Literature Review of Artificial Intelligence Applications in Open-Pit Strategic Mine Planning[1]

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ABSTRACT

The significant increase in data availability and high-computing power and innovations in real-time monitoring systems enable the technological transformation of the mining industry. Artificial Intelligence (AI) and data-driven methods are becoming appealing solutions to tackle different challenges in mining operations where an increasingly larger body of research is being published. Strategic mine planning is one of the areas that can be greatly enhanced with the adaptation of AI techniques to make intelligent data-driven decisions. This paper presents a systematic literature review to identify research trends in this field both in the specific area of application and the AI technique used. Papers from popular scientific databases were compiled and categorized into three main identified research areas in this field: Production Planning and Scheduling, Equipment Management and Grade Control, and individual AI techniques were cataloged. The results indicated an exponential growth in the general number of publications, where the most consolidated techniques across all applications were Genetic Algorithms and Discrete Simulation.

1. Introduction

Artificial Intelligence (AI) has seen a dramatic surge in interest from researchers and practitioners across all industries in the past few years, with successful real-world applications in consumer products, like digital assistants or content recommendation, and industrial settings, such as autonomous equipment and robotics. There is no clear-cut definition of AI, as it is a mixture of different research fields, each with its own goal and methods. A good definition can be found in Russell and Norvig [1] as the designing of intelligent agents that operate within an environment, take actions that affect it and receive feedback signals from it to achieve some goal. It can be seen as a general-purpose technology with sophisticated learning capabilities that can take large amounts of data for a wide range of applications like advanced analytics, process optimization, and automation that promise significant business improvements and new opportunities [2].

Machine learning (ML) is one area of AI that has received the most attention and hype in the past few years, with successful real-world AI applications based on this group of techniques. ML methods can be defined as a set of algorithms that can uncover complex patterns in data and use them to predict future outcomes. ML methods are commonly divided into three areas: supervised learning (SL), unsupervised learning (USL), and reinforcement learning (RL) [3]. SL aims to learn a good function approximation from an input vector, representing the problem of interest, to an output vector or target for future prediction. SL requires labelled data to learn the relation between

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attributes and targets explicitly. USL, on the other hand, is concerned with unlabeled datasets, where the outcome of the target for each data entry is not recorded. Therefore, its main goal is not a prediction but discovering patterns in data. USL's main applications are data clustering, density estimation, and dimensionality reduction [3]. RL proposes a framework in which a computational agent learns by interacting with an environment, real or virtual. In RL, the goal is to learn a mapping between situations (description of the environment) to optimal actions [4].

Moreover, AI also comprises other methods besides ML, such as metaheuristics (MTHs) and evolutionary algorithms, which have played a key role in engineering systems optimization [5]. MTH algorithms are concerned with searching for optimal solutions in challenging mathematical problems drawing inspiration from nature and evolution, and have seen significant applications in mining engineering [6]. Other data-driven approaches have also emerged in recent years, such as Discrete Event Simulation (DES) and Digital Twins (DT), which comprise the development of the detailed simulation of systems and processes for anticipating behaviour and supporting decision-making [7].

The mining industry is poised to reap the rewards of AI and data-driven approaches as it deals with a complex integrated value chain of exploration, extraction, and refining that has a history of integrating high-technology systems for increased productivity [8]. However, it remains one of the industrial sectors with lower levels of adoption of AI and digital technologies [9,10], where some of the major challenges that the mining industry faces for digital transformation are the availability of high-quality data, connectivity of operations and human resources skilled in these new areas [10].

The backbone for the digital transformation of any industry relies on three main pillars: data, connectivity and decision-making [10]. These three components are deeply intertwined, each providing necessary resources for the others to succeed. Connectivity plays an important role where the Internet-of-Things (IoT), a mixture of integrated technologies which can communicate via a network, provide the required infrastructure to enable automatic data collection and workflow control from which the mineral industry can significantly benefit [11]. The mineral extraction industry has already seen important innovations for real-time data acquisition and storage across the entire mineral value chain [12], that have enabled applications such as improved production decision-making with real-time updating and reconciliation of mineral quality models by integrating sensor data [13,14], or accurate estimation of ore production from the truck haulage system with ML and IoT [15].

Jung and Choi [16] present a systematic review of ML applications for mineral exploration, exploitation and reclamation, where a significant growth in the number of studies was observed starting from 2018, with the main applications receiving attention by researchers being mineral exploration and drilling and blasting. On the other hand, McCoy and Auret [17] present a review of ML applications in mineral processing exclusively, identifying equipment fault-detection and diagnosis and machine vision for quality control. The applications of ML and AI within the mining industry as a whole are very broad.

Surface mining methods dominate the mining industry, accounting for more than 95% production of non-metallic minerals and more than 90% production of metallic ones [18]. Surface mining method involves selectively extracting shallow mineral resources by excavation or cut made from the surface using one or multiple benches. One of the key stages in the life cycle of surface mines is strategic planning, which involves decisions taken for the long-term vision of the operation and short-term execution.

Therefore, this paper presents a systematic review focused on the use of AI and data-driven methodologies in strategic surface mine planning to analyze trends in the adoption of different techniques and get insight into what applications in this area are being tackled by researchers and the industry. This paper is organized as follows. In the remainder of this section, a brief overview of surface mining methods and the role of strategic planning and its operations within the mine project life cycle are presented. Section 2 describes the research methodology followed in this paper stating the research questions that will be answered and the literature search strategy and inclusion criteria. Section 3 presents a systematic review, including the classification and detailed review of selected publications and analysis of the research trends in the area. Section 4 discusses the results obtained from the literature review and proposes some directions for future work. Finally, Section 5 presents the conclusions of this research.

1.1. Overview of strategic planning in surface mining

The life cycle of a mining project consists of six main stages or phases: (1) exploration and feasibility, (2) design and planning, (3) construction and development, (4) exploitation, (5) mine closure and (6) post-mining reclamation [19]. The first stage comprises activities such as geological exploration and drilling and determining mineral resource quantity and quality. The second stage of design and planning involves the engineering studies to plan the extraction of the mineral resource from the ground and the design of the integrated system to sell it on the market. The decisions taken at this stage play a key role in the mining project's long-term economic and technical performance. In the third stage, once the extraction plan was determined, the construction of facilities and preparation of the land for the extraction phase takes place. The fourth phase of exploitation also involves key decision-making processes to execute the long-term vision for the mining project at shorter time intervals. During the exploitation phase, revisions to the long-term plan are also conducted periodically to adapt to new circumstances such as different market prices or unexpected behaviour or quality of the mineral rock mass. The final stages of the mining life cycle include all the activities involved to guarantee a safe and sustainable closure to the mining project and restoration of the land for its post-mining use.

The general geometry of an open-pit mine consisting of multiple benches and a haul road network is shown in Figure 1. Strategic mine planning is concerned with the goal of maximizing the value of a mining project from the feasibility stage to the mining production environment, optimizing the utilization of resources such as equipment, labour, and technology, and plays a crucial role in the success of a mining operation. For this purpose, our goal is to understand how AI and data-driven methodologies are starting to disrupt this area and what the potential is for the future. Strategic planning involves two stages in the mine life cycle previously discussed, design and exploitation, under which long-term and short-term planning tasks are carried out [20].

