Review

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Review

Real Time Mining—A Review of Developments Within the Last Decade

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Abstract: Real-time mining (RTM) has become increasingly significant in response to the growing need for sustainable mineral resource extraction, driven by global population growth and technological progress. This innovative approach addresses critical challenges such as declining ore grades, deeper and less accessible deposits, and rising energy costs by integrating advanced online grade monitoring, data analysis, and process optimization. By employing real-time grade control, dynamic mine planning, and production optimization, it enhances the efficiency of resource extraction while minimizing environmental and social impacts. Originally proposed about a decade ago, RTM has gained attention for its potential to revolutionize the industry. This review examines recent advancements in closed-loop concepts, emphasizing the integration of advanced sensors and data analytics to enable continuous monitoring and adaptive decision-making across the mining value chain. It highlights the role of online sensor technologies in providing high-resolution data for process optimization and evaluates various mining optimization techniques. The paper also explores data assimilation methods, such as Kalman filters and artificial intelligence (AI), showcasing their ability to continuously update models and reduce operational uncertainties. Ultimately, it proposes a comprehensive framework for adaptive, data-driven mining operations that promote sustainable development, enhance profitability, and improve decision-making capabilities.

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1. Introduction

The global demand for mined resources has accelerated over the past decade, driven by population growth, technological advancements, and economic expansion. By 2050, the demand for metals is projected to rise substantially—aluminum by 215%, copper and nickel each by 140%, iron by 86%, zinc by 81%, and lead by 46% [1]. Metals such as copper, gold, zinc, and aluminum are essential for the renewable energy transition and achieving Net Zero targets due to their critical role in decarbonization technologies like wind turbines, solar panels, and electric vehicles [2,3].

This escalating demand intensifies pressure on the mining sector, which faces challenges like declining ore grades, deeper and more inaccessible deposits, and increasing energy costs. Moreover, mining activities often raise social and environmental concerns, leading to what is known as the "mineral resource dilemma". This dilemma highlights the tension between the necessity for mineral resources to support technological and societal advancement and the reluctance to endorse mining due to its adverse impacts [4,5]. Balancing these competing interests necessitates greater transparency and sustainable practices in mining operations. The industry must optimize resource extraction while minimizing environmental footprints to meet global demands without exacerbating ecological degradation.

Traditionally, the mining industry has followed a linear value chain comprising sequential steps from exploration to mine closure. The process begins with exploration, where data is collected to

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define the spatial extent, geometry, and geotechnical and hydrological conditions of potential sites using methods like remote sensing, geological mapping, geophysics, and drilling [6]. Resource modeling then creates a 3D orebody model, classifying ore, waste, and rock types to minimize ore loss and dilution [7–9]. Mine planning utilizes this data to design optimal extraction sequences, involving production control and planning to ensure consistent product quality through effective blending [10–12].

Despite its widespread use, this linear approach has significant drawbacks. It is often subjective, time-consuming, and prone to inconsistencies, especially in complex geological settings. Uncertainties in mineral deposits can lead to production deviations from expectations, as resource modeling relies on uncertain data, causing planning inaccuracies [13–15]. Furthermore, the traditional fragmented approach involves specialized experts working independently with minimal communication, resulting in delayed feedback and issues that surface only during operations. This lack of integration and real-time communication hinders prompt adaptation and leads to suboptimal decisions. Integrating advanced technologies and real-time data can enhance data integration and cross-phase communication, improving modeling and planning efficiency while reducing operational uncertainty [6].

To address these challenges, the concept of real-time mining (RTM) emerged about a decade ago [16,17]. RTM aims to optimize resource extraction and minimize environmental impacts through continuous monitoring and immediate data analysis. By employing real-time data from advanced sensors and analytics, RTM enhances process efficiency, maximizes mineral recovery, and facilitates immediate adjustments based on the latest information [18,19]. The core idea is to create a closed-loop management system where operational data feeds back into decision-making processes in real time, enabling dynamic optimization of extraction, processing, and overall efficiency. In general, key constituents of the RTM approach are advanced real-time sensors, optimization algorithms, and data assimilation. Continuous grade control becomes possible, allowing for accurate ore characterization and immediate responses to changes in ore quality [6].

Recent years have seen the emergence of megatrends that have the potential to transform the mining industry. Digital disruption, characterized by the integration of digital technologies into all aspects of operations, is reshaping traditional practices. Advanced online sensors, Internet of Things (IoT) devices, and data analytics methods such as artificial intelligence (AI) and geostatistics enable the collection and analysis of vast amounts of real-time data [20–23]. These innovations improve predictive maintenance, process optimization, and decision-making, enhancing efficiency, safety, and sustainability. AI-driven tools also support intelligent mining systems, enabling precise ore deposit modeling, real-time monitoring, geo-metallurgical modeling, and continuous grade control [7,24–27]. Collectively, these advancements improve resource utilization, reduce environmental impacts, and promote transparency in addressing the mineral resource dilemma.

Significant advances have been made in key constituents of the RTM approach over the past decade, particularly in sensor development and data analytics. Cutting-edge sensors provide near-continuous monitoring of critical indicators, such as ore grade and environmental contamination, enabling early risk detection and timely interventions [6,22,28–32]. Additionally, data analytics techniques—including AI, geostatistics, and Kalman filters—have enhanced data interpretation, facilitating real-time updates to grade control models, optimizing extraction processes, and reducing ore dilution [33–36].

Despite its potential, the full RTM concept remains largely theoretical, with limited practical implementation due to technological and operational barriers. Factors such as inadequate sensor designs for field applications, high initial costs, and the need to demonstrate practical utility have hindered widespread adoption. Integrating advanced sensors into the harsh and variable conditions of mining environments poses significant technical challenges that demand robust and durable designs [22]. The Technology Readiness Level (TRL) framework, which ranges from basic principles (TRL 1) to fully operational systems (TRL 9), highlights the substantial gap between research and application. To date, no operational mine has fully integrated RTM approaches, underscoring the low

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TRL status of these technologies. This status emphasizes the considerable development and testing required to advance key constituents of the RTM approach toward practical deployment.

Additionally, developing real-time data processing algorithms capable of handling the volume and complexity of mining data in operational settings is still underway [7,37]. The absence of pilot projects and field demonstrations means that mining companies are hesitant to invest in key constituents of the RTM approach without clear evidence of their practical benefits and return on investment. Elevating key constituents of the RTM approach to higher TRL levels through collaborative efforts between researchers, technology developers, and industry stakeholders is essential for bridging the gap between concept and practical application.

The primary objective of this review paper is to evaluate the advancements in key constituents of the RTM approach over the past decade, identify the barriers preventing their practical implementation, and propose strategies to bridge the gap between research and industry application. By analyzing existing literature and technological developments, this paper aims to provide insights into transitioning RTM from theoretical frameworks to practical, large-scale operations that meet global demands and optimize ore extraction processes.

The paper is organized as follows: Section 2 delves into the RTM concept in detail, exploring its principles and potential benefits. Section 3 discusses how sensor technologies are transforming mining operations. Section 4 examines mine planning and optimization techniques within the RTM context. Section 5 addresses data assimilation in closed-loop RTM management. Finally, Section 6 proposes strategies for bridging implementation gaps using advanced data analytics, including AI and machine learning (see Figure 1).

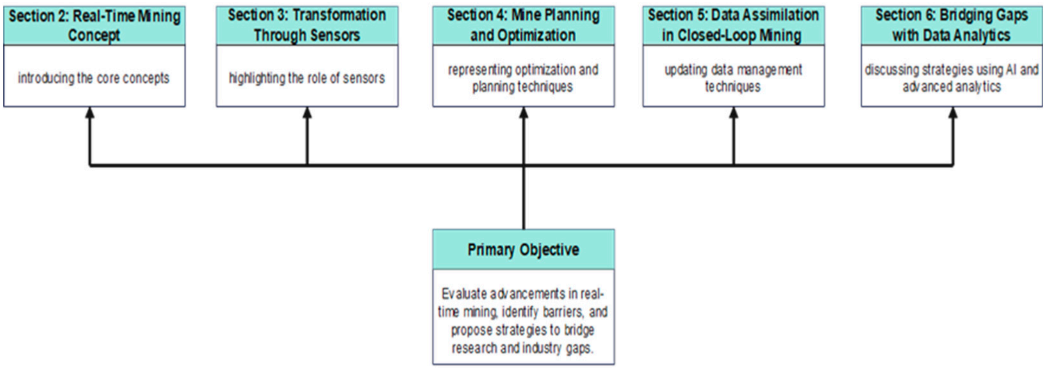

Figure 1. Overview of the structure and objectives of the review paper.

2. The RTM Concept

Over the past decade, the concept of RTM has emerged as a transformative approach in the mining industry, shifting from traditional discontinuous and intermittent monitoring systems to continuous process and quality management frameworks. RTM integrates a real-time feedback control loop that immediately links live data collected at the mining face, throughout material handling and processing, with an updatable sequential resource model (see Figure 2) [16,17,38]. This integration facilitates near-real-time optimization of long-term planning, short-term sequencing, and production control, providing critical insights to improve efficiency and reduce deviations from production targets.

