

Review

Enhanced Measurement and Verification Practices in Deep-Level Mines: The Current State

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Abstract: This article explores operational challenges in mining, with a focus on energy management amid depleting ore grades and rising costs. The urgent need for innovative energy management systems and strategies is highlighted by analyzing the unexplored landscape of mine energy budgeting and forecasting and identifying gaps in current practices. Drawing from the literature, this paper offers new insights into energy budgeting and the evaluation of energy efficiency initiatives by integrating traditional and advanced measurement and verification (M&V) techniques. M&V practices are crucial for energy management, particularly in deep-level mines, with a focus on practical knowledge and advanced methodologies. Key findings from this study show that integrating advanced M&V techniques with unplanned events is crucial to improve the financial management of mines. By leveraging these key findings, this article proposes a roadmap of the next seven milestones needed in advanced M&V research to aid effective energy management in a mining environment. If executed successfully, a practical method for applying advanced M&V processes to deep-level mining operations can be constructed. Such a generic method will enhance mining companies' energy efficiency initiatives and improve financial management practices on a global scale.

Keywords: South African gold mining industry; energy management; budgeting; measurement and verification (M&V); deep-level mines; unplanned events



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1. Introduction

1.1. The Gold Mining Industry: South Africa as a Case Study

South Africa's gold mines operate at considerable depths, ranging from 2000 to 4000 m below the surface. These deep-level mines incur substantial energy costs attributed to cooling, pumping, ventilation, and hoisting activities [1]. Despite abundant gold reserves, the ore grade has plummeted from approximately 20 g per tonne to a mere 4 g per tonne, necessitating efficient energy management strategies to mitigate escalating costs [2,3].

Figure 1 illustrates the diminishing gold production in South Africa compared to global trends, further exacerbating production cost challenges. Factors contributing to rising operational costs include labor expenses, electricity tariffs, and maintenance costs, compounded by regulatory and environmental constraints, all whilst production is diminishing [4,5]. These factors make South Africa an excellent environment for demonstrating the importance of effective financial management in mines.

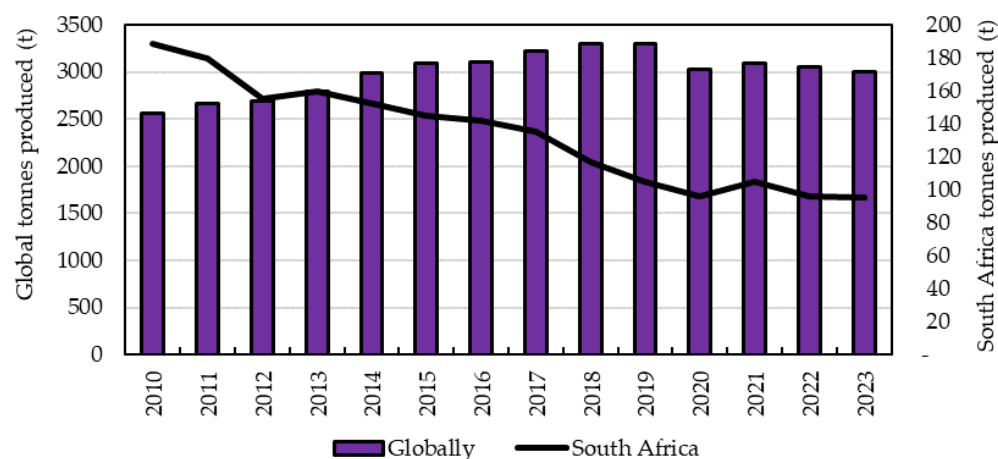


Figure 1. South Africa's gold production vs. global production [4,6].

1.2. Energy Management Challenges

Gold extraction, being energy-intensive in deep-level mining, contributes significantly to electricity expenses, comprising approximately 47% of the industry's operational costs [1].

Although energy prices are increasing globally, electricity costs in South Africa are currently notably higher than those of other developing nations, far exceeding the global average [7]. Consequently, effective energy management has become crucial for South African mines, giving rise to challenges in the national energy supply [8]. These challenges are not confined to the South African mining industry.

To address this, mining companies are implementing energy efficiency projects aimed at curbing energy consumption. Figure 2 illustrates the Eskom (the national power utility) electricity tariffs as of 2022, implying a considerable increase in energy cost for the mining industry [9].

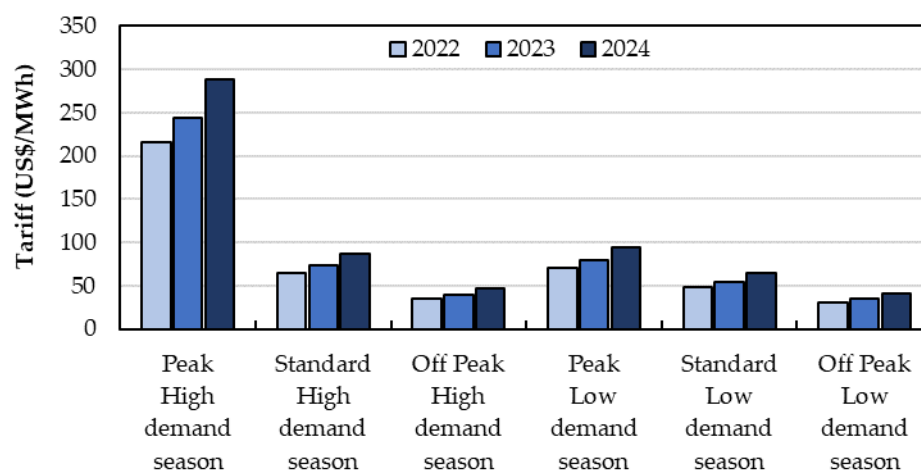


Figure 2. Annual Eskom Megaflex tariffs [9].

