Mining, Metallurgy & Exploration (2023) 40:2087–2106
https://doi.org/10.1007/s42461-023-00875-2

REVIEW

Intelligent Fleet Management Systems in Surface Mining: Status, Threats, and Opportunities

Arman Hazrathosseini[1] · Ali Moradi Afrapoli[1]

Received: 1 February 2023 / Accepted: 23 October 2023 / Published online: 10 November 2023

Abstract
Fleet management systems (FMSs) as the pivotal part of any surface mining operation find it essential to evolve from conventional into intelligent systems because of both Mining 4.0 requirements and some shortcomings inherent in conventional methods. However, this novel transformation needs to be investigated technically and strategically. To this end, the previously published research works on intelligent FMSs are explored to track the latest status of these third generation frameworks within the surface mining context. Following that, their underlying models are compared in terms of five categories of allocation and dispatching features to pinpoint the technical gaps ignored. Having drawn the future lines of research, the present article then leverages the popular SWOT analysis method to outline the strengths, weaknesses, opportunities, and threats associated with the advent of these intelligent FMSs in mines of future. By and large, the analysis indicates that advantages outweigh disadvantages. Solutions are offered to address the existing weaknesses and threats.

Keywords Fleet management system · Mining 4.0 · Technical feature · SWOT analysis · Open pit mining

1 Introduction

The introduction of intelligence into mining material handling systems, such as truck-shovel systems, holds tremendous importance in revolutionizing the mining industry [1]. These intelligent systems leverage advanced technologies to optimize the efficiency and productivity of the mining operations (fleet allocation and dispatching) spanning from 1s to 1 day compared to strategic (long-term and medium-term planning) and tactical (short-term planning) planning horizons [2]. Mining operational activities account for more than half of operating costs, nearly one-third of total energy, and one-tenth of global energy-related greenhouse gas emissions [3–5]. These figures highlight the essence of well-established fleet management systems (FMSs) within the operational stage as even a minor adjustment in the material handling system (e.g., dispatching, maintenance, and fuel consumption) culminates in substantial monetary and environmental benefits due to the size of mining operations. Therefore, the integration of intelligence into mine FMSs is advisable to be investigated because of its significant potentials to boost productivity, reduce expenses, enhance safety, and foster sustainability within the mining industry [6–8]. A technical and strategical investigation can make a significant contribution to identifying tentative faults (e.g., ignoring some allocation and dispatching features) in the formulation process of the intelligent FMSs proposed so far as well as recognizing possible threats and opportunities associated with these frameworks. Not only does this procedure enable the development of more concrete intelligent FMSs in the future, but also unlocks these systems' strengths and weaknesses to provide the designers of intelligent FMSs with deeper insights.

An FMS in a mining operation aims to streamline the loading-haulage system in terms of one or multiple goals through rendering proper allocation and dispatching decisions with the aid of computer programs. Ideally, the FMS is supposed to autonomously act and bridge strategic plans to the real-time production operation. The dynamic allocation of empty trucks is referred to as the dispatching problem. Flexible or dynamic truck allocation is the antithesis

✉ Ali Moradi Afrapoli
ali.moradi@gmn.ulaval.ca

Arman Hazrathosseini
arman.hazrathosseini.1@ulaval.ca

[1] IntelMine Lab, Department of Mining, Metallurgical, and Material Engineering, Laval University, Pavillon Adrien-Pouliot, 1065, av. of Medicine, office 1728, Quebec G1V 0A6, Canada