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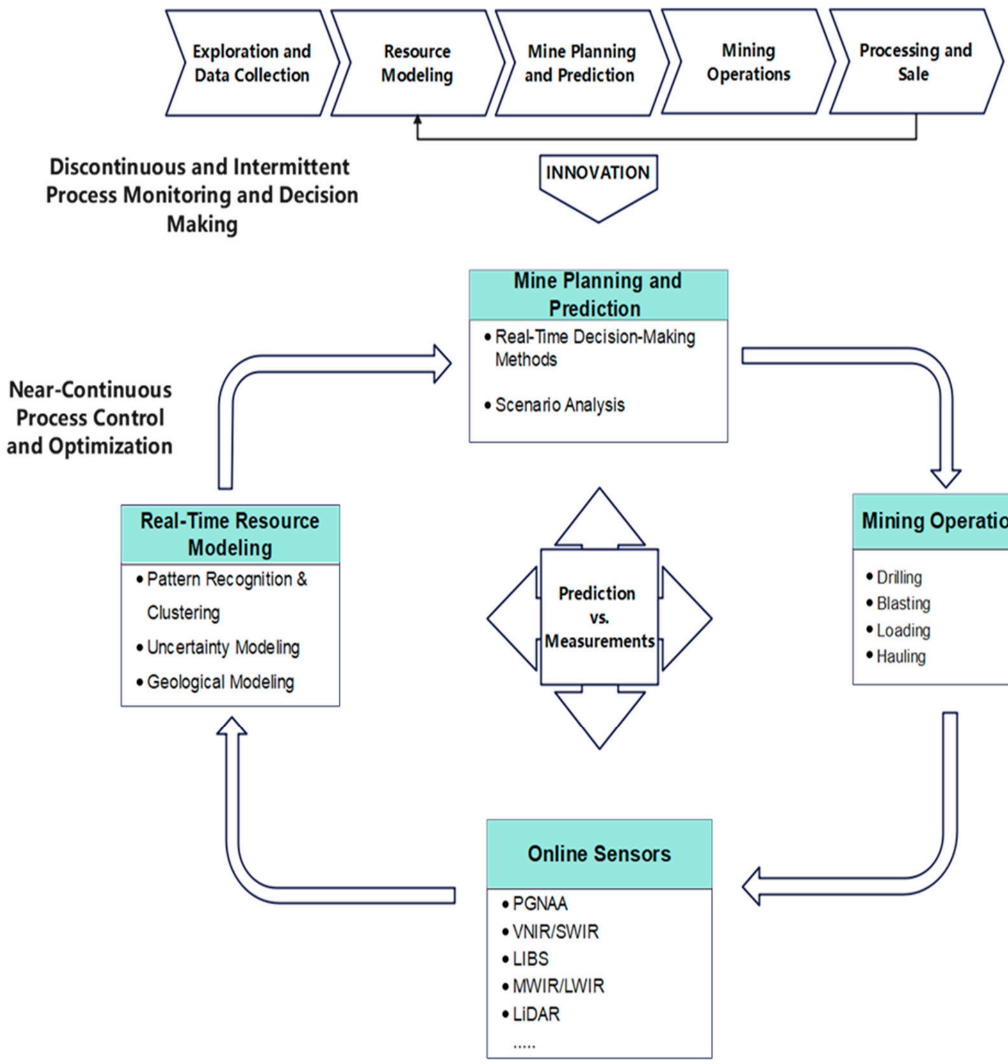

Figure 2. The concept of closed-loop management in RTM.

A closed-loop mineral resource management (CLRM) system in RTM builds a model-based representation of the real system that is continuously updated as new data become available. It builds upon several core elements, as illustrated in the Figure 3. These are sensor networks for production monitoring, system models, optimization algorithms for decision support, and data assimilation for real-time model update. Together, these interconnected elements provide a comprehensive, data-driven approach to optimizing mining operations in real-time.

The "real system" in this context embodies the physical mining environment, which includes activities such as drilling, blasting, hauling, and processing that interact directly with the orebody. The effectiveness of these activities is influenced by control variables like equipment schedules and mine plans. The system is also influenced by inherent variability and uncertainty, which is depicted as "noise" in the figure.

Production monitoring involves sensors that collect real-time data during production. These sensors might measure ore grades, production rates, or equipment performance. Such monitoring can also include higher-level tasks, like interpreting geological information or assessing grade control sampling. This process provides essential feedback about ore characteristics such as grade and hardness. The concept of "noise" here refers to measurement uncertainties and discrepancies in material tracking. These models are developed and continuously updated using data such as exploration data, geological interpretation, geodesy data, and grade control data.

The system models—resource and grade control models—provide a mathematical or computational representation of the mining system. Resource models estimate the quantity and

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quality of mineral resources, while grade control models are focused on the quality of the ore being extracted. Due to the uncertainty inherent in subsurface geology, multiple models are typically created to provide estimates of mineral distribution and orebody characteristics and its uncertainty, using data like exploration results, geological assessments, and grade control measurements.

Within the closed-loop management system, optimization algorithms play a critical role in decision-making. These algorithms generate efficient mine plans and production control strategies, optimizing parameters like equipment schedules and production targets. Optimizers work on different planning horizons, from short-term tasks, like daily equipment scheduling, to long-term plans, such as designing pushbacks. The "blue loop" in the figure represents the continuous optimization process, where real-time data from production monitoring is used to refine mine planning and operations.

Data assimilation is the process of updating the system models to accurately reflect the performance of the real system. Through advanced data analytics, such as AI and geostatistics techniques, data assimilation reconciles discrepancies between model predictions and observed outcomes, thus enhancing model reliability. Whenever measured outputs deviate from model predictions, the model parameters are updated to reduce these discrepancies, thereby improving the predictive accuracy of the models. This process also helps manage the noise present in both control inputs and system outputs. The red loop in the figure represents this iterative updating of system models, which is informed by real-time production data.

The integration of these elements into a closed-loop mineral resource management system is designed to address uncertainties and improve operational outcomes. By combining real-time monitoring, system models, optimization algorithms, and data assimilation, the system ensures that physical operations are continuously observed, and the data gathered is used to enhance planning and operations. This closed-loop structure facilitates adaptive, data-driven decision-making, which leads to increased resource recovery, reduced waste, and minimized operational risks.

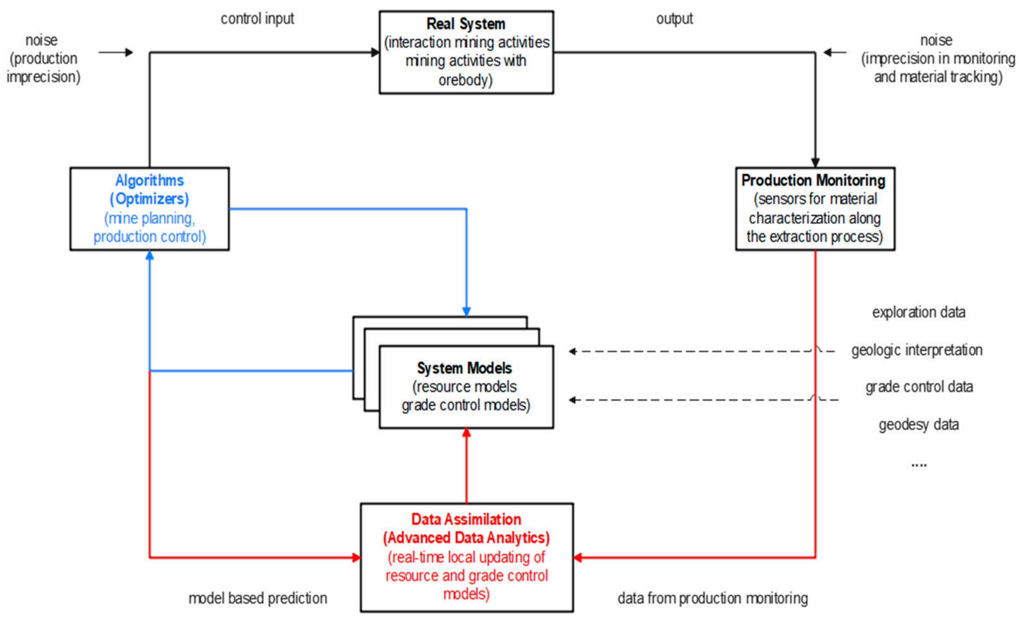

Figure 3. Key parts of closed-loop management system (adapted from after Jansen, et al. [39]).

3. Transformation in Mining Operations Through Sensors

Sensor technologies have transformed the mining industry by offering deep insights into material properties, providing rich qualitative, quantitative, and semi-quantitative data across various dimensions like geochemistry, mineralogy, and texture [22]. By operating within specific electromagnetic spectrums, sensors offer unique chemical information that is critical for improving

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mining operations. Additionally, integrating technologies such as belt scales and geometrical sensors further optimizes process efficiency and ensures operational accuracy.

Sensors enhance efficiency and accuracy across different stages of mining. During exploration, sensors reduce costs by minimizing the need for extensive physical sampling and costly laboratory tests. With real-time data, decisions can be made more swiftly, expediting the exploration process. The high-resolution data from sensors helps precisely determine ore grades and other crucial factors, thereby defining resources with greater accuracy.

In the production and grade control stage, sensors monitor ore extraction in real-time, ensuring adherence to the production plan, minimizing deviations, and distinguishing accurately between ore and waste. This precision prevents costly errors such as processing waste or discarding valuable ore, leading to improved operational efficiency and reduced equipment downtime.

In pre-sorting or pre-upgrading of materials along the production process, sensors play a key role in eliminating waste and low-grade material before reaching the processing plant, thereby simplifying the subsequent processes and making them more energy- and cost-efficient. In the post-stockpile and pre-processing stages, sensors further refine the material by optimizing feed quality, which helps operators increase recovery rates and control costs.

During post-processing and quality control, sensors provide real-time feedback on product quality, allowing immediate adjustments to meet customer specifications. This enhances product value, reduces penalties for off-spec materials, and ensures customer satisfaction.