The Eskom Megaflex tariffs are employed to evaluate heavy industries' energy usage and are designed with considerations for various time-of-day and seasonal fluctuations. Weekdays, Saturdays, and Sundays are divided into peak, off-peak, and standard periods across a 24 h cycle. These divisions correspond to national energy demand patterns, leading to decreased tariffs during times of lower energy usage [9]. Currently, half of all sub-Saharan African countries are employing TOU as an energy-saving strategy [10].

Eskom's Megaflex tariffs are structured to incentivize energy consumption during off-peak periods, thereby promoting cost savings [11]. Additionally, tariff differentials

between summer and winter seasons reflect variations in energy demand and supply, necessitating strategic planning to optimize energy usage and minimize costs. Figure 3 further elucidates the tariff allocation periods, offering insights into the temporal dynamics of energy pricing [9].

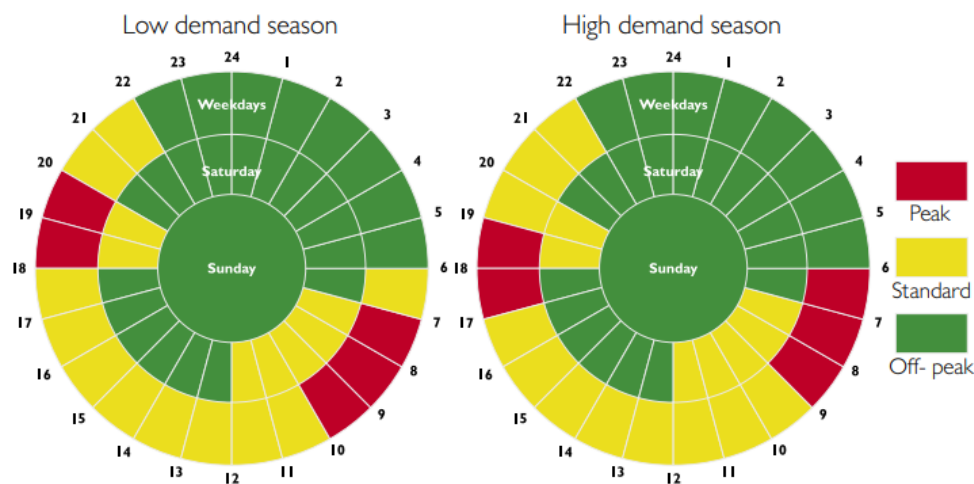


Figure 3. Eskom's Megaflex tariff periods [9].

The energy bill supplied by Eskom to the client (i.e., the mining company) divides the monthly energy consumption into peak, standard, and off-peak for high- and low-demand seasons. The respective consumption is billed accordingly to the fixed rates. Load-shifting projects leverage this cost structure through an Eskom-driven initiative known as demand-side management (DSM) [12]. Energy that would normally be consumed during peak hours is then rather rescheduled to occur during low-tariff hours, resulting in cost savings but with the daily consumption unchanged [13].

1.3. Problem Statement, Objectives, and Research Questions

Escalating energy expenses not only directly impact a mine's operational costs but also contribute to the broader challenge of rising production costs within the mining industry. Expanding infrastructure can strain a developing country's national electricity grid, exacerbating capacity shortages and necessitating tariff hikes to fund essential upgrades [9,14,15]. Consequently, effective financial management becomes imperative for mining companies to navigate these escalating expenditures while still maintaining profitability [16].

To address this problem, the objectives of this paper are as follows:

1. To assess the current state of global M&V practices;
2. To analyze its potential implications for mining;
3. To synthesize the main findings into criteria necessary for a practical method that uses advanced M&V to detect unplanned events in deep-level mines and integrate them into energy forecasting methods.

To ensure the literature review aligns with the objectives of this study, five research questions (Q1–Q5) were identified:

1. Which initiatives currently exist to improve general M&V tasks?
2. How do these tasks improve time management as advanced M&V is expected to do?
3. Which advanced M&V methods have been applied in industry?
4. Do these methods account for unplanned events or other discrepancies?
5. How can these methods be integrated into a mining environment?

2. M&V in Mining Literature

The studies examined in Sections 2 and 3 were identified through keyword searches conducted on Google Scholar, ScienceDirect, SpringerLink and Scopus. The main studies

for this literature review were identified following the systematic literature approach [17]. Databases and search engines used to identify relevant studies included ScienceDirect, SpringerLink, Google Scholar, Scopus, and Wiley. For each keyword variation (shown in Figure 4), the titles of the first 20 articles per database, sorted by relevance, were reviewed.

