered, an investigation on precision) .

Based on a detailed catalogue of requirements, documented in Deliverable 3.1, MIBRAG provided the corresponding data base for the defined test timeframe in year 2014.

Case RWE

The Frimmersdorf seam in the Garzweiler open cast mine is containing marine and fluvial sand intrusions (Figure 37), which are significantly affecting the resource estimation and the operational processes. The current model based on a deterministic approach relies on exploration data and fails to properly predict these sand partings within the lignite seams on a local basis. Consequences are unexpected dilutions or waste as well as deficiencies in the power plant due to slagging. The aim of the RWE case is to improve the accuracy of the resource prediction, in particular by taking sand intrusions into account, utilizing online sensor data (Figure 38). The major contribution will be in the integration of KOLA based online measurement data of ash content produced with the available block model for improving the prediction of coal quality in the Frimmersdorf seam.

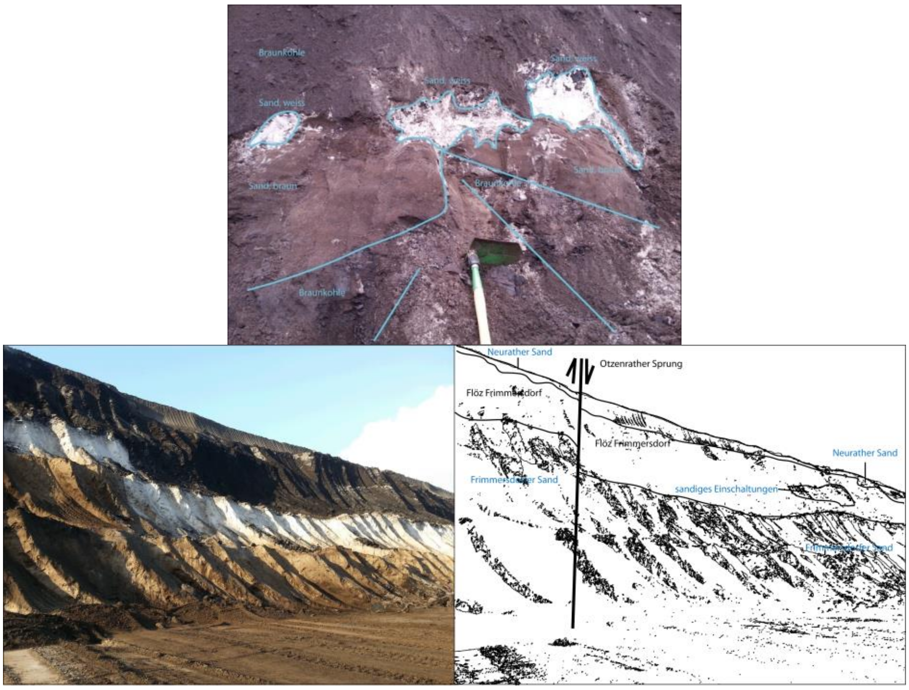


Figure 37: The 'trappy' sand of seam Frimmersdorf.

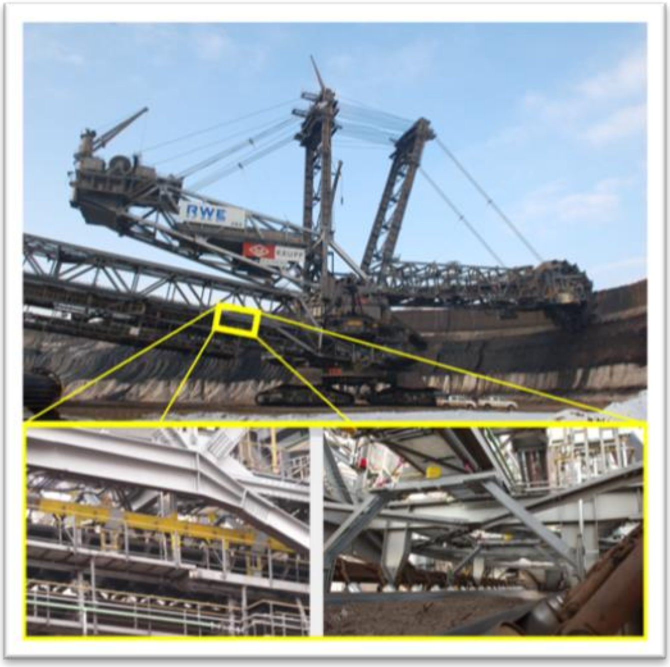


Figure 38: Radiometric sensor measurement from excavator 285.

For the test case a target area has been defined by RWE, which is located in already mined out area of about 1.5km^2 (easting 32000-33000, northing 59000-60500). This allows the validation of the approach using historical data. In this area the 6C Frimmersdorf lignite seam is present. An initial investigation of the applicability of geostatistical methods has been performed for a 4km^2 area, which includes the defined 1.5km^2 area of this case, by van Beuningen [21].

The main difference between the case MIBRAG and RWE is the ability to identify unambiguously the source of differences between model based prediction and sensor measurement. In the MIBRAG case there are five different benches and three different seams contributing to a combined material stream, which is measured by one sensor. The RWE case focuses on one bench and one seam having fluvial sand intrusions. The MIBRAG case focuses on increasing the accuracy of the coal quality prediction, the RWE case focuses on better defining fluvial sand intrusions in the Frimmersdorf coal seam.

Similar to the MIBRAG case, a detailed catalogue of requirements has been specified and documented in RTRO-Coal Deliverable 3.1. RWE provided all corresponding data for the defined test timeframe.

Task 3.2: Extension of the framework of advanced geostatistical methods to integrate data of different source and data quality (exploration, on-line sensor data, optical sensors, etc.) and data support to update the block-based prediction of geological attributes.

As discussed before, the framework for integrating sensor data with prior resource models is combined with Task 2.1 and has already been discussed previously. The reader is referred to section in Task 2.1. Here the second part of the task, namely the updating of geostatistical model parameter, is discussed.

With the availability of online data, new information about the spatial structural behaviour of critical coal attributes becomes available. The initial description of the structural behaviour in the geostatistical model by the means of a variogram or spatial covariance function is usually based solely on exploration data. The new, highly dense sensor data will provide improved insight into the spatial structure, especially at short-scale distances, and allow to improve the inferred geostatistical model parameters und thus the representatively of the model.

A new method for an improved inference of model parameters has been introduced. It utilizes empirical and theoretical differences between two methods of prediction. The differences are then used to infer model parameters based on a back fitting algorithm [22]. The method extends approaches of cross validation in geostatistics in two aspects. Firstly, the model evaluation is not only limited to sample data locations but is performed on any prediction locations of the attribute in the domain. Secondly, it extends the measure used in cross validation, based on single point replacement by using error curves (Figure 39). These allow defining rings of influence representing errors resulting from separate variogram lags. By analysing the different variogram lags, the fit of the complete covariance structure and its several model parameters can be assessed. Therefore, the influence of different data configurations is implicitly taken into account. This offers a potential to automate the task for a sequential improvement of geostatistical model parameters as new data become available.

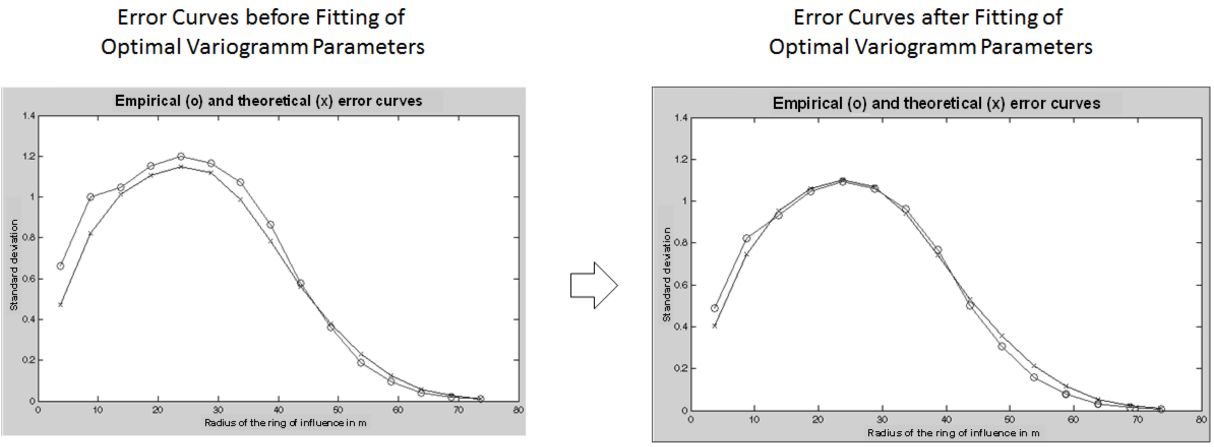


Figure 39: Example of empirical and theoretical error curves before and after fitting optimal variogram parameters.

Figure 40 summarizes the new proposed algorithm for fitting geostatistical model parameters based on Dual Kriging in the presence of a trend.

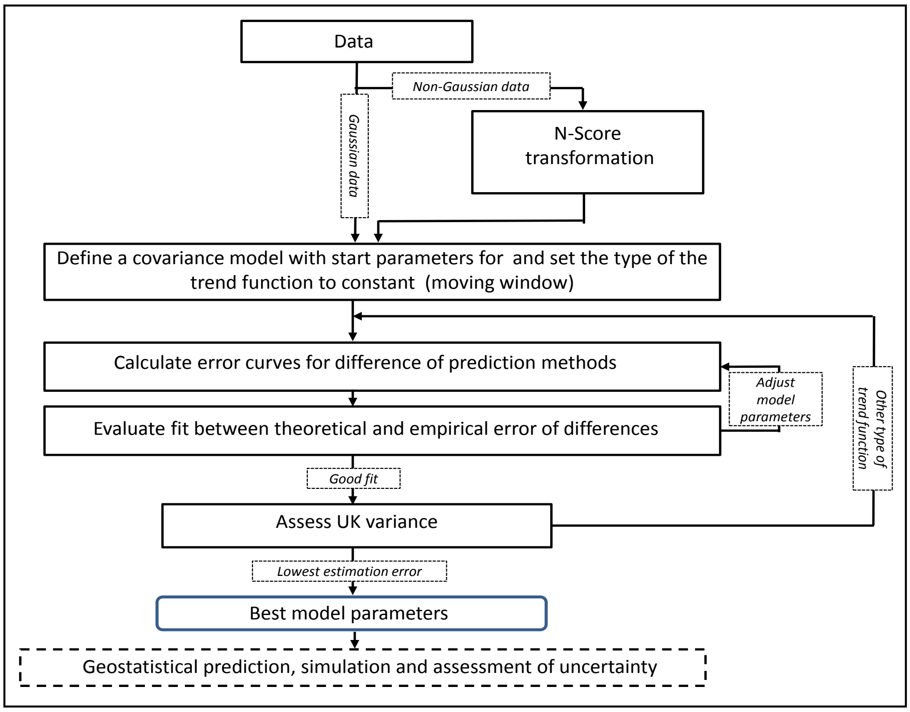


Figure 40: Flow chart of the algorithm for fitting geostatistical model parameters based on Dual Kriging in the presence of a trend.

The algorithm can be defined in 7 steps:

1. Prepare the data set for geostatistical analysis. If data are non-Gaussian, perform an N-score transformation. This step is necessary, since the method assumes a normal distribution of errors of the differences between two methods in prediction.
2. Define an initial covariance model including model parameters σ^2, c and a. This can be achieved for example by calculating the experimental covariance function. Set the type of the trend function model initially to constant (moving window).
3. Calculate the empirical and theoretical error curves of differences between two methods in prediction based on Dual Kriging (equations given in Deliverable 3.2b)
4. Evaluate the fit of the error curves. If curves do not fit, adjust the model parameters σ^2, c and a and go back to step 3. If curves show a nice fit, fix model parameters for the considered type of trend function and go to step 5.
5. Calculate the UK Variance (equations given in Deliverable 3.2b) for the chosen model parameters and the trend function. Choose another trend function to evaluated and go back to step 3 with the next type of the trend function and use initial covariance model parameters. (Optional: to evaluate the performance of a different type of covariance function, go back to step 2).
6. After all types of trend functions (and optionally covariance functions) are considered, choose the one with the lowest UK variance and the corresponding trend and covariance model parameters.
7. Apply the identified trend function and the model parameters for the covariance function to the subsequent geostatistical prediction or simulation.

Note that the algorithm does not call for an initial trend reduction of the data values $\mathbf{z}(\mathbf{x})$. The fitting procedure of the empirical and theoretical error curves of the differences between two methods in prediction separates the influences of the trend and the signal.
Therefore, the resulting model parameters represent the deterministic and stochastic model components capturing the properties of the considered attribute as found in the data. Based on these model components, a realistic and practically relevant assessment of uncertainty in predicting environmental impact is possible using conditional simulation in geostatistics, independent of the distribution of the data.

A detailed description of the algorithm is provided in RTRO-Coal Deliverable 3.2b.

Task 3.3: Implementation and validation of the new geostatistical method in a fully known and completely controllable environment.

The description in Task 2.2 provides already a validation study in a fully known environment. An additional validation study was performed to benchmark the developed real-time updating framework against a proven method. Due to it's simplicity, the Rejection Sampling method was chosen for validation purposes. Rejection Sampling is a Monte Carlo method that proposes a sample from some relatively simple distribution, which is subsequently then tested to decide whether or not to accept it. It is based on the fact that the posterior distribution is generally a subset of the prior distribution, and therefore it can be evaluated by sub-sampling the prior [23].

To generate samples (realizations) from the un-normalized target probability density *f(m)*, let *h(m)* be a probability density that can be easily sampled. Suppose that there is some constant c such as *f(m) ≤ c · h(m)* for all *m*.

To obtain random samples from *f(m)* :

1. Generate a candidate sample *m** from pdf *h(m)*,
2. Generate a decision variable *u* from U(0, c· *h(m*))* ,
3. If *u ≤ f(m*)* then return *m=m**.
4. Return step 1.

The conditional probability density *f(m)* is provided by Bayes rule,

$$f_{(M|D)(m|d_{obs})} = f_{(D|M)(d_{obs}|m)} f_M(m) \Big/ \int f_{(D|M)(d_{obs}|m)} f_M(m)\, dm$$

$$\propto \exp\left(-\frac{1}{2}(\boldsymbol{AZ_0}(x) - \boldsymbol{l})^T \boldsymbol{C}_{ll}^{-1}(\boldsymbol{AZ_0}(x) - \boldsymbol{l})\right) x \exp\left(-\frac{1}{2}(\boldsymbol{Z_0}(x) - \boldsymbol{\mu})^T \boldsymbol{C}_{zz}^{-1}(\boldsymbol{Z_0}(x) - \boldsymbol{\mu})\right)$$

where $\boldsymbol{AZ}_0(\boldsymbol{x})$ is the predicted observation and $\boldsymbol{Z}_0(\boldsymbol{x})$ is the prior model and $\boldsymbol{\mu}$ is the mean vector of the prior model. $\boldsymbol{C}_{ll}$ and $\boldsymbol{C}_{zz}$ are the measurement error covariance and the prior model covariance respectively.

To implement this method, 1000 realizations have been created using the Sequential Gaussian Simulation method, the prior models. The developed updating framework was applied to the prior models in order to generate 1000 updated realizations. As the rejection sampling proposes that the posterior is a subset of the prior distribution, it is expected to obtain the updated posterior distributions by applying rejection sampling to the prior models.

Rejection sampling is applied to both, 1000 prior models and 1000 updated posterior models. Around 290 of 1000 prior models and around 950 of 1000 posterior models were accepted. This shows the significant improvement of the prior models when they become posterior models after updating.

The 290 accepted posterior models and 1000 updated posterior models are compared to each other in order to capture the similarities Figure 41. With this aim, the average mean and variance of the distributions are compared.

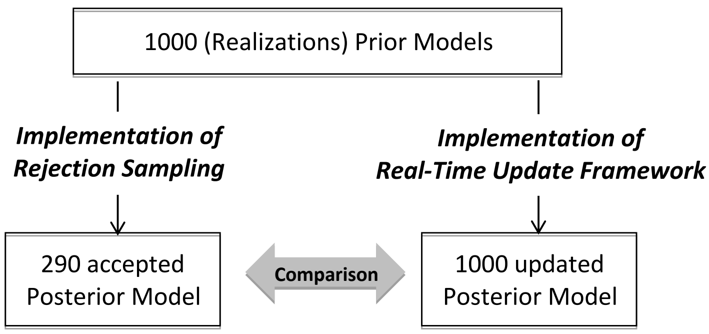


Figure 41: Validation experiment scheme.

Figure 42 and 43 show the average mean and variance of the prior and posterior models respectively. It can be seen that the average mean and variance of accepted prior models (290) and updated prior models (1000) are very similar to each other. Figure 44 is provided in order to capture the deviations between the accepted posterior realizations from rejection sampling (290) and updated posterior realizations from real-time update framework (1000).

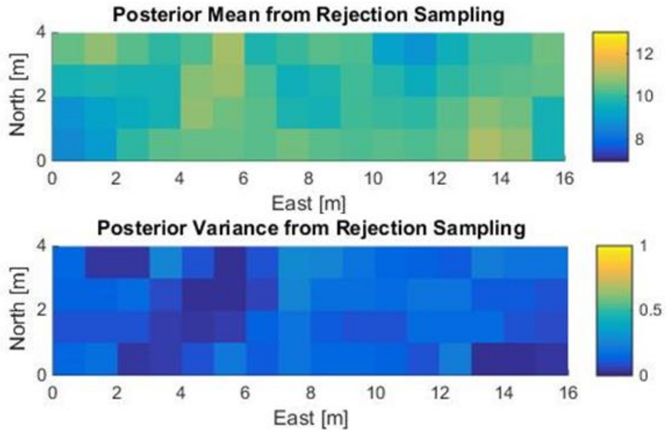


Figure 42: Average mean and variance maps of 290 posterior realizations accepted according to rejection sampling method.

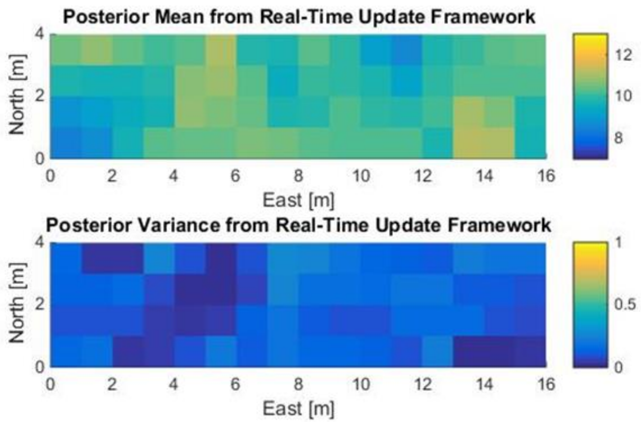


Figure 43: Average mean & variance maps of 1000 posterior realizations updated with EnKF framework.

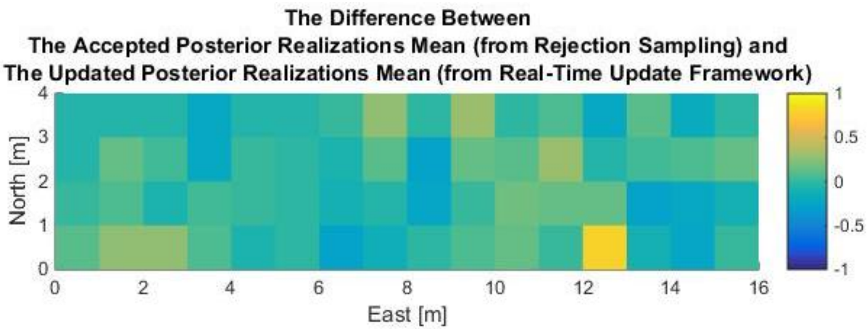


Figure 44: Difference map between the accepted posterior realizations from rejection sampling and updated posterior realizations from real-time update framework.

Based on the presented validation results in this section, it can be concluded that the developed real-time updating framework performs similarly to proven technique of rejection sampling and thus can be used for application.

Task 3.4: Field testing and proof of industrial applicability in a large open pit mining operation.

The focus of Task 3.4 is the MIBRAG case as preparation for Task 6.1 (Integration). Compared to the RWE case presented under Task 2.3, the MIBRAG case is more general and challenging. Whereas at RWE there was one sensor per bench, in the MIBRAG case like in many other mining operations, material quality control measurements are taken at central locations in the downstream process, such as, on a central conveyor belt or from the trains that are loaded after the coal blending yard. In this case the measurements represent a blend or a combination of material originating from multiple extraction faces. The measurement of one sample cannot be tracked back to one origin of the material. However, a collection of multiple measurements over time would allow to solve this unambiguity.

Given the input, as explained under Task 2.4, the updating framework has been applied to the MIBRAG case. The time production areas in the benches during the test time frame are illustrated in Figure 45, coloured based on the production month.

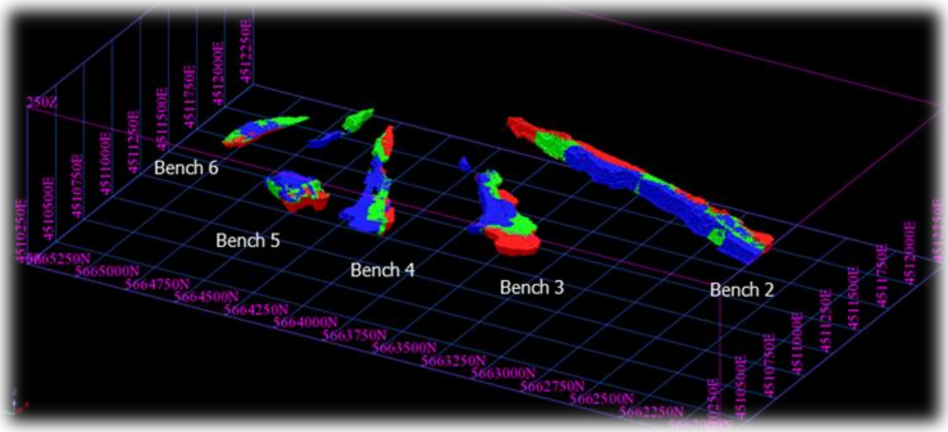


Figure 45: MIBRAG Production benches.

Production in a period between the 1st and 15th of August 2014 was chosen for the demonstration case in order to have a historical benchmark and being able to compare predicted to actual production for different setting. The available data (production data, topography, Block ID's and block locations from production blocks, MIBRAG's short-term plan and RGI measurements) are linked to each other, based on the given time stamps.

The updating experiments are performed for both, drill hole based prior block model realizations and MIBRAG's short-term plan based prior model realizations. This is done in order to compare the updating performance of the updating framework while updating differently generated prior models.

The following graphs provide representative information where the X-axis refers to the time intervals of two hours, $i=1,\dots,n$. The graphs contain the following information:

1. Posterior model box plots: box plot representation of posterior model simulations which are updated
2. Posterior mean: represents the mean of the updated models in the learning period.
3. Prior mean: mean of the prior model that is created based on either the drill hole data or short-term model.
4. RGI sensor data: the averaged RGI data (online ash content) for a given time span.
5. White area: Represents the learning period, where posterior models are produced as a result of updating the prior model, by using the RGI data.
6. Green area: Represents the prediction period, where the mining operations are executed on the four-day-long-updated model.

In these graphs, the prior model is updated for four days. Based on this updated prior model, the posterior model, further mining operations are performed for the next two days. The operation file mines through the posterior model and highlights the area as green. Figure 46 shows the application case using a fully geostatistically simulated prior model and Figure 47 for the short term model.

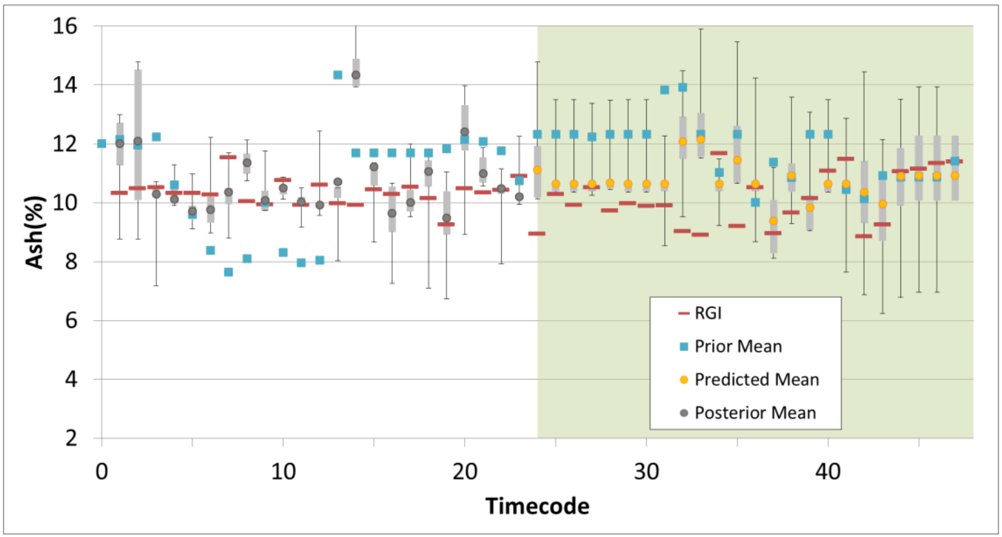


Figure 46: results based on conditional simulation: The green area represents the prediction period. The white area represents the learning period.