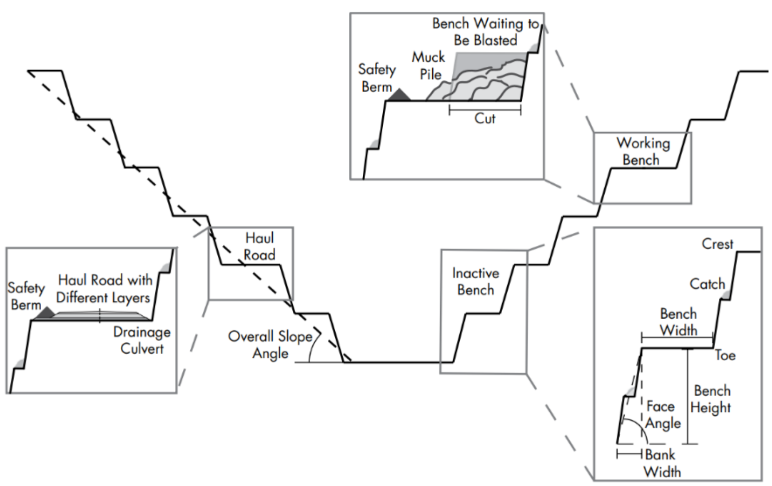

Figure 1. General geometry of an open-pit mine. After [21].

1.1.1. Long-term planning

Long-term planning deals with determining the final pit limits and the life-of-mine production schedule of the operation, where mining extraction sequences and destination policies for the mined areas (i.e. processing plant, waste dump) are decided at long time horizons to maximize the project's economic value. The mineral resource is discretized into a set of blocks, where for each block, different properties are estimated like rock type and metal grade using information gathered from the exploration campaigns. The long-term planning process uses the mineral resource block model, along with an economic scenario, to define the ultimate pit limits (UPL) and the open-pit production schedule (OPS) for the life-of-mine at long-term periods of time usually expressed in years [22].

The problem of defining the UPL can be described as finding the optimal final boundaries for the open-pit operation that maximize the total profit for the extraction of the mineral ore contained within, considering the costs of mining overlying rock waste material. The final pit boundaries must comply with operational and geotechnical constraints such as bench widths and overall slopes. Sophisticated computational methods have been proposed and are used in the industry to solve this problem, for a review of such please refer to Mwangi et. al. [23].

The open-pit production scheduling (OPS) problem can be defined as finding the sequence of extraction and destination of the blocks or benches within the ultimate pit limits under production, metal grade quality, geotechnical and other operational constraints. The long-term production scheduling solves this problem on a time horizon comprising the life-of-mine with decisions expressed in years or larger time periods. Fathollahzadeh et. al. [24] present a comprehensive review of current mathematical solution strategies for this problem.

Due to the large scale of surface mining projects and the complex sequencing constraints and ore quality requirements, it is often computationally intractable to obtain a true optimal mine plan, for which metaheuristics and intelligent computing methods seem particularly promising and have been widely adopted to approximate good solutions under a reasonable amount of time for the open pit scheduling (OPS) problem. A review of metaheuristic approaches for the specific problem of long-term open-pit planning problem is presented by Franco-Sepulveda et. al. [6].

1.1.2. Short-term planning

Short-term planning differs from long-term applications by emphasizing operational level decisions dealing with equipment and resources allocation over a shorter time scale on a monthly, weekly or shift-by-shift basis, usually under the guidance of the long-term plan. At these shorter time scales, mine operations are modelled with greater detail, considering the available equipment and different tasks required to execute the long-term strategic vision of the mine.

Model formulations for the open-pit mine operational planning (OPMOP) vary amongst researchers but commonly seek to minimize deviations from production targets, minimize operating costs or maximize NPV, and include a more detailed mathematical representation of equipment interaction. Common formulations aim to obtain decisions on shovel allocations to mining areas and production scheduling of development and extraction activities such as drilling and blasting and preparation of the working area. For an overview of short-term planning methods for open-pit mining, the users are referred to Blom et. al. [25].

Truck fleet management also represents a key aspect of the short-term and operational planning of open-pit mining, which comprises the allocation of truck fleets to shovels and mine production areas, and the definition of a truck dispatching strategy. For a review of current methods in truck fleet management, the readers are referred to Moradi Afrapoli and Askari-Nasab [26].

2. Research Methodology

This research aims to identify current research trends in applying AI and data-driven approaches for the strategic planning of surface mining operations to understand better the current state of adoption, future potential, and potential flaws of these new technologies in this field.

To fulfill the objectives of this study, a systematic literature review was carried out following the guidelines given by Tranfield et al. [27], who transfers systematic review methods from the medical field to the management sciences, and Xiao and Watson [28], who propose a rigorous methodology for literature reviews in the planning sciences. The main steps for the systematic literature review presented in this study include the formulation of the problem as research questions, the development of the search protocol including the search query and selection of databases, the definition of screening criteria for inclusion and rejection of documents and the synthesis and analysis of the information retrieved.

The review focuses on the following research questions:

1. How and within which main research areas have AI and data-driven technologies been adopted for the strategic planning of surface mining operations?
2. Which are the most common AI and data-driven approaches for strategic planning in surface mining operations?
3. How have AI and data-driven approaches been applied in the strategic planning of surface mining operations over time?

Research question 1 deals with uncovering the main application areas in which AI and data-driven methods have been applied within the strategic planning of surface mines to understand better where most of the research effort is put on. Research question 2 is more specific to the AI and data-driven approaches to understand which methodologies have been more successful when applied to this field. Finally, research question 3 is concerned with synthesizing the evolution of AI and data-driven specific techniques (e.g., neural networks, genetic algorithms) in the literature relating to strategic planning of surface mining operations to point out potentially favourable and possibly obsolete techniques.

The search included papers from the year 2000 up to June 31st of 2021 in the following scientific databases: Science Direct, Springer Link, Scopus, IEEE Xplore, and Taylor and Francis. These databases include most scientific peer-reviewed work in engineering applications, with some containing relevant mining engineering journals.

The general structure of the search query is presented below, which was adapted to match the format for each of the different scientific databases.

(OR[keywords for surface mining]) AND (OR[keywords for AI and Data-driven approach]) AND (OR[keywords for strategic planning])

The [ ] indicates the following set of relevant keywords for the search:

- Keywords for surface mining: Surface mining, open pit mining.
- Keywords for AI and Data-driven approach: Artificial intelligence, machine learning, deep learning, reinforcement learning, data analysis, intelligent system, metaheuristic, simulation.
- Keywords for strategic planning: strategic planning, production scheduling, production monitoring, equipment management, equipment monitoring, grade control.

The OR[ ] notation indicates that the query targets at least one of the keywords from that particular set. Therefore, the query targets papers containing at least one keyword from each set corresponding to surface mining, AI and data-driven approaches, and strategic planning.

Afterwards, the literature records obtained were screened based on the following inclusion criteria:

- Only peer-reviewed journal papers or conference proceedings.
- Only publications from the year 2000 onwards.
- Unique studies with duplicates or similar studies by the same authors on different journals or conferences were removed.

Moreover, to stay in the scope of strategic planning and operations management, the following topics related to surface mining that partially appears as part of the search query were not considered in this review: geological exploration, mining rock mechanics, mining equipment reliability, blasting and mineral processing. These topics can be considered a whole field on their own, and although critical for the success of mining projects, they are out of the scope of this specific research, and to be able to cover them a different search strategy would be needed systematically. For interested readers, an overview of research trends in rock mechanics is presented in Lawal and Kwon [29] and mineral processing in McCoy and Auret [17]. To the best of the authors' knowledge, there is no systematic literature review work in geological exploration, mine safety, or rock blasting; however, there is a significant body of specific applied research in those areas.

By applying the search-query and inclusion conditions, 87 papers were retrieved for a detailed analysis of the research areas and trends. Figure 2 illustrates the general overview of the literature search and compilation.

