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Recent Developments in Closed-Loop Approaches for Real-Time Mining and Petroleum Extraction

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Abstract

Advanced data acquisition and process modelling technology provide 'real-time' data and decision support capacity for different aspects of the resource extraction process. Closed-loop approaches have recently been applied to utilize information extracted from these data in combination with advanced computing technology for improved production control in mineral resource extraction. Similar techniques have been developed in the petroleum industry combining computer-assisted model updating with model-based production optimization. This contribution reviews recent developments and methods applied, highlights differences and assesses the potential value added for both application domains. The focus here is on the two main constituents of closed-loop concepts, data assimilation and optimization. Technological readiness of the constituents is assessed, and gaps for further technology development are identified. The value added is illustrated by means of selected cases.

Key Words

closed-loop reservoir management, real-time mining, data assimilation, optimization

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1. Introduction

The extraction of geo-resources, whether gas, liquids or solids, is a challenging venture characterized by large investments and long pay-back periods involving different types of risks. Contrary to other industries, one specific type of risk is due to the limited amount of information about the primary production factor, the mineral deposit or the hydrocarbon reservoir. Based on this limited amount of information, decisions about the design, long-term- and short-term planning and production control have to be made, ideally in a way that maximizes recovery of the primary natural resources while maintaining the highest standard of safety and process efficiency. While data about the mineral deposit or the reservoir gathered prior to the actual operation are limited, scarce and comparably expensive, modern production monitoring technology allows for obtaining highly dense and comparably inexpensive data during production. Although production data can be of lower precision and only indirectly connected to the properties of the deposit or reservoir, they deliver valuable information.

Leveraging on available production data, closed-loop approaches for geo-resource extraction aim at increased resource efficiency, in terms of recovery or financial measures, using a measurement and control approach. In hydrocarbon production 'closed-loop' or 'real-time' approaches have received growing attention as part of various industry initiatives with names as 'smart fields', 'i-fields', 'e-fields', 'integrated operations', 'closed-loop reservoir management' (CLRM), or 'closed-loop field development'; see Jansen et al. (2005, 2008, 2009) and Hou et al. (2015) for further references. Independent from these developments, more recently similar concepts were proposed in solid mineral resource extraction (e.g. for example Benndorf et al., 2015a; Zogovic et al. 2015). These concepts utilize the classical concept of plan-do-check-act iterative management (Shewhart, 1931). By continuously comparing model based predictions with observations measured during production monitoring, the use of inverse modelling or data assimilation approaches can improve the model forecast for subsequent time intervals, leading to potentially new and better decisions for production control and medium-term planning. The underlying hypothesis in these approaches can be summarized as follows (after Jansen et al. 2009):

"It will be possible to significantly increase life-cycle value by changing reservoir and ore extraction management from a batch-type to a near-continuous model-based controlled activity."

Although the general closed-loop concept can be applied to both solid raw material extraction and oil and gas production, these applications differ in methods, implementation details and time scales. The reason is due to the different nature and scale of extraction, the requirements deriving from subsequent beneficiation, and the level of information available.

- Mineral resource extraction can be seen as a discrete sequential physical extraction of small-scale blocks or smallest mineable units, which, depending on selectivity, can be on a meter by meter to tens-of-meters by tens-of-meter scale. The deposit and its properties remain static over time. Properties of the run-off-mine ore (ROM ore) stream are controlled by navigating the different extraction points or mining faces through the deposit. The aim is to extract blocks in a sequence and utilize production logistics such as blending piles or transport schedules in a way that production targets in terms of ore tonnage produced and related grades of value and deleterious elements are met, which at the end impacts cash-flows and net present value (NPV). A main focus of planning and production control is the reduction of in-situ variability of ore in the deposit to a homogeneous product by means of blending at different stages and scales (e.g. Jupp et al. 2013).

- The recovery of gas or liquids from permeable rock is based on the understanding of global properties and connectivity of the reservoir, the reservoir fluid properties and the surface chemistry of the fluid-fluid and fluid-rock interfaces, and the interaction with control parameters such as well configurations, drilling schedules, water or gas injection rates, well pressures or control valve settings. While the relevant rock properties in a reservoir do not change over time, the fluid distributions may change completely as the degree of exploitation progresses. (An exception is formed by near-wellbore rock properties which may be changed through well interventions like hydraulic fracturing or acid stimulation). Moreover, the displacement of oil by water and the release of gas from oil at decreasing reservoir pressures may drastically change the local resistance to flow. The main focus of well and reservoir management is on maximizing ultimate recovery or NPV.

The different nature of both cases of application requires different system models as a basis for decision making. This contribution aims to review recent developments and compare documented approaches in closed-loop real-time mining and reservoir management highlighting differences and similarities. It is hoped that synergetic effects in research and technical development can be raised, and both disciplines can learn from each other. As any project begins with strategic design decisions and long-term planning, this contribution starts with concepts of long-range planning and the value of robust life-cycle optimization. The underlying methods for generating the input for the latter, namely ensembles or realizations of the spatial distribution of properties within the deposit are discussed. Next, the closed–loop concept is reviewed, and developments within the two main constituents (data assimilation and optimization) are highlighted. Different examples illustrate the concept. A discussion on the potential value added of closed-loop approaches and technology readiness concludes this contribution. To assess technological maturity of methods discussed, the concept of Technology Readiness Levels (TRLs) will be employed using definitions of the European Commission (2014) which are based on earlier definitions developed by NASA for the US space program (Mankins, 1995):TRL 3 – experimental proof of concept, TRL 4 – technology validated in laboratory, TRL 5 – technology validated in relevant environment, TRL 6 system/subsystem model or prototype demonstration in relevant environment, TRL 7 – system prototype demonstration in operational environment, TRL 8 – system complete and qualified, TRL 9 – actual system proven in operational environment. Note that we will interpret 'experimental proof' to include results from large-scale numerical simulation (computer experiments).

2. Robust Decision Making under Geological Uncertainty

2.1 Modelling geological uncertainty

One of the major challenges in reservoir and mining engineering is taking expensive decisions related to design, planning and operations control in the presence of very large uncertainties about the subsurface structure and the parameters that influence fluid flow and raw material production. To cope with this uncertainty, different possible scenarios for the subsurface models can be considered. In reservoir engineering the term "ensemble of geological realizations" is established (e.g. Caers 2011), whereas in mineral resource extraction the terms "realizations" or "scenarios" are commonly used (e.g. Journel, 1974; Dimitrakopoulos et al. 2002; Vann et al. 2012). Common to both fields of application is that modern geostatistical simulation techniques are used to generate these realizations or ensemble members. The requirements resulting from the two fields of applications related to the particular simulation methods used are summarized in Table 1.

Table 1: Requirements for simulation methods to generate realizations and ensemble members

Criteria	Reservoir Engineering	Mineral Resource Extraction
Requirements on models	• Models need to capture reservoir boundaries and in-situ variability of porosity and permeability, connectivity between wells, transmissibilities of faults, and directional/ anisotropic features influencing flow throughout the whole deposits. • Reservoir flow simulation models primarily require capturing flow-relevant geological features (barriers, high-permeability channels) at reservoir scale.	• Models need to capture mineral deposit boundaries and in-situ variability of geological zonation and grade distribution within zones. In general, multiple correlated grade attributes are of importance. The reproduction of connectivity is of lesser interest. • Local focus: geological zonation and the local grade distribution in the different zones at SMU scale.
Data availability prior extraction	• Very limited amount of hard data (e.g. direct bore	• Reasonable amount of information available

	hole data intersecting the reservoir) prior extraction • Indirect data from geophysics and remote sensing are available prior and during extraction	enabling to prove continuity in geology and grade prior extraction • Data represent mostly direct samples (hard data) supported by geophysical interpretations

Given the aim of the model and data availability indicated in Table 1, solid mineral resource extraction uses data driven approaches for local block prediction such as conditional simulation via turning bands or sequential Gaussian simulation (Journel, 1974; Goovaerts, 1997). The large extension of some mineral deposits requires efficient computational methods, such as direct block simulation methods (e.g. Marcotte, 1994; Boucher and Dimitrakopoulos, 2007; Desaisme et al. 2012) or generalized sequential Gaussian simulation (Benndorf and Dimitrakopoulos, 2005). The spatial correlation between grades is captured by methods using models of co-regionalization (e.g. Verly 1993; Soares, 2001) or decorrelation (e.g. Rondon, 2012; John, 2014). The requirement for capturing in-situ variability is in general sufficiently met using two-point statistics, such as variograms or spatial covariance function based methods.