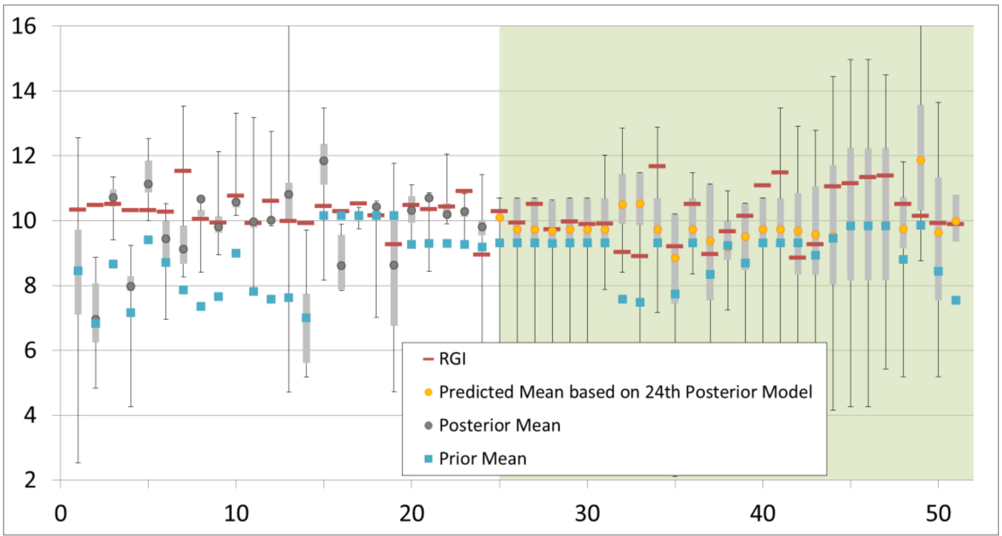


Figure 47: Results based on short-term model: The green area represents the prediction period. The white area represents the learning period.

The relative improvements in prediction are in the order of 10% to 35% for both experiments. The range of improvements is about 2 to 3 days of excavator progress. This is due to the spatial correlation of the coal quality parameter. Blocks, which are mined in 4 to 5 days, will not be affected by the updating. However, it is expected that there is a further improvement in medium term, as blocks are also updated in the mining direction, not only in the digging direction of the excavator, meaning that after shifting the belt conveyor and accessing the next mining path, additional effects in updating are expected.

Comparing both prior models, it is first to mention that they show on this local scale significant differences. This is mainly due to the level of information used to build these models. The simulated model is based on drill-hole information and simulated on a dense grid. The prior model based on the short-term plan are based on block estimated, which have been estimated including next to drill hole data operational data, e.g. from face mapping or face samples. In front of this background it is quite remarkable that the updating for both models performs extremely well. This demonstrates the self-learning ability of the ability and the fact that the choice and quality of the prior model is of lesser significant. The model picks up the true structure after few iterations of updating.

Work Package 4: Long-term Planning Optimization

Task 4.1: Application of recently developed simulation framework in a large coal deposit in Poland and validation of results in a completely known mining environment.

Application of the Generalized Sequential Simulation (GSGS) to a Lignite Field

GSGS was applied to a lignite mining field in Eastern Europe to simulate both, geological structure and major coal quality attributes. A general section of the deposit is shown in Figure 48. There are in total 5 seams, whereas only one seam meets minimum mining requirements, seam II. Seam II is split in an upper bench (Seam II-1) and a lower bench (Seam II-2).

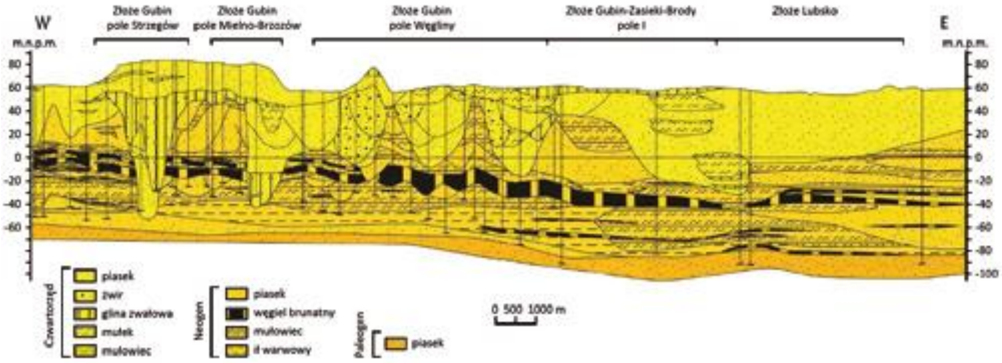


Figure 48: General cross-section through the deposit.

Simulating coal seam geometry

Known applications of conditional simulation in coal deposits are mainly limited to modelling a 2D problem (e.g. [24}, [25]). An exception is Benndorf, who applies the simulation technique to a full lignite field [26]. In geologically complex settings, as in the present case, the impact of the varying geometry on mine planning parameter and coal recovery during operation is significant and requires a more sophisticated modelling approach. To account for the spatial variation of geometry and coal quality and its effect of predicting recoverable reserves, a 3D approach was chosen. This leads to a modelling sequence in two steps. First, the 3D geometry of the three different seams including its splits are simulated followed by the spatial distribution of the key quality parameter inside the seam-intervals.

Modelling a 3D geometry of a coal deposit, including multiple splits, is general a complicated task. A commonly used simplification is the Divide-and-Conquer approach, which divides complex tasks into more simple sub-tasks. Relating this approach to simulating seam-geometry, it is intuitive in a sedimentary environment to divide the 3D object into a set of correlated 2D surfaces. In combination the set of 2D surfaces represents the 3D object.

In the present application in general the roof- surface and the thickness are simulated. Both attributes obtain all necessary information to construct the geometry of the whole deposit. Figure 49 shows schematically the geometrical seam-interval model.

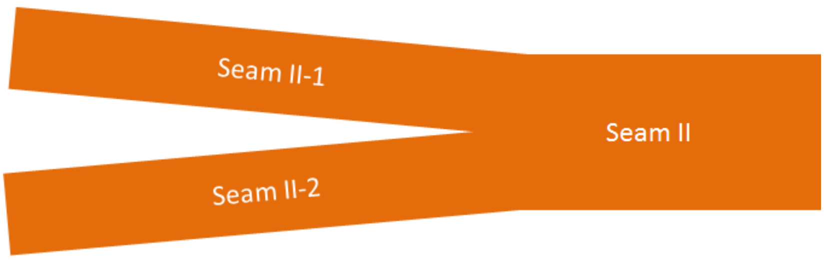


Figure 49: Schematic model of the seam geometry.

An independent simulation of different seams has to assure the plausibility of results. For example, the elevation of a roof-surface of lower strata cannot exceed the elevation of the floor-surface of upper strata at any location. To avoid this type of order relation problem the simulation was performed in the following sequence.

1) Simulation of Seam II-1 Roof
2) Simulation of Seam II-1 Thickness and calculation of Seam II-1Floor
3) Simulation of Seam II-2 Roof with the condition Seam II-2 Roof = min (Seam II-2 Roof; Seam II-1 Floor)
4) Simulation of Seam II-2 Thickness and calculation of Seam II-2 Floor

The exploration in the coal field took place in multiple stages, starting in 1960th to 1990th. In an area of approximately 12000 ha are in total 758 drill holes are available. Figure 50 illustrates the drill hole pattern as well as the intended mining boundary as a reference. The pattern appears regular with an average drill-hole spacing of 300m and shows areas of higher drill-density in the central part and areas with less dens drilling in the north-west. Table 8 lists the usable number of data from the drill-holes per attribute to simulate and some statistical metrics.

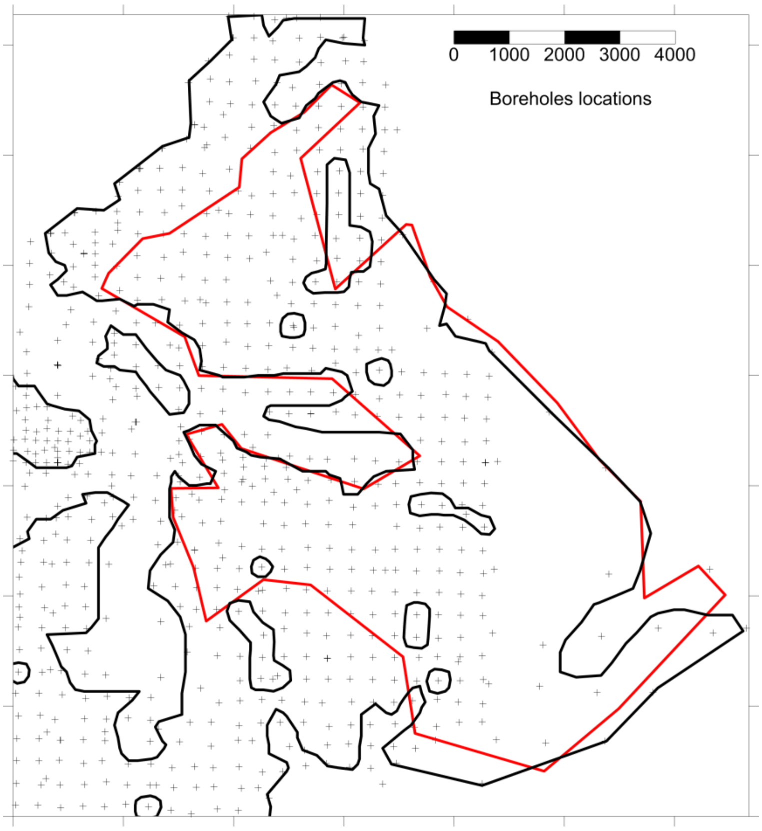


Figure 50: Data basis in the coal field.

Table 8: Data summary for simulating coal geometry.

Attribute	Number of data	Mean	Min	Max	Range	Standard deviation
Roof II-1	753	-9,3 m	-49,7 m	17,0 m	66,7 m	13,1 m
Thickness II-1	747	3,2 m	0,0 m	11,5 m	11,5m	1,7 m
Roof II-2	753	-15,6 m	-49,7 m	7,2 m	56,9 m	11,8 m
Thickness II-1	758	8,6 m	0,0 m	22,0 m	22,0 m	2,4 m

The area to simulate extends about 13,4 km in east-western direction and 13,6 km in north-south direction. The zone exhibits local structures independently from regional trends. Therefor the stationary assumption is appropriate. Furthermore, the spatial extension and the number of available data are judged to be sufficient to estimate a stable variogram for the attributes. It is expected that with a further increase of the study area the mean and the variogram will not change, justifying the ergodicity assumption.

The simulation process and validation results for quality assurance are detailed in Deliverable 4.1.

Figure 51 shows one main result, the E-Type estimate exemplary for the thickness of seam II-1. This is generated by averaging out all 25 realisations at each grid node. The result should show a clear structure as expected from drill holes. As can be seen, the model structure matches the structure recognized in the drill-hole data. As well data values at data locations are reproduced.

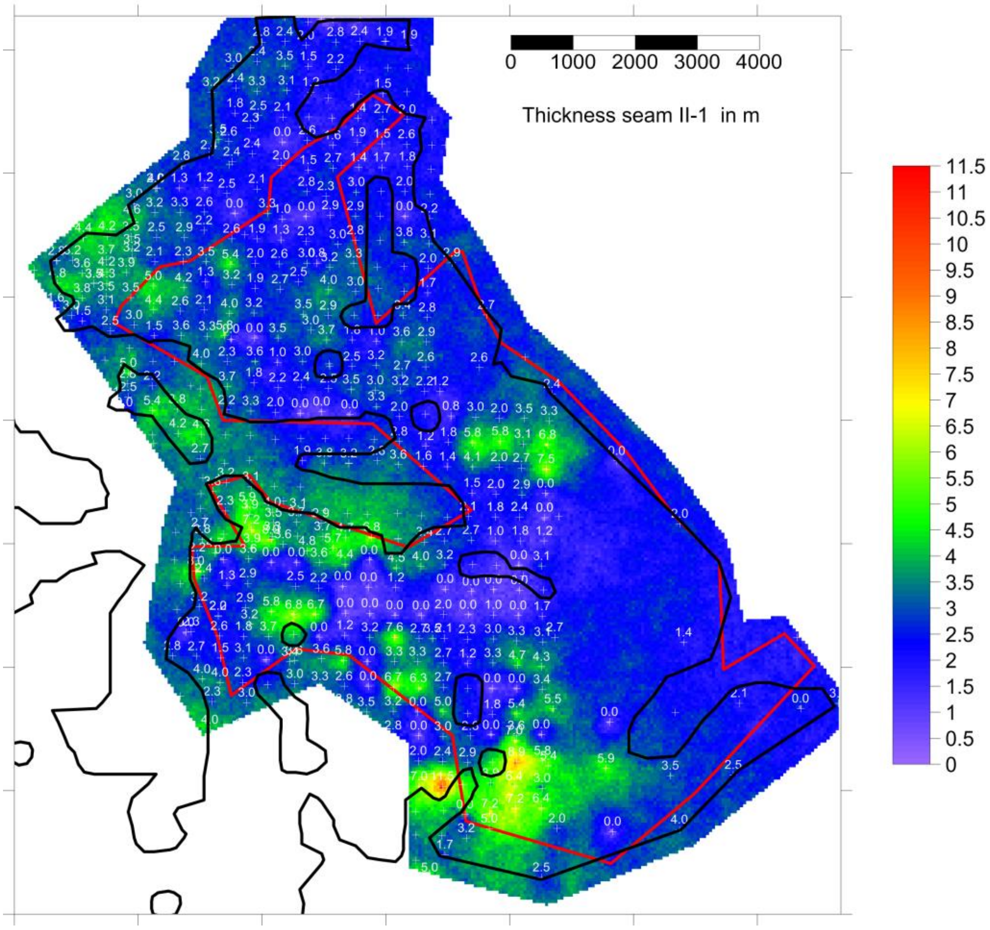


Figure 51: E-Type Model of Seam-II-1 Thickness.

Simulation of coal quality parameters

The simulation of coal quality parameters was performed similar to the seam geometry. For each seam, (II-1 and II-2) the spatial distribution of parameters Calorific Value (CV in kJ/kg), Ash content (Ash in %) and Sulphur content (S in %) is of interest. Table 9 summarizes the available data base as well as main statistical indicators.

Table 9: Data summary for simulating coal quality.

Attribute	Number of data	Mean	Min	Max	Range	Standard deviation
CV II-1	505	9209 kJ/kg	6055 kJ/kg	12312 kJ/kg	6257 kJ/kg	972 kJ/kg
CV II-2	552	9403 kJ/kg	5025 kJ/kg	11850 kJ/kg	6825 kJ/kg	860 kJ/kg
Ash II-1	494	17,3%	6,2%	41,4%	35,2%	7,8%
Ash II-2	542	15,2%	5,7%	45,0	39,3%	7,7%
S II-1	493	1,5%	0,3%	6,8%	6,5%	0,7%
S II-2	541	1,2%	0,1%	9,1%	9,0%	0,7%

Similar to the geology chapter, Figure 52 shows the E-Type estimate. As well, this is generated by averaging out all 25 realisations for each grid node. As can be seen, the model structure matches the structure recognized in the drill-hole data. As well data values at data locations are reproduced.

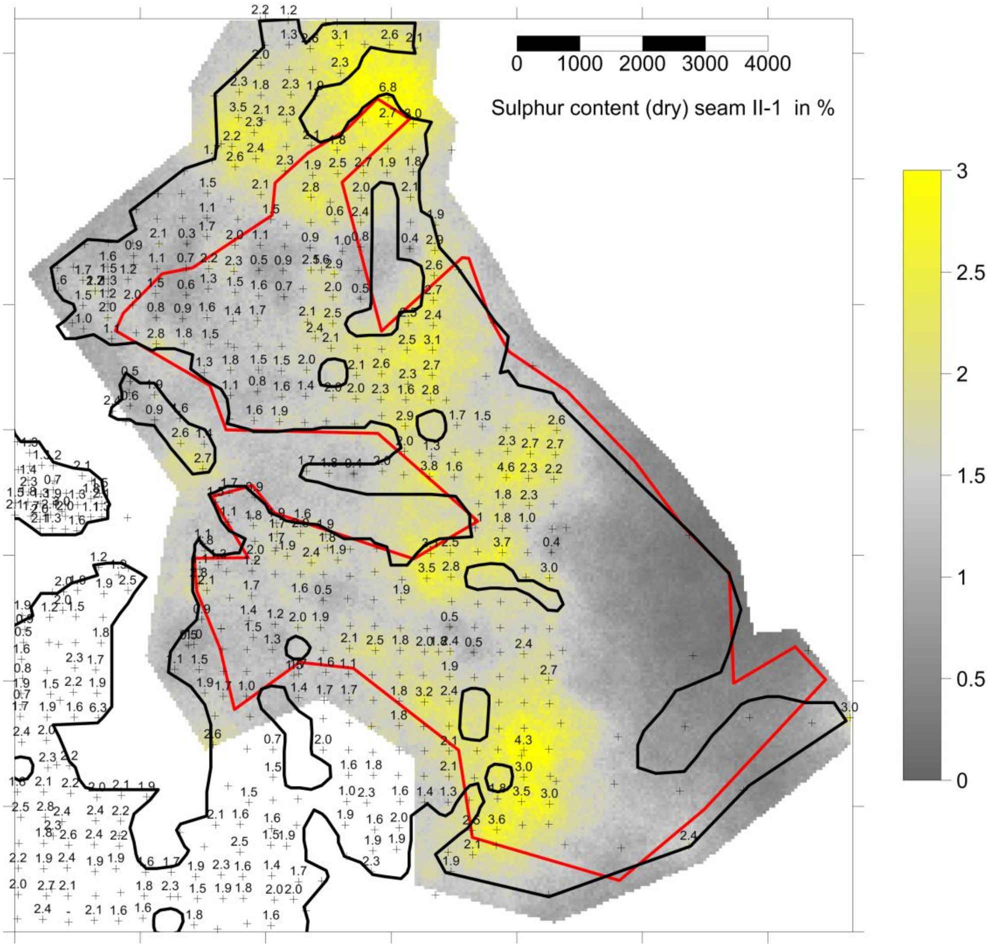


Figure 52: E-Type Model of Seam-II-1 Sulphur.

With 25 simulated models describing geology and spatial distributions of main coal quality parameters, the basis is given to perform an uncertainty based optimization in Task 4.2.

Task 4.2: Development of a new uncertainty based algorithm in long-term mine planning of large lignite deposits integrating the goals of meeting long-term production targets with a high probability and flexibility while maximizing the monetary value in terms of NPV.

Long-term mine planning and production scheduling aim to define the "best" mine plan subject to the constraints imposed by physical and geological conditions, policies and the operational mining approach. The term "best" is defined by management objectives. These typically include maximizing the monetary value of the mining project as well as meeting customer expectations and guarantying a safe operation. Customers' expectations are usually in terms of coal tonnage and coal quality characteristics delivered.

To guaranty high efficiencies in the downstream process, e.g. high power plant efficiencies, multiple coal quality parameters have to be delivered within pre-defined upper and lower limits. These coal quality parameters include the calorific value, ash content, sulphur content of the iron content in the ash. Defining a production sequence that meets these tight production targets is a complex "multi-dimensional" task. Multiple different types of coal from different seams and different working faces have to be blended to produce the anticipated product.

Methods of mathematical optimization, such as linear programming LP [27] or mixed integer programming MIP [28;29;30;31;32] have been successfully applied for over three decades to find optimal solutions for the defined problem. However, applications were mainly focused on discontinuous block mining in diffuse deposits. For continuous mining operation, such as lignite deposits, only very few applications are known to the authors. Kawalec and Specylak [33] report a simplified application of open pit design optimization to a lignite deposit located in the Belchatow field in Poland. The here presented approach extends recent methods of mathematical optimization in mine planning [32] to account for constraints, imposed by continuous extraction technology.

Optimization Model of Long-term Mine Planning in Continuous Mining Operations

In terms of optimization, mine planning can be seen as an extreme value problem with boundary conditions. The optimization problem aims to find the best *decision variables*, in terms of when which mining block should be extracted. The objective is to maximize the overall monetary value of the operation, while meeting production targets and obeying environmental and operational constraints. A linear *objective function* has to be designed that quantifies the achievement of the objectives for a set of decision variables. *Constraints* describe the boundary conditions, such as lower and upper capacity limits per excavator, and define a feasible solution space. In the mathematic model, constraints are represented by a set of equations or inequalities. An extensive description of a general mine planning model is given in [32]. The following sub-chapters present the model formulation for long-term mine planning in a continuous lignite deposit.

Objective Function and Decision Variables

The herein developed formulation extends results obtained from a nationally funded project ibi [34].

The objective function combines multiple goals. (1) Deviations from production targets (Δ_p^t) shall be minimized, while (2) maximizing the expected net present value (*NPV*), when executing the mine according to the plan. Production targets are in terms of tonnage- ($O_{target_p}^t$) and coal quality ($Q_{min_e}^p$, $Q_{target_e}^p$,$Q_{max_e}^p$) to ensure the reliable and continuous delivery of in-spec coal to the customers. Equation (4.1) presents the different parts of the objective function:

$$NPV - \sum_{t=1}^{T} \sum_{p=1}^{P} \left[w_{op} \cdot \Delta_{O_p}^t + \sum_{e=1}^{E} w_{qpe} \cdot \Delta_{Q_p}^t(e) \right]$$

where *T* is the number of periods to schedule (such as months or years), *P* denotes the number of different coal products, such as dust coal or plant coal. *E* represents the different coal quality parameters, such as calorific value, ash or sulphur content. Parameters w_{op} and w_{qpe} are weighting factors for the several objectives. These weights can be interpreted as costs associated with deviations from production targets. The prerequisite for mine planning optimization is a block model of the deposit, which represents the geometry imposed by the mining operation (example in Fig. 53). Relevant attributes, such as coal tonnage, waste volume and coal quality parameters are assigned to each block using methods of spatial interpolation or simulation as described in Task 4.1.

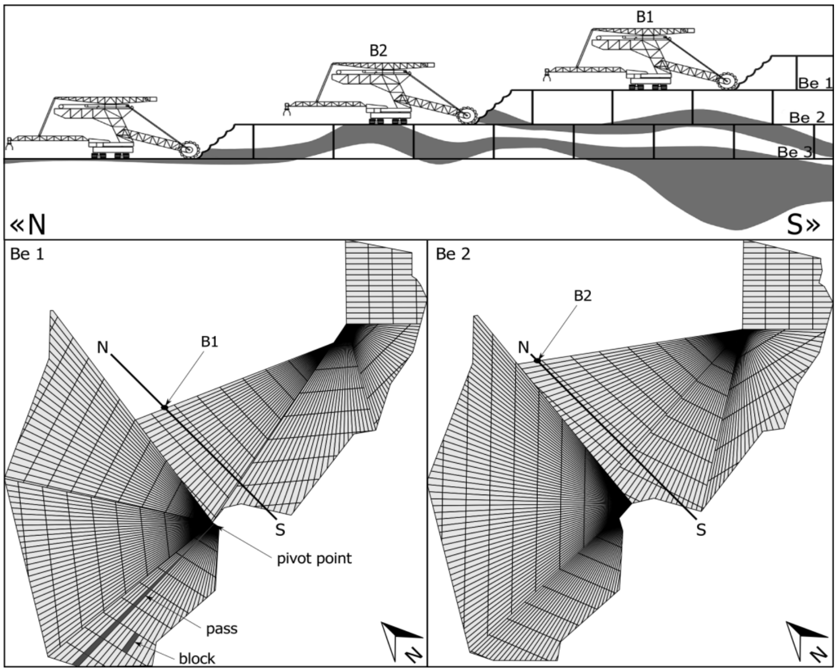


Figure 53: representation of a block model adjusted to the applied excavation technology top: vertical cross section through an open-pit mine with labelling of the first three benches (be) and passes; bottom: illustration of the first two benches' base.

The subdivision of the deposit into mining blocks is in accordance with the following specifications: ultimate pit limit, number and elevation of benches, equipment specifications per bench in terms of geometry, selectivity and capacity, and pivot point for each bench. In this way a representative block model for a continuous mining operation is generated mapping relevant attributes to each block.

A binary decision variable y_{ijk}^t is assigned to each block *ijk* and production period *t* (months, or years) in the optimization model. Solving the optimization problem will result in optimal choices of these decision variables and define the optimal production sequence. If the value *One* is assigned to y_{ijk}^t, the block *ijk* will be mined at *t*, else not.

The deviations in coal quality $\Delta_{Q_p}^t(e)$ are treated in a similar way as the coal tonnage. Here, the lower and upper limits for different coal quality parameters $Q_{min_e}^p$ and $Q_{max_e}^p$ are taken into account, which represent the maximum bandwidth for an efficient operation of the downstream process, such as power plants. Exceeding these thresholds will be penalized. Deviations from coal quality production targets $\Delta_{Q_p}^t(e)$ and $\Delta_{Q_p}^t(e)$ are *Zero*, if coal is produced with a quality inside the quality specifications.

