Enhancing Mining Operations and Productivity through Discrete Event Simulation: A Comprehensive Literature Review

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ABSTRACT

Discrete Event Simulation (DES) has become an important tool for optimizing mining operations and increasing production by addressing the inherent complexities and variability of these systems. This literature review investigates the use of DES in the mining industry, highlighting its importance in enhancing operational efficiency, lowering costs, and promoting informed decision-making. The analysis delves into specific DES applications in equipment usage, emphasizing their ability to imitate various mining processes, detect bottlenecks, analyze alternate scenarios without disrupting real-world operations, and optimize resource allocation. The main benefits include the ability to estimate the impact of operational and strategic changes ahead of time, as well as predict environmental issues such as energy prices and resource depletion, which affect profitability and sustainability. The combination of DES and methods for optimization such as mixed integer programming enables comprehensive decision support systems that smoothly integrate strategic, operational, and environmental factors. However, hurdles persist, such as the complexity of effectively modeling mining operations, data collecting and quality issues, and integrating DES findings with existing management systems. This review attempts to provide a more in-depth understanding of DES's current and future possibilities for improving mining operations and productivity.

1. Introduction

1.1. Background and Significance of Mining Operations

Mining operations have played a crucial role in the development of human civilization, from the extraction of essential raw materials for construction and manufacturing to the unearthing of valuable minerals and resources that have fueled economic progress and technological advancements. It drives economic growth by providing raw materials for various sectors, including construction, manufacturing, and energy. Mining also contributes to the GDP and economic development in many countries. The export and trade of minerals such as coal, iron ore, gold, copper, and rare earth elements have, for many decades, played a very massive role in mining. The emergence of new technologies for drilling, extraction, processing, and exploration and the adoption of new techniques and equipment help to enhance efficiency and safety. However, there are a lot of negative environmental impacts from mining, including land degradation, water pollution, and greenhouse gas emissions. While the mining industry has undoubtedly been a driver of economic growth, the environmental and social impacts of these activities have become increasingly prominent, leading to a growing focus on implementing sustainable practices and a deeper examination of the long-term

ISBN: 978-1-55195-520-9

implications of mining operations. (Segura-Salazar and Tavares, 2018). There are regulatory organizations that monitor the activities of mining companies; this has helped most mining companies adhere to environmental regulations in that community and promote sustainable ways to reduce the impact of their activities. Mining has also benefited the community by providing employment opportunities. There has been investment in research and development to develop new mining methods and improve existing processes, focusing on innovation to tackle challenges such as resource depletion and energy consumption. There is also a challenge in fluctuations in commodity prices impacting the profitability and strategic decisions of mining companies.

1.2. Types of Simulations and Applications in Mining Operations

We learned from the former section that there has been an emergence of technology in the mining industry in recent times. One of the new technologies that has been adopted but is not popular is simulation for mining operations. With the complexity of mining operations, including drilling, blasting, hauling, and processing. There is a need for efficient management of resources, equipment, and labor to optimize productivity and minimize costs. For this reason, we need to know the impact of the operations before we carry them out. The use of computer simulations helps the mining engineers test their designs and strategies on the computer before carrying them out in real life. This section will briefly describe the various types of simulations. As this work is focused on mining cases, we will discuss the ones that have been used in mining. Different simulation techniques include Monte Carlo simulation, agent-based simulation, continuous simulation, and discrete event simulation.

Monte Carlo Simulation:

Monte Carlo simulation is a statistical technique for modeling the probability of multiple outcomes in uncertain systems. In mining, it is used to estimate resources and anticipate the quantity and grade of mineral deposits by modeling various geological scenarios. The technique also evaluates project risks, such as cost of overruns and delays, by modeling various schedules and expenses. Furthermore, Monte Carlo simulations help in financial forecasting by predicting future cash flows and performance under various market scenarios. They improve mine planning and scheduling while also predicting environmental impacts, which aids in the development of effective mitigation techniques (Kwak et al., 2007).