In the petroleum industry, a variety of numerical simulation methods is available to generate numerical ’static‘ reservoir models depending on the depositional environment and the subsequent diagenesis and structural deformation history (faulting, fracturing). Sequential Gaussian simulation, based on two-point geostatistics and conditioned on hard data in the wells, is also a standard technique. However, the importance of well-to-well connectivities, e.g. in the form of fossilized meandering channels in a fluviatile depositional environment, has led to the development of higher-order (multi-point) geostatistical approaches. In particular, training-image-based multi-point approaches have become very popular during the past decade; for overviews see, e.g., Caers (2011) or Mariethoz and Caers (2014). Examples are the SneSim (Strebelle and Journel, 2001) and SGems (Remy et al. 2009) algorithms, which are based on scanning a training image for multi-point configurations and reproducing similar images capturing the main geometrical features. Another popular technique is object-based simulation, based on the random generation of ‘geobodies’ in the form of, e.g., elliptical ‘sand bars’, sinusoidal ‘channels’, or intersecting fault planes (Caers, 2011, Pyrcz and Deutsch, 2014). Finally, it is possible to generate computer representations of multiple hand-drawn maps drawn up by one or more experts. Commercial geological modeling software packages typically use a combination of object-based, training-image-based and stochastic simulation approaches. Figure 1 shows typical realizations for both fields of application.

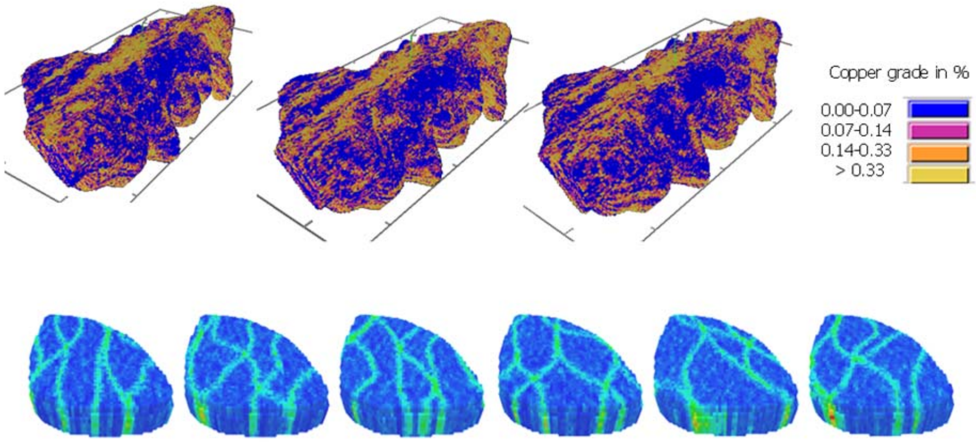

Figure 1: Typical examples for realizations of a deposit - upper part (Benndorf and Dimitrakopoulos, 2005) and an ensemble of geological realizations of an oil field - lower part (van Essen et al. 2009)

2.2 Optimization under geological uncertainty

Based on the understanding of uncertainty, different decisions or control options have to be taken, ideally in an optimal way. These decisions and control options are different for different project stages and are thus based on a different amount of information available at the time. Some of the decisions involve large investments and can be hardly revised; some can be more flexible changed throughout the project. Table 2 provides examples for both fields of application.

Table 2: Examples for control decisions to be optimized at different project stages

Time Range	Reservoir Engineering	Mineral Resource Extraction
Design (prior extraction)	• Recovery mechanism (e.g. depletion drive, water flooding, gas flooding) • Processing capacities • Well locations • Well trajectories (deviated wells) • Drilling sequence • Artificial lift (e.g. beam pumps, gas lift)	• Ultimate pit limits (surface mining) or stope layout (underground mining) • Main infrastructure (e.g. shaft location and capacity) • Mining and processing capacity
Life of project to medium-term	• Target well rates or pressures for flooding optimization • Work-over sequence	• Long-term extraction sequencing (e.g. push back design) • Equipment selection

	(e.g. side-tracks, recompletions)	
Short-range to production control	• Production parameter settings (well head pressures, injection rates, valve settings) • Artificial lift operating parameters (pump speeds, lift gas rates)	• Block classification • Short-term extraction sequence definition • Machine task scheduling • Dispatching, logistic and stockpile management

For decision making under geological uncertainty it is possible to use a robust ensemble- or realization-based optimization strategy to maximize a robust objective function $J_,$ which approximates the expected value of the objective function over all realizations (Yeten et al. 2003; Bailey et al. 2005; Van Essen et al. 2009.) Robust life-cycle optimization can be applied to a fixed configuration of wells, in which case the optimization variables are ‘well controls’, i.e. pressures at the top of the production wells, flow rates in the injection wells, or valve setting in surface or downhole flow control valves (a detailed overview and references will be given in Section 5 below). Robust life-cycle optimization may also involve the optimization of the well locations or well trajectories, or a combination of well locations and well controls as will also be discussed in more detail in Section 5. Moreover, the concept of robust optimization can be extended to minimizing the variance of the objective function or, alternatively, minimizing the ‘downside’, i.e. the risk on low values of the objective function. This leads to trade-offs between improving the mean and reducing the variance or other risk measures; see, e.g., Bailey et al. (2005), Yasari et al. (2013), Siraj et al. (2015), and Capolei et al. (2015).

Figure 2 illustrates the robust optimization concept graphically for mining applications. The mine planning problem can generally be seen as a scheduling problem for discrete tasks applied to periods of extracting mining blocks or tasks. To solve this combinatorial optimization problem taking into account geological uncertainty, during the past decade various different applications were published, including managing risk in large gold deposits (Godoy and Dimitrakopoulos 2004), meeting long-term production targets under joint-element uncertainty in iron ore (e.g. Menabde et al. 2007, Benndorf and Dimitrakopoulos 2013) or defining more robust ultimate pit limits (e.g. Vielma et al. 2009). Optimization problem sizes in mine planning are typically very large. For long-term scheduling problems, binary decision variables have to be defined per mining block and extraction period leading, for average sized problems, to a number in the order of 10^6 to 10^7. Here, theoretical exact optimal approaches, such as integer or stochastic integer programming solutions, approach their computational limits. Recent work focuses on the development of optimization engines to solve extremely large combinatorial problems involving the complete value chain in mining complexes (e.g. Goodfellow and Dimitrakopoulos 2013). Combinatorial optimization techniques, such as simulated annealing (e.g. Kumral and Dowd, 2005), tabu search (e.g. Lamghari and Dimitrakopoulos 2012) or evolutionary approaches (e.g. Gilani and Sattervand 2015, Bijmolt 2016) provide computationally efficient alternatives with a reasonable close-to-optimum result.