Constraints

To prevent the extraction of a block multiple times, the following (in-)equalities need to be fulfilled for each block:

$$\sum_{t=1}^{T} y_{ijk}^t \leq 1 \qquad\qquad \sum_{p=1}^{P} x_{ijkp}^t = y_{ijk}^t$$

In addition, to these restrictions, the amount of extractable material per bench and time period is limited by the deployed equipment:

$$\sum_{i\in I}\sum_{j\in J_i}\sum_{k\in K_{ij}} y_{ijk}^t \cdot \left(O_{ijk}\cdot\frac{1}{V_{iO}^t} + W_{ijk}\cdot\frac{1}{V_{iW}^t}\right) \leq t_i^t$$

V_{iO}^{t} and V_{iW}^{t} represent the equipment capacities for the extraction of lignite respectively waste on bench i. t_i^t corresponds to the equipment's' operating hours on bench i where extraction can take place.
Using belt conveyors (for the transportation of the extracted material) results in an additional constraint. Only after all material in one pass is mined the belt conveyor can be moved further along. For the optimization model this means all blocks of a pass need to be extracted before the blocks of the next pass can be scheduled for mining. Mathematically this can be expressed as follows:

$$\frac{1}{K_{max_{i(j-1)}}} \cdot \sum_{t=1}^{t_{cur}} \sum_{\tilde{k}=1}^{K_{max_{i(j-1)}}} y_{i(j-1)\tilde{k}}^{t} \geq y_{ijk}^{t_{cur}}$$

The inequality states that the binary decision variable of block $y_{ijk}^{t_{cur}}$ can only attain the value One if all blocks of the previous pass have been mined in the current period t_{cur} or in a previous one. In this case, the sum multiplied by the number of the pass's blocks equals *One*. If not all blocks are scheduled for mining, the value of the inequality's left-hand side is smaller than *One*. Consequently, the inequality's right-hand side can only attain the value *Zero*.
To guarantee a safety distance to the coved edge of the underlying bench needs to be satisfied (Fig. 54), a minimum spacing d, which is a horizontal distance that depends on the employed equipment, should always be exceeded. It is a geometrically time-independent problem and can be converted into an easy to formulate constraint that does not enclose any coordinates or distances. In order to do this, the required bench progress has to be calculated such that the pass w of the underlying bench can be extracted. This means that for every pass (w) of a bench i the pass number u of the overlying bench $(i-1)$ needs to be determined till which the mining process needs to advance. For the formulation of the dependencies between two successive benches the determined pass numbers u needs to be used:

$$\frac{1}{K_{max_{(i-1)u}}} \cdot \sum_{t=1}^{t_{cur}} \sum_{\tilde{k}=1}^{K_{max_{(i-1)u}}} y_{(i-1)u\tilde{k}}^{t} \geq y_{ijk}^{t_{cur}}$$

The inequality states that the binary decision variable of block $y_{ijk}^{t_{akt}}$ can only attain the value One if all blocks of the pass u have been mined in the current period t_{cur} or in a previous one.

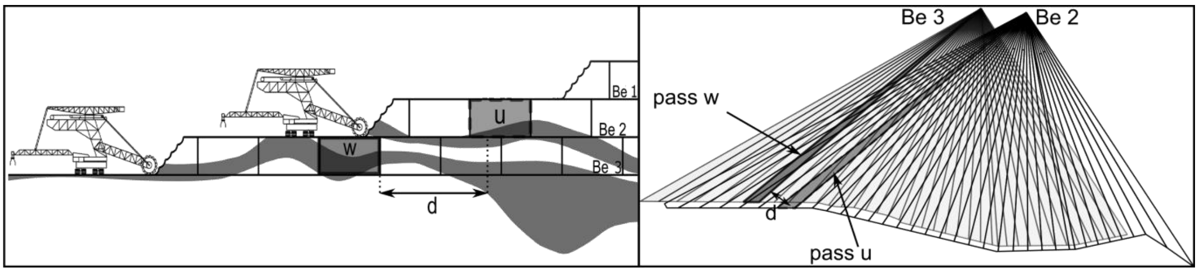


Figure 54: Illustration of minimum spacing d between faces of benches (Be) 2 and 3. Since the spacing would drop below the minimum spacing, before pass w can be mined pass u has to be mined.

Application of the Optimization Model

The developed model will be applied to a data set of a sedimentary lignite deposit consisting of multiple seams in Poland (Task 4.1).

For a period of 5-10 years, the annual advance per cut will be optimized in a given time frame. The block model is currently constructed utilizing the ultimate pit limit and bench geometries (Figure 55).

Figure 55: Pit geometry and bench design and advance for the study period.

The aim of the study will be to homogenies several coal quality parameters, in particular the CV. The current life-of-mine plan shows deviations as displayed in Figure 56 and has potential to be improved.

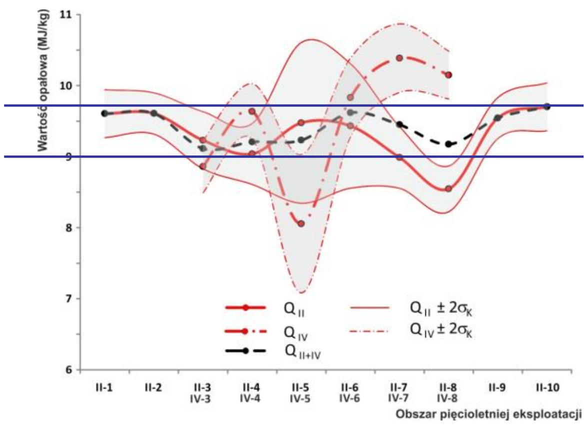


Figure 56: Prediction of long-term coal quality (CV) for un-optimized schedule.

Task 4.3: Validation of plausibility and demonstration of the applicability and economic benefit of the uncertainty mine planning optimization method in an application for life-of-the-mine planning of a large mining project.

Based on block model of the Gubin deposit, prepared in Task 4.1, a case study including all decision variables, the objective function (including maximization of NPV and minimizing deviations from long-term production targets) and all the constraints (including slope constraints, equipment capacities, bench highs, production targets, etc.) is prepared. Due to practical constraints and available data, the case study focuses on a particular long-term part of the deposit Gubin representing an approximately 5-year production period. Although this area does not represent the life-of-the-mine, as suggested in the initial task description, the demonstration of benefits in respect to the ability to meet production targets can be demonstrated without loss of generality.

Block Model

The subdivision of the deposit into mining blocks is based on the applied excavation technology - lignite is extracted on parallel benches (described in Deliverable 4.2). To reach the bottom of the lowest seam, 8 benches were designed. The bench high represents the equipment capability of the planned bucket wheel excavators and was chosen to be 30 to 50 m, depending on geological situation. As already stated in Deliverable 4.1, the deposit consists of five seams but only one seam meets minimum mining requirements – Seam II. This seam is split in an upper bed (Seam II-1) and a lower bed (Seam II-2) and can only be minded from benches 6 through 8.Therefore, benches 1 through 5 only contain overburden material and do not influence the benefits of the new quality driven stochastic mine planning approach. Consequently, these benches are not considered here during optimization. The sequence of bench 1 to 5 is a direct consequence of general slope angle in mining direction and the result of bench 6 to 8. Any deviation from this would decrease the NPV. On the other side it would increase flexibility in case of unexpected downtime of equipment.
The dimension of each mining block is about 100 m by 300 m and was chosen based on the distance for belt shifting and is about a month worth of working time. Each block contains the following information:

- m^3 waste material contained,
- t of lignite contained,
- 25 simulated coal quality values for the calorific value (CV),
- 25 simulated coal quality values for the ash content (A) and
- 25 simulated coal quality values for the Sulphur content (S).

Operational Parameters and Target Values:

The model starts with a predefined state (current mining progress) of the open-cut mine and plans the exploitation on three benches for five time periods (years). To guarantee a safety distance to the coved edge of the underlying bench a minimum spacing between benches should always be exceeded (Figure 57). This constraint defines the precedence relationship of block extraction between benches. A particular block in a lower bench cannot be extracted, before all blocks located in the corridor of minimum at the upper bench have been extracted.
The production target in terms of lignite tonnage is 11 million tons per time period (year) needs. This has to be supplied to the costumer with a defined quality bandwidth for the coal quality parameters calorific value (CV), the ash content, and the sulphur content (Table 10).
Table 11 summarizes the assumed production capacity per bench (operating hours and production capacity in waste and coal production) and also the minimum spacing between benches as discussed.

Table 10: Defined quality bandwidths for the lignite product.

	Min	**Target**	**Max**
CV [MJ/kg]	9.1	9.3	10.2
Ash [%]	13	16	16.5
S [%]	0	1.5	1.8

Table 11: Information about the optimization model parameters.

Be	**operating hours [h/a]**	V_{iW}^{t} **[m³/h]**	V_{iO}^{t} **[m³/h]**	**Minimum Spacing [m]**
6	4100	4000	4000	-
7	4200	3700	3700	145
8	4000	2900	3100	160

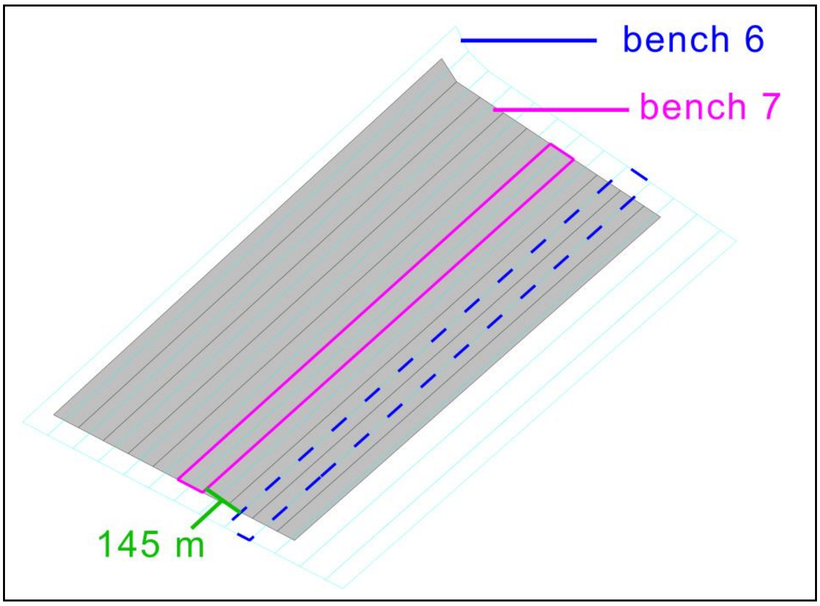


Figure 57: Illustration of the minimum spacing between faces of benches 6 and 7.

Cost Parameters for Deviations from Targets:
Due to confidentiality reasons, no information about contractual penalties is known and hence has been assumed (Figure 58 right side) for optimizing the net present value. To penalize exceeding or a shortfall with respect to defined lignite quality limits Q_{min} and Q_{max}, a slope coefficient of "4" is being used. This represents 4 units of monetary value per unit deviation. Within the quality limits a weight coefficient of "3" is used. Furthermore, a discount factor of 10% is presumed.

For weighing penalizing terms for over- or underproduction, a slope factor of "30" respectively "50" is applied per 10^6 tons (Figure 58 left). As a result, this objective gets a higher priority and the production scheduling of lignite having a better quality but with an insufficient amount is being avoided.

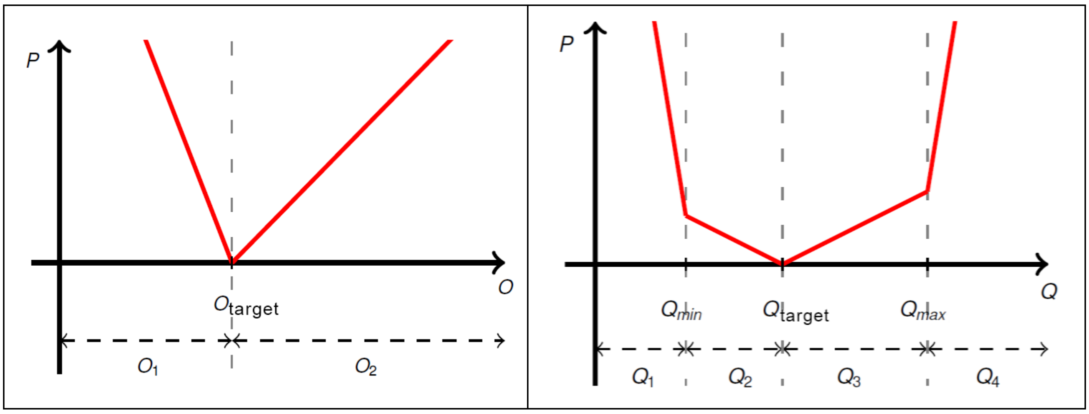


Figure 58: Penalty function for deviating from production requirements (left) and contractual penalty function for lignite qualities (right).

Results

Figure 60 depicts the scheduled progress of mining on the individual benches that was determined using the optimization results calculated by CPLEX. As can be seen from these illustrations, there are distinctive differences between the results of the optimization models. To evaluate the mine plans, a so called transfer function is used. Both optimized mine plans, the e-type based and the SIP – based, are utilized as base plans and their performance is evaluated by running through all 23 possible scenarios about the spatial distribution of coal and coal quality parameters within the deposit. As a results, so called risk profiles are generated. For each period a set of 23 results are obtained for the parameter of interest, which discretize the uncertainty range. If, for example, 3 out of 23 possible realizations are exceeding the thresholds, then there is a chance of p=3/23 that during this period, the threshold of the parameter considered is exceeded. Figure 59 shows the risk profiles for the coal tonnage based on both plans, the e-type plan (left) and the SIP plan (right)

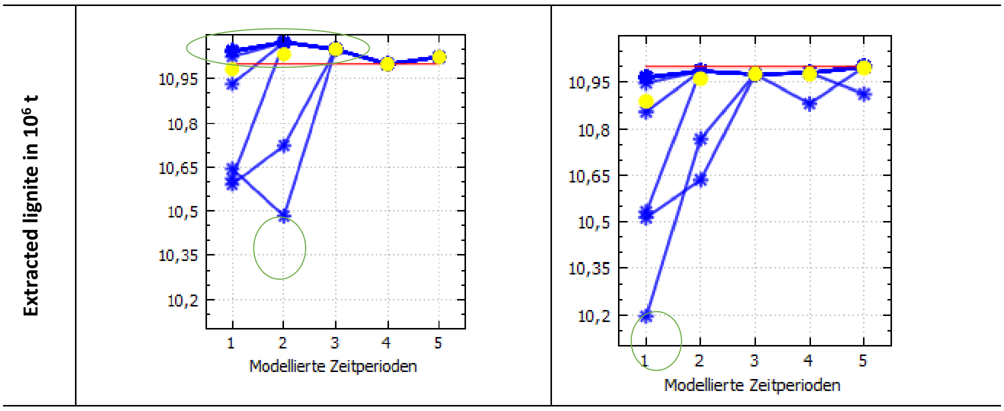


Figure 59: Predicted lignite amount scheduled for mining for the stochastic model (right) and the model based on the e-type (left); red: target value; yellow: e-type; blue: realizations.

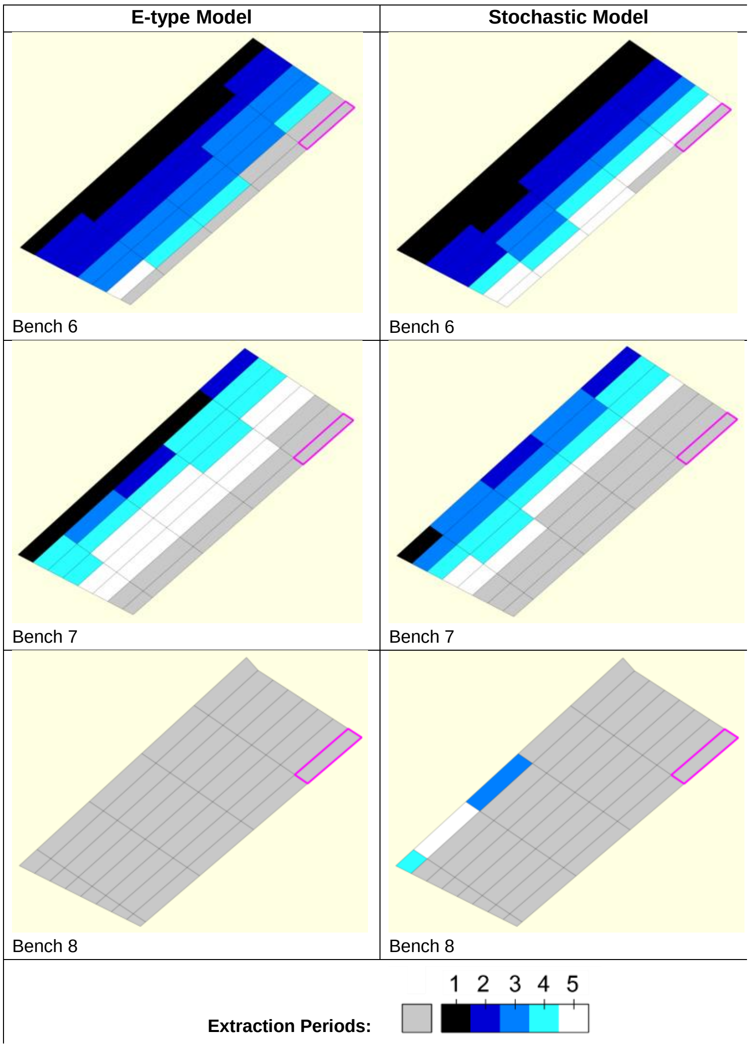


Figure 60: Representation of bench areas' blocks that are scheduled for mining in the modelled timeframe (left: e-type model; right: stochastic model).

Lignite quality parameters ash content, sulphur content and the calorific value are crucial when determining a viable mine plan, pose a risk, and incorporating geological uncertainty into the mine planning process makes it possible to reduce this risk. Figures 61 to 63 illustrate the penalty value per target quality parameter and period. Figure 64 shows penalty values for all periods. The values shown refer to unit penalties per ton of coal.

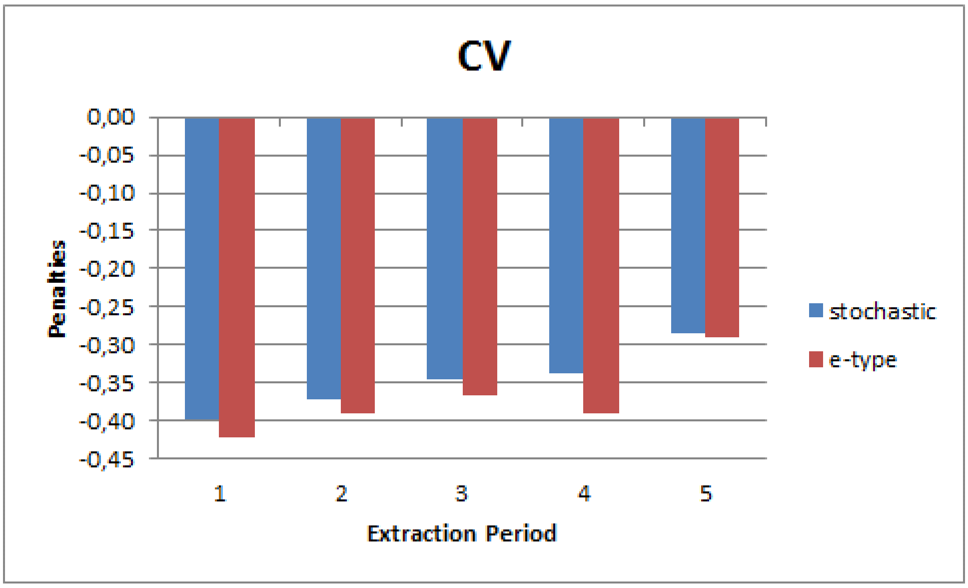


Figure 61: Comparison of penalty values per period between the e-type based schedule and the stochastic schedule for the coal quality parameter CV.

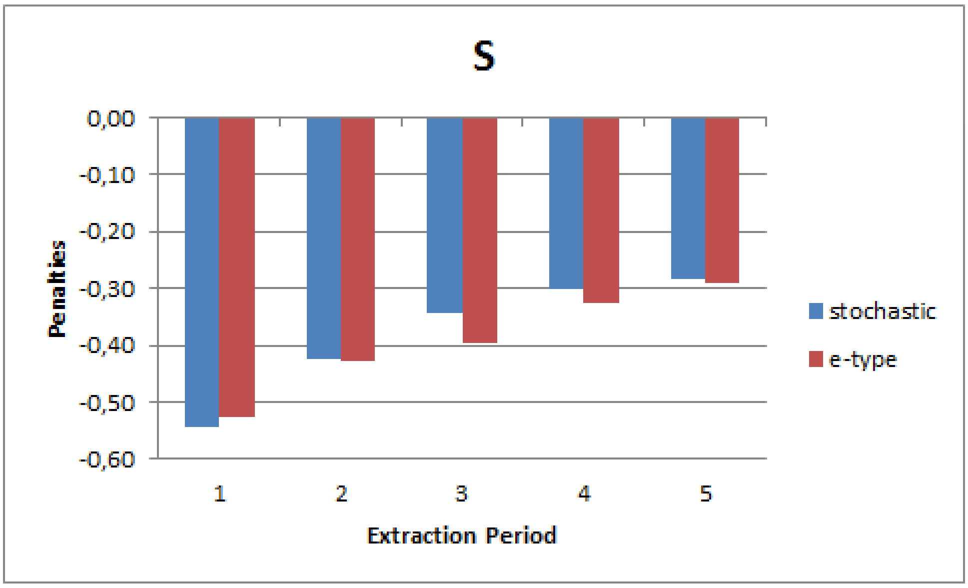


Figure 62: Comparison of penalty values per period between the e-type based schedule and the stochastic schedule for the coal quality parameter S.

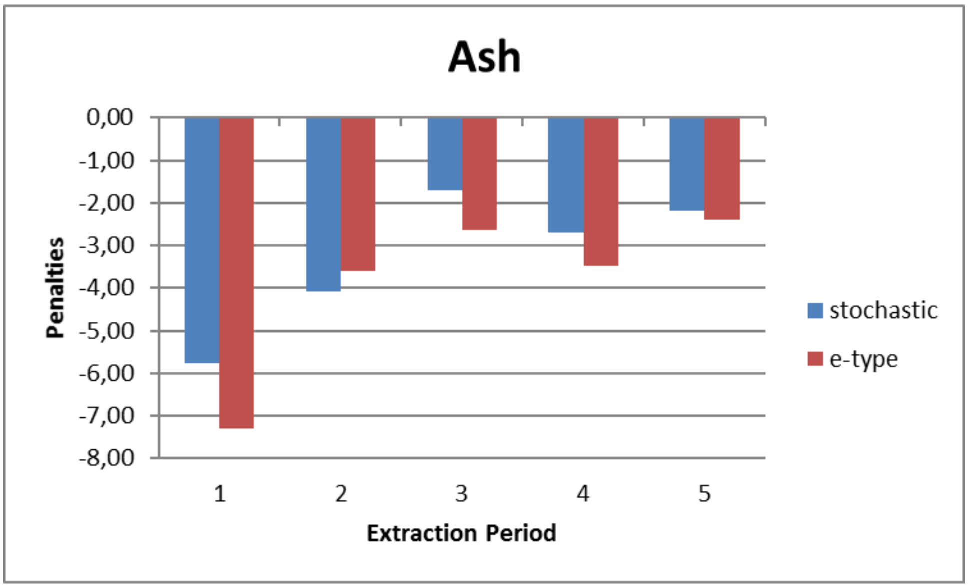


Figure 63: Comparison of penalty values per period between the e-type based schedule and the stochastic schedule for the coal quality parameter Ash.

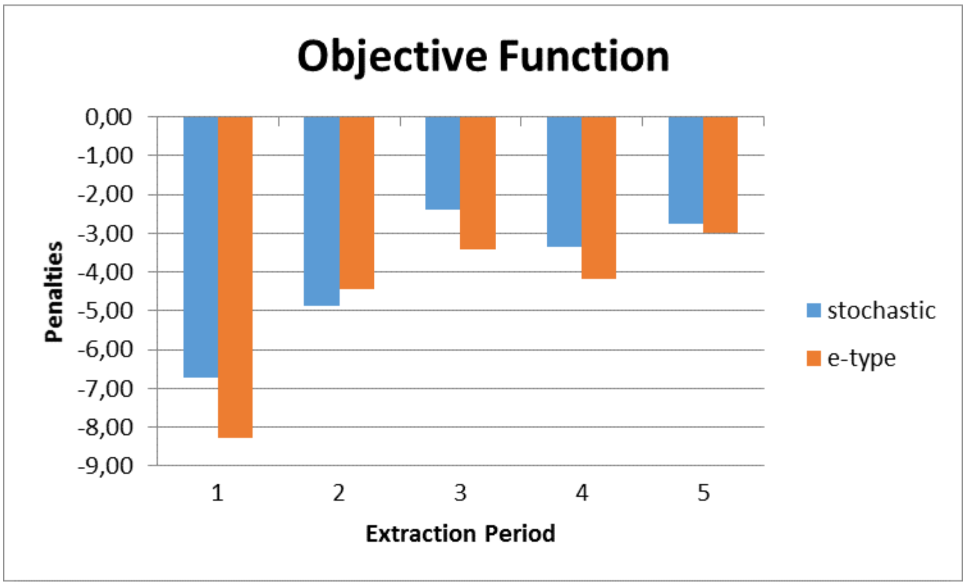


Figure 64: Comparison of penalty values per period between the e-type based schedule and the stochastic schedule for the sum of all penalties (total penalty).