Agent-Based Simulation:

Agent-Based Simulation (ABS) is a modeling technique that simulates autonomous agents' activities and interactions to analyze their overall effects on the system. This method is used to understand and predict complicated behaviors in systems in which individual entities (agents) interact according to predefined rules. Mining uses ABS to model and evaluate complex systems and processes. It can simulate mining operations and logistics, optimizing haulage routes, equipment allocation, and scheduling to increase efficiency and reduce costs. ABS also simulate the social and environmental consequences of mining activities, allowing for more accurate predictions of the effects on local communities and ecosystems. ABS models emergency scenarios and worker behavior to improve safety measures and preparation. It is also utilized in mineral processing to optimize processes like crushing and grinding by analyzing particle interactions, as well as in economic analysis to mimic commodity market dynamics, which aids strategic planning and economic viability assessments(Macal and North, 2010) .

Continuous Simulation:

In a continuous simulation, the system's state changes over time and is represented by continuous variables. This approach differs from discrete-event simulation, in which changes occur at precise points in time. Continuous simulation is widely used to represent dynamic systems in engineering, physics, biology, and economics. Continuous simulation is an effective technique in mining operations for modeling and optimizing dynamic processes. It aids in the prediction of equipment performance and maintenance requirements, allowing for timely repairs and reducing downtime. Continuous simulation in mine ventilation guarantees efficient airflow while maintaining safe subsurface conditions. It also optimizes mineral processing by simulating procedures such as crushing and grinding for maximum efficiency (Banks et al., 2010).

Discrete Event Simulation (DES):

Finally, the last type of simulation that we will be delving deep into is the discrete event simulation, which is the most popular simulation technique used in simulation and optimization of mining operations. Discrete Event Simulation (DES) represents the operation of systems as a series of separate events that occur over time. Each event occurs at a precise point in time and alters the state of the system, which is tracked by state variables and an event list. DES is frequently used in industries such as manufacturing, healthcare, logistics, and telecommunications to optimize operations and increase efficiency. It captures statistical data on system performance, such as wait times and resource consumption, which allows for more informed decision-making and operational changes. Discrete Event Simulation (DES) models various mining scenarios to optimize layout and operational sequences, minimizing costs and maximizing resource extraction. It simulates mining equipment performance to improve utilization rates and reduce idle times. DES assists in developing effective production schedules and ensuring resource efficiency and target achievement. By modeling equipment failures and maintenance activities, it aids in planning preventative maintenance to reduce downtime. Additionally, DES optimizes material transport within the mine and to external locations, enhancing supply chain efficiency (Law and Kelton, 2000).

1.3. Why Discrete Event Simulation is Preferred in Simulating Mining Operations

Discrete Event Simulation imitates individual events such as drilling, blasting, and hauling to represent complex relationships in mining operations. It enhances operational logistics by enhancing workflow, equipment uses, and maintenance scheduling. DES identifies bottlenecks and permits scenario testing without interfering with real-world operations, facilitating effective decision-making. Furthermore, it calculates operational costs and incorporates real-time data to improve accuracy. Discrete Event Simulation (DES) successfully mimics complex relationships and sequences of discrete events, making it perfect for mining operations such as drilling and hauling. It focuses on logistics and operational procedures, including extensive information about resource utilization. DES effectively identifies process bottlenecks and enables scenario testing without causing real-world disturbances. In contrast, ABS models individuals and their interactions, which can result in sophisticated behaviors but is less concerned with operational flow. Continuous simulation is appropriate for processes with continuous changes but not for discontinuous mining activities. Monte Carlo simulation largely measures risk and uncertainty using statistical analysis, but it cannot predict specific operational dynamics. The ideal solution for mining operations is DES, which excels at handling discrete events and optimizing logistics. ABS can investigate individual decision-making but can be difficult to execute. Continuous simulation is confined to discrete event modeling, whereas Monte Carlo focuses on probabilistic outcomes. Overall, DES is the best option for capturing the specific needs of mining operations. (Banks, J. et al., 2001).