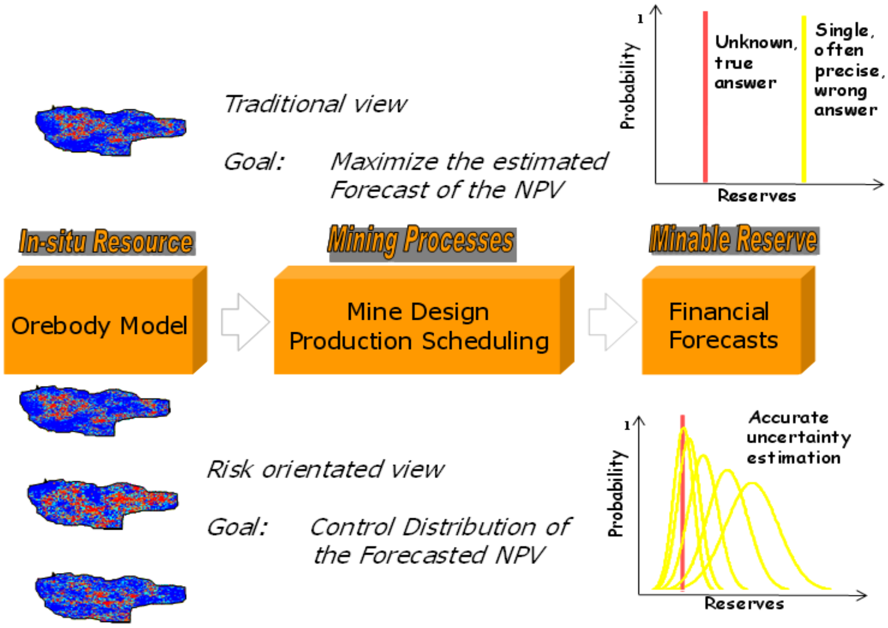

Figure 2: Robust optimization in mining applications (reproduced after Dimitrakopoulos, 2011)

While mineral resource extraction represents a physically discrete extraction of blocks at discrete periods in time, the continuously and dynamically changing nature of states and control parameters in petroleum extraction requires time-continuous optimization methods.

In both fields of application, robust optimization techniques have proven to potentially lead to decisions that generate an increased expected monetary value in the order of up to 10% for petroleum engineering application and up to 25% for mining applications while decreasing risk in project failure (e.g. van Essen et al. 2009; Dimitrapoulos, 2011).

3. Making use of Production Data – Closing the Loop

While the previous discussions focus in general on robust optimized decision making under geological uncertainty, this section will explore the use of additional data, available during production. Examples of data resources for both fields of applications are provided in Table 3.

Table 3: Production monitoring data in hydro-carbon and mineral resource extraction

Petroleum Engineering	Mineral Resource Extraction
• Oil production rates • Water production rates or fractions • Gas production rates or fractions • Wellhead pressures • Downhole well pressures • Distributed temperature data • Production logs (zonal inflow information) • Time-lapse seismic data • Time-lapse gravity data • Passive seismic data • Electromagnetic data	• Equipment location and material tracking data • Online material characterization (texture, mineralogy, geochemistry, particle size distribution) • Surveying and face mapping data • Equipment performance (cutting energy, mill working index, metal recovery)

These data are often soft, meaning of lower accuracy than directly sampled data, and only indirectly related to the underlying system models. However, due to their density in time they provide valuable information for comparing model based expectations with reality.

More often than not, significant discrepancies between expectations and reality are observed. In more traditional approaches, batch type exercises are undertaken to improve the fit of reservoir or mineral resource models to production monitoring observations and improve model assumptions. In reservoir engineering these exercises are known as computer-assisted history matching (e.g. Oliver et al. 2008; Oliver and Chen 2011), while in mineral resource extraction the term reconciliation is used (e.g. Parker et al. 2012). Instead of a batch-type discontinuous approach, modern Information and Communication Technology (ICT) allows to perform this updating loop in a near-continuous fashion. This leads to closed-loop and real-time mining concepts. Here ‘real-time’ should be interpreted in the light of the relatively slow extraction processes. E.g., in petroleum engineering the fronts between reservoir fluids (oil, gas and water) typically move with velocities of up to a meter per day, while pressure transients may take days or weeks to travel the distance between wells. Performing ‘reservoir surveillance’ on a weekly or even a monthly basis can therefore form the basis for a near ‘real-time’ closed-loop reservoir management (CLRM) process. It should be noted that the phrase “closed-loop” in CLRM does not imply removal of human judgment from the loop. The use of model-based optimization and data assimilation techniques should result in a reduction of time spent on repetitive and tedious human activities and thus in more time to be spent on judging results and taking decisions (Jansen et al. 2009). In addition, more short-term (daily to weekly) production-focused closed-loop optimization of oil production can be performed with more room for automation. An example is the real-time optimization of ‘artificial lift’, i.e. the maximization of oil production through pumping or through reducing the hydrostatic head by injecting gas in the well bore. Even shorter real-time ‘coning control’ involves feed-back on a time scale of minutes to hours to counteract local near-well influx of water or gas. For overviews of the various levels of control and the associated time scales in the oil industry, see Saputelli et al. (2006) and Foss et al. (2010). For an overview of short-term real-time production optimization, see Bieker et al (2003).

Also in the mining industry ‘real-time’ refers to different time scales dependent on the control option to be taken. In the case of dispatch decisions this may in the order of minutes, for block classification tasks and production control tasks, decisions can be influenced by new data on a minute to hour scale. In general, production control options may be supported during a working shift, which is less than 8 hours, and for short-term planning applications, a shift-to-shift basis therefore seems a sensible time interval.

Figure 3 illustrates this concept for the Real-Time Mining approach, which is based on the plan-do-check-act (PDCA) iterative management cycle (Shewhart, 1931). It is general and applicable to surface mining and underground operations and can be interpreted as follows:

- P—Plan and predict: Based on the mineral resource model, strategic long-term mine planning, short-term scheduling and production control decisions are made. Performance indicators such as expected ore tonnage extracted per day, expected ore quality attributes and process efficiency are predicted.
- D—Do: The mine plan is executed.
- C—Check: Production monitoring systems continuously deliver data about process indicators using modern sensor technology. For example, the grade attributes of the ore extracted are monitored on a belt conveyor. Differences between model based predictions from the planning stage and actual measured sensor data are detected.
- A—Act: Differences between prediction and production monitoring are analyzed and root causes investigated. One root cause may be the uncertainty associated with the resource model to predict the expected performance. Another root cause may be the precision of sensor measurements. Using innovative data assimilation methods, differences are then used to update the resource model and mine planning assumptions, such as losses and dilution. With the updated resource and planning model, decisions made in the planning stage may have to be reviewed and adjusted in order to maximize the process performance and meet production targets.