Evaluation of Results

For a quantitative evaluation, following statistical indicators are considered:

- Uncertainty in prediction: standard deviation of the coal quality parameter Q around the mean $\bar{Q}$ per period

$$\sigma_Q = \pm\sqrt{\frac{\sum_{Realisations\,i}(Q_i - \bar{Q})}{number\ of\ Realisations}}$$

- Expected value of coal quality parameter above EQ_A or below EQ_B a threshold

$$EQ_A = \frac{1}{number\ of\ Realisations}\sum_{Realisations\,i}\max(0, Q_{Realisation\,i} - Q_{upper\ threshhold})$$

$$EQ_B = \frac{1}{number\ of\ Realisations} \sum_{Realisations\ i} \mathrm{MAX}(0, Q_{lower\ threshhold} - Q_{Realisation\ i})$$

Table 12 summarizes the results as average values over all five periods. The rows % Improvement quantify the relative improvement of the SIP-based schedule compared to the E-type based schedule.

Table 12: Summary indicators.

	Ash (SIP)	Ash (E-type)	CV (SIP)	CV (E-type)	S (SIP)	S(E-Type)
σ_Q	1,23%	1,49%	191 kJ/kg	210 kJ/kg	0,23%	0,25%
Improvement	16 %		8,7%		5,4%	
EQ_A	0,07%	0,28%	n.a.	n.a.	0,005%	0,011%
Improvement	75%		n.a.		54%	
EQ_B	0,026	0,034	15,7 kJ/kg	24,9 kJ/kg	n.a.	n.a.
Improvement	23%		37%		n.a.	

Economic benefits:

It becomes obvious from Table 12 that the stochastic scheduler performs better in meeting production targets for coal quality parameters. On the example of ash, a hypothetic 1€/%/ton deviation from the upper boundary is applied as a penalty for not meeting production targets. For a year of production @ 10.000.000 tons per year, an average deviation of 0,07% for the Stochastic scheduler results in an expected annual penalty of 700.000 €. The scheduler ignoring the uncertainty results in 2.800.000€ penalty. Thus, just for the ash value, cost reductions in the order of 2.100.000 Euro per year (10.400.000 € over 5 years), when using this scheduler. For the parameter CV a similar order of magnitude is expected.

Environmental benefit:

With a very small amount of 0,005% average deviation from the upper threshold for the parameter sulphur, the SIP-base schedule provides a plan that allows a continuous and homogeneous operation of the desulfurization plant. The E-type schedule exceeds on average with 0,011% the upper threshold. This may have strong implications on the efficiency of the desulphurization plant, however, is not discussed here in detail.

Work Package 5: Short-term Planning Optimization

The short-term scheduling of lignite extraction in a continuous mining system is a very complex process. Simultaneously, various excavators work on multiple working levels which results in strong dependencies between different parts of the mining system. The excavators' movements are restricted by the progress of the ones on the upper working levels and by conveyor belts. Conveyor belts are used to transport the extracted material either to a dumping site (in case of waste) or e.g. to a coal bunker where the material is blended to fulfill customer requirements regarding the coal's quality. There are capacity limits that need to be considered, not only in connection with the used equipment (e.g. excavator, conveyor belt) but also regarding the waste dumping site and the coal bunker itself.

A sufficient amount of different products made up of (blended) raw materials need to be produced and delivered to individual customers in a timely manner. Additionally, the mining system is subject to uncertainties caused by different sources. The incomplete knowledge of the deposit causes geological uncertainty. To gain information about the deposit – where the strata are located and what quality values the material they are made of exhibit – holes can only be drilled at a very limited number of locations. In between these locations, assumptions about the deposit are made.

Mining equipment might fail at some point causing (huge) parts of the system to stand still unexpectedly - everything in the system is interconnected. Last but not least, the customers' demand is uncertain and can change over time.

Task 5.1: Definition of a specific optimization formulation for short-term production scheduling of a continuous open pit mining process

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Two case studies were defined, each one focusing on a different aspect of the mining process that may cause bottlenecks and therefore have a great impact on the profitability of the mining operation.

1. *Case RWE: Overburden Management at Hambach Mine, Germany*

Objective: Optimization of the waste management to decrease equipment downtimes/increase efficiency of excavators and spreaders while ensuring a stable dump construction

The existing materials' properties have a huge impact on the mining process in open pit mines. They affect e.g.

- the stability of dump and operational slopes as well as working levels
- the load factor/handling capacity (digging force, depth of a cut, slewing speed)
- wear
- caking, spillages etc.

The waste materials at the Hambach mine are classified as either:

- M1: mixed soils type 1
- M2T: dry mixed soils type 2
- M2N: wet mixed soils type 2

M2N consists of cohesive components. Therefore, it is difficult to drain and is considered an unstable mixed soil. Only a limited amount of this wet material can be placed on the waste dumping site enclosed by polders or dams of dry materials to produce a stable dump construction. Consequently, the extraction sequence and the dispatch decisions have to match the available space on the dumping site per material type. This is very challenging since the geology and as a result the proportions of extracted dry and wet material may fluctuate constantly. If there is too much pending wet material, the corresponding excavators have to stop working until the bottleneck is resolved.

A short-term simulation-based optimization formulation that tackles this issue was defined. The objective function is made up of the following key performance indicators (KPIs):

- Quantity of Extracted Materials
- Effective Capacity
- Plan Compliance
- Specific Energy Usage
- Utilization

Equations for each of these indicators as well as for technical and physical constraints induced by the continuous mining operation have been formulated.

2. *Case MIBRAG: Production Efficiency and Coal Quality Management, Profen Mine Germany (Schwerzau mining field)*

Objective: Optimization of the production control to increase the sustainability of the production and to decrease the influences of uncertainties (regarding demand, geology, and equipment breakdown times) associated with the mining operation

The complexity of depositional features in the Schwerzau field is very high in terms of a strongly varying seam geometry and coal quality distribution. Technical advancements (e.g. in power plant technology) present increasing challenges for the mine planning process. While the power plant's level of efficiency was raised, the allowable quality band width of the delivered raw materials from the mine has tightened. The system is much more vulnerable to material quality violations. They can lead to cinder covers inside the boiler, which need to be removed, reducing the efficiency. Therefore, the production targets relating to coal quantity and the raw material's chemical properties need to be met on a day by day basis. From the Profen Mine, three different coal types with contractually predefined coal quality specs are being mined and deviations from expected process performance should be minimized.

A short-term simulation-based optimization formulation that tackles these issues was defined. The objective function is made up of the following key performance indicators (KPIs):

- Coal Quality
- Coal Quantity
- Effective Capacity
- Plan Compliance
- Specific Energy Usage
- Utilization

Equations for each of these indicators as well as for technical and physical constraints induced by the continuous mining operation have been formulated.

The necessary level of detail was defined as 15 minutes. The optimization/update process is an iterative process. It will start with a big time partition and after checking the system status, the time partition will continually decrease to calculate a more detailed mine plan.

Task 5.2: Development of an innovative simulation-based optimization framework suited for short-term mine planning in continuous open pit mines

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Based on the specific problem formulations of Task 5.1, the following problem characteristics were identified:

- The optimization problem consists of both, discrete decision variables, which determine the extraction sequence of the material (scheduling problem), as well as continuous decision variables to control the effective digging capacities within certain boundaries.
- To provide a detailed enough resolution for scheduling, the amount of decision variables can become rather large – large-scale optimization problem.
- The objective function value is quantified by a simulator that considers the geological uncertainty, unscheduled breakdowns of equipment, and the uncertain quantity demand of customers. One simulation run might take some time. Hence, an optimization algorithm is desirable that does not need to call the simulator too often.
- The objective function value is obtained by summing up the weighted system KPIs, which are calculated using outputs generated by a simulator. KPIs can be e.g. the produced coal quality and quantity, the compliance to long-term planning, the energy usage, and the utilization of the whole system. Therefore, it can be expected that the design problem is multimodal, consisting of multiple local optima. Subsequently, some kind of global optimization mechanism is required that prevents the optimization process from getting trapped in a local optimum.

- Due to the continual gain of additional information during the extraction process, that can be used to update the planning model, the short-term mine planning problem will be re-optimized frequently. Consequently, one optimization run should not take too long.

These characteristics were the basis for the study on applicable simulation-optimization approaches for the short-term mine planning problems defined in Task 5.1.

The simulation-optimization approaches deemed suited for the problem at hand can be subdivided based on the type of decision variables they can handle. For continuous variables, the following approaches have been shortlisted:

- Responsive Surface Method (RSM)
- Stochastic Approximation (SA)
- Gradient Surface Methods (GSM)

For discrete variables, the succeeding approaches were looked at in more detail:

- Random Search Methods
- Genetic Algorithm (GA)
- Ant Colony Optimization Algorithms (ACO)
- Simulated Annealing (SA)
- Tabu Search (TS)

Next, a survey about simulation-based commercial software and applications was performed. This led to the conclusion that one or more tools need to be implemented in order to develop an efficient optimization workflow for short-term mine planning of continuous mining systems.

Last, the theoretical framework was presented. The framework's components, how they will interact, and what algorithms will be implemented for the different components was defined in detail and can be seen in Figure 65.

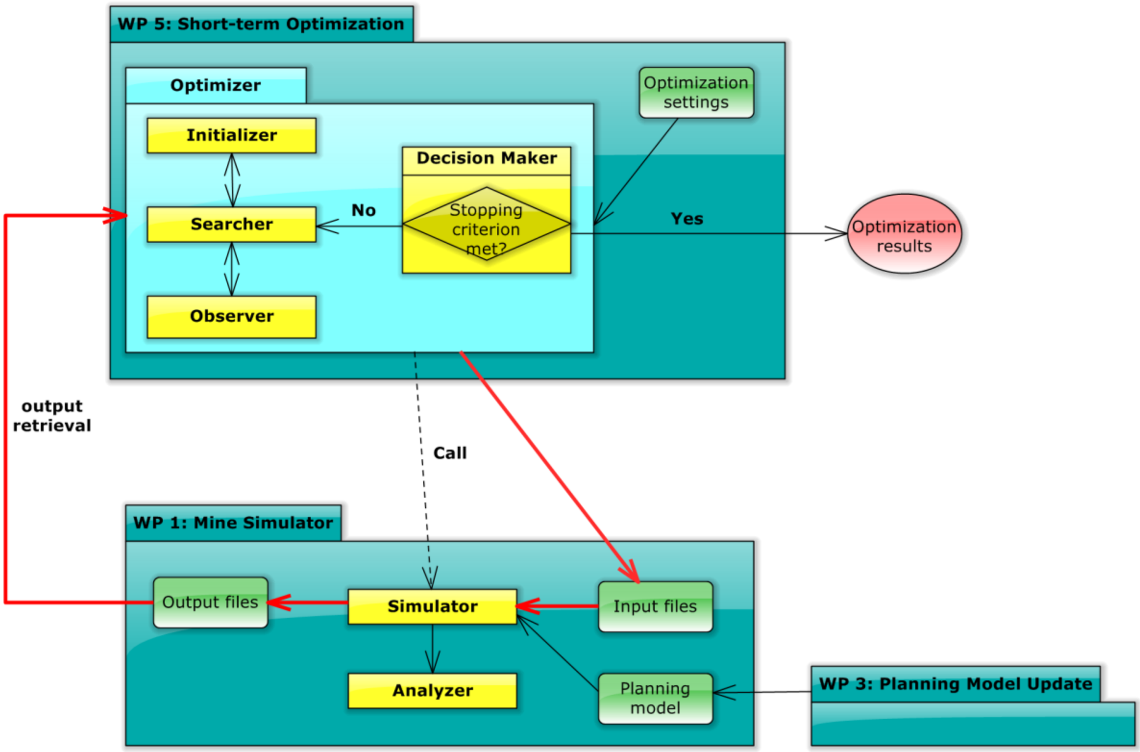

Figure 65: Structure of the proposed framework for simulation-based short-term mine planning optimization.

The modular structure of the framework is designed for flexible use flexible – it is possible to alter individual parts without affecting the whole system/requiring making changes to the entire system. The system is subdivided into smaller logical units responsible for a specific task. Each unit shields its inner workings from one another. Communication between units is accomplished via well-defined interfaces which can either be files to transmit information across system boundaries or functions/implementations of abstract interface objects to exchange information within a program.

The optimizer obtains an optimization problem and setup information for the optimization process as inputs. This information is used by the optimizer to initialize itself and the Simulator. The Initializer chooses an initial decision (plan for the mining process on a short-term basis) and the simulator is called to retrieve a performance measure for the particular decision. Next, the Decision Maker is called to assess whether or not a stopping criterion has already been met. If so, the optimization process is terminated and the current decision is returned as the solution of the short-term mine planning problem. If that is not the case, the Searcher starts its iterative process of proposing solutions that are investigated via simulation experiments in the way just described. After leaving this cycle, due to reaching a stopping criterion, the best of all considered solutions so far will be returned.
During the optimization process the (optional) Observer retrieves information about the optimization process's current status which can e.g. be used to determine the convergence rate of the algorithm.

Task: 5.3: Implementation and validation of the simulation based optimization framework

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Mine planning can be subdivided by the time frame a mine plan encompasses and the contained decisions made for production control. The level of detail increases with decreasing time spans. Short-term mine plans are partitioned into the following types:

- Monthly mine plan
- Weekly mine plan
- Daily and shiftily mine plan

The monthly mine plan (

Figure **66:** Monthly Mine Planning Example - 5 benches with 2 consecutive passes each defining when a belt shift occurs.66) defines an extraction sequence and schedules belt shifts in different benches. The overall goal is to meet the monthly coal tonnage and grade targets and at the same time obeying the priorities set by the long-term mine plan.

Based on the monthly mine plan, the weekly mine plan (Figure **67:** Weekly Mine Planning Example - x indicates that an excavator is being used during the corresponding shift.67) defines during which shift each excavator runs, it is thus a job scheduling problem.

Daily and shiftily mine plans (Figure **68:** Shift-based Mine Planning Example - Average production rate of excavators during a shift/day.68) define, how the coal is blended to meet the quality or material targets. They control the production rates of excavators for different material types to maximize the utilization of equipment.

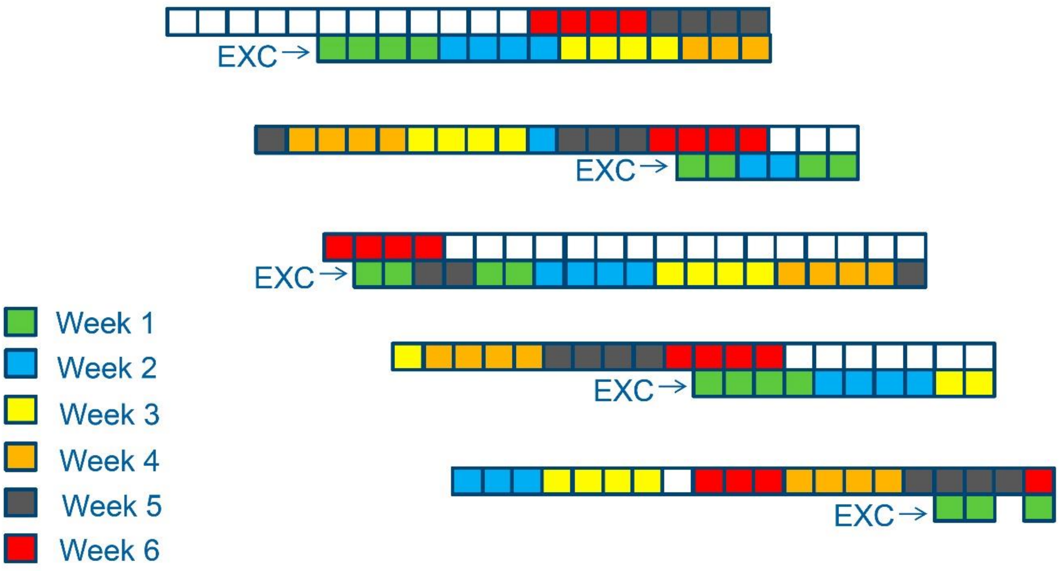


Figure 66: Monthly Mine Planning Example - 5 benches with 2 consecutive passes each defining when a belt shift occurs.

Mo			Tue			We			Thu			Fri			Sat			Sun			
x	x	x			x	x	x	x	x	x	x	x	x	x	x	x	x				Excavator 1
x	x	x	x	x	x	x	x	x			x	x	x	x							Excavator 2
	x	x		x	x		x	x		x	x		x	x		x	x		x	x	Excavator 3
x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	Excavator 4
	x			x			x			x			x			x			x		Excavator 5
												x	x	x	x	x	x	x	x	x	Excavator 6
x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	Excavator 7

Figure 67: Weekly Mine Planning Example - x indicates that an excavator is being used during the corresponding shift.

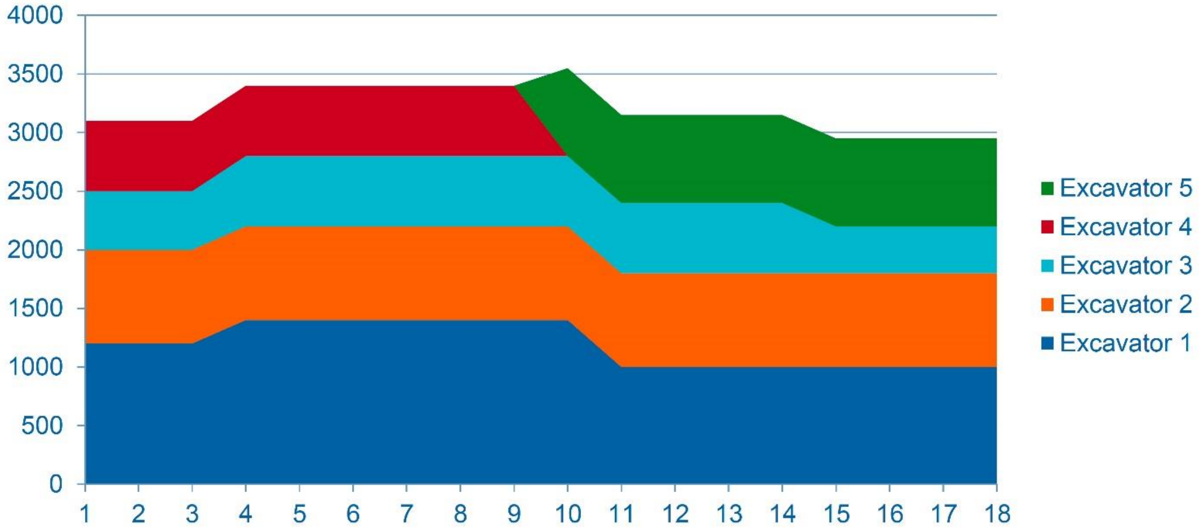


Figure 68: Shift-based Mine Planning Example - Average production rate of excavators during a shift/day.

Next, the three implemented short-term optimization cases are presented:

- Case 1: Optimization of the monthly extraction sequence for meeting coal quality targets at the Profen mine of MIBRAG
- Case 2: Optimization of the weekly job schedule for excavators for a given extraction sequence at the Profen mine of MIBRAG
- Case 3: Optimization of production control during a shift or day production für optimized overburden management at the Hambach mine of RWE.

Case 1: Optimizing the Monthly Extraction Sequence at the Profen mine of MIBRAG

For the monthly mine plan, a mixed integer linear optimization (MIP) model has been formulated. Important parts of this model are summarized below:

The objective function combines multiple goals. Deviations from production targets (Δ_p^t) and waste targets (Δ_W^t) as well as equipment transportation (Δ_{trans}^t) shall be minimized. Production targets are in terms of tonnage and coal quality to ensure the reliable and continuous delivery of in-spec coal to the customers. The subsequent equation presents the different parts of the objective function:

$$\sum_{t=1}^{T} \left[\sum_{p=1}^{P}\left[\Delta_{O_p}^t + \sum_{e=1}^{E}\Delta_{Q_p}^t(e)\right] + \Delta_W^t + \Delta_{trans}^t\right] \rightarrow min$$

where T is the number of periods to be scheduled, P denotes the number of different coal products, and E represents the different coal quality parameters, such as calorific value, ash, or sulphur content.

To define the production sequence, a binary variable y_{ijk}^{t} is assigned to each block ijk and production period t in the optimization model. If the value *One* is assigned to y_{ijk}^{t}, the block ijk will be mined at *t*, else not (Figura 69 a).

While block 1 is mined in extraction period 3, block 2 is not scheduled for mining. In addition, a linear decision variable x_{ijkp}^{t} is assigned to each block ijk, production period t and product *p,* which can take values between *Zero* and *One*. These variables define the contribution to a certain product of each block in each time period (Figure **70:** Partition of block i before and after optimization.70). In this way, a blending process is modelled, which allows to blend different parts of the deposit in order to meet coal quality specifications of different products. Figure 50 summarizes the explained relationships, where O_{ijk} represents the coal tonnage and W_{ijk} the waste volume per block.

Furthermore, to model down time during belt shifts, linear continuous decision variables are used. These variables describe how many percent of the belt shift are performed during an extraction period. Therefore, they can assume values in the range of *Zero* and *One*. In the example in Figura 69 b, the belt shift from pass 1 to pass 2 is performed during the 3rd and 4th extraction period. The belt shift from pass 2 to pass 3 is started and completed in the 6th extraction period.

Block	**Extraction Period**			
	1	**2**	**3**	**4**
1	0	0	**1**	0
2	0	0	0	0

a)

Pass	**Extraction Period**			
	3	**4**	**5**	**6**
1→2	**0,3**	**0,7**	0	0
2→3	0	0	0	**1**

b)

Figure 69: Decision Variables - a) Binary variables to define in what time period a block is scheduled for mining; b) continuous variables between zero and one representing a percentage to define how much of a belt shift is scheduled to be performed during a time step.

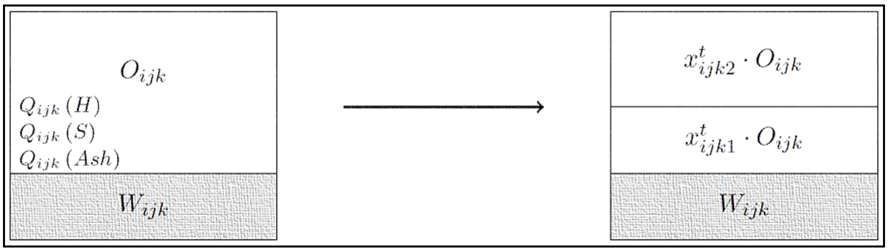
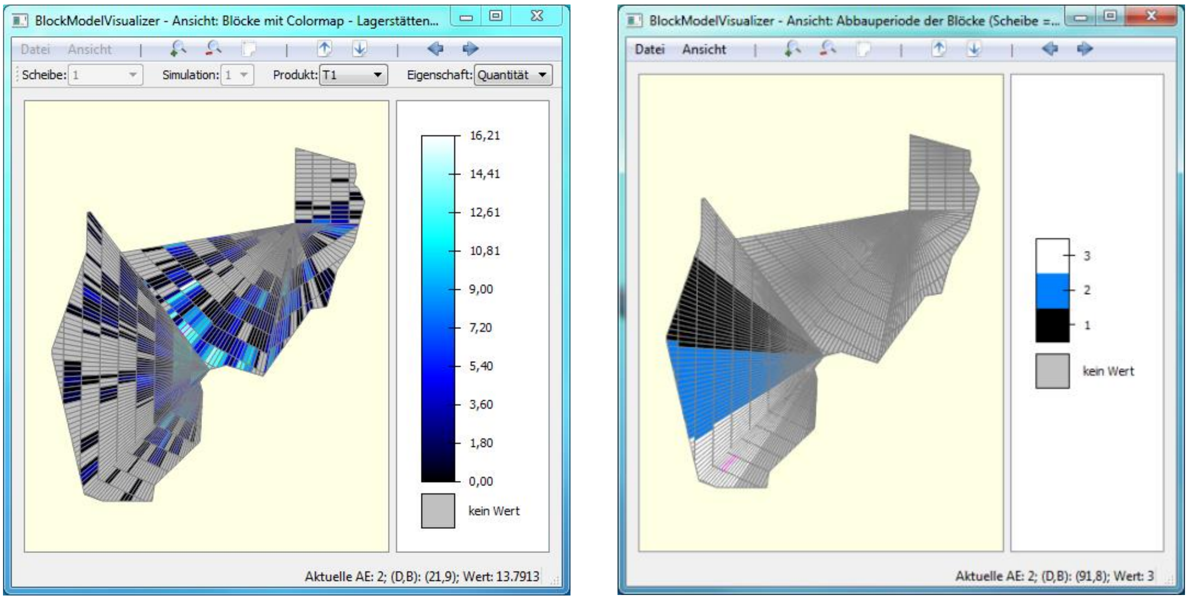


Figure 70: Partition of block i before and after optimization.