of fixed or static allocation. In the dynamic approach, trucks receive a new assignment from the dispatching system instead of being in the service of a single shovel, bringing about 10–15% productivity improvement [9]. Trucks are allocated in two main systematic forms: either single stage or multistage [10]. In the single stage form, without considering production targets, assignments are issued based on one or several heuristic rules (or dispatching criteria) [11]: (1) minimizing shovel waiting time: to optimize the allocation of empty trucks, they are assigned to either the shovel with the longest idle time or the shovel that is projected to become idle first. This approach ensures efficient utilization of resources by strategically assigning trucks to shovels based on their expected idle durations; (2) minimizing truck cycle time: to maximize the overall tonnage productivity, the assignment of an empty truck is based on selecting the shovel that allows for the shortest truck cycle time. This approach ensures efficient utilization of trucks by assigning them to the shovel that minimizes the time required for completing a full cycle, thereby optimizing the total tonnage output; (3) minimizing truck waiting time: to minimize truck waiting time and maximize shovel utilization, an empty truck is assigned to the shovel where the loading operation begins first. This approach ensures that trucks are promptly available for loading, reducing idle time and optimizing the efficiency of the shovel operation; and (4) minimizing shovel saturation: to minimize the waiting time for shovel operations and ensure continuous activity, an empty truck is assigned to each shovel at regular time intervals. This heuristic rule aims to prevent shovels from being idle by maintaining a steady flow of trucks for loading. In contrast, the multistage approach solves three sequential sub-problems using operations research techniques: (1) shortest path model; (2) truck-shovel allocation optimization—upper stage; and (3) real-time truck assignment optimization—dispatching—lower stage [12]. In other words, in the upper stage, the production rates of routes are established by considering short-term planning objectives. This is accomplished using a model from operation research techniques. In the lower stage, trucks are assigned to shovels based on the optimal solutions obtained from the previous stage typically by means of heuristics or mathematical models [10]. Single stage and multistage approaches are comparable from different aspects: (1) efficiency: the multistage approach has an edge over the other in that it attends to a variety of constraints (e.g., shovel capacities, shovel digging rate, and production targets) at the upper stage, rendering dispatching decisions at the lower stage more efficient [10]; (2) complexity: multistage dispatching introduces additional complexity in terms of route planning, scheduling, and coordination of tasks. It requires advanced algorithms or decision support systems to optimize the dispatching process effectively; (3) optimization: multistage dispatching offers more opportunities for optimization by considering various factors and constraints at each stage. It can result in better resource utilization, reduced cycle times, and improved overall productivity; and (4) cost efficiency: multistage dispatching determines the optimum material flow rate on routes needed by each shovel, thereby decreasing the consequent costs caused by the shovel starvation and the truck queue time. Clearly, the multistage approach outweighs its counterpart. The same result has been verified quantitatively in [11], where a multistage dispatching model outperformed a single stage model by at least 60% increase in average production. Furthermore, single-stage dispatching systems have significant weaknesses, primarily due to the limitation of dispatching only one truck at a time and the disregard for operational constraints like ore quality requirements and blending constraints [13]. From another classification perspective and based on the level of human involvement, dispatching systems are classified into three principal categories: manual, semi-automated, and fully automated [14]. Manual dispatching follows a static rule, by which a certain number of trucks are assigned to a certain shovel during the whole working shift by an in-field supervisor who can sometimes have radio communications with a colleague to exchange information on the position of trucks retrieved from a computer or a place dominant on the mine site. This system relies heavily on human intervention and makes decisions based on experience and judgment; thus, it can be prone to human errors, delays, and inefficiencies. On the other hand, it offers flexibility in adapting to changing conditions. The semi-automated system requires an intermediate level of human involvement, in which computers play a role in assignment of trucks using some predefined heuristics or mathematical models. Yet, a human agent is responsible for rendering the final dispatching decision [15]. Although this system reduces human errors and improves operational efficiency compared to manual systems, it poses a problem in large-scale fleets. In a fully automated system, technology controls and manages the fleet without human intervention. These systems optimize operations by continuously analyzing data, adjusting routes, and maximizing efficiency. They offer increased productivity, reduced costs, and enhanced safety by minimizing human errors and improving equipment utilization. This is the topic of interest for the smart mining paradigm initiated by the fourth industrial revolution, where smart mines seek to incorporate fully automated intelligent FMSs into their material handling tasks.

Born conceptually in a 2011 German fair and having officially initiated its era in 2015, Industry 4.0 is a paradigm shift in traditional manufacturing processes, building on interconnectivity, automation, autonomy, machine learning, and real-time data [16]. Instances of such transformative systems implemented in some real-world mining case studies are now noticeable in the market up to an extent.