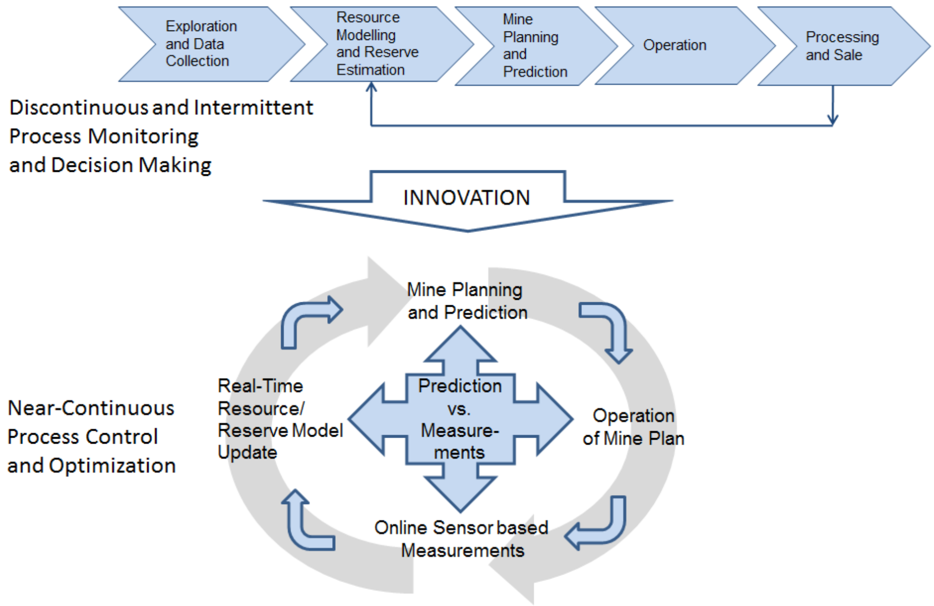

Figure 3: The Real-Time Mining concept (after Benndorf et al. 2015b)

At this moment, the maturity of this concept in mineral resource extraction is judged to be on a TRL 3 to 5. Currently ongoing multi-national European Union funded projects RTRO-Coal (Benndorf et al. 2015a) and Real-Time Mining (Benndorf et al. 2015b) investigate closed-loop concepts for bulk mining and also highly selective mining scenarios. The main aim in these industry driven projects is to progress the technological development to a TRL of 6 to 7, where an integrated system is available validated under industrial environment conditions in full scale.

Figure 4 displays the key elements in the closed-loop reservoir management (CLRM) process (Jansen et al. 2005, 2008, 2009). The top of the figure represents the physical system consisting of reservoirs, wells and facilities. The center of the figure displays the system models which may include static (geological), dynamic (reservoir flow) and well bore flow models. As discussed before, multiple models can be involved to quantify the large uncertainty in our knowledge of the subsurface. At the right of the figure, the sensors that keep track of the processes that occur in the system are displayed. These may be thought of as real sensors measuring production variables such as wellhead pressures or phase rates, either through production tests or on-line multi-phase flow meters or ‘soft-sensors’ that measure production data indirectly. However, sensors may also be interpreted more abstractly as sources of information about the system variables, e.g., interpreted well tests, time-lapse seismic or other surveillance data. Optimization algorithms, indicated by a blue box and arrows, are shown on the left side. Again, these may be interpreted as actual algorithms for production optimization influencing e.g., wellhead choke settings or injection rates, but also more abstractly as decisions in a field development plan, e.g., the choice of well positions. The state variables of the system, i.e. the pressures and saturations in the reservoirs, the pressures and phase rates in the wells, etc., are only known to a limited extent from the measured, usually noisy, output. Even more uncertain are the parameters of the system, i.e. the permeabilities and porosities, fault transmissibilities, fluid properties, etc., while also the system boundaries and initial conditions are uncertain. Finally, even the input to the system is only known to a limited extent; e.g. water injection rates or gas lift rates may be roughly known, but aquifer support may be a major unknown. The unknown inputs can also be interpreted as noise. Data assimilation (i.e. computer-assisted history matching) can be used to reconcile the measured output with the uncertain models to a certain extent. This is done through adapting the model parameters and model structure until the difference between measured and simulated data is minimized in some pre-defined sense, as indicated by the red box and arrows at the bottom. The two essential elements in the CLRM concept are therefore model-based optimization and decision making (blue loop), and model updating through data assimilation (red loop). Various publications describe theoretical studies involving CLRM (recently also referred to as closed-loop field development) using a variety of optimization and data assimilation techniques; see, e.g. Brouwer et al. (2004), Naevdal et al. (2006), Sarma et al. (2006, 2008a), Chen et al. (2009, 2010, 2012), Chen and Oliver (2010), Wang et al. (2009), Peters et al. (2010), Foss and Jensen (2010), Capolei et al. (2013), Shirangi and Durlofsky (2015) and Bukshtynov et al. (2015). For further references, see Jansen et al. (2005, 2008, 2009) and Hou et al. (2015). The potential benefits from the use of CLRM are related to the degree of heterogeneity in the subsurface. In particular the presence of high-permeability zones connected to wells may strongly influence the controllability of the fluid fronts (Jansen, 2011). For the underlying system-theoretical concepts, such as observability and controllability of state variables (pressures and saturations) and the identifiability of system parameters, see Zandvliet et al. (2008b) and van Doren et al. (2013). An attempt to formally quantify the value of information resulting from measurements in a CLRM framework has recently been presented by Barros et al. (2016).

Actual field implementations of the entire CLRM process have not yet been reported and can be classified with TRL 3-4 at best. However, the two key building blocks, data assimilation and recovery optimization are certainly being applied in practice. Especially large-scale data assimilation (‘computer-assisted history matching’) is rapidly being employed throughout the industry and can be classified with TRL 8-9. At the optimization side, merely well location optimization or field development optimization studies increasingly prove to be of value (TRL 6-7). The optimization of well controls is still primarily driven by short-term objectives (TRL 8-9), while formal (mathematical) long-term recovery optimization is only occasionally performed during the field development phase and not yet applied in a more operational setting (TRL 3-4). Theoretical ‘multi-level’ optimization attempts have been published to reconcile long-term reservoir management and short-term production optimization (see, e.g., Saputelli et al. 2006 and van Essen et al. 2013) but practical implementations of such formal multi-level approaches have not yet been reported (TRL 3-4).

A completely different form of closed-loop reservoir management operates at much shorter time scales (minutes to hours) and uses direct feedback from measurements, with relatively simple control rules and without the use of system models. Examples of such an approach, which is not yet frequently applied, are automatic gas coning control in horizontal wells (Jansen et al. 2003, Sagatun, 2010; Dilib et al. 2015), and the control of steam breakthrough in parallel pairs of horizontal wells for steam-assisted production of heavy oil (Patel et al. 2014). Most of these concern theoretical studies (TRL 3-4) although the gas coning control described by Sagatun (2010) is used in practice (TRL 9)

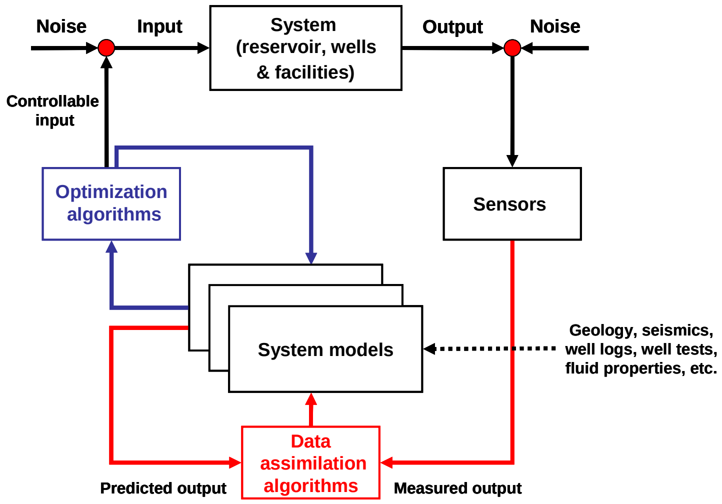

Figure 4: Key elements of the closed-loop reservoir management process (after Jansen et al. 2005, 2008, 2009).

Key to both fields of application, mining and reservoir engineering, are the two main constituents: 1) rapid sequential model updating using data assimilation and 2) fast optimization of control decisions using robust optimization methods. These will be discussed in the subsequent sections. The main differences occur due to the nature of the problem. While mineral resource extraction can be represented in discrete time steps in a static environment formed by the mineral deposit, petroleum production is described in a more complex fashion with the aid of static (geologic), dynamic (reservoir flow) and well bore flow models using systems of partial differential equations. On the other hand, reservoir applications are mainly focused on quantities in terms of water injected or oil/gas recovered, while mineral resource applications address, in addition, a qualitative description of the extracted ore in terms of multiple inter-correlated grades of value- and deleterious elements.