The programming language C++ was used to implement a model generation tool that creates an lp-file containing the optimization problem description (based on the inputs provided to it). These lp-files can be read by solvers like CPLEX that will solve the optimization problem at hand. The optimization results can be exported from the CPLEX-solver into xml-textfiles for further processing and analysis. The implemented software was also extended with modules to visualize the results (Figure **71:** Example of the implemented software's visualization capabilities - a) coal tonnages within block that are used to blend product T1; b) calculated mine plan indicating in which extraction period each block is scheduled for mining.71).



a) *b)*

Figure 71: Example of the implemented software's visualization capabilities - a) coal tonnages within block that are used to blend product T1; b) calculated mine plan indicating in which extraction period each block is scheduled for mining.

Case 2: Optimization of weekly job schedule for excavators for a given extraction sequence at the Profen mine of MIBRAG

To optimize the job schedule of excavators during a weekly production at the MIBRAG Mine, the simulation based optimization approach was used. The basis forms the process simulator of the Profen mine developed within WP1. The simulator was developed using DES for a complex continuous coal mining operation involving six excavators, two spreaders and a stock-and-blending yard interlinked by a conveyor network of 30km. Main features involve geological uncertainty captured by a set of simulated realizations of the coal deposit model, multiple-correlated coal quality parameters, planned and un-scheduled maintenance and uncertainty in demand. The objective function J is evaluated as weighted combination of several sub-objectives including meeting coal tonnage and quality targets on a daily basis using a penalty function for a given set of decision variables, in this case the decision to utilize a particular excavator at a shift. The optimizer explores efficiently the space of decision variables to lead quickly to an optimized plan (Figure 72). An example of coal quality prediction for a week of production including the determination of penalty values is provided in Figure 73.

A combination of genetic algorithm for global optimization and simulated annealing for local optimization was found to perform reasonably well. Exploring only a small sub-set of about 500 combinations from all possible combinations in the order of 10^{35} improved an initial manually derived schedule substantially by approximately 55% (Fig. 74).

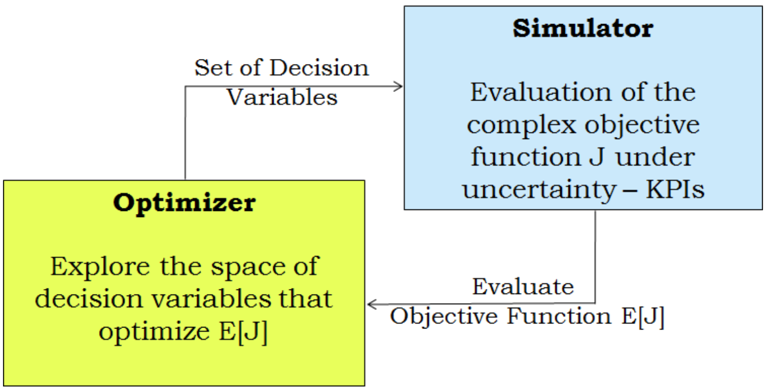


Figure 72: The concept of simulation based optimization (reproduced after Gosavi, 2014).

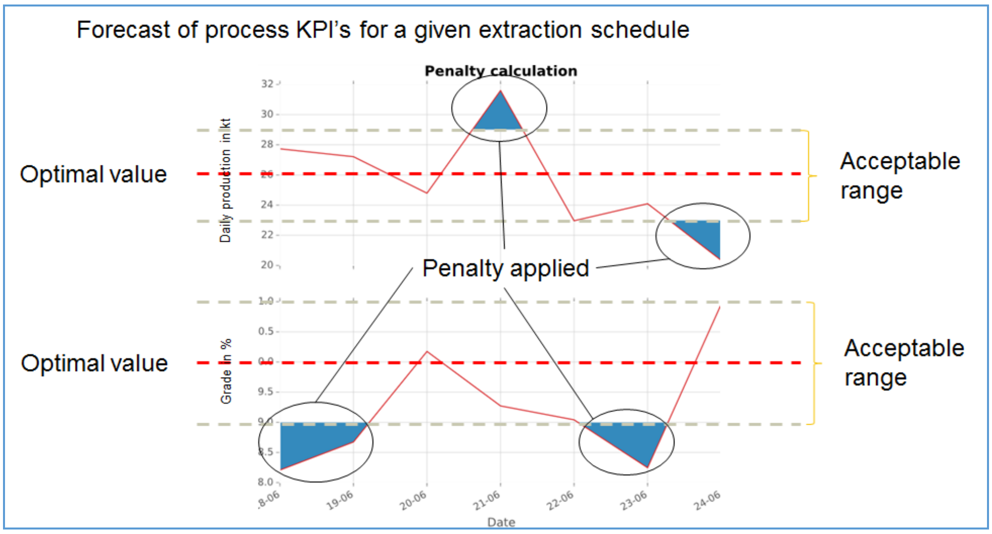


Figure 73: Evaluation of multiple objectives using penalty functions for coal production.

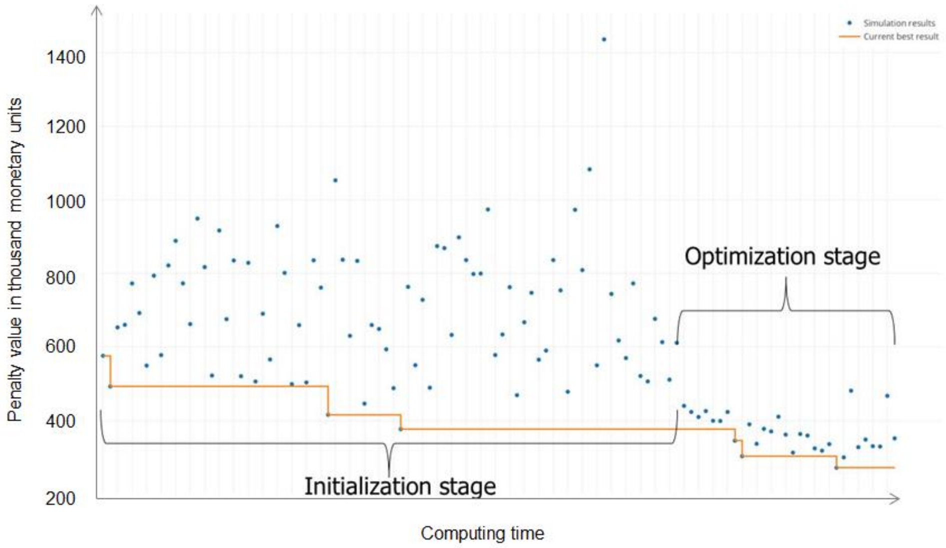


Figure 74: Performance of a simulation-based optimizer applied to task scheduling in a continuous open pit operation.

Case 3: Optimization of production control during a shift or day production for optimized overburden management at the Hambach mine of RWE.

The aim of the Hambach case at RWE is to provide a decision support in material dispatching, in other words to decide, which spreader is the destination of material coming from each excavator (Figure 75). The background are the different material types needed to build up a geotechnical stable dump site. On the other side, on the excavation side these types of materials are distributed unevenly in the given geological column. The objective function is then the minimization of overall costs, including extraction costs, dumping costs, and penalties for deviating from the predefined targets. This will be achieved by decrements in downtimes and effective resource allocation. There are two types of decisions, on the excavator and on the spreader side:

Decision on the excavator side:

- Production rate of each excavator (between 0% and 100%)
- Connection to the spreader

Decision on the spreader side:

- Spreader sequence (depending on material type available)

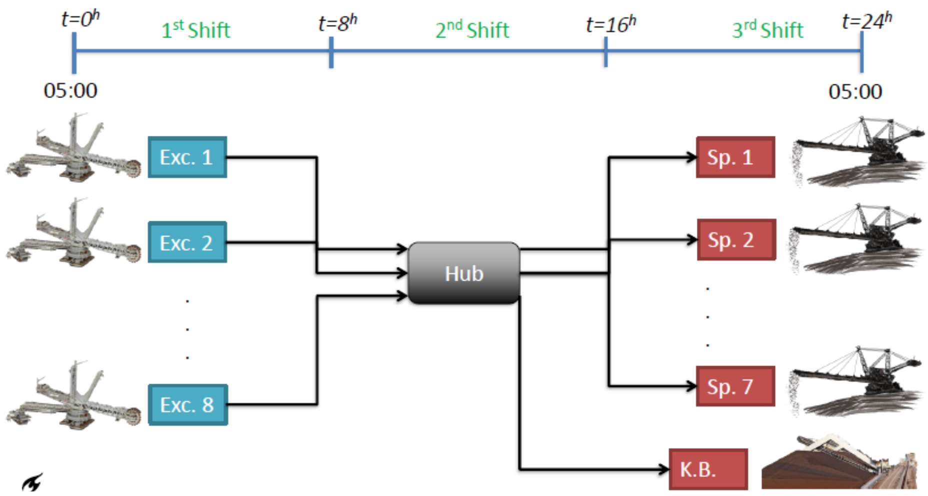


Figure 75: Schematic overview RWE case.

The problem is complex and is not possible to be formulated in a closed-form. The solution approach chosen is simulation based and is broken into several sub-optimization steps:

1. For each spreader a set of feasible random dumping sequences are generated (Define possible scenarios)
2. Given a certain dumping sequence, an optimal connection can be defined using a network model (Define the "Where to connect to")
3. Given the connections, the optimal tasks schedules can be derived using scheduling tools (Define the "When to connect to")
4. Using the stochastic simulator developed in WP1, the KPIs for this plan are evaluated for different dumping sequences taking into account stochastic components defined (Evaluation)
5. Using the subset of the best dumping sequences, go back to step 1 and manipulate and see, if better sequences can be derived.

Figure 76 summarizes the approach. Details are provided in RTRO-Coal deliverable 5.4.

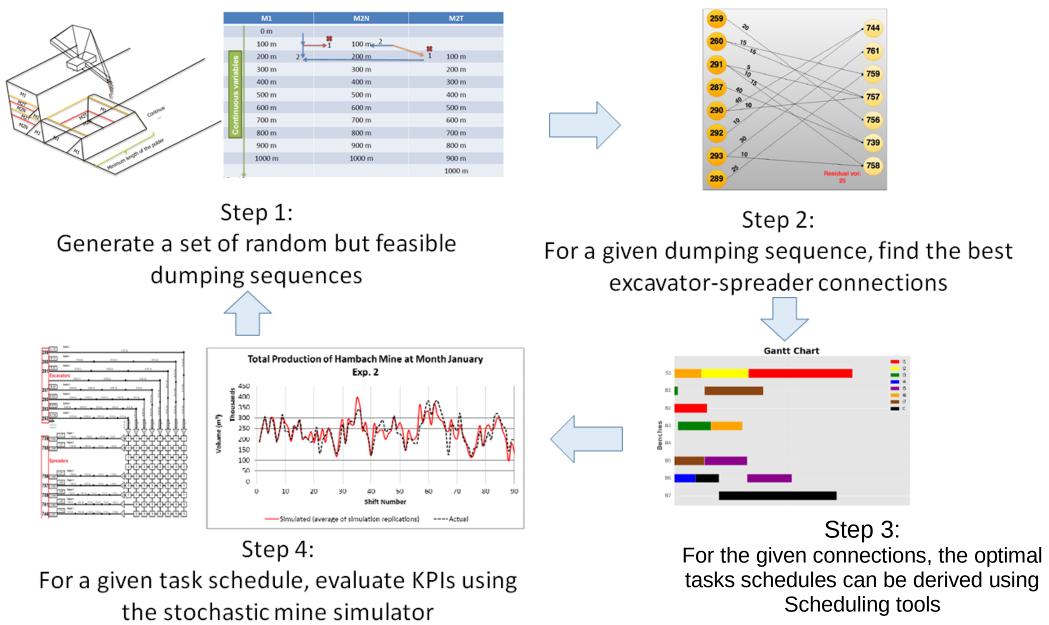


Figure 76: The optimization loop for the RWE case.

For demonstration purposes the RWE case was chosen. For the problem of material dispatching, the optimizer was adapted and all necessary interfaces to operational systems implemented. This resulted in a simulation-based optimization tool for dispatch decisions in continuous mining systems. For a defined test period, historical production data have been collected as basis for demonstration, comparison and analysis of results.

The implementation of the proposed simulation-based optimization approach consists of following major components: the computational control module, the databases, the three modules for the creation of random dumping sequences, transportation problem and job-shop scheduling, the Discrete Event Simulation with its interface, the post-processing module, and finally the control module, Figure 77. The computational control module is responsible for controlling interactions of computational components.

The database contains information about geological block model, the given extraction sequences, and the task schedule. These data are stored in a Microsoft Excel Workflow file. Since the computational control module is coded in Python, a publicly available Pandas library is used to access each cell in the Excel sheets. Big datasets can be readily read and stored in DataFrames with the help of Pandas library.

The Discrete Event Simulation model is built in Arena® simulation environment and was already described I WP1. The post-processing module processes the simulation outputs and creates plots and tables. Finally, the control module calculates the differences between the current results with the predefined targets. If another loop of simulation-optimization is required, the new input parameters are suggested to the computational control module.

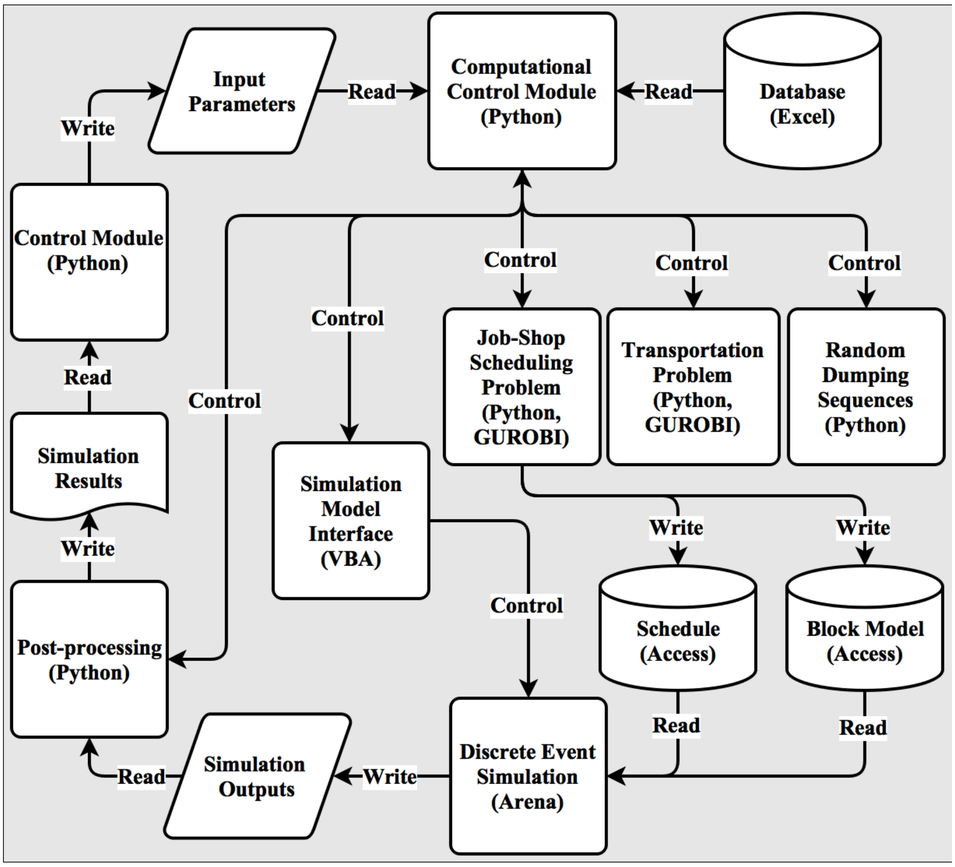


Figure 77: Simulation-optimization platform.

Case Study

To demonstrate the performance of the proposed simulation based optimization approach, a real case study has been developed. A schematic view of the Hambach mine was already provided in WP1. In total eight bucket-wheel excavators (BWEs) have to be scheduled to serve continuously seven spreaders with waste materials and two bunkers with coal. Each BWE excavates either coal or waste in terrace cuts and transfers materials to the face conveyor belt, which carries it along the bench to the main conveyor belt. All excavated materials of the eight benches are distributed to their destinations at the mass distribution centre. Based on a predefined daily schedule, waste is distributed to the seven spreaders for dumping, and lignite is forwarded to two coal-bunkers.

Problem

Waste materials at the Hambach mine are categorized in three types of mixed soils, mixed soils type1 (M1), dry mixed Soils type2 (M2T) and wet mixed soils type2 (M2N). The extraction of M2 type materials is increasingly facing deficiencies in output due to difficult mining materials. This type of soil, specifically M2N, exhibits a high share of cohesive components and is difficult to drain. M2N material cannot be used for stable dump construction and needs to be filled in between prebuilt polders constructed of dry material. The fact that only a limited quantity of these unstable mixed soils can be placed in the waste dump causes downtimes and bottlenecks in the placement process on the dumping side.

Furthermore, historical data show that next to scheduled maintenance, breakdowns of the equipment occur in a random manner. Due to the "in series" system configuration, equipment units feeding or are connected to the ceased equipment are blocked and set out of the operation while the maintenance is being done or the failure is being repaired. In addition, because of the multi-layer nature of the deposit, changes from one material type (e.g. M1) to another material type (e.g. M2N) or vice versa happens very frequently. Each time a material change takes place, the BWE stops excavating. The combined effect of random equipment breakdowns and frequent changes in extracted materials, makes the prediction of the exact material flow rate at any given future time span as a major source of uncertainty.

The objective is to optimize dispatch decisions to decrease downtimes/increase efficiency of excavators and spreaders by effective resource allocation while ensuring stable dump construction using a proposed simulation based optimization approach. Here, decisions on the dumping side are the length of polders to be built while on the extraction side, decisions are production rates of excavators and their connections to spreaders.

Results

The initial set of parameters is set and 1000 random dumping sequences are created. The transportation model is built; in the first and second iterations of simulation-optimization, there was no feasible solution. After 10-th iteration, which in every iteration input parameters have been altered, 464 feasible production schedule were found. For the demonstration purpose, one of the Gantt-Charts is presented in Figure 78.

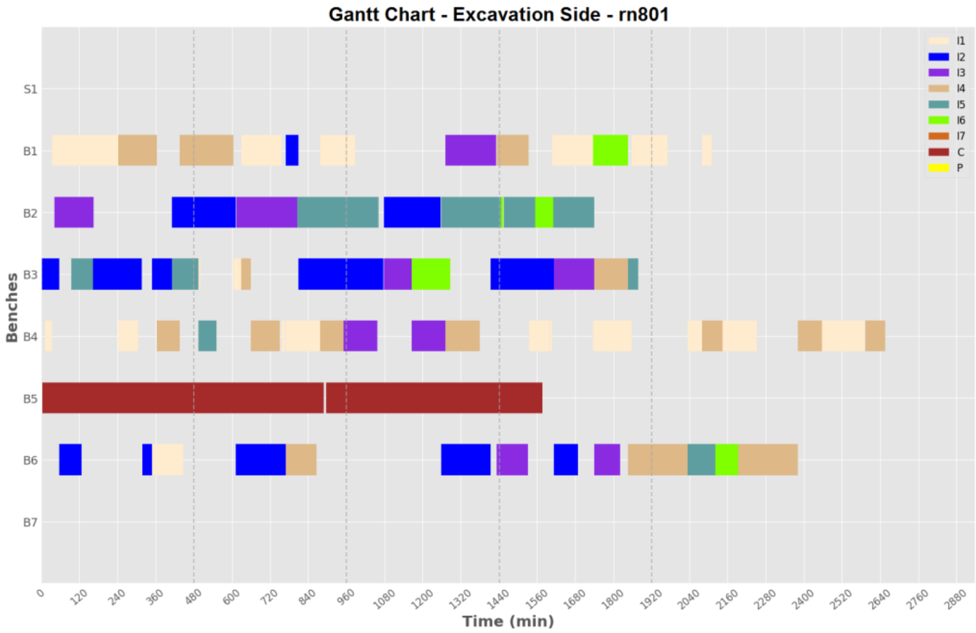


Figure 78: A feasible Gantt-Chart.

Out of these many feasible solution, based on the below mentioned performance measures, a number of solutions are chosen as *n* best-solutions to be tested in Arena®:

- gantt-charts,
- utilizations of excavators (Figure 79),
- utilizations of spreaders (Figure 80) and
- busy and total available hours.

The aim of this selection is to find solutions with higher and realistic utilization (more rebust). This is due that if the utilization is equal to 97%, for instance, there is a high chance that will not happen in the reality when the unscheduled breakdown behaviour is added to the model in the simulation. This can be true for the spreader as well. The selected schedules are run in Arena® and the result of the best schedule is presented in Figure 81.

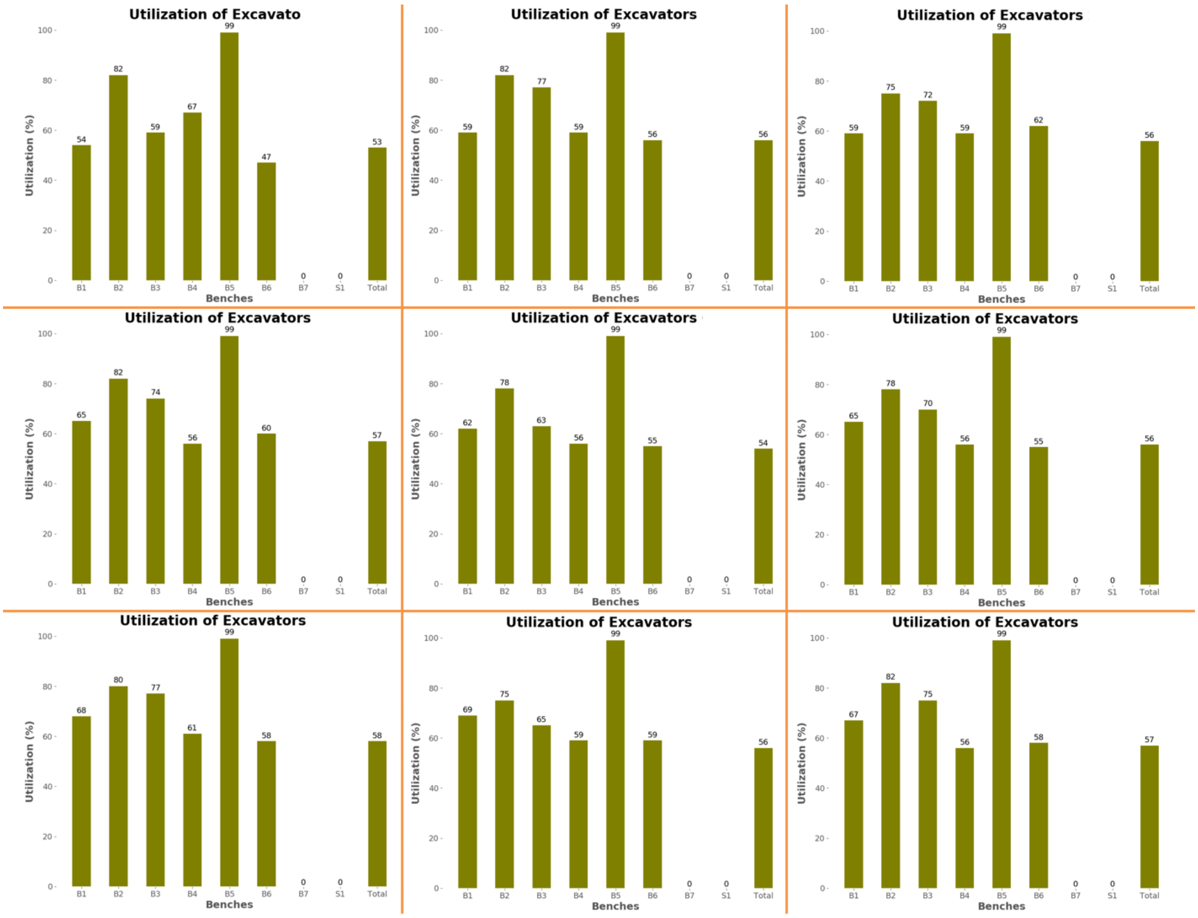


Figure 79: Utilizations of nine different feasible schedules, output of optimization block.