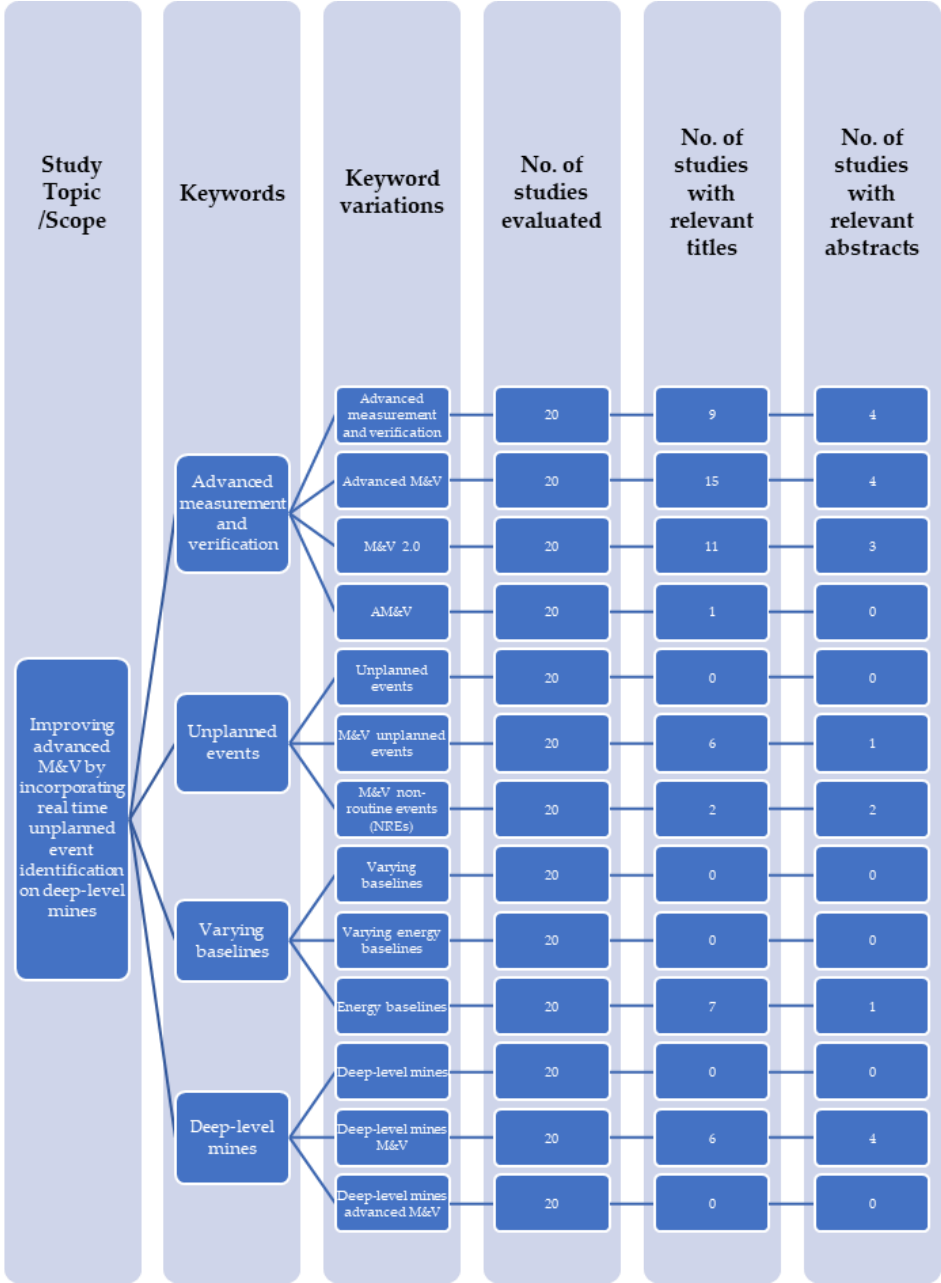


Figure 4. Structured literature review process employed in this study [17].

Variations in the keywords were utilized to expand the search and uncover additional studies. To avoid duplication, the first 20 new articles that had not been previously assessed with a specific keyword were taken into account. From the identified relevant articles, their abstracts were scrutinized and then incorporated into the literature review. The literature review process is summarized in Figure 4.

Initially, 260 studies were screened based on title relevance, from which 57 studies were further assessed based on the relevance of their abstracts. Ultimately, only 21 studies were deemed relevant to M&V in mining, which emphasizes the need for further development in this field.

3. The Role of Finance Management and M&V in the Mining Industry

Effective financial management tailored to the unique needs of the gold mining industry is essential for its success [16]. Budget creation serves as a vital tool for monitoring and planning, requiring accuracy and transparency to withstand performance pressures [16,18]. Comprehensive budgets anticipate growth, cost reductions, and energy efficiency initiatives, facilitating informed decision making [4,19,20]. The evaluation of savings from energy efficiency initiatives is integral, often overseen by M&V specialists [21]. M&V entails a structured process of planning, measuring, collecting, and analyzing data to verify and report energy savings resulting from implemented measures [22].