One can exemplify TIMining Aware® as a 3D visualization tool for real-time mine monitoring and block model visualization remotely [17]. FORESTALL® offers digital assistance tools for making operational decisions, both online and offline, catering for machine health, downtime prediction, and predictive maintenance [18]. A shining example of autonomy is Rio Tinto Co., where autonomous trucks, trains, drills, and robots play a key role in iron ore operations [19]. We can define Mining 4.0, the incarnation of Industry 4.0 in the mining sector, as a digital revolution seeking to inject intelligence into traditional mining operations with the aim of fulfilling resilient and smart systems. These systems are expected to be capable of dynamism handling, interoperability, autonomy, monitoring, optimization, prediction, decision-making, virtualization, and visualization. These functions are achievable through leveraging a variety of underpinning technologies such as internet of things, cloud computing, digital twin, augmented reality, and artificial intelligence. Integration of internet-of-things-enabled devices and sensors in mine FMSs optimizes fleet operations by collecting real-time data for analysis and control. Sensor-equipped trucks transmit information on location, speed, fuel consumption, and engine health, allowing remote monitoring, predictive maintenance, and enhanced safety. Cloud-based platforms aggregate and process large volumes of information, providing comprehensive insights for fleet managers via web-based applications or mobile devices in order to make informed decisions from anywhere. Digital twin allows for real-time monitoring and analysis of fleet performance by generating a virtual replica or "twin" of the physical fleet. Utilizing the sensory data collected by internet of things, the digital replica visualizes operational metrics in no time. It also retrieves historical data from cloud repositories to simulate a variety of scenarios to evaluate strategies without affecting the actual fleet. Augmented reality empowers fleet managers to superimpose virtual information onto smart glasses such as HoloLens to enhance operational agility on fleet characteristics (speed, fuel, engine, etc.) and operational aspects (tonnage, grade, working faces, production targets, roads, etc.). Furthermore, remote assistance becomes more streamlined as experts can offer guidance using virtual annotations: for instance, to overlay repair manuals on the engine of a damaged truck. Artificial intelligence, mainly machine learning, can be utilized to forecast equipment malfunctions by detecting patterns within sensory data. Moreover, machine-learning algorithms have the capacity to supersede conventional operations research techniques in truck allocation and dispatching models, as is the case in a significant number of the research works selected to be reviewed in the present article.

Mine FMSs as the lifeline of surface mining operations are required to be evolved in terms of embedded technologies and architecture. It is mainly because of not only the whole Mining 4.0 paradigm but also some structural shortcomings inherent in conventional methods, as we will see in the next section. These two reasons have orchestrated a new research field known as "intelligent FMSs," on which several studies have been conducted thus far. However, these studies are associated with some technical faults in problem formulation in terms of allocation and dispatching features such as inability in allowing for ore production targets, processing plant feed and head grade, equipment maintenance/failures, etc. Pinpointing these technical faults, as the first goal of the present article, paves the way for developing more concrete systems. This bottom-up analysis is taken using some allocation and dispatching features collected and categorized from previously proposed conventional FMSs to serve as an echelle for judging intelligent FMSs technically. This analysis will provide a roadmap for future research directions in the field of artificial-intelligence-based mine FMSs. The second goal of the article takes a top-down stance through leveraging a strategic scrutiny tool called the SWOT analysis in order to lay out the strengths, weaknesses, opportunities, and threats worth attention in real-life implementation of such smart systems on the open pit mining ground. Some secondary goals are also pursued such as timeline analysis on the history of mine FMSs. It should be noted that this overview article stands out in the mining literature because it provides a distinctive examination of the technical and strategic aspects of intelligent FMSs in open pit mines, which is a neglected research topic to the best of our knowledge. The main contributions of the present work are itemized as follows:

- Developing a timeline infographic on the different generations of mine FMSs to depict their evolutionary path with a particular outlook towards the future (Section 2).
- Developing a five-feature echelle to evaluate the intelligent FMSs developed so far in terms of the allocation and dispatching features addressed or ignored (Section 2).
- Providing an overview of the state of the art in mine FMSs and their underlying algorithms (Section 2).
- Comparing these systems in terms of the echelle introduced earlier to pinpoint possible research gaps to be used for establishing robust frameworks in the future (Section 2).
- Adopting a strategic approach to dissect intelligent FMSs internally/externally and positively/negatively to identify their competitive advantages and areas that require improvement (Section 3).