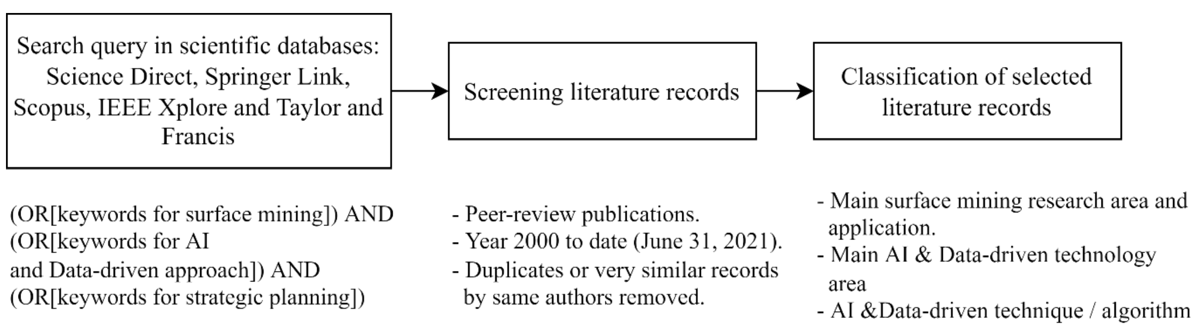

Figure 2. Methodology for literature database compilation.

3. Systematic Review

The literature database obtained from the systematic search was categorized based on main research area, application and AI and data-driven technique used. Then the results were analyzed to answer the research questions posed. This introduced different abbreviations to deal with the variety of applications and methods found in the literature. To facilitate the reader's comprehension, a list of all the abbreviations introduced in this section is presented in Table 1.

Table 1. List of abbreviations

Research Areas (RA)		**AI & Data-Driven Approach (AIA)**	
EM	Equipment Management	*DES* *MT*	Discrete Event Simulation
GC	Grade Control	*H*	Metaheuristic
PPS	Production Planning and Scheduling	*RL*	Reinforcement Learning
		SL	Supervised Learning

USL Unsupervised Learning

AI & Data-Driven techniques

ACO Ant Colony Optimization
BA Bat Algorithm
CLS Clustering
CNN Convolutional Neural Network
FA Firefly Algorithm
GA Genetic Algorithm
HOG Histogram of Oriented Gradients
ICA Imperialist Competitive Algorithm
KNN K-Nearest Neighbors
NN Neural Network
PSO Particle Swarm Optimization
PH Progressive Hedging
RL Reinforcement Learning
RL Reinforcement Learning
S-B Search-based Algorithms
SA Simulated Annealing
SVM Support Vector Machine
T-B Tree-based algorithms

3.1. Classification of literature

All 87 selected papers were reviewed in detail. Then, to answer the research questions, they were classified based on the research area they targeted and the specific mining application and based on the AI and data-driven approach used and technique applied.

- Research area (RA): General area of interest targeted in the publication.
- AI and data-driven approach (AIA): General AI approach from which the techniques used in the publication belong.

The RA observed from the corpus acquired are the following: Production Planning and Scheduling (PPS), Grade Control (GC), and Equipment Management (EM). All papers target a particular application within these broad fields of interest for the strategic planning of surface mining operations. The AIA considers SL, USL, agent-based approaches and RL, MTH, and DES.

Moreover, within each RA, the mining application the research targeted was identified and tabulated. Table 2 shows a summary of the number of research papers by RA and application and by AIA.

Figure 3 illustrates a visual representation of the number of papers by category. PPS is the RA that dominates research efforts, including long-term and short-term or operational production planning and scheduling, and forecasting production capacities and capital costs. The principal AIA taken has been the development of MTH algorithms to tackle the large-scale and complex problems of real-sized mines, with SL impacting cost forecasting applications. RL approaches were tested initially in 2009 by Askari-Nasab and Awuah-Offei [30] for long-term planning and resurfaced again by 2017 over multiple research efforts. Discrete simulation is used extensively for planning and scheduling at an operational level where the interactions between equipment considerably impact production Key Performance Indicators (KPIs).

Table 2. Number of research papers by RA and application (in parenthesis) and AIA.

Research Areas and Applications	AI & Data-Driven Approach (AIA)				
	SL	**USL**	**RL**	**MTH**	**DES**
Production Planning and Scheduling (67)	8	1	6	41	11
Long-term planning (41)	1	1	2	35	2
Short-term planning (22)	4	0	4	5	9
Production capacity forecasting (11)	1	0	1	0	9
Cost forecasting (4)	3	0	0	1	0
Grade Control (14)	3	3	1	7	0
Cut-off grade strategy (5)	0	0	0	5	0
Grade Control and Ore delineation (14)	3	3	1	7	0
Equipment Management (21)	6	0	5	2	8
Equipment tracking (10)	6	0	2	0	2
Equipment dispatch & sizing (13)	0	0	3	2	8

The EM area includes research publications that deal explicitly with mining equipment where tracking, consumption control, and equipment dispatching are the main applications. Multiple types of AIA have been tested in which DES methods are the most favoured approach by researchers. It can potentially exploit large datasets that are more commonly available with the development of sensors and monitoring technologies for mining equipment. Agent-based approaches and RL appear with research focused on the dispatching and optimal routing of trucks and shovels. SL techniques also play a key role here, where large mine records can be used to predict equipment behaviour and consumption.

Research on applications for grade control in open-pit mining operations appeared significantly in the database. Papers under this category cover applications in which the goal is to find techniques to discriminate ore from waste better and delineate ore zones for improved mine planning and determining cut-off grade strategies for the operation. MTHs appear to be favoured algorithms in this area to solve the complex problems of delineating ore boundaries and determining cut-off strategies.

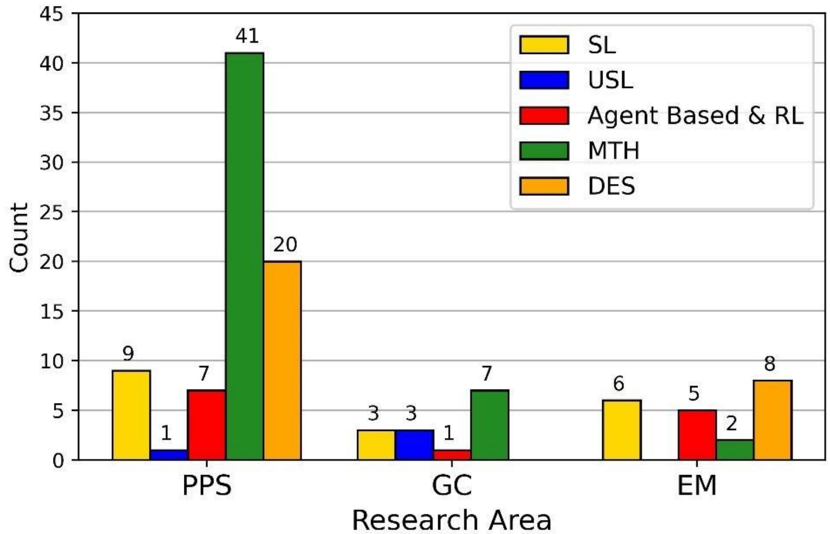

Figure 3. Number of papers by RA and AIA.

Following the research questions, Figure 4 shows the number of papers by specific mining applications and AIA to get some insights into which AI and data-driven approaches have had a broader adoption for mining applications. MTHs, such as genetic algorithms (GA), significantly impact long-term planning and grade control research. These applications solve large and complex computational models for surface mines' scheduling and decision-making process. On the other hand, DES is commonly used for more operational and short-term planning where equipment cycles are more concerned. SL approaches have seen some adoption across multiple applications, RL and agent-based approaches which have been tried for long- and short-term planning, and equipment dispatching.