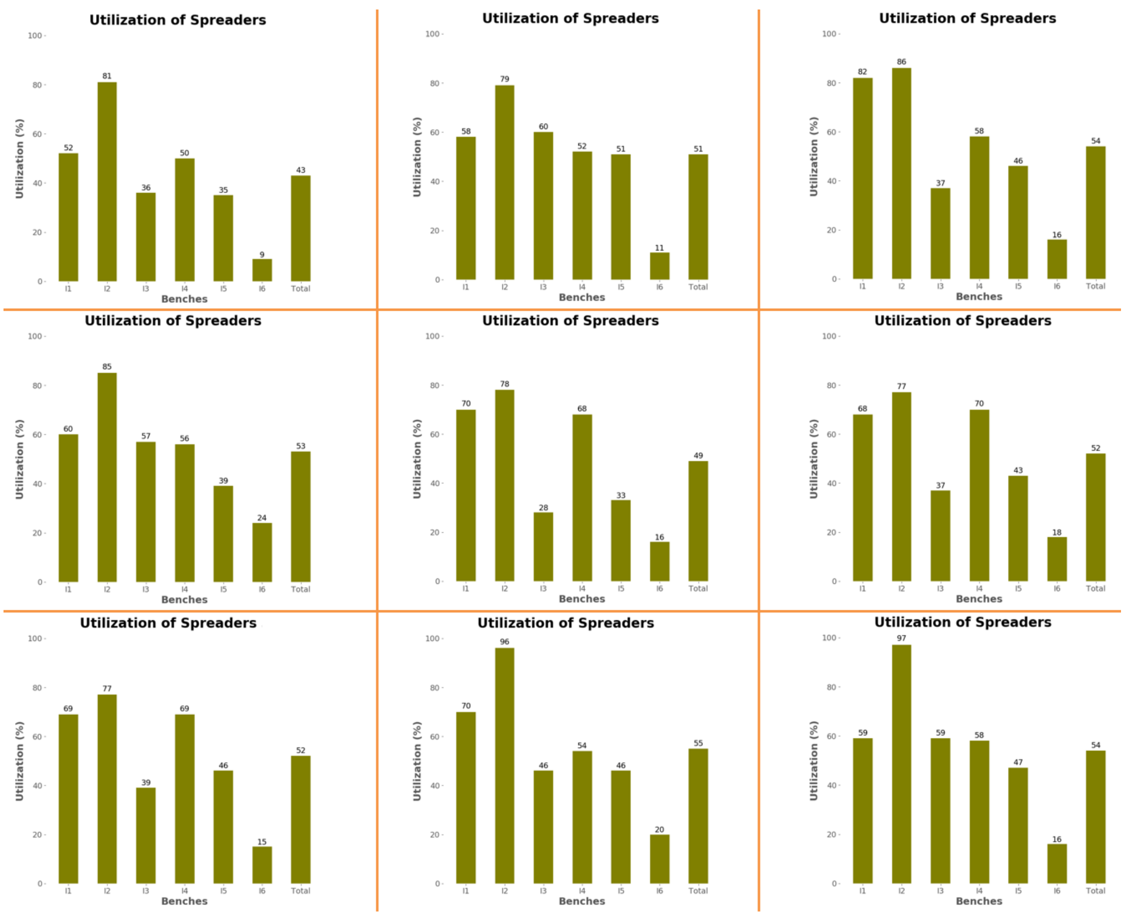


Figure 80: Utilizations of nine different feasible schedules, output of optimization block.

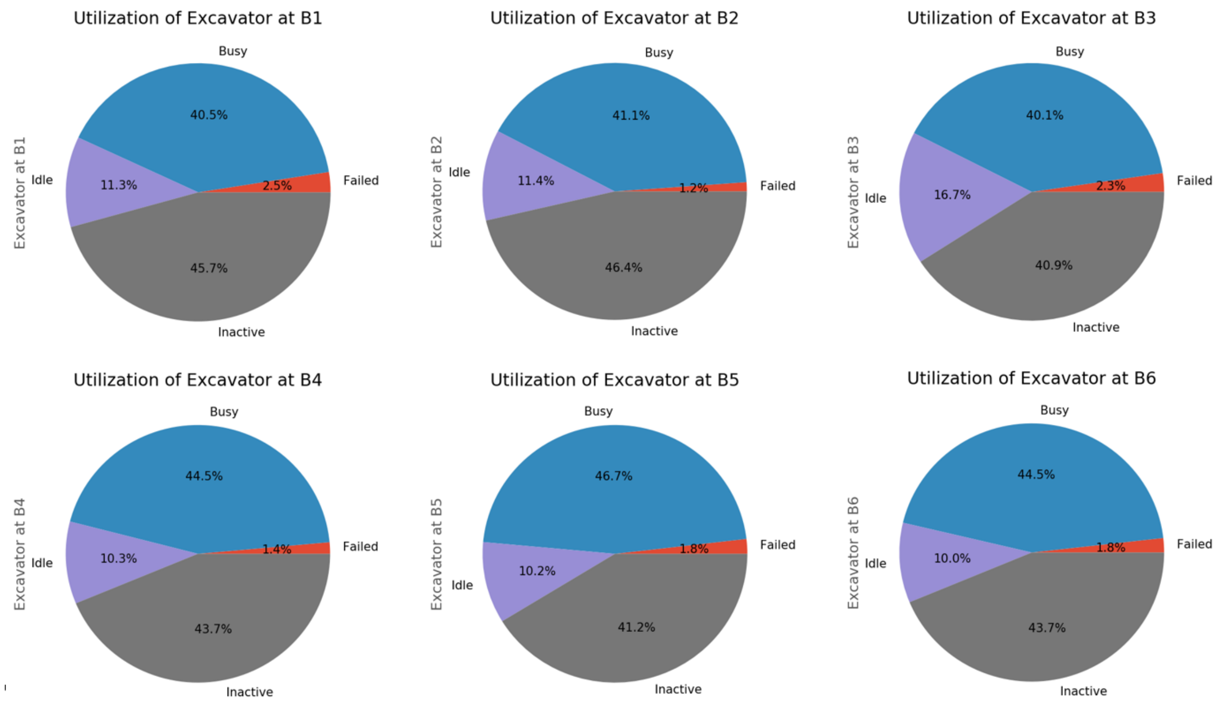


Figure 81: Utilization of excavators after running in Arena for the best schedule.

Work Package 6: Integration and Strategic Decisions

Task 6.1: Integration of all interfaces defined in Work Package 1 to 5 to a framework and set up a field test application in a large mine.

For the test case Profen mine of MIBRAG mbH, a complete closed-loop-system has been implemented. ICT-Interfaces between operational control and planning systems have been defined and implemented. For a defined period, the updating algorithm developed in WP 2 and 3 has been implemented for updating the coal quality parameter ash content in a short-term planning model. The updated model forms the basis for the developed short-term optimizer related to weekly job scheduling of major equipment and monthly extraction sequencing. With this implementation, a closed-loop-system is available that continuously updates the coal quality model based on production monitoring data and provides informed decision support for short-term coal quality control. This test case will be used for investigations in Task 6.2 and 6.3.

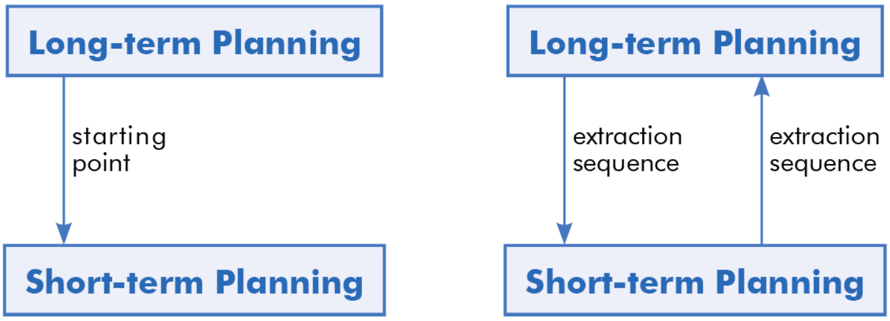
Task 6.2: *Integration of the long-term and short-term planning approach as an iterative process to proactively study feasibility of short-term operations within the framework of the long term mine plan.*

The basis for this task are the optimization models for long- and short-term mine planning developed in tasks 4.2 and 5.3 respectively. Thus far, each optimization model covers a specific planning horizon and determines a mine plan obeying technical constraints (Table 13 But there is hardly any interaction between the models.

Table 13: Characteristics of the long- and short-term mine planning optimization models.

	Long-term mine planning model	**Short-term mine planning model**
Task	Life-of-Mine Plan	Monthly Mine Plan
Objectives	▪ meeting yearly or monthly coal tonnages and grade targets ▪ defining the overall advancement of the mining ▪ operation/extraction progression ▪ maximizing the monetary value	▪ meeting weekly coal tonnages and grade targets ▪ obeying priorities set by long-term planning
Constraints	▪ equipment availability and capacities (production rates) ▪ precedence relationships between benches (minimum spacing distances to ensure structural stability) ▪ precedence relationships within a bench	▪ planned equipment's maintenance schedule (equipment availability) ▪ equipment capacities (production rates) ▪ precedence relationships within ▪ a bench ▪ required equipment downtimes while belt shifting occurs
Decisions	▪ extraction sequence in different benches ▪ blending of different coal products	▪ extraction sequence in different benches ▪ belt shift scheduling ▪ blending of different coal products
Time Step/Bucket	years or month	weeks

Therefore, the aim of this task is twofold. First of all, the short-term planning model is extended to include plan compliance to the long-term mine plan (which is determined based on the extraction sequence differences of the long- and short-term plan). Secondly, the long-term planning model is modified to feedback information obtained from short-term planning (Figure 82 b)). This will enable the mine planner to investigate different scenarios, learn more about the impact of the deposit's geological condition on the extraction planning process, and make well-founded decisions about the extraction sequence etc.



a) b)

Figure 82: Interaction of the developed optimization models: a) without integration additions (Task 4.2 and 5.3); b) with integration additions (Task 6.2).

To create an integrated long- and short-term mine planning framework, the short-term planning optimization model needs to be extended to incorporate information from the long-term mine plan. There are different ways to do this as illustrated in Figure 83.

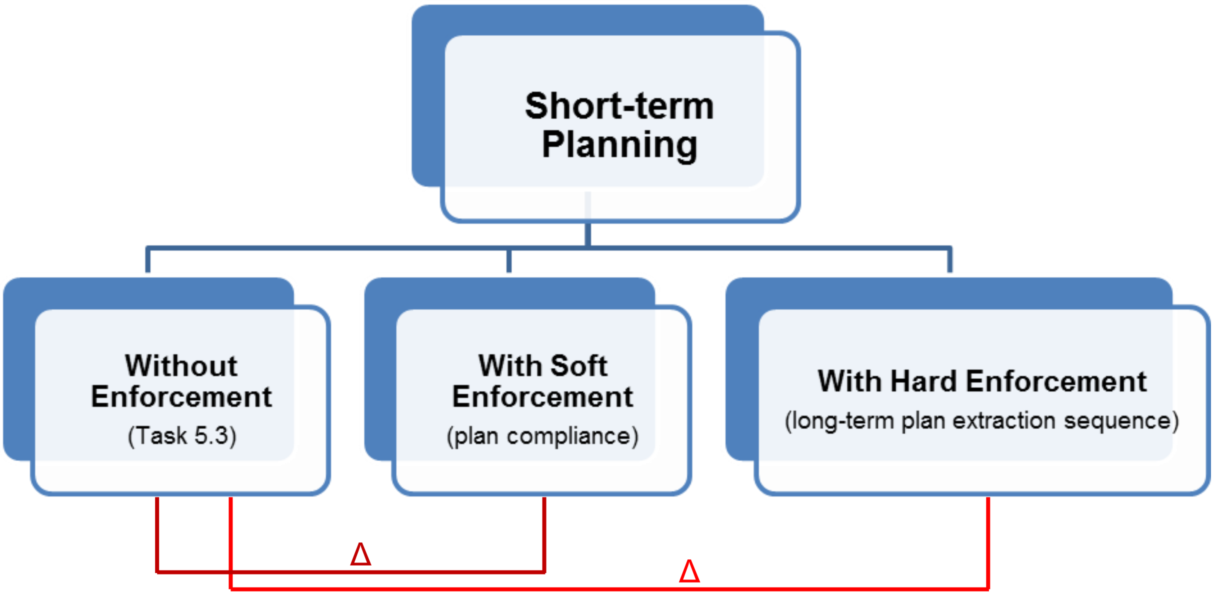


Figure 83: Overview of the different short-term optimization planning models.

<u>Hard Enforcement</u>

The long-term mine plan/extraction sequence is provided to the short-term optimization model as input and is integrated into the model as a hard constraint. Since long-term planning already defines during which month a block of the long-term block model is scheduled for extraction, the short-term optimization problem is reduced to a problem of deciding during which week of the scheduled month the corresponding blocks of the short-term block model are supposed to be minded.

<u>Soft Enforcement</u>

The long-term mine plan/extraction sequence is provided to the short-term optimization model as input and is integrated into the model as a soft constraint, namely the plan compliance.

Deviations from production targets (Δ_p^t) and the plan compliance penalties m_{kt}^+, m_{kt}^- shall be minimized when excavating material from the mine according to the plan. Production targets are in terms of coal tonnage ($O_{target_p}^t$) and coal quality ($Q_{min_s}^p, Q_{target_s}^p, Q_{max_s}^p$) to ensure the reliable and continuous delivery of in-spec coal to the customers. (For more details, please refer to deliverable 5.3.)

A mine plan created with this optimization model will give the mine planner an optimized short-term plan that might disregard the long-term specifications for individual time steps if the mine plan would have been intractable otherwise because of local difficulties resulting from the deposit's geological condition. As a result, the generated short-term mine plan will be feasible but changes would need to be made to the long-term plan to account for these deviations. How that can be accomplished will be explained in the next step in detail.

To create an integrated long- and short-term mine planning framework, the long-term planning optimization model needs to be extended to incorporate information from the short-term mine plan. There are different ways to do this as illustrated in Figure 84.

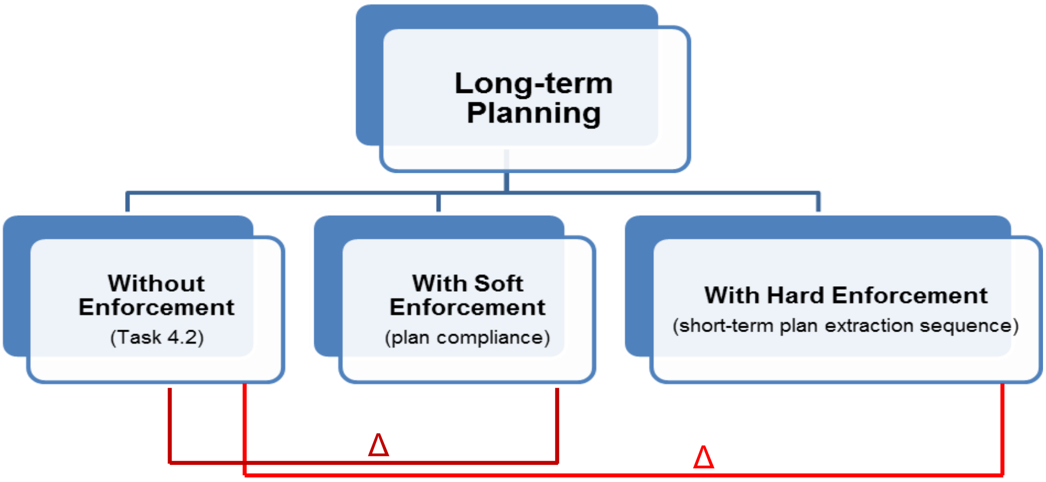


Figure 84: Overview of the different long-term optimization planning models.

<u>Hard Enforcement</u>

The short-term mine plan/extraction sequence is provided to the long-term optimization model as input and is integrated into the model as a hard constraint similarly to the short-term optimization model hard enforcement case.

<u>Soft Enforcement</u>

The short-term mine plan/extraction sequence is provided to the long-term optimization model as input and is integrated into the model as a soft target, a bonus for plan compliance.

The $bonus$-term increases the desirability of long-term extraction sequences respecting the short-term mine plan, making it possible to account for localized changes due to the more detailed knowledge of the short-term model.

The net present value shall be maximized while deviations from production targets (Δ_p^t) shall be minimized when excavating material from the mine according to the plan. Production targets are in terms of coal tonnage ($O_{target_p}^t$) and coal quality ($Q_{min_g}^p, Q_{target_g}^p, Q_{max_g}^p$) to ensure the reliable and continuous delivery of in-spec coal to the customers. (For more details, please refer to deliverable 4.2.)

Case Study

Figure 85 depicts the defined study area. The study area covers slightly more than an eight month mining period. The subdivision of the deposit into mining blocks is based on the applied excavation technology and the planning horizon. Here, lignite is extracted on parallel benches. To reach the bottom of the lowest seam, 6 benches were designed. Bench 1 only contains overburden material and therefore does not influence the benefits of the new quality driven stochastic mine planning approach. Consequently, it is not considered here during optimization. The extraction sequence for bench 1 is a direct consequence of the general slope angle in the mining direction and the result of the scheduled extraction sequences for benches 2 to 6. Any deviation from this would decrease the NPV.

The production target in terms of lignite tonnage is 650 kilo tons per month respectively 160 kilo tons per week. This has to be supplied to the customer with a defined quality bandwidth for the lignite quality parameter ash content.

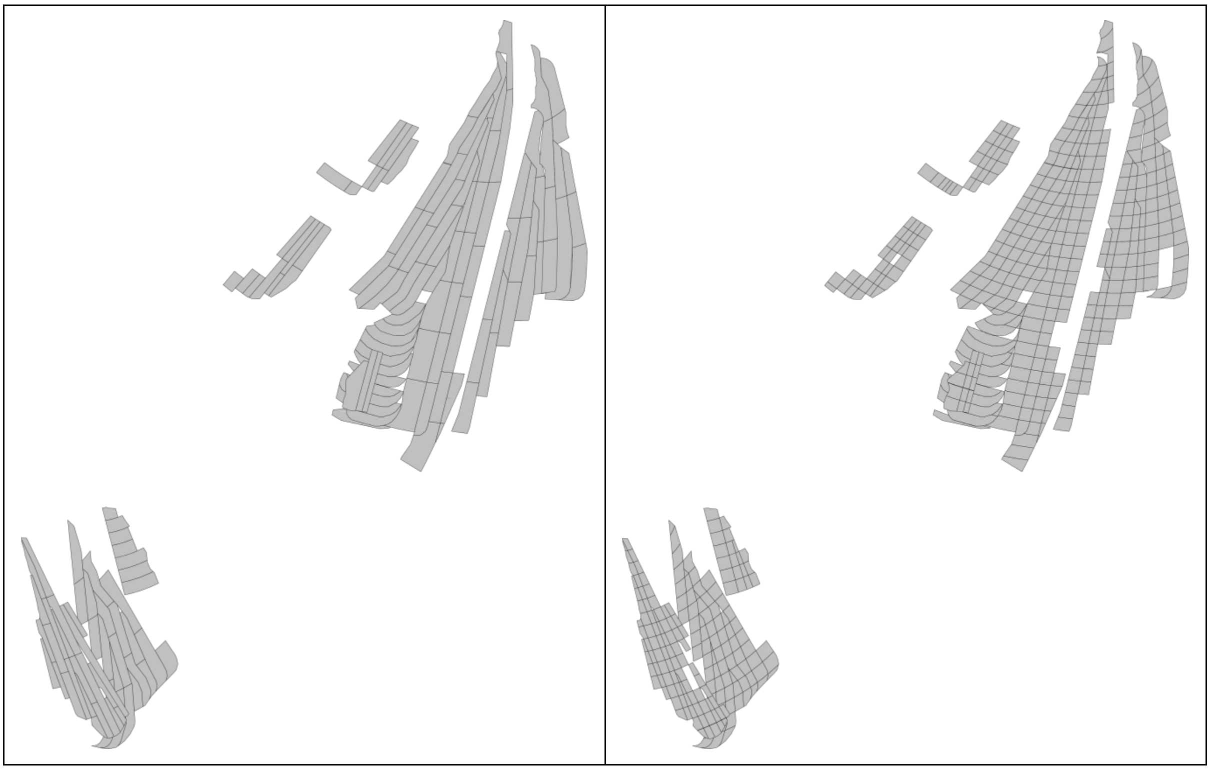


Figure 85: Overview of the long-term (left) and short-term (right) optimization block models.

Figure 85 depicts the experimental setup for the case study of integrating long- and short-term mine planning. First, a long-term mine plane is determined. This mine plan serves as input for the short-term mine planning process in two different ways. The extraction sequence is used to calculate the plan compliance as described in WP 1. At the same time, the extraction sequence is utilized to reduce the size of the short-term optimization model (to reduce the required solution time) by determining which blocks are too far away to get scheduled for mining in the considered short-term mine planning time frame (red arrows). Here, a distance of one and half month is used. That is, if the considered short-term time frame is week 1 through 6, then all blocks scheduled for extraction (in the long-term plan) in months 4 till 8 can be disregarded in the short-term optimization model.

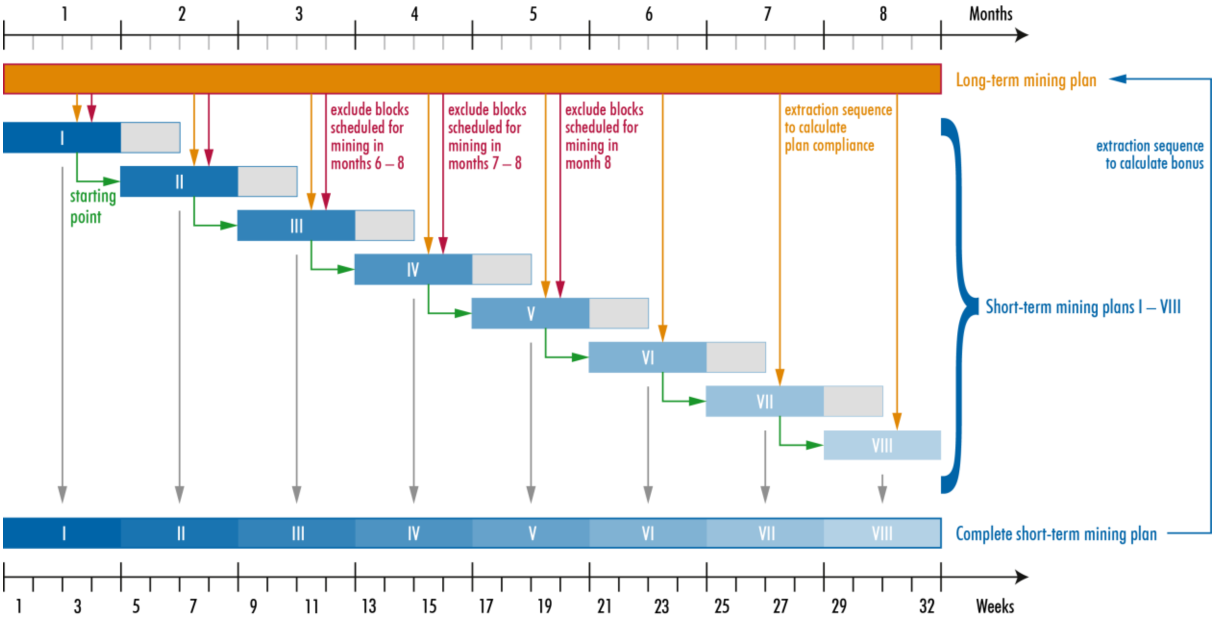


Figure 86: Experimental setup for the case study of integrating long- and short-term mine planning.

The short-term mine planning process splits the optimization task into smaller tasks: For each month, a separate short-term mining plan is determined. Each task considers 6 weeks but the last two weeks of each determined schedule are disregarded to prevent end-of-horizon-effects. To determine the starting point of each short-term optimization task, the determined schedule of the previous month is used as input (green arrow).

After all eight short-term mining plans have been calculated, they are combined to form the complete short-term mining plan and serve as input to the next iteration of the long-term mine planning process to calculate the bonus, which in turn enables the consideration of short-term adjustments to the long-term mining plan as previously described.

Figure 87 shows the results in terms of the long-term and short term plans for the cases (a) without integration and (B) with integration of long- and short-term mine planning. For both planning horizons different extraction sequences are generated, when an integrated approach is used. Figure 88 compares the objective values between the non-integrated and integrated approach for the long- and short-term planning horizon.

For the case of long-term planning the objective value decreases, when an integrated approach is used. This apparent decrease is the expression of the additional constraint of short-term feasibility within the long-term panels. In other words, the slightly decreased objective value considers short-term operational constraints and is thus more realistic.

For the case of short-term planning the objective value increases. This is due to the fact that the short-term plan is guided by the additional information provided by the long-term plan in terms of NPV optimality. The gain in short-term planning can be realized in the operation.

Overall a more robust long-term plan is available, the corresponding short-term plan is able to generate a better financial result.