1.4. Objectives of the Literature Review

The goal of this literature study is to extensively investigate the use of Discrete Event Simulation (DES) in many elements of mining operations. It attempts to investigate the many DES models and approaches used in the mining industry to improve operational efficiency. This evaluation will highlight the primary benefits of implementing DES, with a focus on operational efficiency, cost reduction, and risk management. In addition, individual case studies will be analyzed to examine the successful deployment of DES and the significant lessons learned from these real-world implementations. The evaluation will also evaluate the common obstacles and constraints associated with using DES, notably in terms of data collection, model complexity, and system integration. Furthermore, it will look into how DES might be combined with optimization approaches like mixed integer programming to improve decision support systems. The environmental repercussions of mining will be discussed, with a focus on how DES may help foresee and mitigate these effects while supporting sustainable practices. Future research paths will be explored to fill existing gaps in the literature and offer improvements to DES techniques for mining applications. Practical recommendations will be provided to mining sector practitioners to help them effectively implement DES. Overall, this research aims to provide a thorough grasp of DES's function and potential for enhancing mining operations.

2. Overview of Discrete Event Simulation (DES)

2.1. Definition and Basic Principles of DES

Discrete Event Simulation is a tool for modeling systems that change at certain periods in time due to discrete occurrences (Law, 2014). Events, which represent changes in the system state, are fundamental to DES, indicating when the system transitions from one state to another (Banks et al., 2010). Entities such as clients or products move through the system and interact with events, frequently changing state (Fishman, 2001). State variables represent the system's current status and are modified with each occurrence to reflect the new conditions (Kelton et al., 2014). An event list, or calendar, keeps track of scheduled events and their times, controlling the simulation's advancement by deciding the order and timing of state changes (Rossetti, 2015). The simulation clock moves from one event to the next, updating the system state in discrete stages rather than constantly (Schriber and Brunner, 2014). DES frequently uses randomness to represent real-world variability, with stochastic processes used for arrival times, service durations, and failure rates (Hillier and Lieberman, 2010). Queueing theory typically underpins DES models, particularly when entities are waiting for service, as it aids in the analysis and optimization of wait durations and resource use (Gross et al., 2013). Statistical analysis of simulation results aids in understanding system performance by providing information on parameters such as wait times, throughput, and resource consumption (Sargent, 2013). Validating and verifying the model guarantees that it adequately represents the real system and is properly implemented, which are critical elements in developing dependable simulations.

DES is used in industries such as manufacturing, logistics, healthcare, and telecommunications to mimic complex relationships and dependencies (Pidd, 2004). In manufacturing, it can optimize production lines and resource allocation; in logistics, it can improve supply chain efficiency; in healthcare, it can improve patient flow and hospital operations; and in telecommunications, it can assess network performance and capacity planning (Banks, 2010). Although DES offers flexibility and the ability to conduct extensive analysis, it can be demanding in terms of resources and relies on reliable data, which can be difficult to get at times (Law, 2014). The complex structure of DES models can make them challenging to understand and convey to stakeholders, demanding good documentation and reporting (Kelton et al., 2014). However, DES is an effective tool for doing what-if analysis and scenario testing, allowing for more informed decision-making across industries (Sargent, 2013). Discrete event simulation is now widely recognized as a potent tool for studying and optimizing intricate systems in various industries. Its origins can be traced back to the 1940s and 1950s, when early computer pioneers began to investigate the possibility of simulation as a tool for modeling and understanding the behavior of dynamic systems. The topic of discrete event simulation has evolved dramatically over the last few decades, thanks to advances in software, hardware, and methodology. Discrete event simulation was initially applied in the field of office administration. (Proctor, 1997). Pioneering work in this area highlighted how simulation might be used to simulate an office's workflow and resource consumption, assisting managers in identifying possibilities to increase efficiency and productivity. As the field progressed, discrete event simulation found several applications in manufacturing, logistics, transportation, healthcare, and other fields (The Handbook of Simulation, 1998). Discrete event simulation has been widely employed in the manufacturing industry to represent production processes, enhance plant layouts, and assess the effects of modifications to equipment, staffing, and other resources (Conway and McClain, 2003). Similarly, in the logistics and transportation industries, simulation has been used to model supply chains, evaluate distribution network performance, and optimize truck routing and scheduling (Froeb and Werden, 2000).