By integrating sensors at each stage, mining operations are optimized for precision, efficiency, and cost-effectiveness, ultimately improving both financial performance and product quality [21]. Table 1 highlights the different impacts of sensors on mining operations.

Table 1. Effects of sensors in mining operations [21].

Mine Stage	Sensor Effects	Advantages of Sensors
Exploration	Sensors replace physical sampling and provide real-time data for resource definition (e.g., grade, geometry).	- Reduce costs and time for sampling. - Provide immediate data for decision-making. - Eliminate extensive need for offline laboratory analysis.
Production & Grade Control	Sensors monitor ore grade and material properties at the face to influence real-time extraction decisions.	- Improve compliance with mining plans. - Reduce misclassification of ore and waste. - Optimize production sequencing and equipment allocation.
Pre-sorting/Pre-upgrading	Sensors sort material before crushing, controlling dispatch to specific destinations (e.g., waste or stockpile).	- Reduce material variability. - Increase product homogeneity. - Improve efficiency by removing waste early.
Post-stockpile & Pre-processing	Sensors further refine material by removing residual variability in grade and chemistry.	- Increase feed quality for processing plants. - Enhance process control. - Improve precision of material characteristics.
Post-processing & Quality Control	Sensors ensure final product quality by analyzing the material stream in real time.	- Maintain product specifications. - Provide immediate feedback for process adjustments. - Eliminate off-line quality control analysis.

In contemporary mining operations, the adoption of advanced sensor technologies has resulted in a rich data ecosystem, enabling continuous process monitoring and optimization. One example is Measurement While Drilling (MWD), an online data recording technology used to optimize blast

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patterns based on geomechanical properties of rock masses [40,41]. MWD data facilitates the classification of rock benches by blastability, allowing targeted blast optimization that enhances Mine-to-Mill (M2M) efficiency [42,43]. This M2M optimization is a holistic, data-driven approach that integrates drilling, blasting, and downstream processing operations to maximize overall mining efficiency and productivity [44–46].

Another advanced technology is Prompt Gamma Neutron Activation Analysis (PGNAA), which serves as an elemental analyzer for real-time composition measurement of primary crushed material, significantly enhancing ore evaluation [47]. Fast neutrons from a source like Californium-252 interact with atomic nuclei in the mining medium, producing thermal neutrons that emit prompt gamma rays. The intensity and energy of these gamma rays are analyzed to determine the specific elements present, providing rapid, in-situ analysis that eliminates the need for physical sampling and reduces errors [48].

Additionally, several emerging sensor technologies—such as hyperspectral imaging, infrared technologies, Raman spectroscopy, Laser-Induced Breakdown Spectroscopy (LIBS), and light detection and ranging (LiDAR)—are transforming raw material characterization across broad spatial and temporal scales [49].

Raman spectroscopy is particularly effective for identifying mineral compositions by detecting vibrational modes of molecules. For instance, it reveals microstructural features of carbonaceous materials through identifying the D (disorder) and G (graphitic) bands, which relate to the degree of crystallinity. Raman spectroscopy is advantageous as it requires minimal sample preparation and enables in-line characterization of materials [50]. The use of Wide Area Illumination (WAI) probes enhances its accuracy in analyzing heterogeneous materials, making it suitable for industrial applications, including mineralogy [51].

LIBS is an advanced analytical technique used for the characterization of raw materials by providing elemental compositions based on plasma emission [52]. Similar to how hyperspectral sensors analyze a wide range of the electromagnetic spectrum for identifying minerals to generate a plasma from the surface of a sample. This plasma emits light at wavelengths unique to the elements within the sample, which are then collected and analyzed. The laser operates typically at 1064 nm, and the spectral range covered by LIBS usually spans the ultraviolet (UV) to visible regions, which includes most elements of the periodic table. LIBS is highly effective for rapid, in-situ identification of both major and trace elements in raw materials. For instance, LIBS is capable of detecting elements such as Si, Al, Fe, Ca, Na, and Mg, as well as trace elements like Li, which are difficult to detect using other portable instruments. The emitted light is collected and analyzed to provide real-time data that aids in material characterization. LIBS features several advantages, including the lack of sample preparation, making it particularly useful for field analysis and geological exploration. It also allows for micro-scale spatial analysis, depth profiling, and the detection of elements with low atomic numbers, which are key for understanding mineral compositions and geological histories [53].

In addition, LIBS provides the flexibility of working in challenging field environments due to its ability to operate in different atmospheric conditions, including open-path and stand-off configurations. These features enable it to characterize heterogeneous materials, such as geological samples and archaeological artifacts, by collecting elemental data from multiple spots on the surface and averaging them for comprehensive analysis [54].

Recent advancements in LIBS technology have enhanced its application in geology and mining, particularly for in-situ and real-time elemental analysis of raw materials. Innovations such as improved spectrometer designs and adaptive calibration techniques enable high-resolution characterization of heterogeneous geological samples and mineral ores. These developments address challenges like matrix effects and enhance LIBS' accuracy and repeatability in harsh field conditions [55,56]. Furthermore, LIBS's high-resolution capabilities facilitate the detection of elements, including rare earth elements and toxic components, in complex samples like mining waste, solidifying its role in raw material characterization and monitoring [31].

LiDAR is an active remote sensing technology used to characterize raw materials by providing detailed geometric and radiometric information through the use of laser pulses. LiDAR works by emitting laser pulses at different wavelengths and then detecting the reflected backscatter from target objects to obtain spatial information in the form of point clouds. It is capable of capturing 3D geometric information with high accuracy [57–59]. Multispectral LiDAR (MSL) systems combine both spectral and geometric data, which is particularly beneficial for characterizing complex materials in diverse conditions. MSL operates in multiple spectral channels, typically including visible to short-wave infrared (SWIR) wavelengths. These channels provide a combination of height and intensity data that enables precise classification of minerals and geological features based on their reflectance characteristics [60,61]. As illustrated in recent studies, MSL sensors can collect both spatial and spectral information, allowing for the efficient classification of rock surfaces and the identification of subtle mineral variations [62].

In addition to these advanced sensor technologies, several other sensors are widely used in mining, particularly in material characterization, resource evaluation, and decision-making throughout the value chain. RGB sensors are frequently used for color detection and qualitative analysis in mineralogical applications. These sensors capture visible light in three bands—red, green, and blue—and are particularly useful for recognizing minerals with distinct colors and textures, making them valuable for mineral mapping and fragmentation analysis [63,64].

Another important technology is Hyperspectral Imaging (VNIR/SWIR), which captures data across a wide range of the electromagnetic spectrum. VNIR (Visible-Near Infrared) covers the 0.4–1.0 μm range, and SWIR (Short-Wave Infrared) covers the 1.0–2.5 μm range. These sensors enable precise mineral identification and sorting based on their spectral signatures. Specifically, VNIR is effective in distinguishing sulfide minerals, while SWIR is useful for detecting carbonates, clays, and sulfates. In addition, Mid-Wave Infrared (MWIR) and Long-Wave Infrared (LWIR) sensors, operating in the 2.5–7.0 μm (MWIR) and 7.0–15 μm (LWIR) ranges respectively, are used for detecting and classifying minerals based on their reflectance or emission characteristics. LWIR is particularly effective for analyzing rock-forming minerals [65,66].

Electromagnetic and X-ray-based technologies, such as Dual Energy X-Ray Transmission (DE-XRT) and electromagnetic sensors, are also employed to detect mineral density and other physical properties [67]. These technologies are commonly used in pre-concentration processes to separate ore from waste, improving overall efficiency in mining operations [21,64]. The comparison of sensors can be seen in Table 2.

Table 2. Strengths, weaknesses, and opportunities of material characterization sensors in mining.

Sensor Technology	Application in Mining	Strengths	Weaknesses	Opportunities
Measurement While Drilling (MWD)	Blast optimization, rock mass blastability analysis	Provides real-time geomechanical data, enables M2M optimization	Limited to drilling data, high setup cost	Enhanced bench characterization, integration with M2M systems
Prompt Gamma Neutron Activation Analysis (PGNAA)	Elemental analysis of primary crushed ore	Real-time ore composition, high accuracy	Expensive, radiation safety concerns	In-situ metal grade estimation, reduced sampling errors
Hyperspectral Imaging (VNIR/SWIR)	Mineral identification, ore-waste discrimination	High spectral resolution, rapid, non-contact	Sensitive to environmental conditions (dust, moisture)	Potential for in-situ sorting, dynamic technology

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Mid-Wave Infrared (MWIR)/Long-Wave Infrared (LWIR)	Ore-waste discrimination, mineral classification	Effective for rock analysis, high classification rates	Limited instrument development, weak spectral features	Automation potential, integration with chemometric tools
Raman Spectroscopy	Mineral identification	Detailed fingerprints, in-situ handheld instruments	Fluorescence interference, limited elemental correlation	Real-time applications, expanded mineral libraries
Laser-Induced Breakdown Spectroscopy (LIBS)	Raw material characterization, elemental analysis	No sample prep, effective for major/trace elements	Limited detection range, affected by environmental factors	In-situ exploration, micro-scale spatial analysis
Light Detection and Ranging (LiDAR)	Raw material geometry, mineral mapping	Provides 3D spatial data, operates in various conditions	Limited spectral data, expensive equipment	Multispectral LiDAR for mineral classification
RGB Imaging	Mineral mapping, fragmentation analysis	Portable, rapid data processing, non-destructive	Limited to surface characteristics, affected by dust	Enhanced imaging, ruggedized systems
Electromagnetic Sensors	Mineral density detection, ore-waste separation	Effective for physical property measurement	Affected by mineral mixture complexity	Improved accuracy, expanded detection range
Dual Energy X-Ray Transmission (DE-XRT)	Pre-concentration, ore-waste separation	Accurate density-based discrimination	Limited to specific mineral densities	Application in automated sorting processes

Despite their potential, continuous advancements in sensor robustness and data fusion are essential to address challenges like environmental interference and complex mineral compositions [21]. The convergence of advanced sensor technology and data analytics heralds a transformative shift in mining exploration and operational efficiency.