2 The Technical Analysis

From a broad perspective, FMS can be considered as a component of logistics, which itself falls under the umbrella of supply chain management. FMS is commonly described as a diverse set of solutions pertaining to diverse aspects of transportation operations such as maintenance, allocation, dispatching, and fuel management [20]. The first generation of mine FMSs involved manual dispatching, which relied on crude methods such as two-way radio communications [21] in the 1960s. Later, it evolved to embrace vehicle-tracking technologies thanks to the advent of telematics in the 1980s. However, it was still human-oriented. During the same decade, the iconic work of White and Olson [22] contributed to DISPATCH® as a tool capable of finding the shortest path as well as allocation and dispatching. This phenomenon marked the beginning of the second generation of mine FMSs built on a variety of mathematical models, simulation, and metaheuristics (nicknamed as conventional FMSs). A large number of scholars have been developing these conventional FMSs for four decades starting from the 1980s, and this practice seems to be continued in the future. Although queuing theory was implemented in the 1960s [23], predating the use of mathematical models, its impact on mine FMSs was limited and it did not receive significant popularity. The primitive research conducted by Bastos et al. [24] could be acknowledged as a pioneering study on intelligent FMSs, with little recognition received in its era. Nonetheless, it laid the foundation for more established works in the 2020s [6–8], signifying the commencement of the third generation of mine FMSs benefitting from the technologies favored by Mining 4.0. Figure 1 illustrates these generations embedded into an overturned pyramid timeline infographic over a nearly six-decade period. The diagram is segmented into 1960–1980, 1980–2020, and 2020–onwards eras to represent the first, second, and third generations of mine FMSs, respectively. The initial era is renowned for its reliance on manual dispatching and rudimentary truck tracking instruments, while the second era, encompassing a span of forty years up to the present day, showcases mathematical programming, metaheuristics, and simulation as the prominent components of computer-based FMSs. Mining 4.0 attempts to shape the incipient third generation of FMSs in a manner that incorporates a diverse range of transformative technologies, including artificial intelligence, digital twin, internet of things, and augmented reality. This integration enables these intelligent FMSs to seamlessly dovetail with the requirements of the fourth industrial revolution, encompassing autonomy, virtualization, visualization, optimization, and telematics, in the most cutting-edge way possible. It is worth mentioning that the boundaries of the eras in Fig. 1 are not claimed to be fixed. Actually, these demarcations are only generated to deliver overall insights on the annals of mine FMSs.

The Mining 4.0 paradigm is not the solitary contributing factor to the emergence of intelligent FMSs. Another key driver for change is traceable into some shortcomings often associated with conventional FMSs, which is intended to be brought to light in the rest of this tactical analysis section. In other words, we first take a concise glance at the history of conventional systems to provide the readers with general insights on the underlying approaches used in these systems. Then, the tactical features commonly used into the formulation of the conventional FMSs developed so far are elicited to serve as an echelle for the evaluation of intelligent FMSs. In the next step, we put forward some reasons as to why conventional FMSs need to be evolved into the third generation. Upon establishing the need for change, we examine intelligent FMSs. This analysis helps draw the latest trajectory in the mining scope. Additionally, we compare the features of the models proposed to date. This comparison is intended to pinpoint research gaps and support further work, aimed at creating models with the least possible flaws.