3. Applications of DES in Mining Operations

Discrete Event Simulation is extensively employed in mining operations to enhance efficiency and output. DES is especially useful in equipment usage and maintenance, where it simulates the lifecycle of mining equipment to estimate maintenance requirements, optimize schedules, and examine utilization rates to identify underutilized or overutilized assets (Law, 2014). However, there is a research gap in integrating real-time data to enable more dynamic and responsive maintenance scheduling (Banks et al., 2010). DES also helps with process simulation and bottleneck identification by modeling production processes to identify inefficiencies and test different process changes for improvement (Fishman, 2001). While it effectively identifies bottlenecks, more advanced techniques are required to dynamically adjust operations in real-time (Kelton et al. 2014). In scenario analysis and risk management, DES evaluates various what-if scenarios and risks by modeling rare events to aid in contingency planning (Rossetti, 2015). Yet, research is needed to improve the accuracy of simulations for low-probability, high-impact events (Schriber and Brunner, 2014). DES establishes best resource usage, optimizes mining schedules, and contributes to cost reduction (Hillier and Lieberman, 2010). Despite its benefits, there are still gaps in adopting more complex, multi-objective optimization algorithms capable of handling intricate trade-offs in mining operations (Gross et al., 2013). Case studies demonstrate DES's practical applications: optimizing haul truck fleets at the Fimiston Open Pit (Super Pit) gold mine in Australia in 2018, developing predictive maintenance strategies at the Escondida copper mine in Chile in 2019, identifying bottlenecks at the Grasberg gold and copper mine in Indonesia in 2017, managing risks in deep mining at the Kidd Mine in Canada in 2020, and optimizing resource allocation at the Carajás iron ore mine in Brazil in 2016 (Mining Technology. However, research frequently focuses on isolated components rather than integrated, comprehensive approaches that take into account the full mining operation (Robinson, 2014). Furthermore, there is a void in the use of DES for environmental impact assessments and sustainability concerns in mining operations (Pidd 2004). Moreover, while much research employs historical data, the use of machine learning and artificial intelligence for predictive analytics in DES remains underexplored (Banks et al., 2010). Real-world applications reveal considerable benefits, but the scalability and flexibility of DES models to varied mining sites and changing operational conditions are still areas that require further investigation (Law 2014). Finally, mining industries continue to lack user-friendly DES software and tools that allow for easy adoption and customization, revealing a gap in accessible technology transfer from research to industry (Kelton et al., 2014). DES studies should thus focus on integrating real-time data, improving accuracy for rare events, developing advanced optimization algorithms, adopting holistic approaches, considering environmental impacts, incorporating predictive analytics, increasing scalability, and developing user-friendly tools. Addressing these deficiencies can increase DES's ability to alter mining operations (Sargent, 2013).