3.1. Traditional Methods on Energy Initiative Evaluations

Van Aarde [23] investigated the integration of M&V principles into the budgeting process, focusing on deep-level mines. By incorporating Time-of-Use (TOU) tariffs derived from the Eskom Megaflex structure (Section 1.2) into the budget using hourly data, this study aimed to improve accuracy. To be eligible for this billing structure, a company must have a maximum electricity demand of 1 Mega Volt Ampere (MVA) [11]. Load-shifting projects, aimed at operating equipment outside peak periods to reduce electricity costs, were initiated by industries seeking to benefit from different tariff periods [14]. Each point of distribution also includes a notified maximum demand (NMD) supplied to Eskom which, if exceeded, leads to fines that increase exponentially per infringement. Implementing M&V principles into the budgeting system significantly improved accuracy, with a reported 16.8% enhancement and a notable USD 1.39 million difference [23]. However, this modification increased the time spent on compiling budgets.

Booyesen [24] investigated the impact determination of energy-saving initiatives when multiple projects were implemented on the same system. This study introduced adjusted baselines for subsequent projects, utilizing regression models and graphical representations to assist stakeholders in baseline selection. A control chart was introduced to monitor operational changes affecting the baseline, ensuring proactive revisions. Evaluating each project individually revealed potential missing energy savings of USD 1.44 million on the system [24].

Botes [25] discovered that without implementation intervals between projects, insufficient data were available to construct an adjusted baseline. Stringent rules were in place to ensure transparency in the evaluation process, allowing for the determination of each energy-saving initiative's impact individually. When a single baseline is used for multiple energy-saving initiatives, a regression model is utilized to separate their impacts. The system already had strict regulations in place to comply with legal and technical standards. Several regression models were created to compute energy efficiency savings for tax incentives under Section 12L of the Income Tax Act. This rigorous methodology guaranteed transparency in the assessment process, enabling the identification of each energy-saving initiative's impact separately [25].

3.2. The Evolution of Initiative Evaluations (Advanced M&V)

The studies referenced above employed data sourced from a database to compute their respective baselines, with this database collecting information from instruments monitoring key systems in deep-level mines. These systems are overseen by a central control room equipped with a supervisory control and data acquisition (SCADA) system, which displays data on parameters like power, pressure, and flow [26].

Since the introduction of data logging in the 1970s, this practice has steadily gained traction [27]. Today, companies have the ability to store and retrieve vast amounts of data from power meters, sometimes capturing data every second, through advanced metering infrastructure [28,29]. The advancement of sophisticated techniques has enabled real-time analysis on a large scale, offering nearly immediate insights. Processes such as M&V stand to benefit from instantaneous data analysis, giving rise to advanced M&V. This approach

revolves around automated data processing methods following standard M&V principles to assess the impacts of energy-saving initiatives [30].

While utilizing existing data measurements addresses a challenge in the M&V process—the time constraint—researchers have explored predicting future data points to estimate how energy-saving projects will respond to changes. This underscores the significance of accurate data forecasting methods [31].

3.3. Methods of Advanced M&V Application

Regression stands as a pivotal tool in advanced M&V, with linear regression models prominently featured in numerous studies [32–36]. Granderson [37] offers a comprehensive overview of tools applicable for advanced M&V in practical contexts. However, concerns persist regarding the accuracy of these models.

Granderson [32] utilized linear regression models to evaluate the energy consumption prediction accuracy across 537 buildings in the commercial technology sector. Comparing the results of ten energy models to actual consumption, logged via advanced metering infrastructure, the median coefficient of variation of the root-mean-squared error (CV(RMSE)) for each model, with six months of data, remained below 25%. This aligns with the acceptable CV(RMSE) outlined by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) guidelines [38].

Subsequent studies have further validated the robustness of regression models in advanced M&V. Crowe [39] and Gallagher [40] employed linear regression and machine learning models, respectively, to assess the impact of energy-saving initiatives and predict consumption. Support vector machines, a subset of machine learning, were highlighted in Ma's study [41] for advanced M&V applications.

Building on their research, Gallagher [42] and Severinsen [43] developed tools like IntelliMaV and ShinyRBase for advanced M&V. Ke [44] extended this concept to cloud computing for IntelliMaV, envisioning national-level implementation. Bekker [45] explored the feasibility of coding advanced M&V methods directly onto smart energy meters using Simulink.

Crowe conducted a study on the time efficiency gains facilitated by advanced M&V methods, evaluating over 26 projects. Traditional M&V processes, involving manual data acquisition and auditing, often yield results years after the assessment period. In contrast, using ex-ante savings methods, the time taken for M&V was 156 h, reduced to a mere 6 h with advanced methods, marking a significant 96% improvement. Notably, this calculation did not consider the investigation of unplanned events [39].

3.4. Detecting Unplanned Events

Crowe's study acknowledges the manual identification of unplanned events, which requires significant time and involvement from mine personnel [23]. As multiple energy-saving measures are implemented and planned, the complexity of this process intensifies [24].