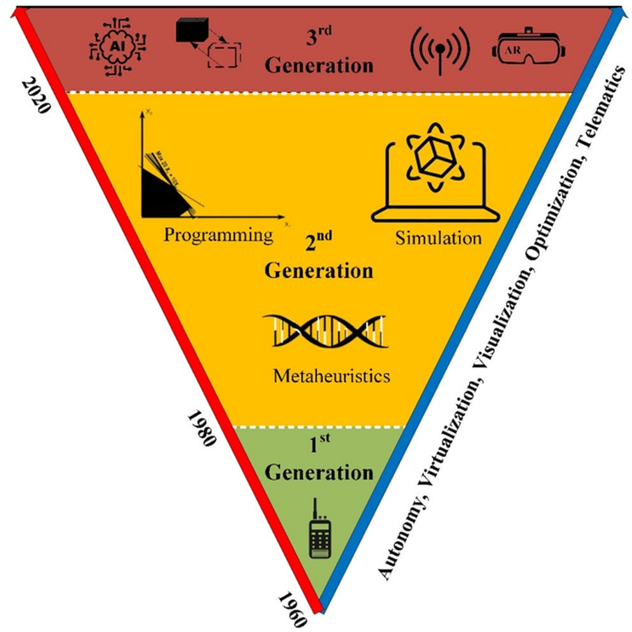

Fig. 1 Timeline infographic on the annals of mine FMSs

2.1 Conventional FMSs

Conventional FMSs have been mainly structured by one of these four approaches: queuing theory, mathematical programming, simulation, and metaheuristics. In a queuing system, a truck is treated as the customer that seeks a service (loading). If the server (shovel) is not available, the truck waits in a queue. Mine FMSs are usually modeled as a multi-server multi-queue problem with the queue discipline of "First in First out." The primitive but pioneering work of Koenigsberg [23] on application of queuing theory in mine haulage systems was expanded by other researchers [25–27] in years later. However, queuing theory has lost much of its popularity in contemporary times due to its limited range of applications compared to other techniques that offer a broader scope [28]. Instead, it is now integrated with multistage systems for truck allocation at the upper stage followed by a linear-programing-based dispatching model at the lower stage [29]. Since the advancements in computing power during the 1980s, mathematical programming techniques have become integrated into mine FMSs. Linear programming and its variants have been the main stream solving methods for both the allocation and dispatching parts. In this regard, one can, for instance, refer to the works of White and Olson [22] on linear programming, Moradi Afrapoli and Askari-Nasab [2] on mixed integer linear programming, Mohtasham et al. [30] on mixed-integer linear goal programming, and lastly Moradi Afrapoli et al. [31] on fuzzy linear programming. Besides, other types of programming models exist in the literature including goal programming [32], non-linear programming [33], and stochastic programming [34]. The evolutionary path of these mathematical models has reached a milestone that we now witness almost mature FMSs programmed as multi-objective models capturing various operational requirements such as fuel minimization, production maximization, and the desired feed and grades for processing plants [30, 35, 36]. This level of maturity owes its existence to simulation to some extent because emulating tools have enabled the realization of testing and verifying even the most complex mathematical models on ubiquitous devices such as laptops. Initially introduced into fleet management of surface mines in the 1960s [37], discrete event simulation was often applied as a testbed for comparing different dispatching rules [15], equipment selection and sizing [38], and equipment failures [39] for a half of century in that simulation is not a standalone optimization tool. However, it transformed from a supplementary tool to a crucial element at the core of mathematical models in the 2010s, contributing to a new research stream known as simulation-integrated optimization models for mine FMSs [40–44]. The operation research techniques reviewed so far are usually criticized because of the need for observing many operational constraints in material handling systems. This phenomenon has attracted the attention of some researchers to incorporate metaheuristic algorithms into truck allocation and dispatching without guaranty for reaching optimal solutions, though. Metaheuristics are characterized by their inherent simplicity of implementation and their ability to maintain a significantly reduced computational complexity, thereby attaining utmost importance in the context of a dispatch system that necessitates prompt decision-making in real-time scenarios. Some sparse works starting in the 2000s are enumerated as ant colony algorithm for dispatching [45], genetic algorithm for dispatching [46], and imperialist competitive algorithm for allocation [47]. The combination of mathematical programming and metaheuristics has been studied by some scholars including applying mixed-integer programming in the upper stage and Tabu search in the lower stage [48]. This concise literature review enabled us to obtain adequate knowledge regarding the main events on the growth path of conventional FMSs without distraction from the scope of the present article. Avid readers are encouraged to consult the specifically intended resources on this area [10, 12, 28, 49, 50].