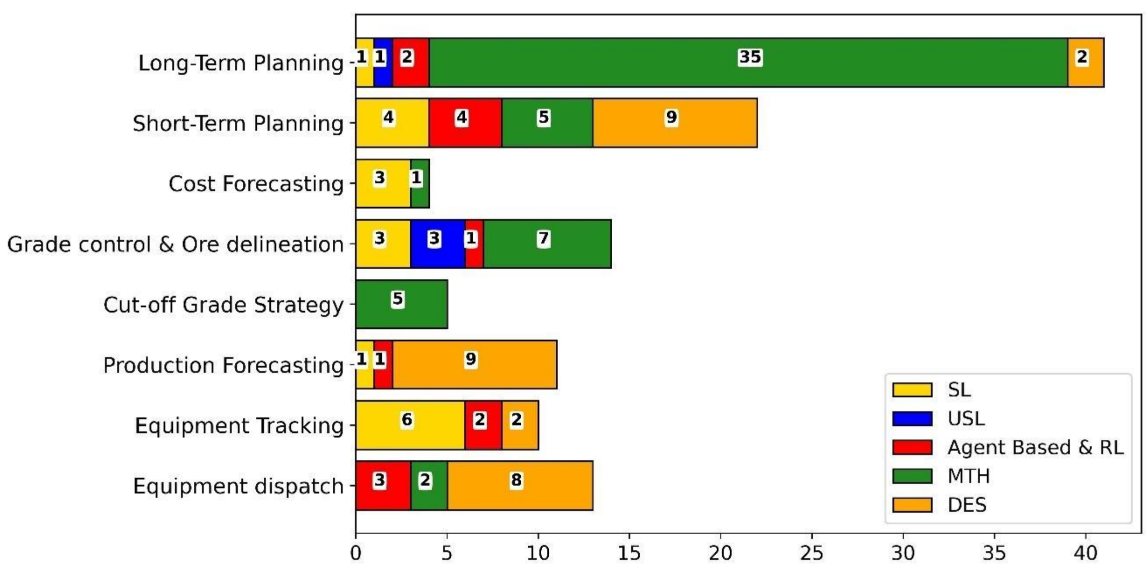

Figure 4. Number of papers by specific mining application and AIA.

3.2. Trend Analysis

Topic modelling and trend analysis techniques provide an important tool for researchers to navigate the large corpus of publications and studies within an area and get an overview of the evolution of topics and techniques explored by the research community [31]. To answer research question 3 and get an idea of the evolution of the adoption of different AIA within surface mining strategic planning, Figure 5 shows the number of publications by AIA throughout the period in question, 2000-2021. The publications were grouped in bins of 3 years to allow for better visualization, including the last year, 2021, in the last group.

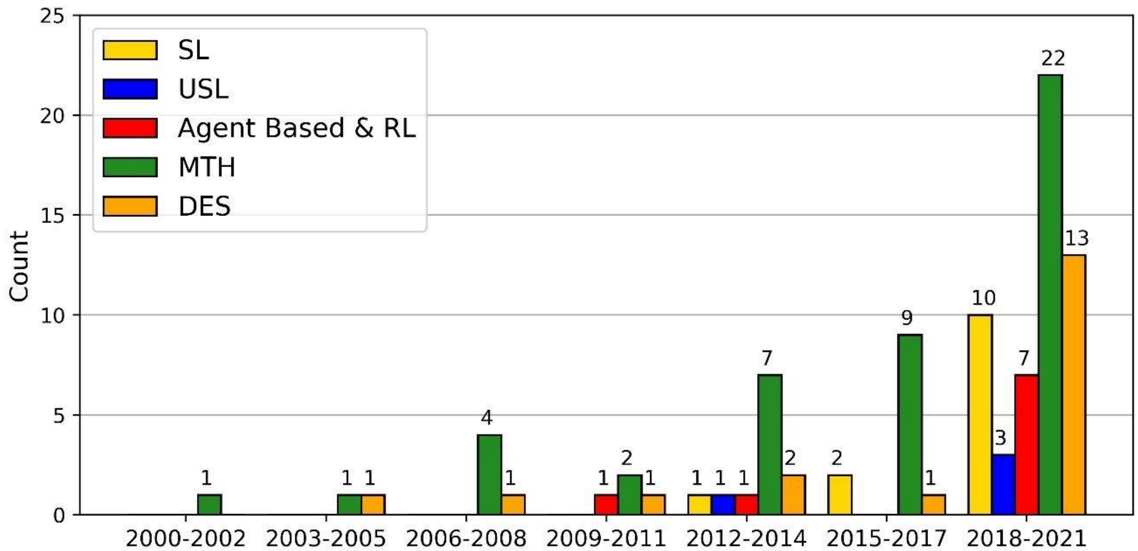

Figure 5. Trend of publications by AIA.

Figure 5 shows that the past few years have seen considerable efforts directed in applying AIA in the mining industry, along with trends in other sectors. MTH approaches have seen the largest positive trend, showing an exponential growth pattern in the number of publications. This type of intelligent computation approach has benefitted immensely from the general increase in computational power and seem to be a reliable option to solve large scale mine production planning and scheduling problems, both at a long-term and operational scale, which require the evaluation of many possible combinations of resource allocation and mining extraction patterns decisions. DES approaches have seen extensive adoption, especially in the past four years. These methods require large databases to reproduce equipment production cycles and interactions accurately and have benefited from the large-scale adoption and focus on data-driven applications within the mining industry.

From the ML approaches, SL has the largest adoption, increasing within the past four years. SL requires large, labeled datasets to work efficiently, which have become more readily available recently with advances in monitoring technology. On the other hand, USL seems to be the least adopted approach, appearing just after the 2012-2014 period. USL tries to discover insights from unlabeled data and is particularly challenging to bring into practical applications since the lack of a ground truth label (e.g., machine failure, ore grade) makes its interpretation challenging. This is a complication in the adoption of USL in other industries as well. Finally, RL approaches appeared as early as 2009-2011 but then faded away from the literature, making a significant comeback just in the past four years. RL is benefited from very recent key breakthroughs that promise to make their application feasible in real-world settings. RL high complexity remains a hurdle for industry adoption; however, it shows great potential as it explicitly combines data-driven learning capacity with decision-making processes.

To get further insight into the specific techniques tried by researchers, a trend evolution map was created for the techniques identified in each paper, shown in Figure 6. Analyzing the research trends of particular AI and data-driven techniques and their evolution through time can provide researchers with a better understanding of what techniques have been already tried and are starting to fade away, what techniques have seen consistent success in their applications and what are some of the new hot topics in the literature, which greatly supports the directions for future research and work as it has been applied in other industries [32]. An example was applied by Bertolini et al. [33] to model the topic trend evolution of ML adoption in industrial processes and understand which techniques have seen a more successful adoption in the field interest and which are becoming obsolete. Bertolini et al. [33] identified five main clusters of techniques based on their position in the trend evolution map denominated: Question Marks, Hot Topics, Consolidated, Stars, and Obsolete. The AI and data-driven methods identified in the compiled literature database are classified in similar clusters based on their trend evolution throughout time as detailed below. This trend score captures both number of appearances in publications and how consistent they appear throughout time, to differentiate methods that appeared in short bursts in past years but then faded away, and methods that are consistently applied by researchers throughout time to tackle a variety of challenges in the strategic planning of surface mining operations.