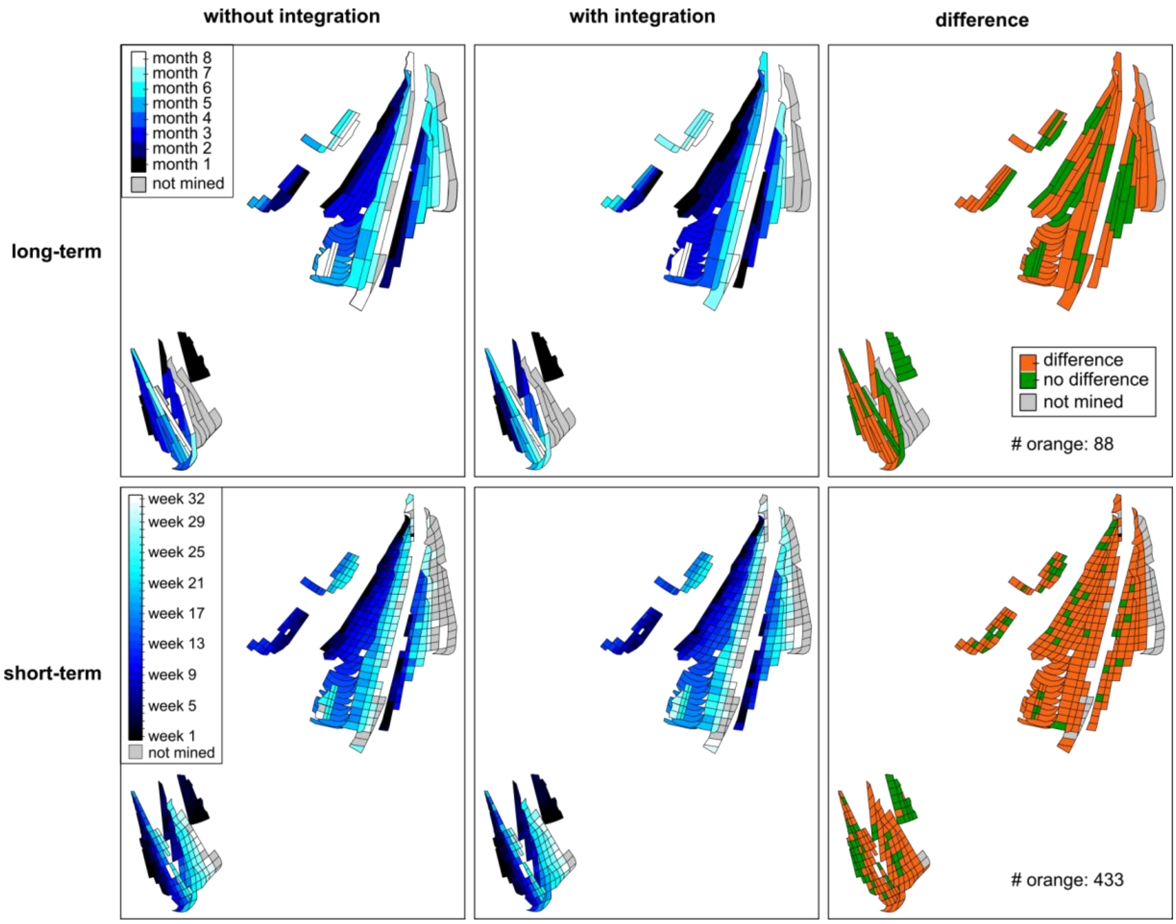


Figure 87: Comparison of extraction sequences (short- and long-term) between a non-integrated and an integrated planning approach.

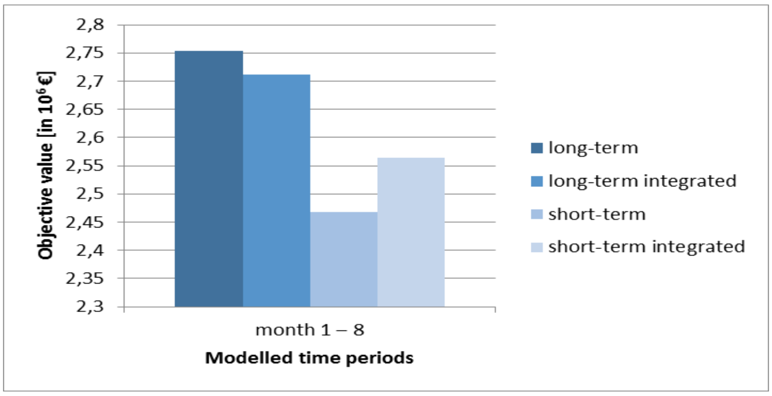


Figure 88: Comparison of objective values for both planning horizons (short- and long- term) for the non-integrated and the integrated approach.

Task 6.3: *Quantification of the value of additional information introduced in the planning model during the production phase and develops a top-down framework for integrating and optimizing short-and long-term exploration and data-gathering.*

Task 6.3 aims to quantify the benefit in terms of the value of additional information introduced in the planning model during the production phase. Deliverables in WP3 and results from Task 6.1 provide a validation and a demonstration in a full scale lignite production of the real-time updating framework. This deliverable indicates the economic impact determined by application of the resource model updating framework.

One of the most well-known tools for assessing the value of additional information added into the system is the Value of Information (VOI) [37;38;39]. In the last decades, VOI gained high popularity in many different fields. A few applications also appeared in the mining industry. [40] make no explicit reference to VOI, yet they discuss the potential benefits to decision makers of gathering information in the mining industry. Barnes [41] applied VOI to incorporate geostatistical estimation into mine planning. More recently, Phillips [42] provided a case study where a VOI decision framework was applied to provide guidance for mine managers regarding the purchase of ore grade scanners.

The essence of the technique is to evaluate the benefits of collecting additional information before making a decision [43]. When using the resource model updating framework, this decision making process would change the short-term mining plan by using a mine optimizer. If the resource model always provides correct coal quality attributes it would deliver perfect information, otherwise it is known as imperfect information. The latter is usually the case in geoscience applications, since the reality is unknown. The resource model updating framework aims to carry forward the current situation from imperfect information to an “improved” imperfect information state, where the current situation lies somewhere between the Perfect Information and previous Imperfect Information (Figure 89). Every updating iteration brings the previous Imperfect Information closer to Perfect Information.

The expected benefit of additional information (integration of the online-sensor measurement into the resource model) is compared to a case where there is no additional information integrated into the process. These benefits are evaluated based on the economic impact, for example the monetary values such as cost per shift, determined by applying the resource model updating framework in the mine planning process.

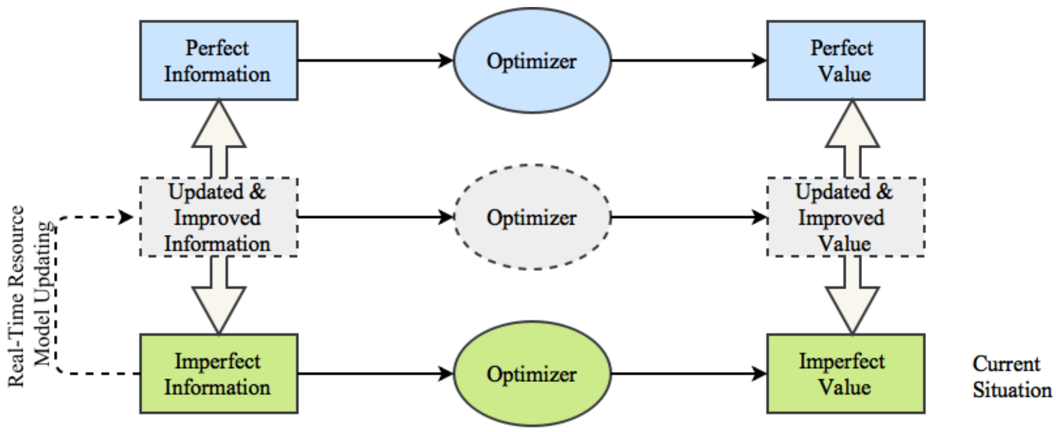


Figure 89: Aim of the resource model updating framework.

For the evaluation, the updating framework was utilized as developed within WP3 and the short-term optimization framework was utilized as described in WP5. Both were operationally implemented and integrated to a full closed-loop-concept in Task 6.1. Value of Information (VOI). For the case study, the value of information for the two coal quality control decisions and optimization tasks, considered within this project, have been evaluated:

- Weekly job scheduling of excavators as described in Task 5.3 and
- Monthly sequencing of extraction blocks, as described in Task 5.3.

The value of information (VOI) concept is used to understand what is gained by integrating the online-sensor measurement data into the resource model when using the updating framework. In general, VOI is calculated in the following manning [43]:

$$\mathrm{VOI} = \begin{bmatrix}\text{Expected value with}\\ \text{additional information}\end{bmatrix} - \begin{bmatrix}\text{Expected value without}\\ \text{additional information}\end{bmatrix}$$

The concept analyses the value of the resource model updating framework's ability to improve the prediction of coal quality parameter, namely the ash percentage (ash%). For this, the expected value of the posterior model ($V_{posterior}$) is compared to the prior model's expected value (V_{prior}). In the present application, the calculation of VOI translates as following:

$$\mathrm{VOI} = V_{posterior} - V_{prior}$$

In mining the monetary value is an important KPI that can also be used to determine an economic impact.

$$\mathrm{VOI}_{economical} = |C_{posterior} - C_{prior}|.$$

The performed research focused on the costs of deviating from the target quality (ash %) during production. Calculation of this KPI is given in the following: Let the costs of deviating from the target production quality when executing the mine plan on the prior model be C_{prior} (€), the costs of deviating from the target product quality per ton of coal is D_{prior} (€/ash% x t), the amount of the deviation in quality is d_{prior} (ash%) and, finally, the amount of the deviated coal is t_{prior} (ton). Similarly, when executing the mine plan on the posterior model, the previously defined parameters are; $C_{posterior}$, $D_{posterior}$, $d_{posterior}$, and $t_{posterior}$ respectively. Then, the costs of deviating from the target production is:

$$C_{prior} = D_{prior} * d_{prior} * t_{prior}$$

The VOI concept considers the value of perfect and imperfect information. Perfect information refers to perfectly reliable information; thus it contains no uncertainties. Perfect information rarely exists, but it provides a best-case scenario for the value of information and it defines an upper limit on the value of additional information [42]. In the context of this research it would answer the question: ‘How much better would the economic aspects of an optimized mine plan be executed after knowing the coal seam geometries and coal quality distributions?”. Since perfect information is not available in this case study, the updated model integrating the most information (posterior model after full updating) will be used to benchmark, and the value of additional information will be evaluated.

Case Study

The experiments performed in this case study calculate the expected values for different resource model based experiments (Figure 90). The base case resource model, namely the prior model, is without any additional information. The other resource models are with additional information and therefore called posterior models. They are created simply by applying the resource model updating algorithm to the prior model. In total, there are five different posterior models which are updated within different time periods:

- The posterior model which resulted from updating the prior model over the 19 July – 1 August period.
- The posterior model which resulted from updating the prior model over the 19 July – 4 August period.
- The posterior model which resulted from updating the prior model over the 19 July – 7 August period.
- The posterior model which resulted from updating the prior model over the 19 July – 10 August period.
- Finally, the posterior model which resulted from updating the prior model over the 19 July – 13 August period.

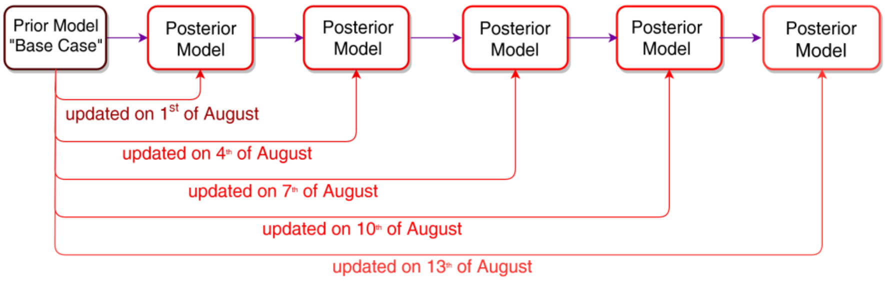


Figure 90: Resource models that are used in the experiments.

The posterior model, which resulted from updating the prior model of case 1 over the 19 July – 13 August period is assumed as the most precise model since this is the most up-to-date resource model created with the highest amount of exploration data and therefore serves as a benchmark.

Optimization Case: Weekly job scheduling of excavators

The optimization task was used as described in Task 5.3. The aim is to schedule the shifts, in which the several excavators are active in a way to minimize deviations from coal quality targets, in particular ash content. Deviations are penalized per unit and a penalty over the week can be calculated, which serves as input into the VOI calculation.

The experimental setup for the calculation of the VOI is shown in Figure 91. Results in terms of costs related to deviations from ash targets for the prior model, the updated models and the benchmark case are presented in Figure 92 for each of the updating periods. Figure 93 shows the resulting graph of the development of the VOI over the updating periods. A benefit of up to 10.000 Euro can be realized per week and only related to the task of excavator scheduling, when using an additional data from production monitoring during job scheduling.

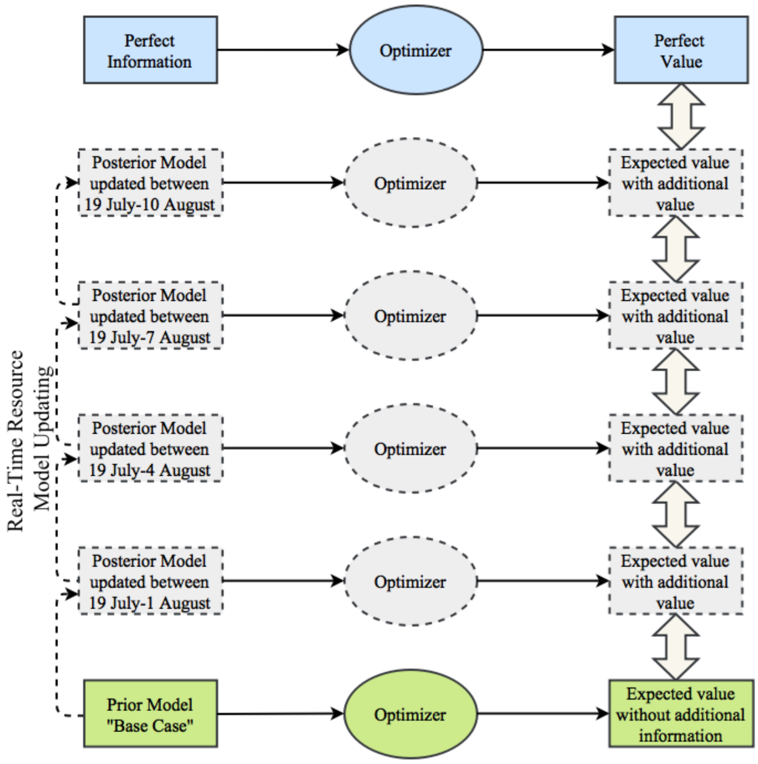


Figure 91: VOI - Experimental scheme for short-term mine planning.

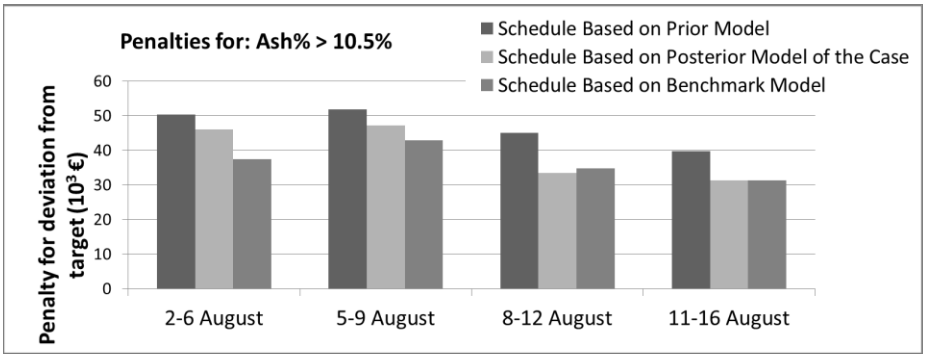


Figure 92: Cost calculations of deviating from the target quality (ash %) - Case 1.

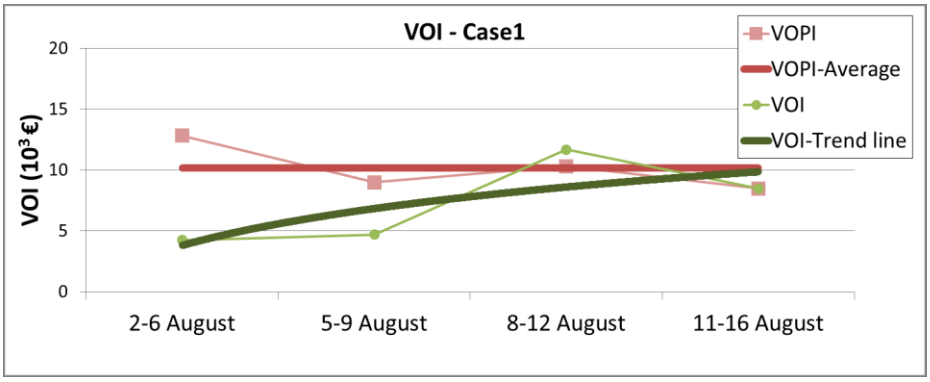


Figure 93: VOI - Optimization Case: Sequence scheduling

The optimization task was used as described in Task 5.3. The aim is to schedule the extraction sequence during the next week or months of mining blocks in order to achieve coal quantity and quality targets. Deviations are penalized per unit and a penalty over the week can be calculated, which serves as input into the VOI calculation.

The optimizer is applied to a selection of the resource models, which defined different updating stages. In total ,there are five different optimized mining plans for an optimization period of 4 weeks, 2-29 August:

1. Optimized mining plan achieved by applying the optimizer to the prior resource model.
2. Optimized mining plan achieved by applying the optimizer to the posterior resource model (which is updated between 19 July - 4 August).
3. Optimized mining plan achieved by applying the optimizer to the benchmark resource model (which is updated between 19 July - 13 August).

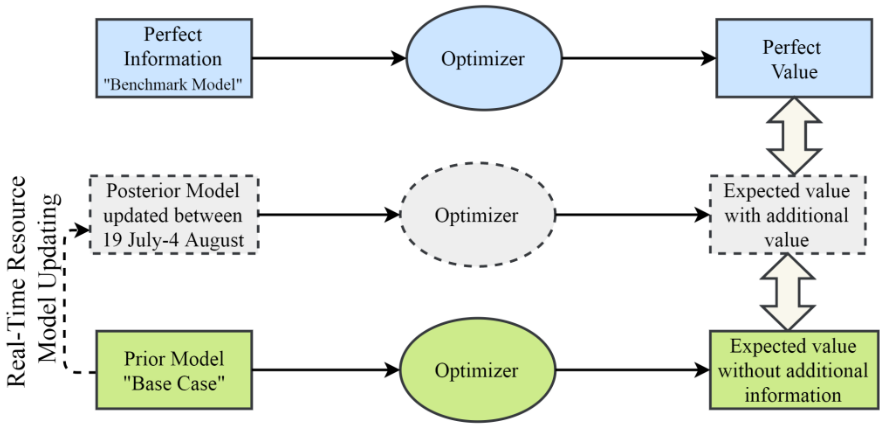


Figure 94: VOI - Experimental scheme for mid-term mine planning.

Next, these obtained best schedules are applied to the benchmark resource model (Figure 94). This is done in order to see the improvements during the mining operations, when using the prior model, the most current model and the benchmark model. Similarly, to the short-term mine planning experiments, the benchmark model is assumed to be the reality since it is the most up-to-date and therefore the most precise resource model. An approximation of VOPI is calculated between the benchmark and the prior model whereas the VOI is calculated between the posterior model (4th August model; updated between 19 July-4 August) and the prior model for
cases 1 and 3.

The optimized mining plans and their differences to the benchmark model's mining plan are presented in Figure 95. Using these mining plans and applying them to the benchmark model's resource model, the resulting lignite's ash content is calculated for each time step and each realization of the benchmark resource model (Figure 96).

Based on this information, the penalties for deviations from the target ash value were calculated and are presented in Figure 97.

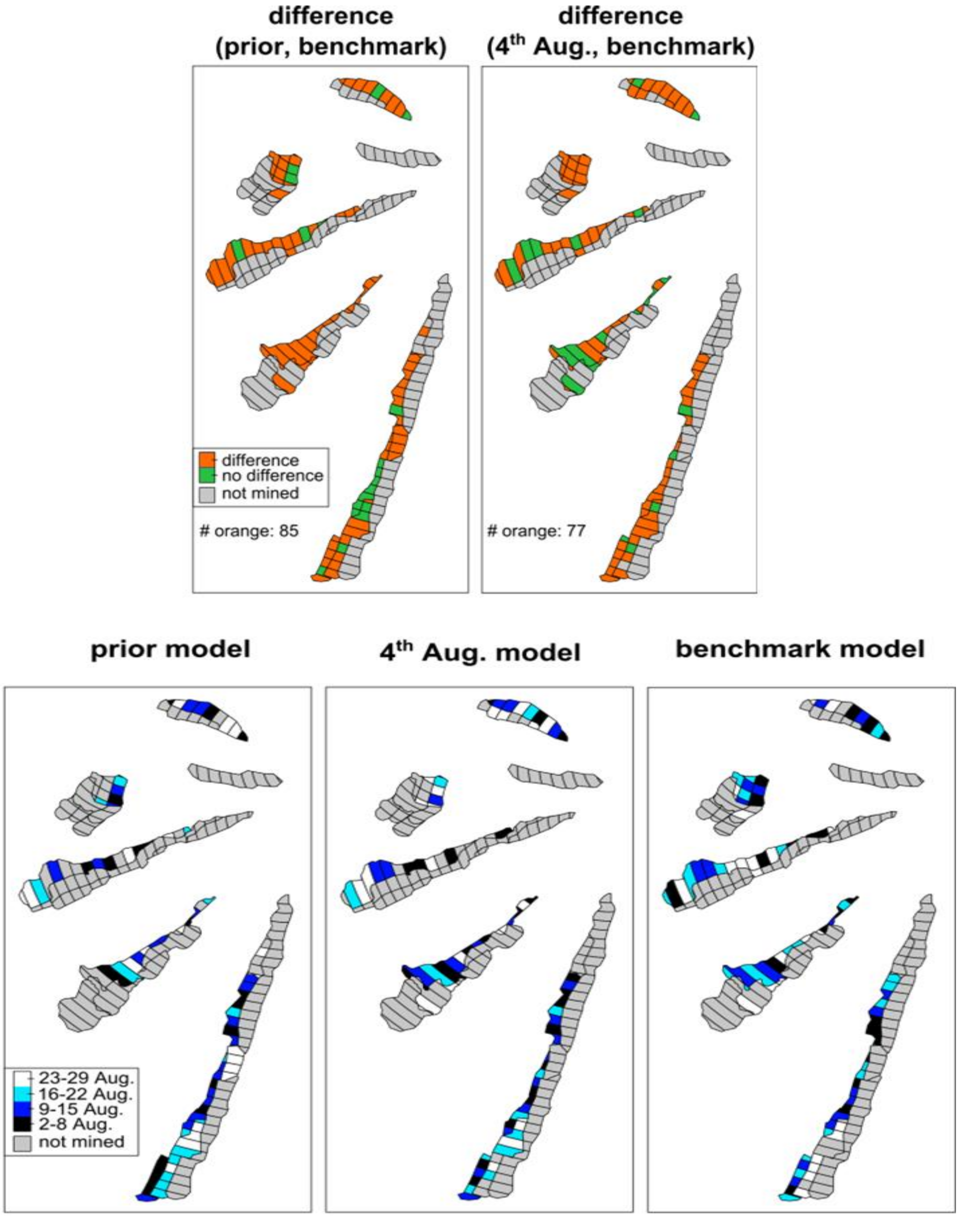


Figure 95: Illustration of the optimized mining sequences and differences to the benchmark model - Cases 1 and 3.

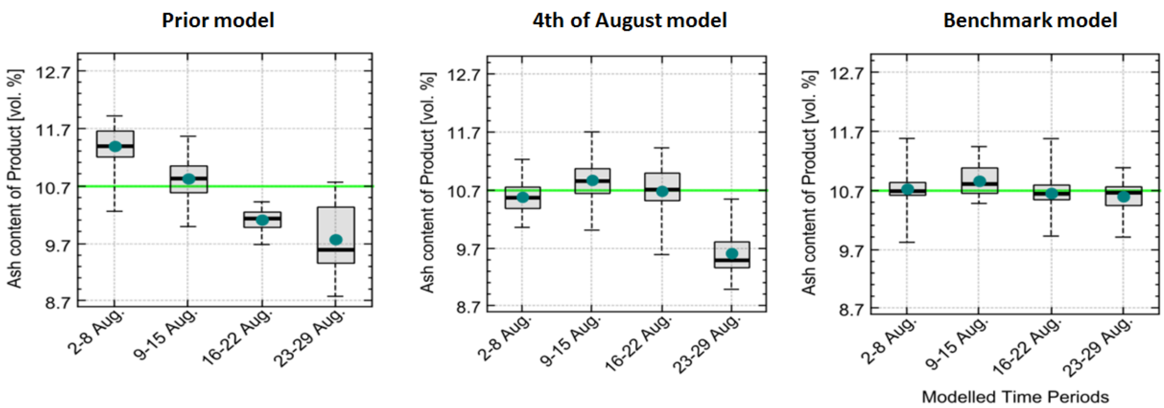


Figure 96: Box plots for quality ash of the weekly scheduled lignite.

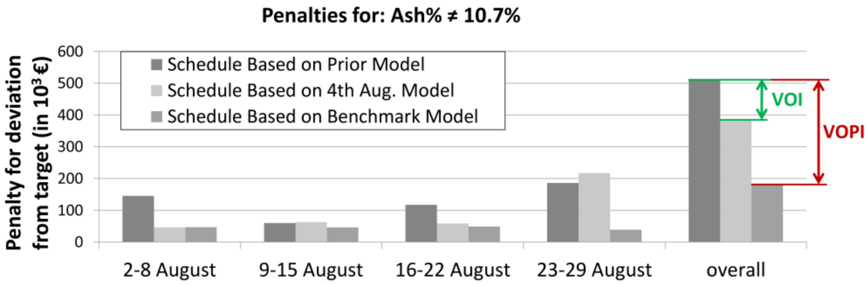


Figure 97: Cost calculations of deviating from the target quality (ash %).

Figure 95: Illustration of the optimized mining sequences and differences to the benchmark model - Cases 1 and 3.95 shows the optimized mining sequences for the three different mining plans calculated by the optimizer. It is expected to observe more mining sequence differences between the mining plans created using the prior and the benchmark resource model than between the mining plans created using the benchmark and the posterior (updated till 4 August) resource model. A difference in the mining sequence means that either a block is scheduled for mining in different extraction periods in the two mining plans in question or that a block is scheduled for mining in on mining plan but not in the other.