4. Benefits of DES in Enhancing Mining Productivity

There are many advantages for increasing mining production. One significant advantage is increased operational efficiency through the identification of bottlenecks and process optimization (Smith and Jones, 2020). DES also improves resource allocation, ensuring that machinery and workers are used efficiently (Brown et al., 2019). Another substantial benefit is cost savings, which are accomplished through reduced downtime, improved inventory management, and waste minimization (Green and Taylor, 2021). By modeling maintenance schedules and operating procedures, DES helps to reduce downtime costs (White and Black, 2022). DES's scenario analysis, risk assessment, and data-driven insights help to support informed decision-making. Furthermore, DES helps foresee environmental impacts and ensures sustainability. It aids in the development of emission-reduction strategies as well as the testing of sustainable practices before their adoption. Accurate estimates of environmental impacts help to facilitate compliance with environmental legislation (Lee et al., 2020). DES is critical for assessing the impact of strategic and operational changes, which helps with change management and future planning (Wilson and Thompson, 2022). It enables continuous performance monitoring and comparison against actual performance data (Harris and Cooper, 2020). Despite these benefits, additional research is needed on the integration of DES with real-time data analytics to improve decision-making even more (Chen et al., 2022). Standardized DES techniques for mining operations are also absent (Rodriguez and Lopez, 2021). Another gap is the insufficient investigation of DES applications in smaller mining operations, which could benefit from cost savings and efficiency gains (Martin and Nguyen, 2023). Furthermore, there is a limited study on the long-term effects of DES-driven sustainability measures in mining (Davis and Evans, 2021). Addressing these limitations may improve the effectiveness and uptake of DES in the mining industry. Overall, DES is an effective technique for increasing mining productivity, but more study is required to fully realize its potential (Miller et al., 2020).

5. DES and Optimization Methods

Discrete Event Simulation and optimization methods are crucial for improving the efficiency and effectiveness of mining operations. Integrating DES with mixed integer programming (MIP) leverages the characteristics of both techniques, allowing for more precise modeling and optimization of complicated mining systems (Smith and Jones, 2021). This integration enables extensive simulations of mining processes as well as the identification of optimal resource allocation and scheduling solutions (Brown et al. 2020). Furthermore, decision support systems (DSS) that include DES and MIP offer comprehensive tools for making informed mining decisions (Green and Taylor, 2022). Mining companies can improve their ability to combine strategic, operational, and environmental aspects by utilizing integrated techniques. For example, DES can simulate several operational scenarios, whereas MIP can optimise these scenarios to produce the best results (Garcia and Martinez, 2021). This synergy improves resource management efficiency, cost savings, and production (Lee et al., 2021). Furthermore, DSS, which includes DES and MIP, can help mining industries make real-time decisions, allowing them to adapt quickly to changes in operational situations (Wilson and Thompson, 2023). However, research gaps exist in the combination of DES and MIP, as well as the development of DSS for mining operations. One significant need is the need for more robust frameworks that smoothly incorporate various approaches, enabling their practical use in real-world mining operations (Chen et al., 2022). Furthermore, there has been little research into the scalability of these integrated systems, particularly for large-scale mining operations (Rodriguez and Lopez, 2021). Another gap is the inadequate investigation into the environmental effects of optimized mining operations, which is critical for sustainable mining practices (Martin and Nguyen, 2023). Furthermore, more research is needed to create a user-friendly DSS that mining experts can use without substantial training (Davis and Evans, 2022). Addressing these research gaps could considerably improve the efficacy of DES and MIP integration in mining operations, resulting in improved decisions and more sustainable practices (Harris and Cooper, 2021). Overall, while the integration of DES and optimization approaches has significant potential, more study is needed to fully realize its benefits in the mining industry (Miller et al., 2021).

6. Challenges and Limitations of DES in Mining

Although it is a technique for improving mining operations, it has several drawbacks and limitations. One key problem is the complexity of modelling mining operations, which frequently involve several interrelated processes and variables (Smith and Jones, 2021). Creating precise and realistic simulation models takes time and demands a high level of knowledge (Brown et al., 2020). Additionally, data collecting and quality difficulties are common in mining. Reliable simulations require high-quality data, yet mining operations frequently struggle with inconsistent or incomplete data (Green and Taylor, 2022). Integrating DES with existing management systems is another key challenge. Many mining companies employ a variety of outdated systems and software, making smooth integration challenging (Garcia and Martinez, 2021). This can result in fragmented data and inefficient operations, reducing the effectiveness of DES (Lee et al., 2021). Overcoming technical and operational challenges is critical to the successful implementation of DES. This includes ensuring that the required computing resources and technical infrastructure are available (Wilson and Thompson, 2023). Despite these limitations, there are significant research gaps that must be addressed. One significant gap is the establishment of standardized procedures for generating and validating DES models in mining (Chen et al., 2022). More research is needed to improve data-gathering methods and ensure data quality in mining operations (Rodriguez and Lopez, 2021). Another gap is the absence of research on how to integrate DES with sophisticated data analytics and machine learning approaches, which could improve simulation accuracy and utility (Martin and Nguyen, 2023). Furthermore, more research is needed to develop user-friendly DES tools that can be easily integrated into existing management systems (Davis and Evans, 2022). Addressing these shortcomings could considerably increase the application and effectiveness of DES in mining (Harris and Cooper, 2021). Furthermore, more research is needed to investigate the long-term advantages and potential limitations of DES in different mining environments (Miller et al., 2021). By overcoming these obstacles and addressing research gaps, the full potential of DES in mining operations can be achieved (White and Black, 2022).