The SL techniques include convolutional neural network (CNN), tree-based classification and regression (T-B), support vector machine (SVM), neural networks (NN), k nearest neighbours (KNN), and histogram of oriented gradients (HOG). USL techniques include clustering (CLS), and RL techniques account for a single group of RL and agent-based algorithms. MTH techniques include ant colony optimization (ACO), particle swarm optimization (PSO), genetic algorithm (GA), simulated annealing (SA), search-based algorithms (S-B), bat algorithm (BA), imperialist competitive algorithm (ICA), firefly algorithm (FA) and progressive hedging (PH). DES techniques account for a single group.

Each topic is represented as a bubble whose size is proportional to the number of publications that use that technique. In Figure 6, the x-axis (Age) indicates the number of years since its first appearance in the literature. The y-axis (Trend) shows a percentage deviation from the technique publication life's ‘center of gravity’. A stable topic that has appeared consistently in the literature since its first publication without a recent surge in a short amount of time would have a trend value near zero. A positive trend indicates that a topic is appearing more frequently in recent years or has had a significant comeback after initially fading away. A negative trend indicates a topic that is disappearing from the recent literature. From these definitions, six topic clusters can be identified.

- Stars (High age and positive trend):

  Techniques that have appeared consistently since early on the research time period and experiencing a surge in applications include GA and DES. These techniques seem to have the most success and are reliable to solve problems within surface mining strategic planning.

- Consolidated (Medium-to-high age and positive trend):

  Techniques applied for a long time in the literature with still significant research interest include SA, S-B, ACO, and PSO. These techniques have proven to be successful in research efforts for a long time and are a solid choice to tackle complex problems within this field.

- Emerging trends (Low-to-medium age and positive trend):

  Techniques that have been recently adopted and seem to have had some success with increasing research interest include RL, NN, and CLS. Given due time, these techniques could either move to become consolidated choices in the field or fade away.

- Hot topics (Very low age and positive trend):

Very recent techniques that have seen a large interest. Only includes CNN, a very recent deep learning technique that has also seen a surge in applications across multiple fields. These techniques are new promises that are yet to stand the test of time to become solid choices within this field.

- Question marks (Very low age and zero to negative trend):

  Very recent techniques that have seen limited introduction and could potentially see a follow-up in the coming years include FA, KNN, SVM, and T-B.

- Exiting/Obsolete (Medium to high age and negative trend):

  Techniques that have been tried in research for some time now but that have faded away include ICA, BA, PH, and HOG. These techniques do not seem to give good results within surface mining strategic planning or have been displaced by newer developments. For example, HOG is an approach to computer vision problems that have been replaced by the appearance of CNN in general use.

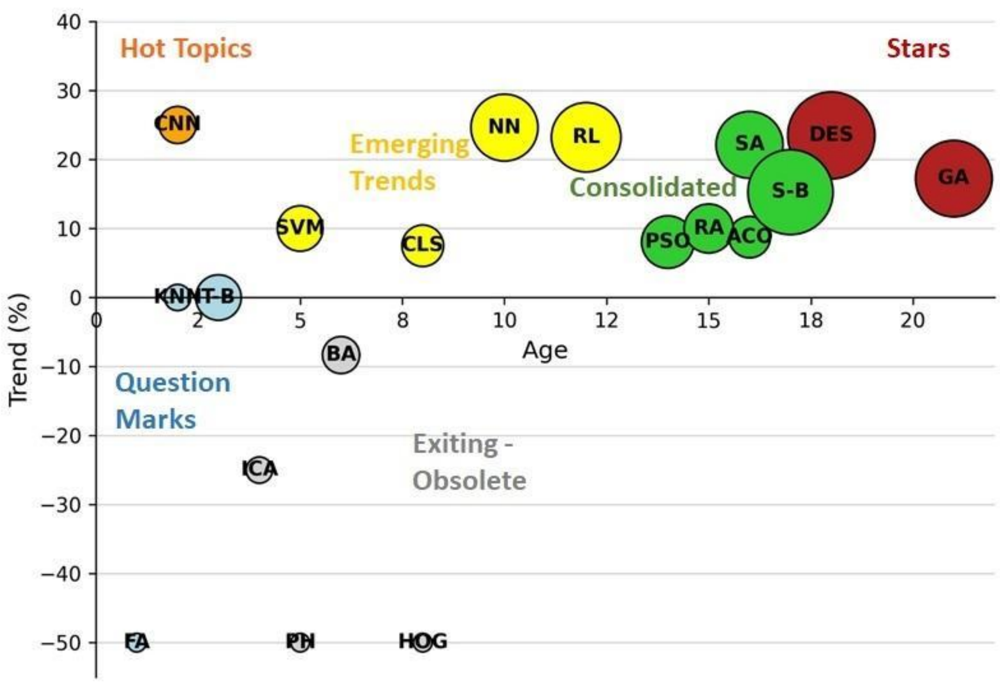

Figure 6. Trend evolution of specific AIA techniques during the research period 2000-2021.

3.3. Detailed Review by Research Area

3.3.1. Production Planning and Scheduling

The production planning and scheduling area concerns applications in which AI and data-driven techniques support tactical decision-making for the mining operation strategy, both long-term and short-term, including decisions on resource allocation and ore extraction to achieve economic and production targets. Research classified into this area includes specific long-term planning, short-term planning, production and cost forecasting applications.

One of the earliest efforts is presented by Pendharkar and Rodger [34]. They developed a Genetic Algorithm (GA) to determine the production, transportation, ore blending schedules, and selection of markets for multiple coal mines, highlighting the potential of GA for complex decision-making processes within the mining industry. GA has become a reliable technique to solve open-pit long-term production scheduling (OPS) problems. Moosavi et al. [35] developed a hybrid model using a GA and augmented Lagrange multipliers to solve OPS for two pushbacks of an iron mine containing 6770 blocks. Alipour et al. [36] compared a GA approach with the commercial software SimSched DBS for OPS, where they reported the GA achieves a 4% increase in the net present value (NPV) for the Marvin mineral resource dataset. In this research, the authors state that the commercial solver IBM CPLEX [37], a state-of-the-art optimization engine, could not solve the OPS after 25 days, whereas the GA reached a competitive solution within 20 to 30 minutes.

GA has also been extensively used to introduce uncertainty and extend stochastic optimization models to the OPS problem. For example, Samantha et al. [38] formulated a multi-objective GA for OPS with mineral grade uncertainty, represented via orebody conditional simulations, for an iron deposit. The objectives of the GA were defined to obtain a schedule that minimizes deviations from targeted grades of iron, silica, and alumina elements. Moreover, Franco-Sepulveda et al. [39] incorporated market uncertainty as well in the future prices of the minerals of interest, with a GA formulated to maximize NPV and minimize its standard deviation. Additional GA-based methods to solve the OPS problem under uncertain inputs are presented by Alipour et al. [40] and Paithankar and Chatterjee [41], highlighting GA's flexibility as a technique for robust decision making.

Other successful evolutionary computing approaches for long-term planning include Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). ACO methods are based on the ability of ants to find the shortest paths to food and are efficient algorithms to search for shortest paths over-weighted graphs. The earliest ACO application found was by Riff et al. [42], who named their approach Miner Ants Colony. They tested their model on 50 artificial mine block models, which were similar to a confidential real mine. They reported positive results in obtaining close to optimal solutions for some of the largest and more complex datasets in about one hour. Shishvan and Sattarvand [27] presented a similar but more detailed presentation of an ACO algorithm for OPS. Their model provides some insights into the calibration of the different parameters of the algorithm and obtains good results within reasonable computing times for a large-scale problem. Gilani and Sattarvand [43] developed an ACO-clssed framework to integrate geological uncertainty via multiple conditional simulations of the ore deposit. The framework was tested on a large-scale dataset (about 2.5 million blocks), obtaining an NPV improvement of about 8% from a commercial software solution.