4. Mine Planning and Optimization

Mine planning is a comprehensive process that analyzes the economic conditions of mining operations using geological, structural, and mineralogical data collected during the exploration phase. The primary goal is to determine the optimal sequence for ore block extraction while accounting for blending and geometric constraints, with the objective of maximizing the net present value (NPV) of the operation. Effective mine planning is crucial to the performance of mining operations, as deviations from the planned schedule can significantly affect profitability. Typically, mine planning is divided into distinct phases: short-term and long-term planning. Each phase incorporates elements of production control and logistics, varying in detail and timeframe, but they are interdependent; plans for each phase must align with both immediate operational needs and overarching strategic objectives.

4.1. Long-Term Mine Planning: Strategic Production Scheduling and Ultimate Pit Definition

The aim of long-term mine planning is to establish an optimal production strategy for the entire lifespan of a mining operation. This involves analyzing extraction sequences and destination policies to optimize the operation's economic value. A resource block model characterizes rock types and

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mineral grades, enabling the identification of ultimate pit limits (UPL) and the development of an open-pit production schedule (OPS) for the entire project duration [68,69].

Traditional deterministic methods, such as the Lerchs-Grossmann algorithm, are widely used for defining ultimate pit limits and establishing life-of-mine schedules [70]. However, these methods do not account for geological uncertainty, which can lead to suboptimal planning outcomes. To address this limitation, stochastic approaches have been developed. For example, Albor Consuegra and Dimitrakopoulos [71] utilized simulated annealing to enhance pit limit determination, resulting in a 17% larger pit and a 10% higher Net Present Value (NPV) compared to conventional methods. Another example includes the hybrid augmented Lagrangian relaxation method applied by Moosavi, et al. [72], which effectively solved large-scale long-term production scheduling problems, improving convergence speed and achieving better solutions compared to traditional linear methods.

4.2. Short-Term Mine Planning: Detailed Scheduling, Production Control, and RTM

Short-term mine planning focuses on developing a detailed production schedule covering a timeframe from several weeks to a few years. This level of planning involves equipment allocation, resource scheduling, and operational decisions to ensure production targets are met. It is operational in nature, optimizing detailed production sequences and allocating equipment such as trucks and shovels [12].

For example, Both and Dimitrakopoulos [73] presented a joint stochastic optimization model for short-term production scheduling and fleet management, simultaneously addressing uncertainties related to geological conditions, equipment performance, and operational logistics. Their method reduced shovel movement costs by 56% and improved truck allocation efficiency, demonstrating the value of integrated short-term planning approaches. Additionally, Mousavi, et al. [74] and Mousavi, et al. [75] compared metaheuristic algorithms—such as simulated annealing and Tabu search—for short-term open-pit block sequencing, demonstrating that hybrid approaches outperformed individual algorithms.

It is important to mention that the significance of short-term mine planning has increased due to its critical role in RTM operations. In RTM, dynamic adjustments are often required to deal with uncertainties inherent in mining activities, such as equipment breakdowns, geological variations, and market demand changes. The ability to adapt production schedules in real time ensures that the mine operates efficiently, minimizing production delays and optimizing resource utilization. Techniques like simulation-based optimization and metaheuristic approaches enable planners to adjust schedules dynamically, incorporating new data and real-time feedback from the mine site [6,76].

4.3. Stochastic and Deterministic Approaches in Mine Planning

Mine planning can generally employ both deterministic and stochastic approaches. Stochastic methods account for geological uncertainties, resulting in more robust solutions. For instance, Goodfellow and Dimitrakopoulos [77] presented a two-stage stochastic optimization framework for mining complexes that integrates material extraction, blending, and transportation, leading to enhanced production target achievement and increased NPV compared to conventional deterministic methods. Similarly, Lamghari, et al. [78] introduced a hybrid approach combining linear programming and variable neighborhood descent, which efficiently addressed the complexities of open-pit production scheduling, providing new best-known solutions for benchmark instances.

In contrast, traditional deterministic methods, such as the Lerchs-Grossmann algorithm, are foundational for defining ultimate pit limits and developing long-term schedules. However, they do not consider geological uncertainty, which can lead to suboptimal planning outcomes [70]. Recent approaches have also sought to combine deterministic and stochastic elements, such as the hybrid augmented Lagrangian relaxation combined with genetic algorithms, which has shown improved performance for large-scale long-term scheduling [72].

4.4. Optimization Approaches

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Beyond traditional deterministic and stochastic methods, advanced optimization algorithms have been increasingly applied to mine planning to tackle complex, large-scale problems. Particle Swarm Optimization (PSO) and Evolutionary Strategies (ES) are examples of nature-inspired algorithms that mimic biological processes to explore the solution space efficiently [79,80]. These algorithms are particularly effective in handling multi-objective optimization problems where trade-offs between different objectives, such as cost, NPV, and environmental impact, must be balanced.

Reinforcement learning, as part of AI methods, has recently emerged as a promising approach in mine planning optimization. Reinforcement learning algorithms learn optimal policies through interactions with the environment, enabling adaptive and dynamic decision-making processes. Reinforcement learning has gained significant attention in recent years for mining optimization applications [81–83].

Hybrid approaches, which combine multiple optimization techniques, have also shown significant promise. For instance, the integration of Genetic Algorithms (GA) with Simulated Annealing (SA) leverages the global search capability of GA and the local search efficiency of SA, resulting in superior performance in finding optimal or near-optimal solutions [74]. Similarly, combining Linear Programming (LP) with Variable Neighborhood Descent (VND) [78] has proven effective in addressing the intricacies of open-pit production scheduling, yielding new best-known solutions for benchmark instances.

In the following section, we discuss recent advancements in mining optimization techniques, which are summarized in Table 3.

Table 3. Advancements in mining optimization techniques over time.

Author(s)	Method	Case Study	Result	Advantages
Pendharkar and Rodger [84]	Nonlinear programming and genetic search	Coal mines (Illinois, Virginia, Pennsylvania)	Improved production scheduling under cost and geological constraints	Potential to enhance decision support for coal production and blending
Leite and Dimitrakopoulos [85]	Stochastic optimization, simulated annealing	Copper deposit	26% increase in NPV	Efficient scheduling with risk analysis; reduced likelihood of production target deviations compared to conventional methods
Askari-Nasab, Frimpong and Szymanski [70]	Discrete stochastic simulation	Iron ore deposit	$422 million NPV vs $414 million (conventional)	Better optimization of pit limit using a stochastic production simulator, outperforming Lerchs-Grossmann algorithm
Albor Consuegra and Dimitrakopoulos [71]	Simulated annealing	Copper deposit	17% larger pit limits, 10% higher NPV	Integration of uncertainty to derive optimal pit limits and production schedule improvements

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Sayadi, *et al.* [86]	Artificial neural network	Esfordi phosphate mine (Iran)	Generated pit with higher profit under impurity constraints	Improved pit limit classification and profitability compared to Lerchs-Grossmann algorithm
Moosavi, Gholamnejad, Ataee-Pour and Khorram [72]	Hybrid augmented Lagrangian relaxation and genetic algorithm	Long-term production scheduling	Better feasible solutions than traditional linearization method	Effective for large-scale problems; faster convergence than standard methods
Souza, *et al.* [87]	Hybrid heuristic (GRASP and GVNS)	Open-pit mining operational planning	Near-optimal solutions (less than 1% gap)	Dynamic truck allocation, minimized number of trucks while meeting production goals; efficient computing time
Mousavi, Kozan and Liu [75]	Hybrid branch-and-bound and simulated annealing	Short-term open-pit block sequencing	Optimized extraction sequences over short intervals	Efficient in solving short-term sequencing under machine capacity and precedence constraints
Mousavi, Kozan and Liu [74]	Comparative analysis of metaheuristics	Short-term open-pit sequencing	Hybrid TS-SA was superior to SA and TS	Enhanced performance and feasibility for real-scale open-pit problems
Goodfellow and Dimitrakopoulos [77]	Two-stage stochastic mixed integer nonlinear programming	Mining complexes	Improved production targets and NPV compared to deterministic methods	Joint optimization of extraction, blending, processing, and transportation under uncertainty
Both and Dimitrakopoulos [73]	Stochastic mixed integer programming	Real-world mining complex	56% reduction in shovel movement costs and 3.1% reduction in truck costs	Improved short-term production scheduling and fleet management by integrating shovel relocation, truck allocation, and uncertainty management
Shishvan and Benndorf [88]	Simulation-based optimization	Continuous mining system	Minimized idle time, improved material dispatching	Integrated deterministic optimization and stochastic simulation for

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				adaptive material dispatching
Lamghari, Dimitrakopoulos and Ferland [78]	Hybrid method (linear programming and variable neighborhood descent)	Open-pit mine scheduling	New best-known solutions for benchmark instances	Efficient and superior in computational performance compared to recent literature methods
Lamghari and Dimitrakopoulos [89]	Hyper-heuristic with reinforcement learning and tabu search	Generic mining operations	Comparable or better results than state-of-the-art methods	Robust against problem-specific details, effective for complex scheduling involving multiple processing streams
LaRoche-Boisvert and Dimitrakopoulos [90]	Simultaneous stochastic optimization	Open-pit gold mining complex	Maximized NPV; SAG mill identified as bottleneck	Integrated production scheduling across three mines and stockpiles under supply uncertainty
Levinson and Dimitrakopoulos [91]	Stochastic programming and reinforcement learning	Copper mining complex	Jointly optimized short- and long-term schedules	Reduced risk of misalignment across timescales, enhanced operational feasibility
Levinson and Dimitrakopoulos [92]	Reinforcement learning and stochastic optimization	Copper mining complex	Improved production schedule using infill drilling data	Reduced uncertainty in production schedule, optimized drilling location selection

Mining optimization involves a complex interplay of data-driven decision-making processes aimed at maximizing economic returns while managing geological uncertainties and operational constraints. Short-term and long-term planning are interdependent phases that, when effectively synchronized, lead to significant improvements in production efficiency and economic value. By integrating mathematical, statistical, and AI-based optimization techniques, mining operations can address uncertainties, optimize resource allocation, and enhance profitability. The advancements presented demonstrate the critical role that innovative approaches play in achieving greater accuracy, reducing costs, and maximizing value in mining projects.