As demonstrated in Fig. 1, conventional methods have been acting as the key player in mine FMSs for four decades. A large number of scholars have made constructive efforts to streamline these systems theoretically and practically. This level of maturity can serve as a foundation for realizing new approaches, like artificial-intelligence-enabled FMSs, that aim for a flawless architecture. This is the case in this research work. In other words, we have collected and categorized main factors, parameters, and optimization goals commonly noticed in the conventional FMSs developed so far in Table 1. It aids to establish an echelle to evaluate intelligent FMSs effectively. In fact, this table helps us to benchmark intelligent FMSs against their mature counterparts to identify the potentials for improvement. Scrutinizing the components described in Table 1 unveils the fact that all the factors and parameters are reducible to five chief feature classes as follows:

Class 1: Production (ore production target, ore processing target, ore grade uncertainty, stripping ratio, block precedence),
Class 2: Shovel (heterogeneity, scalability, failures, movement time, fuel consumption, scheduled maintenance),
Class 3: Truck (heterogeneity, scalability, failures, fuel consumption, scheduled maintenance),
Class 4: Operation (bunching, weather condition, route finding, drilling/blasting),
Class 5: Destinations (processing plant capacity, processing plant head grade, crusher capacity, stockpile capacity, stockpile grade requirements)

Despite having sculpted a large fraction of research works on mine FMSs, conventional methods are encountered with several drawbacks. Queuing theory runs into trouble in uncertain and complex problems, in addition to its limited scope [51]. Mathematical techniques pose a problem in terms of complexity and runtime, especially in multi-ore multi-pit surface mines with complicated operational requirements and fleet heterogeneity. Another major feature often overlooked is stochasticity, which is crucial due to inherent uncertainties present in most real-world problems. Metaheuristics often lead to non-optimal results. They are problem-specific, and usually yield excellent results for the problem they have been designed for, but they are not readily applicable to other variants of the same problem [52]. In

Table 1 Summary of chief optimization components captured in thus-far published works on FMSs

No.	Items	Components
1	Factors	(1) Stripping ratio, (2) heterogeneity, (3) the mill feed rate, (4) the mill head grade, (5) geological uncertainties, (6) operational uncertainties, (7) uncertain truck failures, (8) scheduled maintenance, (9) scalability, (10) linkage with short term plans, (11) large equipment movement, (12) traffic jam (bunching), (13) grade blending requirements at stockpiles, (14) shovel assignment, (15) block precedence.
2	Parameters	(1) Truck capacity, (2) shovel capacity, (3) shovel digging rate, (4) mills' feed rate, (5) mill's head grade, (6) crusher capacity, (7) dump capacity, (8) all types of timing (loading, hauling, spotting, dumping etc.), (9) optimal flow rate for the path from a shovel to a dump based on upper stage decisions, (10) loaded-and-empty truck velocity, (11) road characteristics and distances, (12) utilization of trucks and shovels, (13) grades of elements, (14) vertical and horizontal precedence of blocks, (15) number of trucks and shovels, (16) match factor, (17) availability of mining face.
3	Goals	(1) Maximize production, (2) maximize truck fleet utilization, (3) maximize shovel fleet utilization, (4) maximize shovel production, (5) minimize plants' feed rate deviation, (6) minimize deviations in head grade, (7) minimize truck operation costs, (8) minimize greenhouse gases, (9) distance minimization, (10) minimize shovel movement costs, (11) minimize the summation of shovel idle times, (12) minimize the summation of truck wait times, (13) minimize the deviation in the path flow rate compared to the desired flow rate.

addition to the aforementioned restrictions for conventional methodologies, another constraining facet inherent in the framework of these approaches pertains to the requisite task of reoptimizing the model whenever alterations are made to the configuration of the mining complex, whereas it is not the case for the FMSs enabled with some artificial-intelligence-based methods [7]. Lastly, the conventional methods often adopt a centralized approach; i.e., a central decision-making model issues a new assignment for a truck in need. Thus, ensuring effective coordination between shovels and trucks is challenging due to the formation of truck queues in front of shovels and crushers, as well as causing idle times for shovels [53]. The shortcomings related to conventional methods and the potentials of alternative solutions coupled with the Mining 4.0 requirements have encouraged some researchers to introduce intelligence into mine FMSs. In the next subsection, we investigate the basics in artificial intelligence followed by a review of research works on incorporation of machine learning and reinforcement learning into mine FMSs. Then, these intelligent models are put into comparison using the five-feature echelle developed earlier to draw research lines for future works on intelligent mine FMSs.