PSO algorithms follow a similar approach where solutions to a problem dubbed ‘particles’ are moved around searching for an optimal solution; it was inspired by the movement of collective organisms in nature. Ferland et al. [44] presented an early attempt to adapt a PSO solution for OPS, where the only constraints considered were slope and mining capacity. Furthermore, Khan and Niemann-Delius [45] designed a PSO that could handle processing capacity as well, testing on a 7,836 blocks orebody. Results were benchmarked against an exact solution using CPLEX, which after 22 hours, reported a solution with a 4.5% optimality gap. In contrast, the PSO achieved a better optimality gap in under 12 minutes for different parameter settings. A stochastic approach was developed by Gilani et al. [46], for mining sequence decisions under mineral grade uncertainty. Under different PSO strategies, improvements around 9% to 12% in NPV were achieved with a required time of about 15 hours. An application by Gu et al. [47] described a PSO method for an in-pit crushing and conveying system to determine the optimal crusher location that minimizes transportation costs.

Simulated Annealing (SA) is another successful metaheuristic applied in the long-term planning and production scheduling of surface mines, which is a method inspired by the annealing technique in metallurgy that deals with the heating and controlled cooling of materials. The earliest application found by the search query was done by Kumral and Dowd [48]. They detailed a SA algorithm for OPS considering three objectives: minimizing deviation from required tonnage, penalty and opportunity cost, and mineral content variability. The authors report a case study on a

Western Australia iron ore body containing 2,773 and considering iron, silica, and alumina variables, obtaining a result in approximately 25-30 minutes, although no benchmark was presented. Danish et al. [49] considered the single OPS to integrate stockpiling management with material mixing. They presented three test cases with the largest comprising 12,822 blocks, where the CPLEX was unable to generate a solution, whereas the SA framework proposed achieved a solution with a 7.78% optimality gap within 2 hours.

SA techniques have been especially successful for the OPS problem under uncertainty. Leite and Dimitrakopoulos [50], integrated geological uncertainty by multiple orebody simulations and a SA detailed that seeks to find a production schedule that minimizes deviation from production targets, reporting a 20% increased NPV and better risk management than deterministic counterparts on a copper deposit test case. Albor Consuegra and Dimitrakopoulos [51] analyzed the same stochastic SA algorithm's sensitivity, reporting no significant improvement after 10 orebody simulations and an increase of 17% of mineral reserves due to an increased final pit limit. Montiel and Dimitrakopoulos [52] presented a similar SA to handle multiple process destinations depending on material types (e.g., acid leaching, bio-leaching) and tested on the Escondida Norte mine in Chile, a massive copper deposit. Thy benchmarked against a schedule generated by commercial software and reported a 4% increase in NPV and average deviations in the mill and waste production smaller than 5%, whereas the commercial software schedule yielded average mill production deviations of 20% and 12% for waste. On the same problem, Montiel and Dimitrakopoulos [53] integrated multiple material transportation options. Kumral [54] used a SA to jointly solve the block sequencing problem with the ore-waste classification problem, considering metal uncertainty. The SA approach uses multiple orebody simulations to determine whether a block should be considered ore or waste rather than relying on a previous cut-off.

Goodfellow and Dimitrakopoulos [55] proposed a stochastic SA to optimize the whole mineral value chain, including multiple pits, processing streams, transportation options, and markets under geological uncertainty. Two test cases were reported for nickel laterite and copper-gold mineral value chains obtaining an increased NPV and a better production risk profile in both cases. Multiple extensions to this algorithmic framework appear in the literature. Saliba and Dimitrakopoulos [56] incorporated market uncertainty, Kumar and Dimitrakopoulos [57] integrated geo-metallurgical variables, Levinson and Dimitrakopoulos [58] added waste management decisions and Saliba and Dimitrakopoulos [59] tailings management of acid generating material, including the capital and operating costs involved.

Local search-based MTHs have seen some success in the literature as an alternative to solve the OPS problem, particularly tabu search and variable neighbourhood search algorithms. Both are local search methods that explore immediate neighbours of a potential solution to discover an improved one. These methods have been particularly appealing to the stochastic version of OPS to obtain a near-optimal mining schedule robust to mineral grade uncertainty. The particular implementation of these search-based strategies are discussed by Lamghari and Dimitrakopoulos [60], Senécal and Dimitrakopoulos [61], Lamghari et al. [62], and Lamghari et al. [63].

Although other MTHs have been tested to solve the OPS problem for strategic planning, researchers have not seen similar levels of attention suggesting that they may not be efficient in tackling the structure of OPS. These are bat algorithm (BA) by Moosavi [64], imperialist competitive algorithm (ICA) by Mohammadi et al. [65], and progressive hedging (PH) by Lamghari and Dimitrakopoulos [66]. Tolouei et al. [64] presented a comparison between BA and firefly metaheuristic algorithm (FA) to solve OPS under metal uncertainty, reporting that the FA achieved better results.

RL approaches to solve the OPS problem were initially proposed by Askari-Nasab and Awuah-Offei [30] in 2009, under the name of intelligent agent-based open pit mine planning (IOPS), to determine the optimal combination of pushbacks that maximized the expected return over the pit life-of-mine. The authors developed a discrete simulation engine to model pit pushback expansions and how it impacted the project's economics to train the scheduling agent, as detailed in [67]. Although they highlighted the potential of RL techniques to address complex decision-making in long-term OPS, there were no follow-up revised methods or attention from other researchers. Lamghari and Dimitrakopoulos [68] reintroduced some RL concepts for long-term OPS within a hyper-heuristic framework. The hyper-heuristic approach is described as a heuristic selection framework, in which given multiple heuristic choices for solving the OPS problem, the framework learns which is better at each iteration to produce an optimal solution.

Souza et al. [69] presented different search-based MTHs for short-term mine scheduling and truck and shovel allocation plans to minimize deviations from production goals and number of trucks used, which were benchmarked against an exact solution obtained using the CPLEX solver and found to be competitive but requiring significantly lower time. Alexandre et al. [70], on the other hand, reported a GA that obtained better short-term schedules than the search-based MTH for the same problem. Mousavi et al. [71] introduced shovel allocation decisions and proposed a tabu search, and simulated annealing hybrid metaheuristic to solve the problem. Both and Dimitrakopoulos [72] integrated uncertainty in fleet production capacity by simulating production capacity scenarios based on the mining block location and truck cycle uncertainty, along with metal uncertainty, by orebody simulations, in the OPMOP. The authors develop a SA approach to solve the problem, remarking it is impractical to solve via an exact solver like CPLEX.

More recent research efforts aim to combine discrete simulation with optimization engines to obtain operational schedules that explicitly account for equipment interaction within mine layout. Integration of DES could potentially allow more robust and data-driven based schedules. Upadhyay and Askari-Nasab [73] presented a detailed discrete simulation of mining operations that uses CPLEX engine to obtain optimal shovel allocations to mining faces. They extend their approach in [74] to optimize mining faces extraction sequences, truck and shovel allocations using a multi-objective optimization approach within the simulation engine. Shishvan and Benndorf [75] proposed a similar framework for simulation-optimization of operational decisions for a coal continuous mining system in Germany. The simulation captures the details of the excavation and dumping practices of the mining site. The optimization model seeks to minimize downtimes of excavators and spreaders to minimize cost and maximize production.