Building on these foundational concepts, RTM bridges short-term and long-term planning, offering substantial opportunities to revolutionize production control and logistics through continuous data collection and adaptive decision-making. By integrating advanced analytics, real-time adjustments, and AI-driven optimization, RTM refines resource allocation, reduces risks, and boosts profitability. Despite its considerable promise in enhancing both production control and logistics, gaps in current research indicate ample scope for further exploration and development of RTM in mining contexts.

5. Data Assimilation in Closed-Loop RTM Management

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The closed-loop concept in RTM involves continuously updating resource models based on real-time data, integrating sensor measurements with predictive models to enhance decision-making and operational efficiency. Figure 4 presents a closed-loop workflow where sensor measurements from production monitoring are compared with model-based predictions to quantify discrepancies, thereby driving ongoing model updates. Data from exploration, geodesy, and grade control inform these models, accounting for ore deposit characteristics and the inherent uncertainties. Through continual iteration, sampling information and real-time sensor feedback align the estimated resource and grade control models with actual operational outcomes. The discrepancy quantification process ensures that any divergence from predictions is captured and integrated into subsequent model refinements. This adaptive feedback loop facilitates timely decision-making for mine production and planning, ultimately optimizing operational strategies. By assimilating up-to-date information at each iteration, the system maintains robust, data-driven resource management.

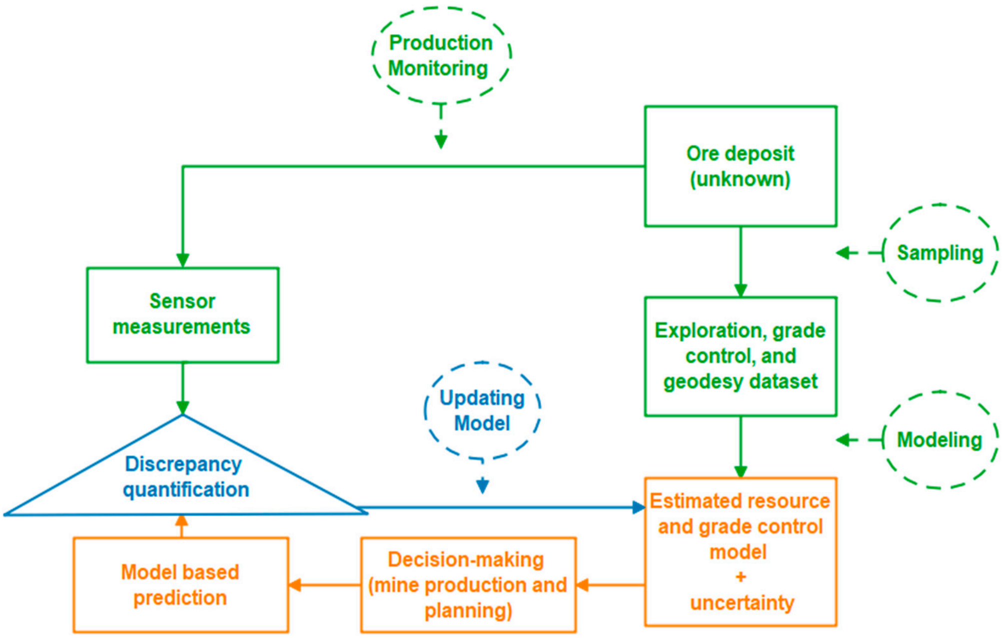

Figure 4. Closed-loop workflow for real-time resource and grade control management in mining operations (adapted from after Benndorf [6]).

5.1. Methods for Updating Data Assimilation in RTM Concept

Over the past decade, model-updating methodologies have advanced considerably, evolving from traditional linear Kalman Filters to cutting-edge machine learning approaches such as reinforcement learning. This progression responds to the growing complexity and scale of RTM applications.

One of the most widely used techniques, the Kalman Filter, offers a simple yet effective way to handle linear systems and parameter estimation. Its key limitation, however, lies in its reliance on linear dynamics and Gaussian assumptions, making it less suitable for capturing highly non-linear relationships. Consequently, it performs best in scenarios where system updates are relatively moderate and largely linear in nature [33,93,94].

Another prevalent approach is the Ensemble Kalman Filter (EnKF), which accommodates moderate non-linearities and sequential data assimilation better than the classic Kalman Filter. Nevertheless, EnKF still depends on Gaussian assumptions, limiting its performance when variables deviate significantly from Gaussianity or when discontinuities are present. In complex or highly dynamic environments, hybridizing EnKF with other non-linear methods can improve its robustness and assimilation accuracy [30,95,96].

Most recently, reinforcement learning has emerged as a particularly promising strategy for RTM, thanks to its ability to adapt to complex, high-dimensional datasets and rapidly changing mining conditions [35,97]. Although it demands extensive training data and robust computational resources, its capacity for real-time, adaptive decision-making holds significant potential for optimizing operations in dynamic mining environments.

The diversity of data-assimilation approaches for RTM [34,35,76,98–100] illustrates a tension between simplicity and comprehensiveness. Although linear methods—such as the Kalman Filter [33,94]—have relatively low computational cost and can be easily implemented, they are typically effective only when the state-updating process remains close to linear. By contrast, EnKF-based approaches [30,95,101–103] and state of the art machine-learning methods such as reinforcement learning [34,35] are better suited to severe non-linearity and higher-dimensional problems. However, they demand significant computational resources and expertise. Thus, the all-important question is how much complexity (and hence computational overhead) can an RTM application stand and still reach its project goals. Some practitioners exist on a spectrum of trade-offs: simpler algorithms are often adequate in relatively stable or mildly non-Gaussian conditions (more examples can be found in Table 4) while more complex hybrid and, most especially, reinforcement-learning-based methods are likely to become increasingly important for sharp dynamic, non-linear, and high-dimensional mining challenges. The essential element for successful RTM is to find the sweet spot between computational tractability and accuracy within sense of the-RTM extent.

This methodological evolution is illustrated further in Table 4, as it begins with simple linear algorithms (Kalman Filter) and works its way up to state-of-the-art machine learning techniques (reinforcement learning). Easier approaches work well for linear or weakly non-Gaussian systems, while more complex algorithms can more effectively be applied to, dynamic, higher-dimensional, or non-linear problems—but at a corresponding ignition cost. Thus, the most suitable method usually involves a trade-off between computational efficiency and accurate enough outputs for sound decision-making in RTM.

Table 4. Strengths, weaknesses, and opportunities of RTM methods.

Methodology	Strengths	Weaknesses	Opportunities
Kalman Filter	Simple and effective for linear systems; well-established methodology for parameter estimation	Assumes linearity and Gaussianity; struggles with non-linear relationships	Use in systems with predominantly linear relationships and smaller-scale updates
EnKF	Widely used for sequential data assimilation; handles non-linear problems reasonably well	Limited by Gaussian assumptions; can fail with strongly non-Gaussian or discontinuous variables	Hybridize with other non-linear techniques for improved assimilation of complex datasets
Normal-Score EnKF	Addresses non-Gaussian characteristics by transforming variables into Gaussian distributions	Transformation may not ensure joint multi-Gaussianity; requires multiple transformations	Use in settings with moderate non-Gaussianity where the linear update assumption mostly holds
Indicator-Based Data Assimilation	Suitable for non-Gaussian relationships; effective for transforming model parameters	Limited in handling very complex relationships; covariance-based association may be insufficient	Extend the approach to hybrid models using additional non-linear statistics
EnKF with Compositional Data	Suitable for geometallurgical variables; uses transformations to maintain compositional consistency	Log-ratio transformations add complexity; requires careful handling of	Apply in compositional geoscience models where maintaining