4. Data Assimilation for Rapid Model Updating

This section reviews one of the two main constituents for closed-loop management, data assimilation, which is the adaptation of the parameters of a system model to measured data. Parts of the text of this review have been taken from Jansen et al. (2009).

4.1 Application case reservoir engineering

Data assimilation, or computer-assisted history matching in the case of reservoir engineering, implies updating model parameters $\boldsymbol{\theta}$ using measured output data $\mathbf{d}$. (We use bold face lower case letters to indicate vector quantities, and bold face capitals to indicate matrices). Often this inverse problem is formulated as an optimization (minimization) problem with an objective function defined as the root-mean squared mismatch between measured output $\mathbf{d}$ and the simulated output $\mathbf{y}$, with an additional regularization term to minimize the (squared and summed) deviation of the estimated parameters θ from their prior estimated values θ_{prior}; see e.g., Tarantola (2005), Evensen (2007), Oliver et al. (2008) or Oliver and Chen (2011):

$$J(\mathbf{y},\boldsymbol{\theta}) = (\mathbf{d}-\mathbf{y})^T \mathbf{P}_{\mathbf{y}}^{-1}(\mathbf{d}-\mathbf{y}) + (\boldsymbol{\theta}-\boldsymbol{\theta}_{prior})^T \mathbf{P}_{\boldsymbol{\theta}}^{-1}(\boldsymbol{\theta}-\boldsymbol{\theta}_{prior}) . \qquad (1)$$

Here $\mathbf{P}_{\mathbf{y}}^{-1}$ and $\mathbf{P}_{\boldsymbol{\theta}}^{-1}$ are weight matrices, which are usually chosen as the inverse of the error covariance matrices of the measurements $\mathbf{d}$ and the prior parameters θ_{prior}. The parameters are often taken as grid block permeabilities and porosities, but may also include fault transmissibilities, fluid properties, system boundaries or initial conditions. Usually an ensemble of reservoir models (based on geological 'realizations') is defined each with its own prior θ_{prior}.

Assimilation approaches used in reservoir engineering include optimization-based methods, ensemble Kalman filters (EnKF), and other techniques. Optimization-based methods aim to minimize the objective function (1), usually by considering all data over the preceding measurement period. The most efficient ones use gradient information which can be efficiently computed using the 'adjoint' method, which is a form of implicit differentiation hard-coded in the reservoir simulator (Chavent et al. 1975; Gavallas et al. 1976; Li et al. 2003. For an in-depth treatment, see Oliver et al. 2008.) As opposed, EnKF methods typically use the data as they become available. Moreover, they usually require significantly less programming efforts than the optimization-based methods, and they naturally fit in with the ensemble-based approach to describe geological uncertainty. This is the major reason for the recent rapid increase in popularity of the EnKF which can be implemented relatively easy 'around' an existing reservoir simulator (Evensen 2009; Aanonsen et al. 2009). Kalman filtering was originally developed to estimate uncertain states, and not parameters, in linear dynamic systems from noisy measured data (Kalman, 1960). Assuming Gaussian distributions for the uncertainty in the prior states and the measurements, posterior estimates for the states and the corresponding uncertainties can then be computed with the aid of closed-form matrix expressions. For nonlinear problems, of which parameter estimation problems form a subset, the ordinary Kalman filter breaks down because the nonlinearity results in non-Gaussian noise when propagated through the system. In the EnKF the analytical error propagation is replaced by a Monte Carlo approach, in which the model error covariance is computed from an ensemble of models which are all propagated in time (Evensen, 2003, 2009). Reservoir-focused implementations of the EnKF also treat parameters as unknowns, which leads to the use of an extended state vector. Over the past decade a very large number of publications have appeared that apply the EnKF to reservoir engineering problems and treat specific implementation problems; here we just refer to the textbook of Evensen (2009) and the review paper of Aanonsen et al. (2009) for in-depth treatments and references. More recent developments include an increased use of Ensemble Kalman Smoothers (EnKS), which also update states and parameters in the past, especially in combination with iterative techniques to ensure consistency between the parameter and state updates (Emerick and Reynolds, 2013; Le et al. 2016).

In addition to these ‘classic’ data assimilation methods there are ‘non-classic’ techniques from the machine learning or artificial intelligent community such as genetic algorithms, particle swarms, or simulated annealing; see, e.g., Schultze-Riegert et al. (2002), Mohamed et al. (2010) and Jin et al. (2012). Because these methods typically require a very large number of function evaluations (i.e. reservoir simulation runs), they are restricted to the assimilation of a limited number of parameters. Often, the computational burden is reduced with the aid of ‘surrogate’ or ‘proxy’ models, in the form of response surfaces that require a large number of upfront ‘training’ simulations but can subsequently be evaluated very many times and very quickly during the history matching procedure (Omre and Lødøen, 2004; Cullick et al. 2006; Yang et al. 2007; Alpak et al. 2009). We note that machine learning techniques are sometimes also used to predict production performance more directly from past well performance, i.e., in a black-box or gray-box fashion without the use of reservoir flow models (Cao et al. 2016).

Other assimilation methods employ ‘streamline simulation’, a computationally efficient reduced-physics simulation method that also allows for rapid assimilation of oil-water fluid fronts; see Datta-Gupta and King (2007) and Batycky et al. (2008). Yet another category avoids the explicit modeling of geological parameters and uses a capacitance-resistance representation of well connectivities (Sayarpour et al. 2009; Zhao et al. 2016), but has not (yet) found widespread application. The same holds for several other data assimilation techniques which we will not list here; for further references see, e.g., Aanonsen et al. (2009) or Jansen et al. (2009).

Whether one uses ‘classic’ optimization-based or filtering approaches or ‘non-classic’ methods, the data assimilation problem in reservoir engineering is nearly always very ill-posed, especially if uncertain parameters (permeabilities, porosities) are associated which each grid block in the reservoir model. Even although these parameters are spatially correlated there are typically many more unknowns in the vector $\boldsymbol{\theta}$ than can be resolved from the data $\mathbf{d}$. Regularization in the form of prior geological knowledge is therefore essential (Gavalas et al. 1976). Alternatively, various techniques to reduce the size of the parameter estimation problem have been proposed using, e.g., zonation (Gavalas et al. 1976), pilot points (Bissell et al. 1997), wavelets (Sahni and Horne, 2005), eigenvalue decomposition of the parameter covariance matrix (Gavalas et al. 1976) and its nonlinear version, kernel principal component analysis (Sarma et al. 2007), the discrete cosine transform (Jafarpour and McLaughlin, 2009), compressed sensing (Jafarpour et al. 2010) or sensitivity matrix decomposition (Tavakoli and Reynolds, 2010).

Traditional computer-assisted history matching is performed on the reservoir flow model, which usually only contains a strongly up-scaled version of the underlying detailed geological model. As a result, 'updates' to the model are sometimes geologically completely unrealistic. The predictive value of a properly history-matched model is never guaranteed (and, in fact, usually rather limited), but it is generally accepted that a geologically realistic model will have a higher chance of properly predicting the future reservoir behavior than an unrealistic one. A major trend in reservoir data assimilation is therefore to perform the data assimilation directly on the fine scale geological model, a technique sometimes referred to as 'big loop' history matching, and to extend the range of unknown parameters to include structural features; see, e.g., Seiler et al. (2010) and Hanea et al. (2015).