Touzani [46] explored statistical methods for identifying unplanned events, also known as non-routine events, during real-time evaluations. Collaborating with Granderson [47], a tool was developed, although manual confirmation was still necessary to validate flagged events. Earni [48] challenged assumptions regarding the dynamic nature of static elements like operating hours, which could cause unplanned changes. Opperman [49] utilized cumulative energy savings to pinpoint turning points in a gold processing plant's operations.

Fernandes [50] synthesized these studies, compiling a diverse set of methods for handling unplanned events within the context of advanced M&V. However, an identified barrier is the accuracy of event detection, along with a lack of guidance on addressing necessary changes affecting energy savings.

3.5. Examples of M&V on Deep-Level Mines

Advanced M&V techniques have seen significant advancement, with Opperman [49] leading the application of these methods in surface mining operations, contrasting with the continued predominance of traditional approaches in deep-level mines.

Cilliers [51] conducted a comprehensive evaluation of mining complexes, grouping sections to facilitate a detailed analysis of energy consumers. This subdivision improved the understanding of factors influencing energy fluctuations in each subsystem, aiding M&V practitioners in pinpointing areas for investigating energy discrepancies. Hamer [52] further applied this approach to mitigate uncertainties in calculating energy initiatives for mining projects.

Previously, assumptions during the baseline period, as observed by researchers like Gouws [53], could lead to inaccuracies in identifying the metering equipment involved. The introduction of more meters over time has sparked differing perspectives on the future of advanced M&V. Some, like Conradie [54], have turned to simulations to predict the impact of projects on energy consumption, although this method is perceived as slow, cumbersome, and reactive. Additional energy monitoring tools such as live simulations and dashboards were used by Nell [1] and Ngwaku [55], respectively.

4. Importance of Practical Knowledge Utilization in Mining

All the aforementioned studies contribute to improving the M&V process, whether through model evaluations or practical applications. However, traditional M&V methods remain prevalent in deep-level mines, and there has been little integration between these methods and advanced M&V techniques. Therefore, practical experience is essential for successfully implementing advanced M&V in deep-level mines.

Mining systems, given their complexity, are prone to unplanned events, posing challenges for M&V processes focused on value. Identifying and resolving these events effectively require the expertise of experienced mining personnel. Regular access to these personnel may not be possible, due to the nature of the mining work environments. These employees may spend large portions of their day underground away from the telephone with limited office hours to discuss an event. Thus, it is important to transfer their experience in an effective manner.

4.1. Impact of Practical Knowledge

Practical knowledge, cultivated through work experience and hands-on application, plays a crucial role in various domains. Probst [56] developed a model to help companies manage workforce experience effectively, facilitating knowledge sharing among employees. Connelly [57] explored how experienced schoolteachers prioritized curriculum aspects differently based on their understanding of student challenges. Gulikers [58] observed that final-year university students approached learning more selectively than first-year students, optimizing their study time. These two studies indicate that experienced professionals address specialized tasks more efficiently as they have a more comprehensive understanding of the challenges. Their inputs while guiding others can be crucial to effective time management and ultimately the success of the task or project.

These studies highlight the importance of practical knowledge and its impact on task approach and time management. Black [59] investigated methods such as drawings, conversations, and metaphors rooted in personal experience to enhance learning and information processing. Woolliscroft [60] applied practical knowledge training in a manufacturing plant through workshops and classes, improving employees' capabilities and facilitating on-the-job learning through guidelines when workshops were not feasible.

In the mining industry, the value of practical knowledge and experience cannot be understated and is likely the main form of knowledge transfer.

4.2. Guidelines

The existing guidelines on baseline development are inadequate, resulting in inefficiencies as employees are left to self-train [24]. Developing a guideline can be systematically approached [61–66]. Davis [61] compiled an approach based on clinical practice guidelines presented by the National Partnership for Quality in Health (NAPAQH).

Firstly, there should be a recognition of the need for a guideline for a specific task. Secondly, a comprehensive review of available data and its relevance to the task is conducted. The third step involves filtering and presenting the data in the form of a guideline. The fourth step includes reviewing the guideline, either by a sponsor or an expert in the field. Next, in the fifth step, the guideline is distributed for use. The sixth step involves actively promoting the guideline for implementation. Lastly, the seventh step consists of reviewing and updating the guideline based on industry changes [61].

Davis [61] identified a gap in the sixth step during their experiment, specifically in monitoring how the guidelines were implemented. This gap resulted in skewed outcomes and justified revising a guideline in the seventh step. Various factors could contribute to the failure of a guideline, including its quality, user characteristics, setting, incentives, and regulations. Addressing these factors is essential for the successful implementation of guidelines. Guidelines for utilizing practical knowledge and improving task performance are essential for enhancing organizational efficiency.

5. State-of-the-Art Summary

The studies were categorized using a comprehensive matrix, as depicted in Table 1. The categorization criteria attempt to answer the research questions, namely task optimization related to M&V (Q1), time allocation for M&V tasks (Q2), the deployment of advanced M&V methods in the industrial sector (Q3), the use of advanced M&V principles to tackle unplanned events (Q4), and the integration of practical knowledge into a set of guidelines for application in the mining industry (Q5). In Table 1, “O” indicates the reference’s relevance to the respective research question, while “X” indicates that the criteria were not addressed in the reference study.