2.2 Intelligent FMSs

Initially introduced during the historic Dartmouth conference at the middle of the twentieth century [54], artificial intelligence (AI) has taken an adventurous trip from the ordinary Turing test up to the cutting-edge autonomous vehicles noticed on the street nowadays. AI is the study of how to make computers do things at which, at the moment, people are better [55]. The inference is that AI could eventually achieve human level intelligence, and even superior, as we witnessed in classic Atari games [56]. Attainment of abstract thinking, decision-making, adapting to new environments, creativity, and social skills is the ultimate goal of general AI [57]. Machine learning (ML), as a major subset of AI, uses input data to achieve a desired task without being literally programmed (soft coded); that is, the algorithm automatically alters its architecture (through a process named training) to progress with increasing success at achieving the desired task [58]. ML is branched into three learning strategies: supervised learning (SL), unsupervised learning (USL), and reinforcement learning (RL). In SL, both train and test data are available; therefore, the model is taught by labeled data for either regression or classification. In contrast, USL is the training of a model using unlabeled information for clustering or association. Despite the two previous learning strategies in which models were trained by datasets, training in RL is based on trial/error or experience. To put it differently, an agent interacts in an environment to find the optimum policy based on rewards and penalties. Common ML techniques include linear and nonlinear discriminant analysis, decision trees, random forests (RF), k-nearest neighbors (kNN), support vector machines (SVMs), artificial neural networks (ANNs), linear regression, principal component analysis (PCA), and Q-learning. A special category is allocated to ANNs named deep learning (DL) due to its significance, where human agents have no direct interference into the feature extraction process of the input data fed. DL was inspired by the structure of the human nervous system, and is established through a tortuous network of neurons interacting among input, hidden, and output layers. McCulloch and Pitts invented the first computational model of a neuron for processing of binary values [59]. In 1958, a psychologist added learnable weights to the McCulloch-Pitts neuron and named it "Perceptron" [60]. After introduction of backpropagation algorithms and multi-layer perceptron (MLP) networks by Rumelhart et al. [61], more attentions were attracted towards neural networks' capabilities to such an extent that the first convolutional neural network (CNN) was devised for the recognition of handwritten numbers in the late 1980s [62]. However, DL witnessed a two-decade stagnation due to lack of big data, and decent software/hardware before regaining popularity in the ImageNet challenge in 2012. From then on, this scope of science has been evolving staggeringly in the way that Gartner predicted the time interval of 2 to 5 years for DL and ML to reach the plateau of productivity [63]. SVM and DL are reported to be the most widely used techniques in the second decade of the twenty-first century, and RL is an increasingly growing domain in the mining industry [64, 65]. In the exploitation stage of mining, ML applications can be chiefly classified as production scheduling, drilling/blasting, and equipment management.