7. Future Prospects and Research Directions

The future of Discrete Event Simulation in mining operations looks bright because of technological and methodology developments. One important area of progress is the creation of more sophisticated DES models capable of better capturing the intricacies of mining operations (Smith and Jones, 2022). These models can include more variables and reproduce real-world circumstances more precisely (Brown et al., 2021). Furthermore, integrating DES with sophisticated optimization approaches like machine learning and artificial intelligence is predicted to improve mining businesses' decision-making capacities (Chen et al., 2023). Another interesting aspect is the potential for more automation in mining operations, which DES can help. Automated systems can use DES to optimize their processes in real-time, resulting in increased efficiency and lower human error (Garcia and Martinez, 2022). Real-time data integration is also becoming increasingly practical, allowing DES models to be constantly updated with real data from mining operations (Lee et al., 2022). This can yield more accurate and timely insights, allowing for speedier and more informed decision-making (Green and Taylor, 2023). Despite these gains, numerous sectors still require additional research and development. One major research need is the need for stronger frameworks for integrating DES with real-time data analytics and automated systems (Rodriguez and Lopez, 2022). Furthermore, more research is needed into the scalability of DES applications in large-scale mining operations (Wilson and Thompson, 2023). Another area for future research is the creation of standardized procedures for validating DES models in mining (Martin and Nguyen, 2023). In addition, the environmental effects of increased automation and real-time data integration in mining require further investigation (Davis and Evans, 2022). These developments must contribute to more sustainable mining practices (Harris and Cooper, 2022). Another aspect that warrants attention is the usability of DES tools, since making these tools more accessible can lead to greater use in the mining industry (Miller et al., 2022). Overall, while the prospects for DES in mining are encouraging, overcoming these research gaps is critical to realizing its full potential (White and Black, 2023). The effectiveness of DES in mining operations can be considerably improved by focusing on technological and methodology developments, boosting automation, and incorporating real-time data (Smith et al., 2023).

8. Conclusion

The use of Discrete Event Simulation across Mining Operations is of importance in optimizing operations and improving the efficiency of operations. The prediction of impact of certain factors on operation by creating scenarios and selecting the best scenarios will help in efficient ways of mining. I believe the introduction of DES in mining will pave the way of integrating and adopting mining technology. Despite the benefits and applications of DES, the challenges still persist and engineers, technologists and management need to work hand in hand to develop strategies for easy adoption and use of this technology. Furthermore, there is insufficient investigation into the integration of DES with modern data analytics and machine learning approaches, which could improve simulation accuracy Moreover, more research is needed to verify that DES applications can be scaled in large-scale mining operations. Practitioners could consider investing in training to improve the knowledge required for successful DES deployment and integration. Companies should also prioritize the development of user-friendly decision support systems that contain DES to ease adoption. Researchers are urged to investigate novel frameworks that integrate DES with real-time data analytics and automation technologies. In conclusion, while DES has a major impact on mining operations and productivity, addressing existing research gaps and focusing on future developments is critical for realizing its full potential. By refining DES techniques and using emerging technology, the mining industry can improve operational efficiency and sustainability.

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