Table 1. State-of-the-art matrix indicating focus areas of previous studies on M&V in mining.

Source	Methods to Optimize M&V Tasks (Q1)	Methods to Optimize Time Management for M&V Tasks (Q2)	Advanced M&V for the Industrial Sector (Q3)	Advanced M&V on Unplanned Events (Q4)	Advanced M&V on Deep-Level Mines (Q5)	Comments
1. van Aarde [23]	O	X	X	X	X	Used TOU tariffs to create more accurate baselines. The method added more steps to the process, increasing time.
2. Booysen [24]	O	O	X	X	X	Methods to identify multi-project baselines. Neglects baseline increases during the performance.
3. Botes [25]	O	O	X	X	X	Evaluated the accuracy of efficiency models. The model does not account for varying baselines.
4. Granderson [37]	X	X	O	X	X	Summarized current advanced M&V tools available. This study only focuses on the list.
5. Granderson [32]	X	X	O	X	X	Tested the accuracy of using regression models. Models based on an isolated above-ground system.

Table 1. Cont.

Source	Methods to Optimize M&V Tasks (Q1)	Methods to Optimize Time Management for M&V Tasks (Q2)	Advanced M&V for the Industrial Sector (Q3)	Advanced M&V on Unplanned Events (Q4)	Advanced M&V on Deep-Level Mines (Q5)	Comments
6. Crowe [39]	O	O	O	O	X	Using regression for advanced M&V. Manually detect unplanned events.
7. Gallagher [40]	O	O	O		X	Used machine learning to predict energy savings. Used a constant baseline.
8. Ma [41]	O	O	O	X	X	Used support vectors for advanced M&V. Improvement parameters based on buildings.
9. Gallagher [42]	O	O	O	X	X	Advanced M&V tool based on machine learning. Built for industrial buildings.
10. Severinsen [43]	O	O	O	X	X	Advanced M&V tool based on linear regression. The tool cannot identify data discrepancies.
11. Ke [44]	O	O	O	X	X	Advanced M&V application based on multivariate regression. The tool does not provide data discrepancies information.
12. Bekker [45]	O	O	O	X	X	Smart meter with local data to reduce server sizes. The meter must be connected to calculate energy savings.
13. Touzani [46]	O	O	O	O	X	Statistical changes in data track unplanned events. Requires M&V practitioner to check flagged items and make amendments.
14. Granderson [47]	O	O	O	O	X	Advanced M&V application based on statistics. The tool is based on the above study with the same issues.
15. Earni [48]	O	O	O	O	X	Identified factors which could lead to unplanned events. Method was manual.
16. Opperman [49]	O	O	O	O	X	Tracked unplanned events on mines using cumulative savings. Applied only to an isolated surface plant.
17. Fernandes [50]	O	O	O	O	X	Investigated strategies to address unplanned events. Disregard automation due to noise/event distinction.

Of the 21 studies examined, four exclusively focused on utilizing M&V to evaluate the energy impact of initiatives in deep-level mines, serving as exemplars of current energy savings calculation methods. The remaining 17 studies focused on enhancing M&V methods and streamlining the time required for M&V tasks. Among these 17 studies, 14 explored the application of advanced M&V methods in practical scenarios, predominantly within the context of buildings. Only five studies specifically addressed unplanned events, offering recommendations for their mitigation.

The literature reviewed encompasses a range of studies aimed at improving methods, tools, and time efficiency for financial management through M&V. Each study offers unique insights and methodologies, along with their respective limitations relevant to this study's focus and research questions.

Study 1 by van Aarde improved budget accuracy by constructing annual budgets based on hourly intervals using TOU tariff intervals, leading to a 16.8% improvement, albeit at the cost of increased data points and time spent on the process. Study 2 by Booysen developed methods to evaluate data quality for industrial DSM projects, enhancing baseline accuracy, yet failing to incorporate unplanned events into baselines. Study 3 by Botes focused on selecting the best energy baseline model, resulting in improved accuracy but lacking consideration for variations during the performance period.

Granderson's studies (Studies 4 and 5) compiled various approaches to advanced M&V and assessed the accuracy of advanced M&V methods in practical environments, respectively, highlighting readiness for conversion but overlooking unplanned events. Crowe's study (Study 6) evaluated challenges in implementing advanced M&V, showing its feasibility but relying on the manual detection of unplanned events. Gallagher's studies (Studies 7 and 9) explored machine learning techniques for advanced M&V, offering promising results but failing to address baseline variability.

Ma's study (Study 8) specialized in support vector machines for advanced M&V but lacked relevance to mining systems. Severinsen's study (Study 10) developed a tool for the Norwegian food retail sector, which lacked adaptability to mining systems. Ke's study (Study 11) introduced a cloud computing platform for real-time M&V, empowering stakeholders but overlooking the potential impact of unplanned events. Bekker's study (Study 12) proposed a theoretical framework for M&V meter support, reducing data server sizes but requiring data retrieval for calculations.