RL for mining operational decision-making was introduced by Paduraru and Dimitrakopoulos [76,77], in which an RL agent is trained to learn optimal destination decisions for each mining block for a given production schedule. Although it does not capture the full dynamics of truck-shovel operations and focuses more on the global supply chain, a DES serves as an environment. Furthermore, Kumar et al. [78] and Kumar et al. [79] extend this same research to account for real-time new information obtained through sensors or other monitoring technologies, focusing on a mechanism to incorporate new information on mineral grades and characteristics. They highlighted the potential of RL for adaptive and self-learning mining systems.

Another major application of AI approaches in the literature for PPS is for production forecasting. This includes research directed towards predicting the productivity of a mine given its layout and equipment. It is a problem where uncertainties due to the movement of trucks and operation of shovels within a shared mine layout (roads, mining faces, crushers) can have a significant impact and lead to overestimated production capacities or unfeasible production schedules. The favoured approach to tackle this problem seen in the literature is using data-driven DES to reproduce the equipment interaction within the mine layout and evaluate multiple scenarios for strategic decision-making.

Awuah-Offei et al. [80] presents an early practical application to estimate truck and shovel requirements for a production period of 4 years in an African mine. A DES model was built using historical records of the operation in the SIMAN programming language. More recent applications have transitioned to using the Rockwell ARENA software to build discrete simulation models. Multiple variations in data sourcing and KPI targets have been proposed to build and use the DES of truck-shovel production cycles for operational decision-making. For instance, Tan et al. [81] proposed using GPS data from mining truck control systems along with a DES to evaluate dispatching strategies. Soofastaei et al. [82] proposed a DES of truck-shovel cycles to evaluate the effect of truck payload variance on cycle times and productivity for a mine in Arizona, USA. Other similar DES research applications are presented in Upadhyay et al. [83] for an accurate estimation of Tonne per Gross Operating Hour (TPGOH), a critical productivity KPI in open-pit mines, and by Ozdemir and Kumral [84] to evaluate the productivity improvement of a proposed dispatching model benchmarking against historical mine records. Ozdemir and Kumral [85] proposed integrating the capability of evaluating dynamic variables along with discrete events under a framework known as agent-based Petri net simulations. They highlighted the possibility of tracking dynamic variables such as equipment fuel consumption more accurately under this approach. Different applications for data-based DES models are presented by Ugurlu et al. [86] for surface drilling operations productivity and Yaghini et al. [87] to evaluate the impact of shovel operator performance on different mine productivity key performance indicators.

A different approach to production forecasting was proposed by Choi et al. [15]. A large dataset collected by Internet-of-Things (IoT) devices installed in an open-pit was analyzed using supervised learning techniques to predict ore production. The authors reported that SVM achieved the best performance amongst the techniques tested. This recent effort highlights the possibilities of fully utilizing data generated by mine monitoring systems.

Estimating capital costs for mining projects is another recurring application where AIA appears as a promising method in the literature. Nourali and Osanloo [88] tested tree-based regression methods on a dataset comprising 28 copper porphyry mines reporting annual waste and ore production and capital cost. They reported encouraging results in predicting capital costs based on rock production; however, the dataset used was of small size, and conclusions from it may not be entirely accurate for new mining projects. The authors extended their research in [89] to a dataset comprising 52 copper porphyry mines, recording annual mine and mill production, reserve tonnages, and stripping ratio. A support vector regression (SVR) algorithm was tested to predict mining capital cost from these parameters. Guo et al. [90] tested multiple techniques to predict mining capital costs based on annual mine and mill production, reserves average grade and mine life for a dataset of 74 open-pit copper projects, and found a NN predictor to yield the best results with an average error of 7.77%. Zhang et al. [91] explored the NN method in more detail, combining it with an ACO MTH for the NN training and reported improved results on the same dataset. The main drawback of AI approaches for cost estimation is the availability of datasets, which hinders the performance of more complex AI methods like NN that require tuning a large number of hyperparameters.

3.3.2. Grade Control

Grade control and ore delineation is another major area of research interest. Under this category, we found applications dealing with finding the optimal cut-off grade strategy, ore classification, and dig limits delineation. The cut-off strategy for an open-pit mine refers to determining values over which mineral resource units are considered ore throughout the lifespan of the mine. An early application by Ataei and Osanloo [92] formulated the cut-off strategy problem as a nonlinear optimization problem. They proposed the use of GA to obtain the cut-off strategy for multi-metal mines. GA based approaches are further proposed by Azimi et al. [93], to incorporate variable commodity prices and in Ahmadi and Bazzari [94]. Other MTH to solve the cut-off grade strategy problem have appeared in recent literature, such as the Imperialist Competitive Algorithms (ICA) and Particle Swarm Optimization (PSO) algorithms described by Ahmadi and Bazzazi [95].

Beretta et al. [96] proposed a framework for automatic lithology classification of a mining face. They used unmanned aerial vehicles to obtain imagery of a mining bench and then compared k-nearest neighbors (KNN), SVM, and tree-based methods (T-B) to classify the bench imagery into waste, ore, vegetation, and soil areas. Although they reported promising results, they recommend further investigation of more complex image classifiers like CNN. CNN were studied by Pu et al. [97] to classify coal images as ore or gangue reporting accuracy of 82.5% and remarking the potential of CNN methods for ore/waste image-based discrimination.

Aggregation of mineral resource blocks into selective mining units groups blocks of adequate size for the mining method and equipment to be employed. Tabesh and Askari-Nasab [98] presented a hierarchical clustering algorithm to group mineral blocks into larger units based on grade and rock type similarities, applying a shape control method afterward to adjust for feasible mineable shapes. The approach is extended in Tabesh and Askari-Nasab [99] to account for geological uncertainty and create mineable units that are less sensitive to metal variability. In Li et al. [100] the impact of block aggregation in the downstream mineral processing process was considered, testing different clustering techniques. The authors reported a k-means based clustering algorithm as the top performer that maximized the profits from the mining-mineral processing integrated system. Another application by Williams et al. [101] focused on developing a CNN to evaluate the quality of mining dig limit clusters generated by a GA. Although they reported multiple hurdles to overcome before a real-world deployment initial results were encouraging for short-term planning where fast computations are required. One of the main drawbacks of block clustering is the loss in ore-waste discrimination and potential dilution. Lotfian et al. [102] proposed a GA for the clustering process. They reported long-term planning using their clustering framework achieved at least an 82% of the NPV obtained from scheduling original blocks in some test cases.

RL approaches also see an application in Dirkx and Dimitrakopoulos [103]. A multi-armed bandit framework was applied to select the best infill drilling pattern amongst a set of patterns within a budget, accounting for multiple geological elements' uncertainty. They remarked on the applicability of the method for general infill drilling campaigns.

3.3.3. Equipment Management

Mining operations depend on efficient control and allocation of equipment to meet both production and financial targets. In the equipment management research area (RA) we detail research found in the application of AI and data-driven approaches directed towards mining equipment consumption control and equipment allocation and dispatching.

The allocation and sizing of truck fleets to shovels, and shovels to available mining faces are key decisions in the operational planning of mining activities, where data-driven approaches such as Discrete Event Simulations (DES) have been widely used to evaluate different strategies, and metaheuristics like Genetic Algorithms (GA) have been popular to generate equipment allocation and routing plans. In the strategic planning section, we detailed some applications that overlap with this category but that emphasize short-term production planning; here, the remaining research is described.