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		relationships between variables	data consistency is crucial
MPS with EnKF	Maintains geological realism in facies models; handles complex spatial patterns effectively	Computationally expensive; requires careful calibration to maintain geological realism	Improve computational algorithms to allow for faster and more efficient assimilation in realistic models
MPS with Soft Data Integration	Enhances facies model calibration by incorporating soft data; maintains geological continuity	Sensitive to initial conditions; computationally intensive	Utilize for integrating additional soft data in highly uncertain geological environments
EnKF with P-Field Simulation	Enhances facies modeling by incorporating probability maps; better integrates geological information	Requires additional assimilation steps; increased computational requirements	Useful for complex geological settings where standard EnKF struggles to reproduce accurate facies
EnKF with TPG Models	Assimilates data while maintaining facies realism; handles categorical variables through truncation maps	Difficult to handle non-monotonic truncation maps; requires derivative adjustments for accurate data matching	Use in channel facies modeling where categorical boundaries are critical
EnKF with DCT	Helps reduce dimensionality and improves history matching for high-dimensional problems	Increases computational complexity; sensitive to non-Gaussian data distributions	Apply for history matching in high-dimensional geological models where data compression is critical
SEOD with EnKF	Provides optimized sampling strategies and enhances model parameter estimation	Time-consuming optimization; computational overhead when dealing with complex geological data	Combine with simpler methods to balance accuracy and computational efficiency
EnKF with DWT	Helps reduce geological boundary uncertainty; enhances real-time data assimilation	High computational requirement; depends on quality of initial realizations	Extend application for sensor-based geological boundary identification
Reinforcement Learning (DDPG)	Learns adaptively in complex environments; able to handle dynamic, high-dimensional datasets	Requires extensive training data; computationally intensive and relies on strong computational resources	Apply in dynamic mining environments where adaptive decision-making is beneficial
Actor-Critic Reinforcement Learning	Learns adaptively in dynamic environments; can self-optimize based on incoming data	Computationally heavy; requires large datasets for effective learning	Use in industrial-scale mining for optimizing resource extraction and adaptive decision-making

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5.2. Applications of Updating Data Assimilation in RTM Concept

Several studies have demonstrated the potential of closed-loop data assimilation for RTM. For instance, Benndorf [33] introduced a closed-loop framework employing sequential resource model updating via the Kalman filter. By using synthetic data (representing a fully known environment), this approach showcased significant improvements in prediction accuracy whenever sensor-derived data were assimilated. The mean squared error (MSE) between estimated and actual block values served as the primary evaluation metric, showing substantial reductions in uncertainty—even in scenarios that involved multiple extraction sites and blending.

The updating approach uses the Kalman filter to estimate unknown state parameters recursively, based on differences between predictions and observations. Let Z(x) represent a spatial random field with elements $Z(x_i)$,where i=1,…,n denotes the index of discrete extraction locations. The production matrix A describes the contribution of each mining block to the total production during a specific time interval. The relationship between the predicted resource model and sensor measurements can be expressed as (Eq. (1)):

$$z_t^* = Az^*(x_t) \tag{1}$$

where z_t^* is the model-based prediction of extracted material for time intervals. Kalman filter updating can then be represented as (Eq. (2)):

$$z^*(x)_{t+1} = z^*(x)_t + K(y_t - Az^*(x)_t) \tag{2}$$

where K is the Kalman gain matrix, determined by Eq. (3):

$$K = C_{t,t}A^T\left(AC_{t,t}A^T + C_{v,v}\right)^{-1} \tag{3}$$

where $C_{t,t}$ represents the covariance of the prior model, while $C_{v,v}$ is the covariance of the measurement noise. The Kalman gain controls how much the observed differences (or innovations) between predicted and measured values influence the updated resource model. If the measurement noise is low and the prior model error is high, the Kalman gain increases, resulting in significant updates to the resource model.

Building upon this foundation, Yüksel, Thielemann, Wambeke and Benndorf [96] implemented a closed-loop concept for real-time resource model updating in the Garzweiler lignite mine, focusing on coal quality control. By continuously integrating online ash content measurements from the KOLA system into the model, they achieved up to a 70% reduction in model uncertainty. The EnKF gain determined the weight assigned to new sensor data versus the existing model, guiding the sequential updating process.

Extending this work, Yüksel, Benndorf, Lindig and Lohsträter [95] applied the closed-loop concept to a lignite mining case with multiple production benches. Online ash content measurements were taken using a radiometric sensor on the central conveyor belt, measuring blended material from multiple excavators. The forward simulation technique was used to associate sensor measurements with respective blocks, considering travel time from different excavators. Significant improvements were reported, with an average absolute error (AE) reduction of up to 73% using the updated model, where AE is defined as (Eq. (4)):

$$AE = \frac{1}{n}\sum_{i=0}^{n}|l_i - z^*(x)_i| \tag{4}$$

where l_i represents the sensor measurements and $z^*(x)_i$ are the updated model values. Significant improvements were reported, with an average error reduction of up to 73% when using the updated model compared to the prior model.

Furthermore, the study compared two approaches for generating prior models: one based on geostatistical simulation using drill hole data and the other based on a simplified short-term model, which introduced fluctuations around the company's mining plan. The simplified approach offered comparable improvements in model predictions, demonstrating the practicality of using a less

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computationally intensive method for RTM applications. By reducing the computational burden, the short-term model approach facilitated easier operational implementation without the need for complex geostatistical simulations.

Moreover, Wambeke and Benndorf [32] expanded the closed-loop concept through the development of geostatistical models for grade control reconciliation, utilizing the EnKF to handle the complexities involved in large-scale mining operations. They developed a sequential estimation method for updating the grade control (GC) model in real time based on new sensor observations. The algorithm is designed to integrate blended observations from multiple extraction points, making it particularly useful in mining environments where material streams are combined before measurements are taken.

The forward simulation step is crucial for estimating the contribution of individual blocks to blended material streams. This allows for linking each measurement back to its constituent blocks, despite blending from different extraction locations. Unlike previous methods, their forward simulator does not require an analytical formulation of the observation model, enhancing practicality in complex mining scenarios.

Subsequently, Wambeke and Benndorf [30] analyzed the influence of system parameters such as measurement volume, blending ratios, and sensor precision on algorithm performance. Conducting 125 experiments, they explored how these factors affect the EnKF-based grade control model updating. The blending ratio defines the proportion of material in the blended measurement volume originating from different extraction zones, while the measurement volume represents the amount of material characterized by the sensor over a given time interval.

The updated GC model significantly improved the alignment of predicted versus actual production data. Specifically, the reduction in root-mean-square deviation (RMSE) between predicted and measured values was used to quantify improvements by Eq. (5):

$$RMSE_t = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(z^*(n) - E[z_t(n)])^2} \tag{5}$$

where $z^*(n)$ represents the true state, and $E[z_t(n)]$ is the expected value of the estimated block values at time t. By incorporating new sensor observations sequentially, the model progressively reduced uncertainty, resulting in improvements of up to 74% in some scenarios.

Lan, et al. [104] proposed a sequential ensemble-based optimal design (SEOD) method to enhance real-time parameter estimation in groundwater reactive transport models, which has direct parallels to closed-loop concepts in RTM. They employed the SEOD method in both one-dimensional and two-dimensional groundwater models to jointly estimate hydraulic conductivity and geochemical parameters. The results showed significant reductions in RMSE and ensemble spread, indicating the effectiveness of the method in reducing uncertainty and improving model predictions.

The SEOD method utilizes the EnKF to estimate both physical and geochemical parameters, continuously updating the system model based on optimal sensor data collection. This is similar to previous approaches in RTM, where sensor measurements and forward simulations are integrated to update resource models, aiming to reduce uncertainties in model predictions.

The closed-loop concept, as described in this study, involves an iterative process to refine the resource model in real-time by assimilating sensor-based observations. The SEOD framework addresses some of the inherent challenges in such systems, including the optimization of sensor placement to maximize information gain, using the Kullback-Leibler divergence (also known as relative entropy, RE) as a metric for determining the value of information obtained from measurements.

Mathematically, the SEOD framework is implemented through the following stages:

1. Forecast Step: The EnKF-based SEOD begins with a forecast step, where the forward model G is used to propagate the current ensemble of state vectors x_(i,j)^a to the next time step (Eq. (6)):

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$$x^f_{i,j+1} = G(x^a_{i,j}) \tag{6}$$

where x^f and x^a represent the forecast and analysis states respectively.

2. Optimal Sampling Design: The SEOD framework aims to determine the optimal locations for collecting new measurements, which is achieved by maximizing the relative entropy (RE) between the prior and posterior distributions. For a Gaussian distribution, RE is given by Eq. (7):

$$RE = J_b + [ln\, det(BA^{-1}) + Tr(AB^{-1}) - n] \,/\, 2 \tag{7}$$

where J_b is the signal part of RE, A and B are the covariance matrices of prior and posterior distributions, respectively. The optimal sampling locations are determined using a genetic algorithm (GA) by solving the following optimization problem (Eq. (8)):

$$H_{opt} = arg\, max\, RE(H) \tag{8}$$

where H represents the candidate sampling strategy.

3. Analysis Step: After determining the optimal sampling strategy, the analysis step is performed to assimilate the collected data and update the state vector by Eq. (9):

$$x^a_{i,j} = x^f_{i,j+1} + C_{YD}(C_{DD} + C_D)^{-1}(d_{obs} - d_i) \tag{9}$$

where C_{YD} is the cross-covariance between forecast states and predicted data, C_{DD} is the covariance of the predicted data, and C_D represents the measurement error covariance.

The SEOD method thus represents a dynamic approach to integrating measurement data for the purpose of parameter estimation. This approach shares similarities with RTM practices where data assimilation techniques like EnKF are used to refine geological models and optimize production processes. A critical difference, however, lies in the use of an optimal sampling strategy to enhance the quality of parameter estimation, leading to more efficient computational performance and better model accuracy compared to traditional methods.

Several studies addressed the limitations of the EnKF in handling non-Gaussian distributions and maintaining geological realism. Nejadi, et al. [105] incorporated the EnKF with Probability Field (P-Field) simulation to improve characterization of facies boundaries in reservoir models. Jafarpour and McLaughlin [102] combined the EnKF with the Discrete Cosine Transform (DCT) parameterization to reduce dimensionality and preserve geological features. Hu, Zhao, Liu, Scheepens and Bouchard [101] applied a closed-loop concept by combining multipoint simulation (MPS) with the EnKF for real-time reservoir history matching, maintaining geological consistency in facies models. Oliver and Chen [106] discussed data assimilation in truncated plurigaussian (TPG) models, addressing non-monotonic relationships between latent variables and facies types.