Another development in reservoir data assimilation is the increasing use of 'time lapse' seismic data. By repeating seismic surveys after a period of production it is often possible to identify the fronts between water or gas displacing oil, and this information can help to drastically increase the quality of the update; see e.g., Skjervheim (2007), Trani et al. (2012), Jin et al. (2012), Emerick and Reynolds (2013) and Hadavand and Deutsch (2016). Also, the increasing use of different geophysical measurements such as gravity or electromagnetic surveys can be of help to obtain a better picture of the subsurface fluid distribution, and, through inversion, of the reservoir model parameters; see e.g., Glegola et al. (2012) and Katterbauer et al. (2016).

Finally, an increasing research effort is aimed at the development of techniques for formal uncertainty quantification beyond the use of an ensemble of reservoir models. All rigorous methods for uncertainty quantification use some variety of the Monte Carlo method, which is, however, in its full form computationally completely infeasible for realistically sized reservoir models. Short-cuts, either in the form of 'surrogate' reservoir models or through drastically simplified uncertainty handling (of which the EnKF method is an example) lead to results with varying trustworthiness; see, e.g., Mohamed et al. (2010). Practical approaches for quantifying the uncertainty in future reservoir performance therefore still rely on a mixture of human judgement and the use of ensembles of geological realizations. For the latter, it is essential to create an as-large-as-possible diversity in the geological concepts and models and frequently assess alternative interpretations with a wide range of geoscience experts (Caers, 2011).

From the various elements in the CLRM workflow, computer-assisted history matching is by far the furthest developed and is nowadays being used in operational practice by pioneers and fast followers in the oil industry. The corresponding TRL level of the mature techniques (i.e. adjoint-based optimization, proxy-supported 'non-classical methods, streamline-based methods, and especially the EnKF and the EnKS) varies between 8 and 9.

4.2 Application case mining engineering

Vargas-Guzman and Dimitrakopoulos (2002) presented an approach that can facilitate fast-updating of generated realizations of a mineral resource model based on new data, without repeating the full simulation process. The approach is termed conditional simulation of successive residuals CSSR and was designed to overcome the size- limitations of the LU decomposition Davis (1987). The novel column partitioning requires the speciation of a sequence of (future) data locations. A stored L matrix can then facilitate the conditional updating of existing realizations if and only if the sequence of visited subsets and used production data are the same as the one used for generating the initial realizations (Jewbali and Dimitrakopoulos, 2011). A major limitation of these techniques results from the necessity to store and propagate the conditional nonstationary covariances.

To circumvent this limitation, the previously discussed sequential linear estimator can be integrated into a Monte Carlo framework similar to the above discussed EnKF, which has been shown to work successful in different fields in geosciences (Evensen and van Leeuwen, 1996; Xu and Gómez-Hernández 2015; Chevalier et al. 2015). Benndorf (2015) recognized the potential of sequential updating in the field of solid resource extraction and proposed an adapted version of the EnKF for mineral resource model updating in a static linear system environment deposit. Note that contrary to typical Kalman Filter descriptions a state transition matrix is not applicable to mineral resource model updating, as the actual deposit, which is represented by the block model, does not evolve over time. Wambeke and Benndorf (2015) further developed this approach and integrated features necessary to handle typical mining applications. The approach allows reconciling the resource model easily and fast against data from different process steps along the mining value chain from extraction to mineral processing. Features include a set of Gaussian Anamorphosis steps to handle typically asymmetric and non-Gaussian distribution of ore grades, empirical calculation of covariances for different data support to relate point data direct to SMU scale and also a localization or neighborhood strategy to attain acceptable computation times and derive a local updating. Similar to the application case reservoir engineering, production data can be integrated by comparing model based prediction and measurement data. The flexibility of the realization-based empirical updating approach originates from the fact that it can also be easily implemented ‘around’ an existing mining simulator or material tracking system (Fig. 5). These can be implemented as Discrete Event Simulators (e.g. Hall, 2000; Shishvan and Benndorf, 2015) of the mining process or state-of-the-art material tracking systems based on RFID tag technology (e.g. La Rosa, 2007).

An example in a fully known and controllable environment illustrates the concept. It mimics the reconciliation of a blend of 16 measured truck loads originating from two mining blocks of different size at different benches. Figure 6 shows a cross-section through one of the two benches considered. For all selected grid nodes, the mean and 95% confidence intervals are plotted prior and post updating. It can be seen that in addition to the improvement in predicting the grade for the excavated block, in a 40 m long area east of the sampled region the best estimate is considerably improved and matches the true state reasonably well. This is a significant improvement and allows making better decisions in subsequent short-term planning steps and production control. For further details, the reader is referred to Wambeke and Benndorf (2015)

At this moment, the maturity of the methods is judged by the authors on a TRL 5 scale, which is that concepts are proven in an artificial and laboratory environment. Current work focusses to prove the applicability of these techniques in full-scale industrial test cases leading to TRL7. A recent application related to updating local coal quality attributes of mining blocks based on radiometric online sensors in large continuous mining operations including multiple split seams demonstrates improvement in local prediction of 40% (Yueksel et al. 2016).

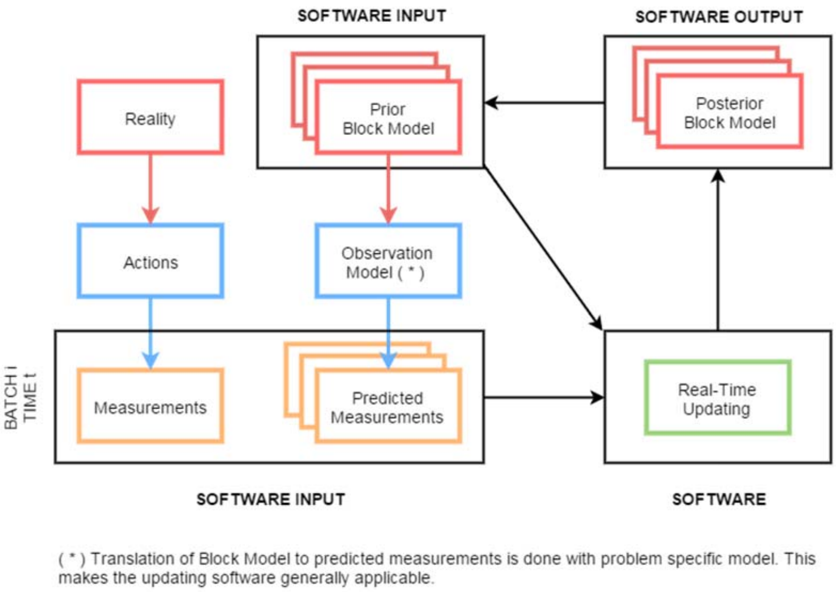

Figure 5: Closed-loop reconciliation framework to integrate on-line sensor measurements from the material streams along the whole mining process into the resource model (after Wambeke and Benndorf 2015).

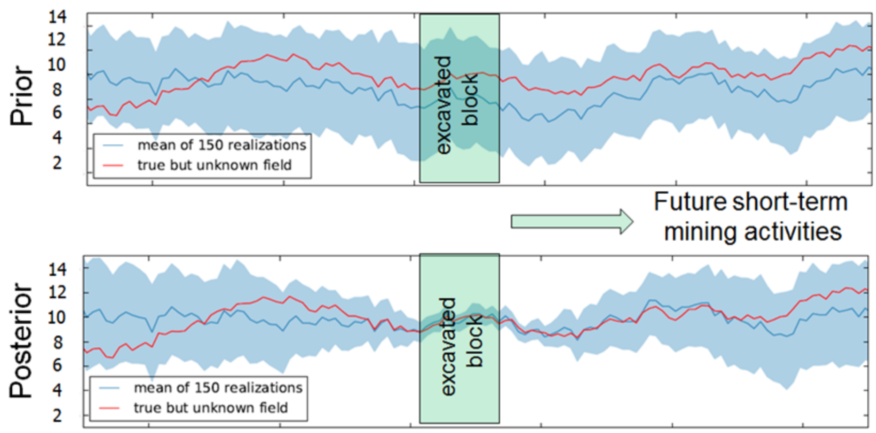

Figure 6: Example for mineral resource model updating – a cross section through a bench prior and post updating (after Wambeke and Benndorf 2015).