Mena et al. [104] described a simulation-optimization approach for allocating trucks' mine routes, to maximize the expected productivity of each truck on each route. They proposed a detailed DES simulation based on historic mine data to interact with the optimization engine and remark the need for accounting of equipment productivity and reliability in operational planning. Moradi Afrapoli et al. [105] combined an optimization model for truck dispatching with a rich data-driven DES of an operating mine and processing plant. They applied the framework in a test case to determine an optimal truck fleet configuration, reporting meeting production targets with 13% fewer trucks than the configuration estimated without using a DES to account for uncertainties. Moradi Afrapoli et al. [106] detailed a DES built to benchmark a proposed dispatch optimization model against commercial alternatives applied to a mine test case, which remarks the potential use of DES as a powerful tool for accurate data-driven scenario and mine strategy evaluation.

Agent-based approaches have also been explored for the truck-dispatching problem in which, rather than posing a global optimization problem, trucks are considered individual agents that receive information from the mining system and seek to optimize a goal. The first record of this application retrieved by the query is by Bastos et al. [107], in which an agent-based optimization algorithm is proposed to find the optimal routing of loaded trucks between shovels and dumping stations, using a DES of the upcoming mining shift as the training environment. On the other hand, Icarte et al. [108] proposed a novel approach in which truck dispatching problem as a multi-agent system in which trucks, shovels, and unloading points (e.g., crushers, dumps) are represented by independent intelligent agents, and these collection of agents interact with each other in the shared mine environment. The truck-shovel interaction was modelled using a Contract Net Protocol (CNP). In CNP a shovel sends a call for proposals to the truck agents, which check their current state and the condition of the unloading agents and send a proposal to the shovel. The shovel then selects the best proposal amongst trucks for the assignment. They benchmarked their approach against a heuristic rule and mathematical optimization model using a DES of a real copper mine in Chile and reported achieving production targets with an 18% decrease in operating costs. Furthermore, the researchers extended their work in Icarte et al. [109], to add a mechanism to handle machine failures by rescheduling trucks optimally.

Researchers have also used AI and data-driven approaches to accurately predict mining truck fuel and energy consumption. Siami-Irdemoosa and Dindarloo [110] reported good results when testing a NN to predict fuel consumption per operating cycle of mining trucks based on truck payload, loading times, idled while loaded, and idle while empty times. Soofastaei et al. [111] developed a NN to predict truck fuel consumption (liters/h) based on gross vehicle weight, truck velocity, and total road resistance using data from a coal mine in Australia.

Some applications were found that proposed a practical implementation of AI systems for equipment tracking and visual sensing. Rezazadeh and McCabe [112] described a framework for identifying and tracking mining trucks throughout the production cycle in real-time video recordings. The authors proposed a Histogram of Oriented Gradients (HoG) computer vision technique and presented an application to recognize and count hauling trips. Yao et al. [113] proposed a CNN – NN framework to estimate the piled-up status and payload distribution (PSPD) of bulk materials in a dump truck from camera images. The PSPD describes the alignment and amount of bulk material in a dump truck's body and helps determine dumping positions to improve stress state and equipment service life. The authors presented some successful pilot tests.

Ali and Frimpong [114] proposed a framework to improve autonomous truck steering capabilities named DeepHaul. An object recognition module was proposed to detect mining equipment, humans, and animals using a CNN from images and video recordings in the haul truck’s path. Afterwards, a RL framework was used to optimize the truck steering decision capabilities based on the visual sensing detection by putting the truck in multiple scenarios involving different objects in its path throughout a haul road.

4. Discussion and Future Work

The vast majority of research is directed into the open-pit production planning and scheduling problem, where a big focus has been on developing metaheuristics and intelligent computation techniques to solve complex large-scale production scheduling for the life-of-mine strategic plan. The specific problem of long-term and short-term planning has received the most attention with a large variety of solution methods, mostly metaheuristics. The challenge with metaheuristic methods is that their implementation tends to be very problem-specific, and their performance could vary wildly between problem instances. However, Genetic Algorithms (GA) and Simulated Annealing

(SA) have proven to be the most consistent techniques used throughout the period analyzed. Although metaheuristics are a promising approach to tackle these complex problems, the presentation of new metaheuristic techniques should follow some good practices such as those proposed by Osaba et. al. [115] for a clear statement of assumptions, implementation details and results reporting to encourage transparency and reproducibility of methods.

Discrete Event Simulation (DES) has also been widely adapted as an approach to support data-driven decision-making for mine planning and operation. Researchers have used DES to improve mine plans by providing an environment that simulates the interaction between the different processes and equipment during the mine operation and build algorithms that incorporate this dynamic to improve on decision-making to achieve the desired goals. DES also plays a key role for truck fleet management, especially for research applied for the truck dispatching problem, which requires near real-time decisions that have a significant impact on mining production.

To successfully implement a DES model, a large amount of historical data on equipment behaviour is required. Data compilation and cleaning from raw databases is one of the main hurdles for the adoption of AI and machine learning techniques for any industrial case [33]. So it also represents an important challenge here. Future work should also focus on guidelines and good practices for how to best handle mining operation databases to build a DES or digital twin model to support decision-making.

From the more traditional Machine Learning (ML) domain, the Supervised Learning (SL) techniques are the most widely used across applications such as short-term planning, cost forecasting, grade control and equipment tracking. SL techniques rely on the availability of large amounts of labelled data to implement algorithms that learn patterns on it to make accurate predictions. For this purpose, equipment tracking and control applications seem particularly fitting for SL techniques, where problems such as forecasting truck fuel consumption and payload, and estimating hauling cycles appear in the literature. These problems use large equipment databases that have been available for a long time and improve internet network connectivity in surface mining operations.

Grade control applications also reap the rewards of recent advances in SL techniques for image processing, which have enabled researchers to present automated rock type and ore classification algorithms using drones and digital camera images, as well as determining optimal ore dig limits. Future work in the direction towards a real-time ore and waste discrimination system based on digital images could positively impact the mining production environment to tackle issues such as unplanned dilution.

Cost forecasting applications also appear in the literature, however, in all cases, the authors report use cases with very few data points, usually less than 100, which present a major hurdle for its potential application. This specific use case reflects one of the major challenges in developing AI and data-driven approaches, which is the availability of data.

More recent applications involve Reinforcement Learning and agent-based (RL) techniques used for production planning and scheduling, and equipment management. Although the idea of RL has been around for a long time, it has not seen much real-world application and is just starting to show some successful use cases [116]. More work in this area is needed to showcase its potential on different applications within surface mining systems, as it has seen large volumes of research for production planning and control in dynamic systems [117], vehicle routing [118], problems very similar in structure short-term production planning, and truck dispatching.

5. Conclusions

This research systematically reviewed applications of AI and data-driven approaches for open-pit strategic planning. The research goals were to uncover trends in AIA adoption in the period

2000-2021, understand which applications in this field are being solved using these approaches, and which specific AIA techniques have been more successful as measured by the number of appearances in peer-reviewed research publications. A comprehensive search query was designed, and 86 publications were reviewed in detail.

The goal achieved by this paper was to establish the current state of use of AI and data-driven technologies for the strategic planning of surface mines, identifying the algorithms and workflows that have been implemented for specific application cases in this domain. Overall, the adoption of AIA within open-pit strategic planning has seen exponential growth within the period considered, with successful applications across different areas of interest. The large adoption of metaheuristic and intelligent algorithmic techniques indicates the attractiveness of fast and reliable computation methods for large and complex problems. The increased attention in discrete simulation points to an interest in using large historical mining databases to recreate operations for decision-making support as a sort of digital twin. The surge in supervised learning and reinforcement learning techniques shows the potential of ML adoption operational management tasks. Finally, researchers have shown willingness to adapt state-of-the-art AI and data-driven techniques to solve open-pit strategic planning problems, showing these technologies' potential to unlock value within the mining industry.

6. References

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