For preserving non-Gaussian geological features, Kumar and Srinivasan [98] introduced Indicator-Based Data Assimilation (InDA), preserving non-Gaussian characteristics of geological models during assimilation. Ma and Jafarpour [99] integrated soft data into MPS simulation for facies model calibration, improving consistency with training images and observed data.

Zhou, et al. [107] transformed the original state vector into a univariate Gaussian using the normal-score EnKF (NS-EnKF), preserving non-Gaussian distributions in the updated models, crucial for maintaining geological realism. This method is particularly useful in RTM, where maintaining the complex spatial features of geological formations, such as channels or facies boundaries, is essential for accurate model updates. The closed-loop approach presented in this study demonstrates how transforming state variables into Gaussian space can improve data assimilation in non-Gaussian contexts, ultimately enhancing the quality of real-time geological models and reducing uncertainty in decision-making processes.

In smaller-scale grade heterogeneity studies, Li, Sepúlveda, Xu and Dowd [94] presented a rapid updating method to predict grade heterogeneity at smaller scales using a Kalman filter framework, integrating production data for near real-time resource model downscaling. The method improved

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mining selectivity and ore recoverability by accurately predicting grade heterogeneity within larger mining blocks. The advantages of the proposed method include its ability to integrate different types of sensed data without requiring complex co-kriging or simulation techniques, as well as its computational efficiency.

Prior, Benndorf and Mueller [103] proposed a closed-loop framework for updating resource and grade control models in underground mining, integrating sensor-based information using the EnKF. The approach improved prediction accuracy for ore grade and vein thickness, even with sparse initial conditioning information.

Prior, Tolosana-Delgado, van den Boogaart and Benndorf [36] introduced a closed-loop updating framework for compositional geometallurgical variables, employing log-ratio transformations and flow anamorphosis to handle compositional data in the EnKF while preserving their relationships.

Machine learning approaches have also gained traction. Avalos, et al. [108] applied machine learning and deep learning techniques in RTM to forecast energy consumption in semi-autogenous grinding mills. By leveraging recurrent neural networks to model temporal dependencies, they achieved significant improvements in prediction accuracy, enabling dynamic energy management and operational efficiency in real-time settings. Ortiz, et al. [109] highlighted the integration of geometallurgical data and process models within a RTM framework to optimize the mining value chain. By addressing uncertainties through stochastic modeling, the study demonstrated enhanced mine designs and operational strategies for improved economic and environmental outcomes.

Kumar and Dimitrakopoulos [35] proposed a novel approach to updating geostatistically simulated models of mineral deposits in real-time using a reinforcement learning framework. They developed a self-learning algorithm based on the deep deterministic policy gradient (DDPG) reinforcement learning method, incorporating actor and critic agents. The purpose of this approach is to learn from incoming data collected during mining operations and to update the geostatistical models accordingly. This approach allows the model to account for high-order spatial statistics, enabling more accurate representation of the mineral deposits' geological structure and grade distribution.

The proposed method applies reinforcement learning where the mining grid is sequentially visited in a random path. The environment provides the state for each grid node, which includes the properties of blocks, sensor data, conditioning data events, and other contextual information. The actor agent takes actions that predict updated properties for the grid nodes, and these predictions are evaluated by the critic agent. This setup allows for a dynamic model that learns and adjusts based on new incoming information.

Mathematically, the reward at each step is calculated to ensure that the updated properties align with both high-order spatial statistics and the incoming temporal sensor data. The actor-critic system is designed such that the state at time step is updated by incorporating new sensor data and conditioning events to maximize the reward function, which includes terms for spatial and temporal consistency.

Talesh Hosseini, Asghari, Benndorf and Emery [100] integrated the Discrete Wavelet Transform (DWT) with the EnKF to update and improve geological boundary definitions at the Golgohar Iron Ore Mine, significantly increasing boundary accuracy while maintaining consistency with production data.

Finally, de Carvalho and Dimitrakopoulos [34] presented an actor-critic reinforcement learning approach for short-term production planning and fleet management in mining complexes. By defining shovel and truck allocation policies adaptively, the model addressed operational constraints and uncertainties dynamically, resulting in a 47% improvement in cash flow compared to traditional fixed fleet assignments. The continuous update of orebody models based on sensor-collected data further emphasized the practical advantages of integrating RL for adaptive decision-making. The performance of these studies are shown in Table 5.

Table 5. Summary of studies on closed-loop data assimilation.

Author(s)	Method	Case Study	Result	Advantages
Jafarpour and McLaughlin [102]	EnKF with DCT	Synthetic Reservoirs	Reduced dimensionality, preserved geological realism	Reduced computational cost; better preservation of channel connectivity
Zhou, Gomez-Hernandez, Franssen and Li [107]	Normal-Score EnKF	Synthetic Bimodal Aquifer	Preserved non-Gaussian distributions, improved characterization	Preserved complex spatial features; enhanced quality of real-time geological models
Hu, Zhao, Liu, Scheepens and Bouchard [101]	MPS with EnKF	Fluvial Reservoir	Maintained geological consistency, effective history matching	Maintained geological features; effective in real-time history matching
Benndorf [33]	Kalman Filter	Synthetic Data	Reduced MSE, improved prediction accuracy	Improved decision-making by incorporating real-time sensor data; reduced uncertainty even with blending
Nejadi, Trivedi and Leung [105]	EnKF with P-Field Simulation	Reservoir Models	Improved facies boundary characterization	Preserves statistical properties; prevents overfitting; ensures ensemble diversity
Yüksel, Thielemann, Wambeke and Benndorf [96]	EnKF	Garzweiler Lignite Mine	Up to 70% reduction in model uncertainty	Direct incorporation of real-time measurements; better decision-making and quality control
Yüksel, Benndorf, Lindig and Lohsträter [95]	EnKF	Lignite Mining with Multiple Benches	Error reduction up to 73%	Practical and less computationally intensive; improved model predictions
Wambeke and Benndorf [32]	EnKF	Grade Control Reconciliation	Enhanced accuracy, practical for complex scenarios	Improved operational efficiency; reduced uncertainties; better resource extraction
Wambeke and Benndorf [30]	EnKF	Analysis of System Parameters	RMSE reduction up to 74%, improved model alignment	Mitigated discrepancies; enhanced production processes
Lan, Shi, Jiang, Sun and Wu [104]	SEOD with EnKF	Groundwater Models	Reduced uncertainty,	Optimal sensor data collection; efficient

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			improved predictions	computational performance; better model accuracy
Oliver and Chen [106]	EnKF with TPG Models	Synthetic Reservoir	Improved data match, reduced uncertainty	Handled nonlinearity and non-monotonic relationships; robust in complex geological environments
Kumar and Srinivasan [98]	Indicator-Based Data Assimilation	Synthetic Reservoir	Preserved non-Gaussian distributions, accurate spatial features	Overcomes EnKF limitations; maintains geological features; accurate in non-Gaussian contexts
Ma and Jafarpour [99]	MPS with Soft Data Integration	Facies Model Calibration	Improved consistency with training images and data	Maintains geological consistency; integrates soft data; effective framework
Li, Sepúlveda, Xu and Dowd [94]	Kalman Filter	Synthetic Dataset	Improved model accuracy, better mining selectivity	Integrates sensed data without complex methods; computational efficiency; practical for rapid decision-making
Prior, Benndorf and Mueller [103]	EnKF	Underground Mining (Reiche-Zeche)	Improved prediction accuracy for ore grade and vein thickness	Improved mining selectivity; effective even with sparse initial data
Prior, Tolosana-Delgado, van den Boogaart and Benndorf [36]	EnKF with Compositional Data	Bauxite Deposit	Accurate updates, preserved compositional characteristics	Reduced uncertainty; improved accuracy for decision-making
Kumar and Dimitrakopoulos [35]	Reinforcement Learning (DDPG)	Synthetic Dataset	Dynamic model updates, accounted for high-order statistics	Integrates new information dynamically; suitable for complex mining operations
Talesh Hosseini, Asghari, Benndorf and Emery [100]	EnKF with DWT	Golgohar Iron Ore Mine	Improved geological boundary accuracy, high compatibility	Enhances block model quality control; reduces spatial uncertainty; preserves statistical parameters
de Carvalho and Dimitrakopoulos [34]	Actor-Critic Reinforcement Learning	Copper Mining Complex	47% improvement in cash flow	Dynamic fleet allocation and production

		scheduling based on real-time data.

These studies demonstrate significant advancements in data assimilation methods within closed-loop RTM management. The integration of Kalman filters and their variants with innovative techniques like DCT, MPS, and reinforcement learning approaches has led to improved prediction accuracy, reduced uncertainty, and maintained geological realism. The table summarizes these advancements, highlighting the methods employed, case studies undertaken, and the results achieved. Collectively, these works emphasize the practical effectiveness of continuous model updating in modern mining practices, underscoring its value in enhancing operational decision-making and efficiency across diverse mining environments.

6. Bridging RTM Implementation Gaps with Advanced Data Analytics

Much progress has been made over the past decade; however, fully integrated RTM concepts remains largely unimplemented in practical, real-world settings. A key tool for assessing the maturity of RTM approaches is the TRL framework. Originally developed by NASA, TRL is a metric that ranges from basic principles observed—TRL 1—to fully operational systems—TRL 9. The framework has been adopted by the European Union and many industries to evaluate innovation across a wide range of sectors, linking technological development to funding and implementation milestones [110–112]. When applied to RTM components, this framework reveals a large gap between research and its practical application, demonstrating the need for strategic pathways to move these technologies toward higher TRLs.