5. Fast and Robust Optimization Techniques

Given updated system models, fast (relative to the time scale involved) and computationally efficient optimization techniques form the second main constituent in closed-loop approaches. This section summarizes recent developments.

5.1 Application case reservoir engineering – long-term reservoir management and short-term production optimization

A major task in reservoir management is to define an optimal long-term production strategy, variably referred to as a 'recovery optimization', 'flooding optimization' or 'life-cycle optimization'. For a given configuration of wells, and in particular for a flooding scenario involving multiple injectors and producers, the long-term well control optimization variables are typically pressures at the top of the production wells, flow rates in the injection wells, or valve setting in surface or downhole flow control valves. More elaborate optimization studies also involve the optimization of well locations or well trajectories (references will be given below).

As discussed in Section 2, robust well control optimization can be used to maximize the expected value of an objective function over all geological realizations (Yeten et al. 2003; van Essen et al. 2009.) Many different optimization techniques can be applied to perform suchrobust well control optimization. Just like in data assimilation, the most efficient ones use gradient information obtained with the 'adjoint' method. For the use in robust optimization, see van Essen et al. (2009); for a general overview, see Jansen (2011). Alternative, less code-intrusive, robust methods use approximate gradient and/or stochastic methods (Chen et al. 2009; Chen and Oliver, 2010; Li et al. 2013; Fonseca et al. 2015, 2016) or 'non-classical' methods such as, e.g., streamline methods (Alhutali et al. 2008), evolutionary strategies (Pajonk et al. 2011), or polynomial chaos expansions in combination with response surfaces (Babaei et al. 2015), with further references given in Echeverrıa Ciaurri et al. (2011).

In addition to robust optimization studies there is a large number of papers describing deterministic well control optimization over the life cycle of the reservoir both with and without the use of gradients; see, e.g., Sudaryanto and Yortsos (2000), Brouwer and Jansen (2004), Sarma et al. (2008b), van Essen et al. (2010), Forouzanfar et al. (2013a), Kourounis et al. (2014) or, for overviews, Jansen (2011) and Echeverrıa Ciaurri et al. (2011). Moreover, all of the CLRM studies referred to in Section 3 involve robust or deterministic well control and/or well location optimization.

Recently, there has been an increasing interest in methods that extend long-term model-based well control optimization to include aspects of short-term production optimization. Here use is made of the fact that typically the long-term control problem is over-parameterized, i.e. after optimizing the long-term objectives there are remaining degrees of freedom to hierarchically optimize a secondary objective (Van Essen et al. 2011). Alternatively trade-offs between long-term and short term optimization may be presented in the form of a Pareto front. Robust versions of such hierarchical and/or multi-objective optimization studies have been published by, e.g., Chen et al. (2012), Fonseca et al. (2015), Chang et al. (2015) and Liu and Reynolds (2016).

Many studies have been published on the optimization of well locations or trajectories. Although some of them are adjoint-based (Wang et al. 2007; Zandvliet et al. 2008a; Sarma and Chen 2008; Vlemmix et al. 2009), the most effective techniques use 'non-classical' methods such as genetic algorithms, particle swarm optimization or evolutionary strategies (e.g. Güyagüler et al. 2002; Yeten et al. 2003; Bangerth, 2006; Owunalu and Durlofsky, 2010, 2011, Bouzarkouna et al. 2012; Forouzanfar et al. 2013b, Jesmani et al. 2016). There is also an increasing number of studies involving the joint optimization of well controls and locations (e.g. Bailey et al. 2005, Isebor et al. 2014b; Forouzanfar and Reynolds, 2014; Humphries and Haynes, 2015; Forouzanfar et al. 2016). Finally there are some studies that address comprehensive field development planning optimization including, e.g., surface facilities, artificial lift options and drilling schedules (e.g. Litvak and Angert, 2009; Couët et al. 2010).

Although there is a considerable number of publications covering long-term well control optimization, the actual use of these optimization strategies during the field development planning phase is still very limited (TRL3-4). As opposed to the slow uptake of long-term well-control optimization, the use of well location optimization is currently rapidly increasing and has reached TRL 6-7, although it took more than a decade before the first serious attempts were made to use these methods on real field development plans.

The optimization methods described above are all primarily aimed at long-term (life-cycle) reservoir management at typical time scales of months to years or even decades. However, the upstream oil industry increasingly applies formal optimization methods for short-term production optimization at a time scale of days to weeks. These are usually open-loop, to compute set points for regulatory controllers but gradually start to be applied in a closed-loop fashion, especially for application that require a fast response. Some applications of direct feedback control, i.e. without optimization, have been reported in Section 3. We will not discuss these emerging 'real-time' applications in detail (TRL levels range from 3 to 9) but refer to Bieker (2007), Awasthi (2008) and Bakshi et al. (2015) for further information.

5.2 Application case mineral resource extraction – short-term planning and material stream management

Process control decisions regarded in mining applications include production sequencing, digging capacity control or stock-pile management. A particular example is to optimize the equipment schedule and effective production rates to control the quantity and quality of different material streams of extracted material (ROM ore). In this scenario, on a given bench, an excavator has access to different types of ore and waste. The demand for different ore products with different specifications and waste differs due to blending constraints and available dump space on the spreader site of the open pit.

To investigate suitable techniques for optimization, following aspects of the mineral resource extraction problem have to be taken into account

- The optimization problem consists of discrete decision variables (extraction sequence) and continuous decision variables (effective digging capacities) within certain boundaries.
- To provide a detailed enough resolution for scheduling, the amount of decision variables can become rather large resulting in a large-scale optimization problem.
- The objective function is a complex expression involving multiple performance indicators as a function of continuous and discrete decisions variables
- In general several stochastic components can be considered, including the resource model, unscheduled breakdown of equipment and uncertainty in demand of product.
- 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.

Methods of mathematical programming, such as Dynamic Programming or Mixed Integer Programming, are well acknowledged in the field of mine planning optimization (e.g., Newman et al., 2010). Most of the mathematical programming approaches are limited by the amount of decision variables, as applications become large and suffer from reduced computational efficiency. An alternative offer simulation-based optimization techniques; the concept is shown in Fig. 7 (e.g., Gosavi, 2014). Using general system simulation techniques, the objective value *J* of a complex objective function can be evaluated for a given set of decision variables. The potential suite of optimization approaches is versatile and may classify using the algorithms' properties like convergence, separate them by the applied techniques (e.g., heuristics or gradient methods) or use the solution space (e.g., discrete or continuous) and the objective function (e.g. single or multiple objectives) to set methods apart from one another (e.g. Hachicha, et al. 2010). For problems similar to short-term mine planning in mining, several documented studies have demonstrated the effectiveness and value added; these refer in particular to job allocation and scheduling problems involving multiple factories in different manufacturing industry (Chung, et al. 2009; Ganesterer, et al. 2014; Lin and Chen 2015),

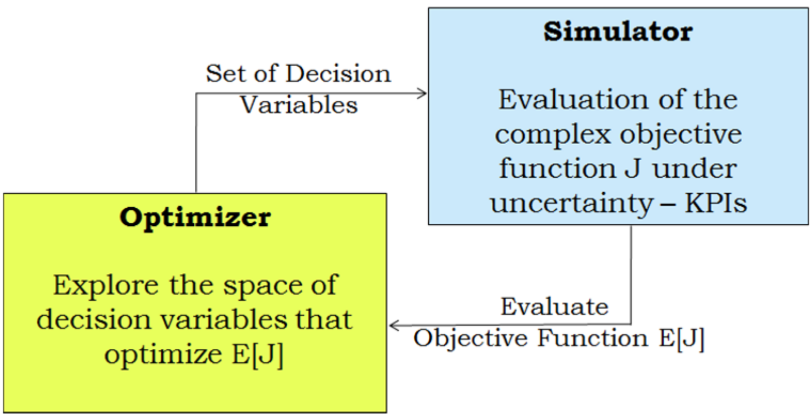

Figure 7: The concept of simulation based optimization (reproduced after Gosavi, 2014)

An application of this concept applied to short-term production scheduling in continuous open pit mining has recently be documented by Shishvan and Benndorf (2016) and Mollema (2015). 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 unscheduled maintenance and uncertainty in demand. The objective function J is evaluated as a weighted combination of several sub-objectives including meeting coal tonnage and quality targets on a daily basis using a penalty function (Fig. 8).