Touzani's study (Study 13) introduced statistical change detection for energy consumption but relied on manual adjustments by M&V practitioners. Earni's study (Study 15) evaluated static factors affecting operations but lacked automated detection methods for unplanned events. Opperman's study (Study 16) investigated models for unplanned event detection in mining operations but filtered data, limiting its applicability to highly variable events. Fernandes's study (Study 17) examined strategies for identifying unplanned events, highlighting challenges in separating noise from events and emphasizing manual adjustments to baselines. A timeline of these studies is illustrated in Figure 5.

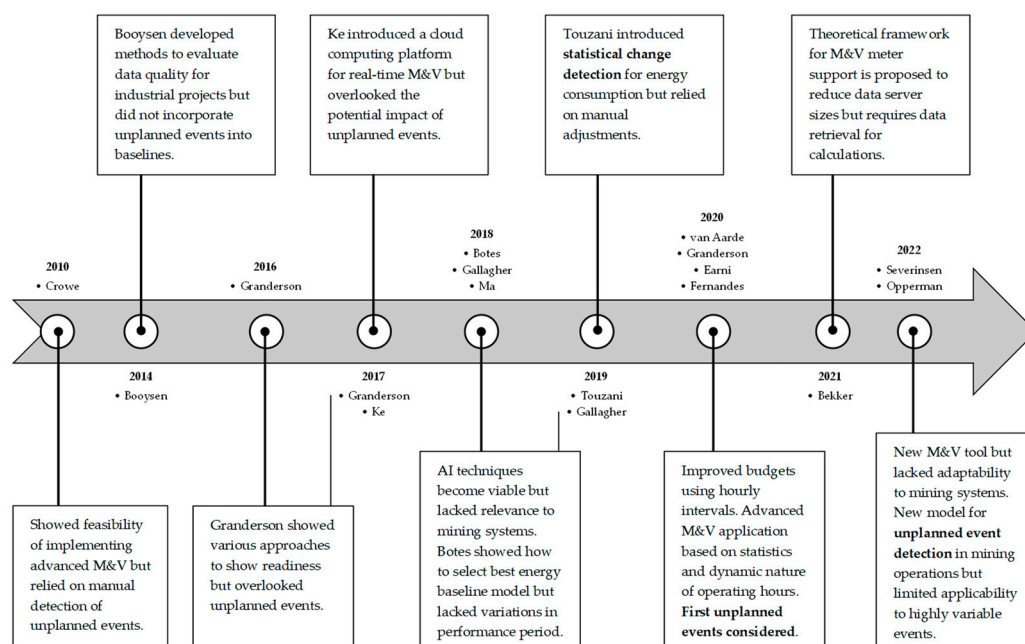


Figure 5. Timeline summarizing the development of M&V practices and techniques in mining [23–25,32,37,39–50].

Overall, while these studies offer valuable insights, coupled with Table 1, they collectively underscore the need for methodologies that effectively incorporate unplanned events into M&V practices, particularly in the context of deep-level mines.

The studies assessed in Section 5 consistently employ a constant baseline, with advanced M&V techniques relying on it to compute real-time savings. As noted by van Aarde [19], “The savings obtained, when compared with the baseline, are rarely seen on the budget. This raises the question of whether the budgets are correctly developed”. Furthermore, Booysen [21] raised crucial questions regarding changes caused by unplanned events: How do we integrate these changes into advanced M&V? How do we address and prioritize them? Both queries contribute to a broader deficiency that this study aims to rectify.

6. Discussion on Advanced M&V in Mining

The studies being assessed appear to operate under the assumption that their forecasts remain unaffected by external influences. However, in practice, projects can be subject to various factors such as operational shifts, delays, labor strikes, and weather conditions [46,67]. In traditional M&V processes, any changes in energy consumption not directly attributable to the initiative are acknowledged and accounted for [68]. These adjustments are typically integrated when calculating the project’s impact [69].

Existing M&V procedures are excessively time-consuming, primarily attributed to manual data collection and auditing. This inefficiency could lead to significant delays in obtaining results by up to a year [70]. Across 26 distinct projects analyzed, researchers noted that a total of 156 h was dedicated to the M&V process. By implementing advanced M&V techniques in these projects, the time spent on M&V was drastically reduced to a mere six hours, marking a remarkable 96% enhancement [39]. However, this critical concept has yet to be applied in advanced M&V. The current method for determining the impact of an initiative lacks a mechanism to incorporate real-time adjustments, as depicted in Figure 6.

$$\text{Project impact} = (\text{Baseline} - \text{Actual}) \pm \text{Adjustments}$$

Traditional M&V

Advanced M&V

Figure 6. Project’s impact equation for traditional M&V compared to advanced M&V.

Not all the studies depicted in Table 1 conform to the equation depicted in Figure 6. Studies 4 and 5 focus solely on the accuracy of the methods. Studies 1 to 3 utilized the traditional M&V section. Studies 6, 7, and 9 incorporated manual adjustments like traditional M&V or excluded them entirely. Studies 8 and 10 to 12 consisted of created models based only on the advanced M&V section. Studies 13 to 17 focused on identifying the adjustments.

The evidence presented highlights the need for a predictive method capable of accurately anticipating data points despite operational fluctuations. Such a method should be able to recognize these changes and provide guidelines on how to address them effectively. While advanced M&V has made some strides, its integration with mining systems remains limited, and practical guidelines for implementing a prediction model are still lacking. The evidence above highlights the need for a prediction method which can accurately incorporate operational changes.