Figure **96:** Box plots for quality ash of the weekly scheduled lignite. presents the lignite's ash content for each time period calculated by applying the optimized mining plans to the benchmark resource model. When the optimized mining plan is calculated based on a more accurate/up-to-date resource model, the following observations can be made:

- a better fitting of the average ash values to the target ash value of 10.7% is achieved,
- a better fitting of the average ash values into the target ash value area (defined from 0-15%) is accomplished, and
- a decrease in the uncertainty range is attained.

To quantify these findings and the VOI, penalties for deviating from the target ash value are used (Figure **97:** Cost calculations of deviating from the target quality (ash %).97).

The darkest column represents the calculated penalties for the best mining plan, which is optimized based on the prior resource model and later this mining plan is applied to the benchmark resource model. The lightest column represents the calculated penalties for the best mining plan, which is optimized based on the posterior resource model (4th August) of that case and later this mining plan is applied to the benchmark resource model. The medium darkest column represents the calculated penalties for the best mining plan, which is optimized by using the benchmark resource model and later this mining plan is applied to the benchmark resource model. It is expected to observe a decrease in penalties when the optimized mining plan is calculated based on a more accurate/up-to-date resource model.

It can be concluded, that just for the task of sequencing mining blocks during weekly planning, a VOI of approximately 25.000 to 30.000 Euro can be realized per week, when using additional production monitoring data. This is related just to the ash quality parameters using conservative coast assumptions.

Combining both case studies it can be concluded that over a year VOI of approximately 1.500.000 Euro to 2.000.000 Euro can be realized annually when considering only these two control options and only one coal quality parameters. The benefit of a multi-mine operation combined with a full application may be significant higher.

Furthermore, for every minute that the excavator needs to work in addition due to non-optimality of the mine plan, CO_2 will be released unnecessarily. This is unsatisfactory not only for the environment but also for the cash flow and profits.

2.4 Conclusions

The overall aim of the RTRO-Coal was to develop an integrated framework for Real-Time- Reconciliation and Optimization (RTRO) of the production process in large open pit coal mining operations. The research was aimed to progress from the state-of-the-art and develop new methods in stochastic mine system simulation, intelligent data analysis, advanced geological modelling, quantifying geological uncertainty and process optimization. These developments would foster the utilization of all relevant ICT-based data and information available along the production process and integrate them in a real-time manner to optimize production of in-spec coal products as required in the subsequent value chain. With this aim, results are expected to have a significant impact towards the digitization in the mining industry.

Concluding based on the results presented before it can be stated the overall aim has been achieved. Methods for

- process simulation in large continuous mining operations
- updating resource models based on operational monitoring data
- risk based long- and short-term optimization integrating geological uncertainty

have been theoretically developed, verified in controllable environments and validated in full industry case studies. Further, the operational implementation demonstrated the benefit of the integrated closed-loop-framework with a significant economic potential of multiple Mio. Euro per year for the specific test case.

Following conclusions are presented in a logical order and not necessary in the order of WP's.

- *Discrete Event Simulation* is a valid tool for evaluating short-term production schedules of continuous mining operations with respect to defined KPI's. In particular, the prediction of coal qualities and quantities to be expected and also excavator and system utilization can be realistically assessed. Limits of the simulator with respect to the timely and spatial resolution of the used reserve block model are mainly due to complex geological features, which short-term behaviour can hardly be captured. Therefore, the smallest digging unit in a deposit for the cases is defined as a mining block (MIBRAG) or a mining slice (RWE). (WP1)
- The technique of conditional simulation can be efficiently applied to coal for generating multiple possible scenarios of the spatial distribution of critical attributes within the deposit based on data available. Efficient algorithms, such as the Generalised Sequential Gaussian Simulation, in combination with a transparent validation procedure guarantee realistic results in terms of mapped variability and uncertainty. (WP4)
- The combination of modelled geological uncertainty with the Discrete Event Simulation of the mining process results in a more realistic prediction, which avoids local biases introduced by traditionally used smoothed estimated models. The predicted uncertainty ranges for KPI's based on modelled geological uncertainty coincides well with observed deviation characterized by its amplitudes and corresponding frequencies. (WP1)
- Kalman-Filter approaches are well suited to integrate online production data in the short-term resource model of lignite deposits. For applications related to coal attributes, which behave typically non – Gaussian, a modified approach is proposed tested and validated, named the Normal-Score Ensemble Kalman Filter. It updates ensemble members generated by conditional simulation individually and allows to integrate more complex observation models linking the resource model and the sensor measurement. (WP2-3)
- Full scale demonstration cases in two different mining applications have shown that the updating of the short-term resource model can result in a decrease in uncertainty by an order of up to 40% for neighbouring blocks, which will be excavated in the next shift, days or weeks. The method is flexible and performs well even if multiple excavators mine simultaneously and one sensor measures the combined material flow. It is expected that this increase in prediction confidence leads to better decision making. (WP2-3)
- For short-term optimization of production scheduling simulation based optimization approached appear to be most suitable. The combination of the simulator (WP1) with meta-heuristics like

genetic algorithms, simulated annealing, ant colony optimization or tabu search and also hybrid methods combining strength of individual meta-heuristics promise to provide an efficient way of fast exploring the solution space for fining improved decisions in task scheduling and block sequencing in continuous mining operations. (WP5)

- Three typical applications for short-term optimization in large continuous coal mines have been investigated, which are the monthly block sequencing for coal quality control, weekly job scheduling for excavators and production control for waste material management on a shift base. For all three cases, the optimizer framework has been developed, implemented and demonstrated. Results demonstrate the significant value, these optimization methods can generate in terms of improved economic and environmental performance.

- The operational implementation showed that the methods developed within RTRO-Coal can easily be integrated in typical operational control systems, available as state-of-the-art in typical lignite mines. Methods have been simplified for practical use.

- The full operational implementation of the closed-loop-framework in a case study illustrated its ability to:

    - produce more robust mine plans on both, the short- and long-term basis

    - produce feasible long-term mine plans that obey constraints imposed by short-term activities and unexpected deviations from expectations

    - create significant upside potential in the order of multiple million Euro

when online information, typically available at mining operations, are intelligently used by feeding them back in decision making models in a real-time manner and thus allow improved decision making on a rapid timely basis. Thus, the results of RTRO-Coal contribute to the currently ongoing digital revolution by providing validated and demonstrated methods and algorithms for utilizing available online data from production monitoring for improved production control, in other words:

"...to turn online production monitoring data into operational intelligence"

2.5 Exploitation and impact of the research results

Applications, Value proposition and Impact

The RTRO-Coal solution enables full utilisation of product quality data as well as other production monitoring data through real-time updating of the resource model. The updated model is more accurate thus allowing optimized planning decisions and increased value extraction from the mineral asset. The improved data utilisation creates opportunities to streamline data acquisition activities and realize related cost efficiencies. Implementing the solution would typically substitute or alter existing business processes and such require only little organizational change. The annual potential to be lifted per operation (extraction to processing) due to a more streamlined quality management are estimated in the order of €500.000 to €5.000.000.

Results of RTRO-Coal have been partly implemented at the Profen mine from MIBRAG and Hamach mine from RWE. In both cases, results of the case study have been very promising and a full operational implementation is planned. Demonstration cases suggested a significant economic benefit and related decreased environmental footprint This directly translated to specific energy usage per ton of coal and also subsequent efficiencies of power plant technology, which is linked to an improved efficiency and decreased CO2 emissions in a similar order of magnitude. In addition, a corresponding decreased spatial footprint is expected as a result of streamlined desulfurization plants and waste management.

In general, results of RTRO-Coal provide an innovative solution for continuously improvement of spatial geo-models based on online-monitoring data and couple these models with fast decision support systems for mine production control. Having this solution available, related fields of application can be explored, such as geo-mechanical models used in geo-mechanical ground control geo-environmental models used to manage environmental impact of mining such as contamination of water or air. The developed solution facilitates the utilization of big-data and contributed to the vision of a fully automated mine formulated in the vision Mining 4.0.

Potential Markets of the RTRO-Coal solution

The RTRO-Coal solution addresses all industries that rely on spatial geo-models for informing planning decisions. The primary target customer is the global bulk commodity, metal and non-metal mining industry that is producing ore from underground or open pit operations. For a market transfer, following potential customers of the solution could be of interest:

- Bulk mining operations (e.g. coal operations in Europe, iron ore operations)
- Selective mining operations (e.g. gold mining, tungsten mining, polymetallic ore mining) – for this one, research has to be expanded especially on the sensor and resource/grade control modelling side, which is the scope of a currently running European H2020 project Real-Time Mining.

To broaden the scope from initially grade control and resource models to geo-models in general, studies on updating mining induced ground movement predictions based on satellite and ground monitoring data would be of interest, e.g. for a after mine care in german coal mining.

Knowledge transfer activities and way to market

Planned short-courses and training activities

- For the implemented test cases, training activities are planned. The implemented demonstrated are planned to be further exploited in the context of focused studies to increase the understanding of optimal operational implementation parameters and added value in terms of economic environmental benefit.
- Key staff at operation site will be trained. Potentially, operational implementation will be performed at other mine sides.
- In addition, a short-course is planned to be created that will teach the concepts and applications for professional development of staff.

Upscaling using available funding mechanisms

To enter other markets, next o lignite, it is planned to foster an upscaling project in a related field, e.g. underground mining, selective ore mining and also related to geo-mechanical and geo-environmental applications. For this, during the curse of the next months, suitable funding opportunities will be evaluated. The overall aim is to found a start-up that leverages the results of this project.

Dissemination activities, Publications and patents.

From 2013 to 2017 seven key publications have been published in international peer reviewed journals and presented at international conferences. Further, on the basis of scientific work related to the RTRO-Coal project, two PhD studies at TU Delft and one at TU FRG have been undertaken successfully.

International Peer Reviewed Publications:

- Benndorf, J.; Yueksel, C.; Shishvan, M.S.; Rosenberg, H.; Thielemann, T.; Mittmann, R.; Lohsträter, O.; Lindig, M.; Minnecker, C.; Donner, R.; Naworyta, W. RTRO–Coal: Real-Time Resource-Reconciliation and Optimization for Exploitation of Coal Deposits. Minerals 2015, 5, 546-569.
- Soleymani Shishvan, M., and J. Benndorf, 2016. The effect of geological uncertainty on achieving short-term targets: A quantitative approach using stochastic process simulation. *Journal of the Southern African Institute of Mining and Metallurgy* 116.3 (2016): 259-264.
- Yüksel, C., Thielemann, T., Wambeke, T. and Benndorf, J., 2016. Real time resource model updating for improved coal quality control using online data. International Journal of Coal Geology, 162, 61-73.
- Yüksel, C. and Benndorf, J, 2016. Performance Analysis of Continuous Resource Model Updating in Lignite Production. In: Gómez-Hernández J, Rodrigo-Ilarri J, Rodrigo-Clavero ME, Cassiraga, E Vargas-Guzmán JA (Eds), Valencia Geostatistics 2016, Volume 2, Springer, page 65 ff.
- Shishvan, M.S.; Benndorf, J. (2017). Operational Decision Support for Material Management in Continuous Mining Systems: From Simulation Concept to Practical Full-Scale Implementations. Minerals 2017, 7, 116.
- Yüksel, C.; Benndorf, J.; Lindig, M.; Lohsträter, O. (2017) ´Updating the coal quality parameters in multiple production benches based on combined material measurement: a full case study.International Journal of Coal Science and Technology (2017), p. 159-171
- Yüksel,C. Minnecker,M., Soleymani Shishvan, MS., Benndorf, J., Buxton, M. (2017) Value of Information Introduced by Resource Model Updating Framework. Mathematical Geosciences (submitted).

Presentations at conferences:

- Yüksel, C., Benndorf, J., 2015. Application of the Ensemble Kalman Filter for Improved Mineral Resource Recovery. Presentation at the 10th International EnKF Workshop, Flåm, Norway, June 8-10, 2015.
- Presentation at the Ensemble Kalman Filter Workshop 2015 in Fontenbleau, France
- Presentation at conference Mine Planning and Equipment Selection 2015 in Johannesburg, South Africa
- Presentation at conference Mine Planning and Equipment Selection 2017 in Lulea, Sweden
- Presentation at the Geostatistics conference, 2016 in Valencia, Spain
- Poster presentation at the IAMG conference 2017 in Perth, Australia
- Presentation at the conference Geokinematischer tag 2017 in Freiberg
- Presentation at the conference Geomonitoring 2018 in Clausthal Zellerfeld, Germany

PhD – Dissertations:

Cansin Yüksel (12/2017): Real-Time Resource Model Updating in Continuous Mining Environment Utilizing Online Sensor Data, TU Delft (Promotors: Prof. J.D. Jansen and Prof. J. Benndorf).

Masoud (expected 05/2018): Simulation-based Optimization for Decision Making Under Uncertainty in Opencast Mines, TU Delft (Promotors: Prof. J.D. Jansen and Prof. J. Benndorf).

Corinna Minnecker (09/2018): Applied mathematical optimization for uncertainty based mine planning in large coal mines, TU Freiberg (Promotors: Prof. H. Schaeben and Prof. J. Benndorf).

References

1. Chiles, J.P.; Delfiner, P. Geostatistics, Modelling Spatial Uncertainty; John Wiley & Sons: New York, NY, USA, 2012.

2. Rosenberg, H. Detection of materials and deposits as a basis for innovative operations management systems employed as part of opencast mine process optimizations. World Min. Clausthal Zellerfeld 2007, 59, 173–180.

3. Knipfer, A. Decision support for operating lignite mines with high geological variability based on mine surveying and production monitoring. Bergbau Zeitschrift für Rohstoffgewinnung Energie Umwelt 2012, 4, 148–152. (in German)

4. Sládková, D.; Kapica, R.; Vrubelm, H. Global navigation satellite system (GNSS) technology for automation of surface mining. Int. J. Min., Reclam. Environ. 2011, 25, 284–294.

5. Scholze, P.; Koehler, U. Complex control functions and management systems in the opencast mines of Vattenfall Europe Mining AG. World Min. GdmB 2012, 1, 31–39.

6. Gärtner, D.; Hempel, R.; Rosenberg, H. Market-Oriented, Flexible and Energy-Efficient Operations Management in RWE Power AG's Opencast Mines. In Proceedings of the 12th International Symposium Continuous Surface Mining—Aachen 2014; Niemann-Delius, C., Ed.; Springer International Publishing: Gewerbestrasse, Switzerland, 2015; pp. 339–353.

7. Buxton, M.; Benndorf, J. The Use of Sensor Derived Data in Real-Time Mine Optimisation: A Preliminary Overview and Assessment of Techno-Economic Significance. In Proceeding of the 142nd SME Annual Meeting and Exhibit, Denver, CO, USA, 24–27 February 2013; pp. 13–38.

8. Kelton, W.D.; Law, A.M. Simulation Modeling and Analysis, 3rd ed.; McGraw Hill: Boston, MA, USA, 2000.

9. Panagiotou, G.N. Computer Simulation of the Mining Operations in Opencast Lignite Mines Operating BWEs, Conveyors and Stackers. In Proceedings of the First Conference on Use of Computer in the Coal Industry, New York, NY, USA, 1–3 August 1983; pp. 150–157.

10. Michalakopoulos, T.N.; Arvaniti, S.; Panagiotou, G.N. Simulation of a Continuous Lignite Excavation System. In Proceeding of the Fourteenth International Symposium on Mine Planning and Equipment Selection (MPES), Albert, Canada, 31 October–2 November 2005.

11. Michalakopoulos, T.N.; Roumpos, C.P.; Galetakis, M.J.; Panagiotou, G.N. Discrete-Event Simulation of Continuous Mining Systems in Multi-Layer Lignite Deposits. In Proceedings of the 12th International Symposium Continuous Surface Mining—Aachen 2014; Springer International Publishing: Gewerbestrasse, Switzerland, 2015; pp. 225–239.

12. Fioroni, M.M.; Franzese, L.A.G.; Zanin, C.E.; Fúria, J.; de Toledo Perfetti, L.; Leonardo, D.; da Silva, N.L. Simulation of Continuous Behavior Using Discrete Tools: Ore Conveyor Transport. In Proceedings of the 39th Conference on Winter Simulation: 40 Years! The Best is yet to Come, Washington D.C., DC, USA, 9–12 December 2007; pp. 1655–1662.

13. Shishvan, M.S.; Benndorf, J. Performance Optimisation of Complex Continuous mining System Using Stochastic Simulation. In Engineering Optimisation; Taylor and Francis: London, UK, 2015; pp. 273–278.

14. Isaak, E.H.; Srivastava, R.M. Applied Geostatistics; Oxford University Press: New York, NY, USA, 1989.

15. Benndorf, J. Application of efficient methods of conditional simulation for optimizing coal blending strategies in large continuous open pit mining operations. Int. J. Coal Geol. 2013, 112, 141–153.

16. Parker, H. und Dohm, C.E., 2014: Evolution of Mineral Resource Classification from 1980 to 2014 and Currect Best Practices. Finex 2014 Julius Wernher Lecture, available online.

17. Benndorf, J.; Yueksel, C.; Shishvan, M.S.; Rosenberg, H.; Thielemann, T.; Mittmann, R.; Lohsträter, O.; Lindig, M.; Minnecker, C.; Donner, R.; Naworyta, W. RTRO–Coal: Real-Time Re-

source-Reconciliation and Optimization for Exploitation of Coal Deposits. Minerals 2015, 5, 546-569.

18. Benndorf, J. Making use of online production data: Sequential updating of mineral resource models. Mathem. Geosci. 2015, 47, 547–563.

19. SAKOV, P. & BERTINO, L. 2011. Relation between two common localisation methods for the EnKF. Computational Geosciences, 15, 225-237.

20. ZHOU, H., GÓMEZ-HERNÁNDEZ, J. J., HENDRICKS FRANSSEN, H.-J. & LI, L. 2011. An approach to handling non-Gaussianity of parameters and state variables in ensemble Kalman filtering. Advances in Water Resources, 34, 844-864.

21. van Breuningen, F., 2013. Appraisal of geostatistical methods and geostatistical prediction of predominantly marine sand inclusions in the Frimmersdorf lignite seam in the Garzweiler open cast mine, Germany. MSc Thesis, TU delft, Resource Engineering.

22. Hillmann, T (1997). Eine iterative Methode zur Schätzung der Kovarianzfunktion für geostatistische Vorhersagen. Unpublished PhD-Thesis. TU Bergakademie Freiberg, Institut für Markscheidewesen und Geodäsie; Freiberg.

23. JEONG, C., MUKERJI, T. & MARIETHOZ, G. Iterative spatial resampling applied to seismic inverse modeling for lithofacies prediction. 81st Annual International Meeting, SEG, Expanded Abstracts, 2011.

24. Hohn, M.E., McDowell, R.R., 2001. Stochastic simulation of coal bed thickness and economic decision-making, in: Merriam, D.F. and Davis, J.C. (Eds.), Geologic Modelling and Simulation: Sedimentary Systems. Kluwer Academic/Plenum Publishers, New York, pp. 271-283.

25. Costa, J.F.; Zingano, A.C.; Koppe, J.C. Simulation an approach to risk analysis in coal mining. Explor. Min. Geol. 2000, 9, 43–49.

26. Benndorf, J., 2009. Nutzung der geostatistischen Simulation zur Berücksichtigung der geologischen Unsicherheit in der Bewertung von Lagerstätten am Beispiel des Braunkohlenbergbaus. Schriftenreihe des Institutes für Geotechnik und Markscheidewesen der TU Clausthal, Heft 18/2009, 211 p.

27. Johnson, T. B.: Optimum open pit mine production scheduling (No. ORC-68-11), California Univ Berkeley Operations Research Center, 1968

28. Gershon, M.E.: Optimal mine production scheduling: evaluation of large-scale mathematical programming approaches, International Jounal of Mining Engineering, v. 1, pp. 315-329, 1983

29. Benndorf, J., and Dimitrakopoulos, R.: Stochastic long-term production scheduling of iron ore deposits: Integrating joint multi-element geological uncertainty, Journal of Mining Science 49.1 (2013), pp. 68-81

30. Dimitrakopoulos, R., and Ramazan, S: Uncertainty based production scheduling in open pit mining, SME Transactions, No. 316, pp. 106-112, 2004

31. Ramazan, S., and Dimitrakopoulos, R.: Stochastic optimisation of long-term production scheduling for open pit mines with a new integer programming formulation, Conference of Orebody Modelling and Strategic Mine Planning, pp. 385-391, 2007

32. Ramazan, S. and Dimitrakopoulos, R.: Recent Applications of Operations Research and Efficient MIP Formulations in Open Pit Mining, SME Transactions, No. 316, pp. 73-78, 2004

33. Kawalec, W., and Specylak, J.: Open pit optimisation of a lignite deposit, in Panagiotou and Michalakopoulos, eds., Mine Planning and Equipment Selection 2000: Balkema, Rotterdam, The Netherlands, pp. 217-222, 2000

34. John, A., Minnecker, C. and Donner, R. 2014. „Innovative Braunkohlen-Integration in Mitteldeutschland -ibi". Schlussbereicht Verbundprojekt VP1:„Integriertes Lagerstättenmanagement", TU Freiberg, BMBF (in German language).

35. Gosavi, A. 2015. Simulation-Based Optimization Parametric Optimization Techniques and Reinforcement Learning. Springer New York.

36. Branke, J., Deb, K., Miettinen, K., and Slowiński, R. 2008. Multiobjective optimization: Interactive and evolutionary approaches (Vol. 5252). Springer.

37. Howard, R. A. 1966. Information value theory. IEEE Transactions on systems science and cybernetics, 2, 22-26.

38. Raiffa, H., 1968. Decision Analysis: Introductory Lectures on Choices Under Undertainty, Addison-Wesley.

39. Matheson, J. E,. 1990. Using influence diagrams to value information and control. Influence diagrams, belief nets and decision analysis, 25-63.

40. Peck, J. & Gray, J. 1999. Mining in the 21st century using information technology. CIM bulletin, 92, 56-59.

41. Barnes, R. J. The cost of risk and the value of information in mine planning. 19th APCOM Symposium, 1986. 459-469.

42. Phillips, J., Newman, A. M. & Walls, M. R., 2009. Utilizing a value of information framework to improve ore collection and classification procedures. The Engineering Economist, 54, 50-74.

43. Bratvold, R. B., Bickel, J. E. & Lohne, H. P., 2009. Value of information in the oil and gas industry: past, present, and future. SPE Reservoir Evaluation & Engineering, 12, 630-638.

List of acronyms and abbreviations

AGORHUT	...	Akademia Gorniczo-Hutnicza im. Stanislawa Staszica; Krakow, Poland
CA	...	Consortium Agreement
CIRCABC	...	collaborative platform for distribution and management of documents
DES	...	Discrete Event Simulation
EC	...	European Commission
EnKF	...	Ensemble Kalman Filter
FTE	...	Full Time Employee
GA	...	Grant Agreement
KF	...	Kalman Filter
KPI	...	Key Performance Indicator
MIBRAG	...	Mitteldeutsche Braunkohlengesellschaft mbH; Theissen, Germany
NS-EnKF	...	Normal Score Ensemble Kalman Filter
NPV	...	Net Present Value
PC	...	Project Coordinator
RTRO-Coal	...	Real-Time Reconciliation and Optimization in large open pit coal mines
RWE	...	RWE Power AG; Essen, Germany
TUDT	...	Delft University of Technology, the Netherlands
TU FRG	...	Technische Universität Bergakademie Freiberg, Germany
UK	...	Universal Kriging
WP	...	Work Package

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ABSTRACT

The overall aim of the RTRO-Coal project was to develop an integrated framework for Real-Time - Reconciliation and Optimization (RTRO) of the production process in large open pit coal mining operations. The research progressed from the state-of-the-art and developed new methods in stochastic mine system simulation, intelligent data analysis, advanced geological modelling, quantifying geological uncertainty and process optimization. These developments foster the utilization of all relevant ICT-based data and information available along the production process and integrate them in a real-time manner to optimize production of in-spec coal products as required in the subsequent value chain. With this aim, results have a significant impact towards the currently ongoing digitization strategy within the mining industry.
Concluding and based on the results presented in this report, it can be stated the overall aim has been achieved. Methods for

- process simulation in large continuous mining operations,
- updating resource models based on operational monitoring data and
- risk based long- and short-term optimization integrating geological uncertainty

have been theoretically developed, verified in controllable environments and validated in full industry scale case studies. Further, the operational implementation demonstrated the benefit of the integrated closed-loop-framework with a significant economic potential of multiple Mio. € per year for the specific test cases.
Results of RTRO-Coal have been published in seven peer reviewed journal papers, presented at multiple international conferences and were the basis of three PhD studies at the University of Technology Delft and the University, NL of Technology Bergakademie Freiberg, FRG.

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The overall aim of the RTRO-Coal project was to develop an integrated framework for Real-Time - Reconciliation and Optimization (RTRO) of the production process in large open pit coal mining operations. The research progressed from the state-of-the-art and developed new methods in stochastic mine system simulation, intelligent data analysis, advanced geological modelling, quantifying geological uncertainty and process optimization. These developments foster the utilization of all relevant ICT-based data and information available along the production process and integrate them in a real-time manner to optimize production of in-spec coal products as required in the subsequent value chain. With this aim, results have a significant impact towards the currently ongoing digitization strategy within the mining industry.
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