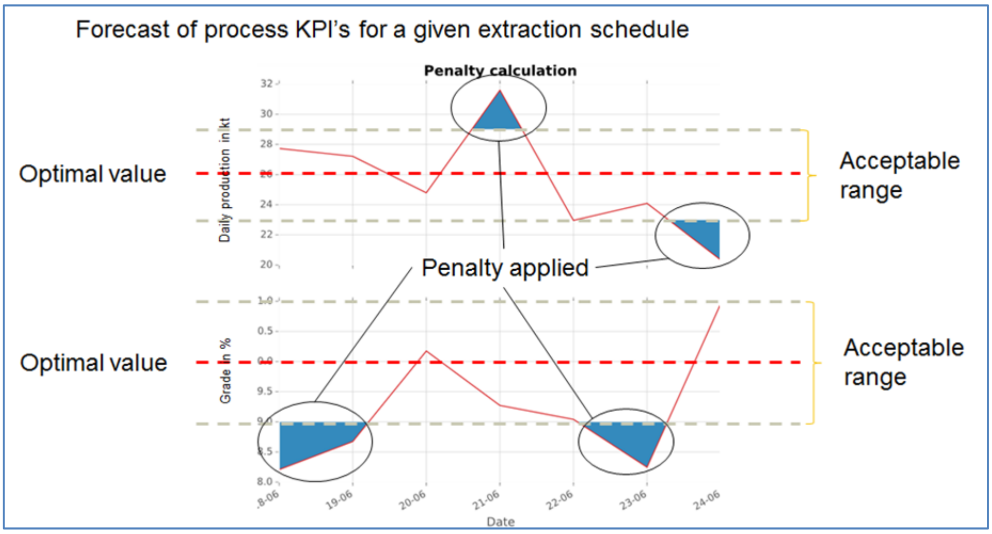

Figure 8: Evaluation of multiple objectives using penalty functions for coal production (reproduced after Mollema, 2015).

A first investigative study focused on optimizing the task schedule for a short-term scheduling and showed that a combination of a genetic algorithm for global optimization and simulated annealing for local optimization works 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. 9).

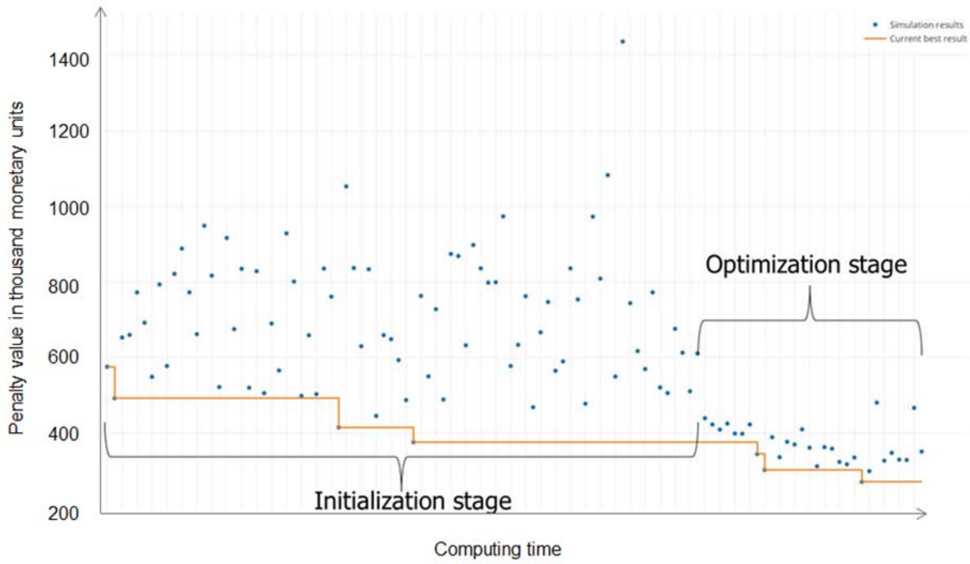

Figure 9: Performance of a simulation-based optimizer applied to task scheduling in a continuous open pit operation (after Mollema 2015).

6. Conclusion and Discussion

Closed-loop approaches have the potential to generate substantial benefit during extraction of geo-resources. Studies in reservoir engineering predict scope for improvement in NPV in the order of 5% to 10% (e.g. Jansen et al. 2009). This potential derives from improved reservoir recovery and cash-flow by combining data assimilation, to keep reservoir models 'evergreen', with near-continuous production optimization. A preliminary investigation of the techno-economic benefit of including online-production data for improved mine planning and extraction process control indicates a benefit in the order Mio.$ 5-10 for an average sized mining operation of 10Mio tons of ore production per year (Buxton and Benndorf 2013). This number represents a first order estimate and has to be evaluated for different operations and commodities separately. This potential for improvement is mainly raised due to less misclassified blocks, elimination of zero-value material from the logistic chain and improved grade streaming for enhanced metal recovery during the subsequent beneficiation and processing steps.

Techniques for closed-loop management are established at different technological maturity levels in both fields of application. While elements of the closed-loop approach in reservoir engineering are already investigated for more than a decade, and in particular the use of data assimilation and well location optimization rapidly matures, the complete use of a closed-loop approach has not yet been implemented in practice. Although the necessary computational methods and algorithms have been developed over the past decade to a significant level of maturity, actual application in operational practice is hampered by the inherent uncertainty in oil field development and production operations, the tension between short-term operational requirements and more long-term optimal development decisions, the inertia of traditional ways of working and the difficulty to quantify financial gains up-front in projects that take typically decades to complete. Developments in solid mineral resource extraction started during the last decade. Table 4 provides a judgement from the authors on TRL for closed-loop concepts in both fields of application.

Table 4: Judgement on technology readiness for closed-loop concepts in both fields of applications

Criteria	Reservoir Engineering	Mineral Resource Extraction
Modelling geological uncertainty	TRL 8-9	TRL 8-9
Robust long-term optimization	TRL 3-4 (well controls) TRL 6-7 (locations)	TRL 5-6
Data assimilation for model updating	TRL 8-9	TRL4
Fast optimization for real-time decision support	TRL 4-5 (niche applications: 8-9)	TRL4
Integrated closed-loop concept	TRL 3-4	TRL 4-5

Table 4 indicates that approaches discussed in the text are theoretically well developed and tested in a controlled environment. Currently, the concepts in mining applications sit between TRL 3 – 5. The intention of current research initiatives is to evolve this to TRL 6-7 by focusing on investigating performances on large industry-scale problems and solve related implementation issues. For both fields of application integrated demonstration cases in full-scale environments are necessary prove economic benefits. This should also include training of reservoir and mining engineers in these fields on a professional and as well an academic level.

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