7. A Roadmap for Improving M&V in Mining

In essence, the current challenge revolves around the absence of a method that employs advanced M&V to detect unplanned events in deep-level mines and seamlessly integrate them into predictions. The recommendation of this study is to approach this challenge systematically by following these recommended steps:

1. Assess various statistical methods for predicting outcomes.
2. Offer examples of simplifying complex datasets for presentation.
3. Explore methods for validating prediction models.
4. Develop a model or technique for accurately forecasting energy consumption for savings calculations, irrespective of unplanned events.
5. Identify investigation pathways at both macro- and micro-levels.
6. Recognize unplanned changes in the baseline during savings calculations, along with potential contributors.
7. Compile a practical guide on navigating the M&V process in deep-level mines and addressing unplanned events.

Each recommendation stems from a distinct problem and corresponding necessity, laying the groundwork for new innovations in this field. While delivering several contributions aimed at enriching advanced M&V through the integration of the real-time identification of unplanned events in deep-level mines, the following novel opportunities may be explored further:

a. Integrate real-time adjustments into the prediction model

Traditional M&V, as elucidated in Figure 6, is utilized to compute project savings, accommodating adjustments in the formula. Conversely, advanced M&V solely considers the baseline and actuals. A new model is required to incorporate these adjustments into the Advanced M&V. The model should be robust enough to apply to any heavy industry [71].

b. Develop a method to identify, quantify, and prioritize system adjustment in real time using prediction models

Prior studies, as reviewed in Section 4, aimed to validate and enhance energy consumption prediction models. However, these models typically rely on constant baselines, neglecting operational changes such as unplanned events. An alternative approach is required, which can be applied to other sectors [72].

c. Formulate a practical guideline for the M&V process in deep-level mines while incorporating advanced M&V methods

While the evaluated studies focus on monitoring projects and acknowledge the potential impact of unplanned events on prediction models, they lack explicit guidelines on addressing these events.

In summary, a roadmap of M&V in mining, from problem to opportunity, can be tracked using Figure 7.

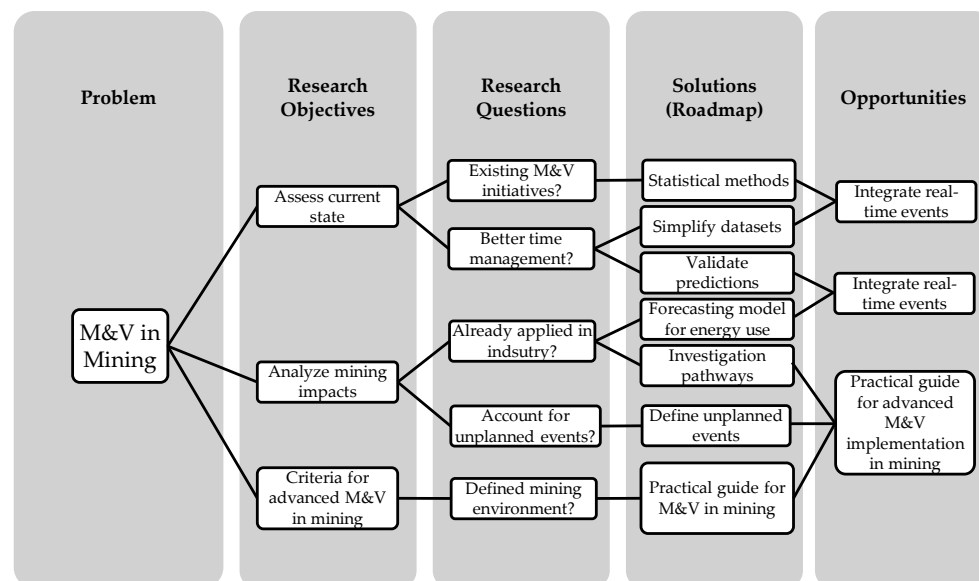


Figure 7. Problem statement to novel opportunities roadmap for M&V in mining.

8. Conclusions

A review of the current literature on financial management in the gold mining industry reflects ongoing efforts to enhance efficiency and transparency in budgeting and evaluation processes. Traditional methods are evolving, leveraging data analytics and machine learning to optimize energy efficiency and mitigate operational risks. Continued research and innovation in this field are essential to ensure the sustainability and profitability of global gold mining operations.

This paper identified the gaps that are still hindering the holistic application of enhanced M&V practices for effectively overcoming operational challenges. The importance of addressing unplanned events in M&V practices is highlighted for mines and a roadmap of recommendations is provided to overcome current barriers.

Three novel opportunities were identified, namely (1) integrate real-time adjustments into a prediction model, (2) develop a method which can identify, quantify, and prioritize system adjustment in real-time using prediction models, and (3) formulate a practical guideline for the M&V process in deep-level mines while incorporating advanced M&V methods. Additional considerations, such as the effect of geophysical methods and the use of geographic information systems on advanced M&V, should certainly be considered in future studies.

By integrating this study's proposed roadmap with existing M&V processes, mining companies can enhance energy efficiency initiatives and optimize financial management practices on a global scale.

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