In the context of RTM, the maturity levels of key components are as follows: the real system, comprising physical mining activities such as drilling, hauling, and processing, stands at TRL 7, reflecting successful prototype demonstration in operational environments but still requiring fully integrated automation and data workflows. Production monitoring, which involves advanced sensor networks that measure ore grades and equipment performance, is at TRL 8, with systems routinely deployed and thoroughly tested, though consistent data standardization remains a challenge. By contrast, system models (e.g., digital twins and resource models) currently reach only TRL 5, as they have been validated in relevant mining environments but are not yet fully operational on a large scale—largely because many mines operate with incomplete or inconsistent databases. Optimization algorithms, providing real-time decision support, stay at TRL 4, with most testing confined to laboratory or pilot-scale settings and lacking robust deployment in live production due to the need for specialized data scientists and IT infrastructure on-site. Data assimilation, which updates system models in near real time by blending sensor data and historical records, reaches TRL 6, having been demonstrated in pilot environments but not widely adopted for continuous industrial use. Taken together, these elements form an overall RTM system whose readiness is estimated at around TRL 6, owing primarily to challenges such as a lack of consistent geodata infrastructure, limited availability of geo data scientists in operations, and interoperability complexities that inhibit seamless integration across sensors, models, and algorithms (see Figure 5). Overcoming these hurdles—through standardized data protocols, expanded on-site analytics, and interdisciplinary collaboration—is critical to achieving TRL 8–9 and realizing a fully operational, field-proven RTM system.

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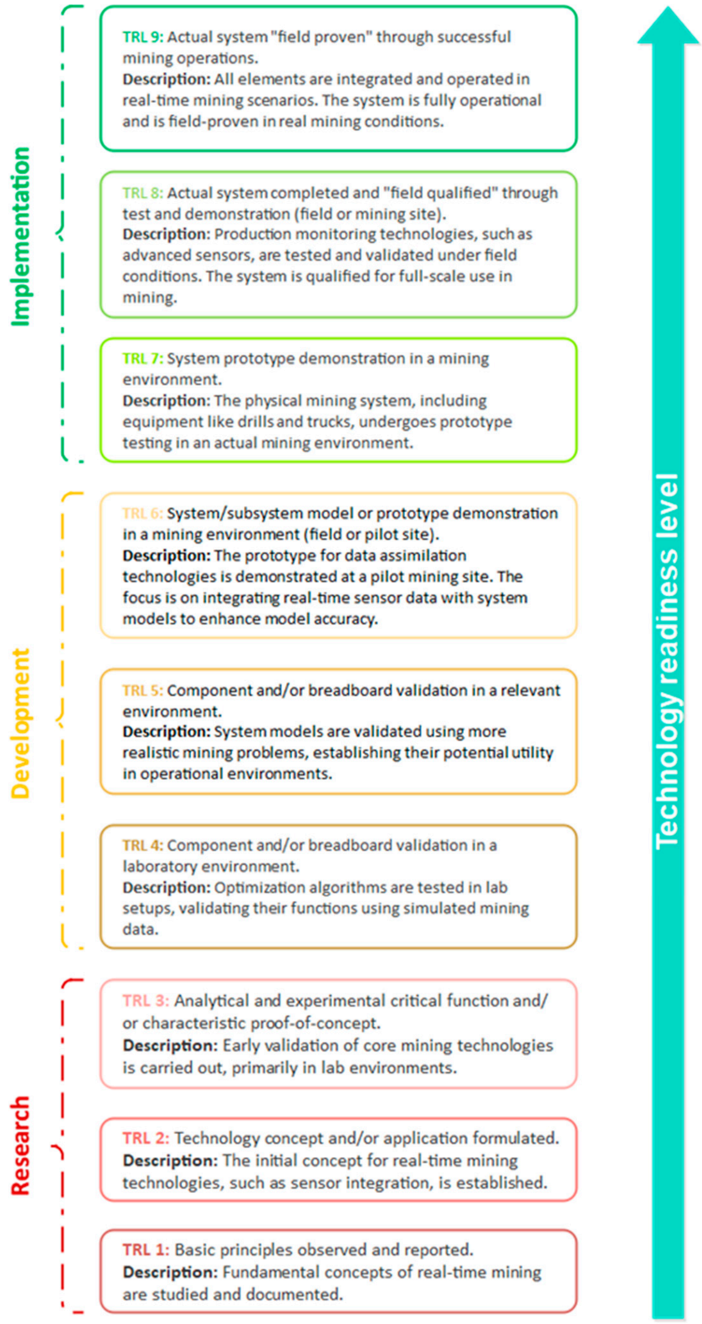

Figure 5. TRLs for RTM: from research to full-scale implementation.

To advance RTM components toward higher TRLs, strategic collaboration and targeted innovations are paramount. Advanced data analytics and AI are particularly indispensable in enhancing the adaptability, scalability, and operational efficiency of RTM. One foundational requirement involves the development of robust, field-ready sensors capable of withstanding the challenging conditions inherent to mining environments. Partnering with sensor manufacturers can accelerate this process. Moreover, leveraging machine learning—especially reinforcement learning—can bolster predictive capabilities while enabling real-time operational adjustments. These improvements are further supported by digital twins, which dynamically simulate and optimize mining processes.

Integrating AI into optimization algorithms offers real-time decision support by rapidly analyzing and assimilating large volumes of sensor data. Such integration not only expedites technological development but also ensures operational reliability through proactive equipment

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failure prevention and efficiency optimization. However, these gains hinge on establishing comprehensive material tracking systems and maintaining consistent geodatabases. The absence of such infrastructure, coupled with a lack of on-site geodata specialists, poses a significant bottleneck to effective RTM implementation.

Moving forward, RTM methodologies stand to benefit from hybrid models that merge AI with geostatistical techniques, thereby increasing both adaptability and precision. Advanced computational platforms, including cloud computing and parallel processing, can alleviate current computational bottlenecks. Additionally, the inclusion of diverse data sources—such as soft data and advanced sensor networks—promises to enhance model resolution and accuracy. By harnessing these advancements, RTM can solidify its role as a cornerstone of intelligent mining practices, driving efficient, adaptive, and data-driven resource management.

Advancing key constituents of the RTM approach requires coordinated efforts among researchers, technology developers, and industry stakeholders. Establishing pilot projects and field demonstrations will showcase practical benefits and return on investment, encouraging adoption. Economic incentives and funding mechanisms can offset initial costs, while standardizing protocols ensures compatibility and ease of integration. By leveraging advanced data analytics and AI, the mining industry can bridge the implementation gaps in RTM, advancing key components to higher TRLs. This progression will transform RTM from a theoretical concept into a practical, efficient, and sustainable operational system, effectively addressing the mineral resource dilemma and meeting global demands.

7. Conclusions

Real-time mining (RTM) is a novel paradigm for confronting the growing complexity and sustainability challenges of modern mining. RTM facilitates continuous monitoring, optimization, and control of the mining value chain by deploying advanced sensor technologies, data analytics, and adaptivity in decision systems. By promoting responsible mining practices in this way, this closed-loop system not only minimizes the environmental and social impacts of resource recovery but also, with the help of accompanying circular economic futures and efficient recycling technologies, promotes a new appreciation for and exploration of our planetary resources while making their extraction possible and responsible. Data assimilation in the form of artificial intelligence, Kalman filters, and similar techniques enables frequent updating of resource models to reduce uncertainties and enhance operational efficiencies.

This review presents significant development of sensor technologies and data-centric approaches as presented in different research works, while also acknowledging the potential for future research aimed at synchronizing theory with practical applications. Advancements in Technology Readiness Levels (TRLs) of RTM components necessitate improvements in sensor robustness, data fusion techniques, and adaptive control systems. Moreover, the innovation of field-worthy sensors, pilot project collaboration, advanced tracking systems, continuous geodatabases, and incorporation of leading AI models are significant to convert our practical large-scale applications. RTM is a critical enabler of data-driven, adaptive, and resilient mining operations that can respond to changing conditions on the fly. RTM has the potential to revolutionize the mining industry to be a more sustainable, tech-driven industry by eliminating ambiguities in production, resource recovery, and operation. This strategy facilitates the growing global demand for minerals in a way that reduces environmental and social impacts.

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Abbreviations

The following abbreviations are used in this manuscript:

AE	Absolute Error
AI	Artificial Intelligence
CLRM	Closed-Loop Mineral Resource Management
DCT	Discrete Cosine Transform
DE-XRT	Dual Energy X-Ray Transmission
DDPG	Deep Deterministic Policy Gradient
EnKF	Ensemble Kalman Filter
GA	Genetic Algorithm
GC	Grade Control
InDA	Indicator-Based Data Assimilation
IoT	Internet of Things
LIBS	Laser-Induced Breakdown Spectroscopy
LiDAR	Light Detection and Ranging
LWIR	Long-Wave Infrared
M2M	Mine-to-Mill
MWD	Measurement While Drilling
MWIR	Mid-Wave Infrared
NS-EnKF	Normal-Score Ensemble Kalman Filter
NPV	Net Present Value
OPS	Open-Pit Production Schedule
P-Field	Probability Field (in EnKF/P-Field simulation)
PGNAA	Prompt Gamma Neutron Activation Analysis
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
RMSE	Root-Mean-Square Error
RTM	Real-Time Mining
SEOD	Sequential Ensemble-Based Optimal Design
SWIR	Short-Wave Infrared
TPG	Truncated Plurigaussian
TRL	Technology Readiness Level
VNIR	Visible-Near Infrared
WAI	Wide Area Illumination

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