A variety of SL methods or generally ML strategies come to notice in equipment management. Some of the most highlighted works over the last few years are introduced here. Choi et al. compared six ML techniques to predict ore production of a truck haulage system at a limestone quarry using Internet of Things (IoT) as a data collector, with the SVM model exhibiting the most superior performance [66]. Sixteen variables (e.g., number of dispatched trucks, average travel time) were selected and downscaled from initial observations to serve as input variables for predicting ore production. Then, the effectiveness and precision of the ML techniques were compared using three validation datasets via some statistical indicators including root-mean-squared error, determination coefficient, and mean-squared error. In fact, 80% of the scaled-down dataset was used for training and the rest for testing the ML models. The same methodology and comparison strategies were used in another study, where authors conducted the prediction using a combination of Harris Hawks Optimization and SVM before comparing it with RF and ANNs [67]. The optimization algorithm demonstrated a pivotal role in enhancing the accuracy of SVM, thereby leading to the proposal of their integration as the most superior intelligent model for forecasting ore production in mines. Choudhury and Naik made a comparison among three models, i.e., SVM, kNN, and RF to predict the traveling time of trucks, thereby minimizing the cycle time and allocating an optimized number of dumpers to one shovel using a linear programming optimization model [68]. The mining field data collected from an FMS installed in a bauxite mine as well as atmospheric-conditions-related data were utilized to train and test the ML models, where RF showed more accuracy in traveling time prediction. Sun et al. employed SVM, kNN, and RF for prediction of the real-time travel time of open-pit trucks, where SVM and RF resembled in accuracy and both methods outperformed kNN [69]. Truck, road, and meteorological features, reaching sixteen in number entirely, were used as data input to train the ML methods. These data types were collected from an open pit coal mine, an FMS in-use in the mine, and a meteorological administration. Nobahar et al. optimized the type of loader and the number of trucks required to meet the processing plant's throughput by comparing five algorithms including linear regression, decision tree, kNN, RF, and gradient boosting algorithm, with the latter being indicated as the most precise [70]. Five years of data were collected form a kaolin mine to serve as inputs for training the ML methods. These data types encompass the date of operation, weather condition, season, weekday, routes, and loader types. The gradient boosting decision tree algorithm was identified as the most suitable choice, achieving an 85% accuracy in predicting the values of the test data.

Although there exists an abundance of historical data pertaining to truck assignments, effectively utilizing such data to devise an optimal dispatching policy poses a formidable challenge. Actually, a prominent obstacle lies in the fact that modifications to the dispatching policy have a profound influence on the future dynamics of assignments, rendering it arduous for SL methodologies to adeptly discern and address these dynamic real-time fluctuations [71]. This is the case especially in mining environments, where high-dimensional dynamic and stochastic events govern. In fact, one of the major reasons causing the SL techniques and conventional approaches to be incapable of addressing the dynamicity efficiently is the centralization aspect of these methods. To be more precise, these methods have a central unit for rendering decisions on the next dispatching assignment requested by a truck, while decentralization of FMSs through defining the problem as a Multiagent System (MAS) seems to be a more effective solution in order to benefit from local intelligence [53]. MAS refers to a computer-based system comprised of distributed autonomous agents that interact with each other to adjust to the dynamic changes in the working environment [72]. MASs possess a range of fundamental attributes, such as autonomy, decision-making capabilities, and self-awareness, which are integral to their functioning [73]. These systems can demonstrate some characteristics including locality (no global view exits), decentralization (no designated agent responsible for centralized control), robustness (agent failure tolerability), and scalability (flexibility to change requirements) [74]. In the context of mine FMSs characterized with numerous trucks as agents, the MAS paradigm has been employed in the two configurations of negotiable scheduling and RL.

Regarding the negotiable scheduling configuration, intelligent agents are used to symbolize tangible objects, such as shovels and trucks. The primary objective can be to achieve the production plan goals with minimal expenses, which is accomplished through the collaborative interaction of these agents. They work together and negotiate to generate schedules for each individual equipment. To facilitate this process, a negotiation mechanism like the Contract Net Protocol (CNP) [75] is employed. The CNP is a communication protocol utilized within MASs to streamline the allocation and coordination of tasks. It is typically applied in scenarios where the collaboration of multiple agents is necessary to accomplish intricate assignments. By encouraging competition among agents, and enabling dynamic negotiation and task assignment, the CNP facilitates decentralized task allocation in MASs. The agents involved in the CNP can be categorized into two main types: managers (shovel-agents) and contractors (truck-agents) [75]. The manager's role encompasses monitoring task execution and processing the outcomes, while the contractor is responsible for executing the tasks in practice. The process commences with a shovel-agent, who initiates the negotiation by issuing a call for proposals to truck-agents. Subsequently, the contractors have the option to respond with a proposal if they express interest or with a reject if they decline participation. Once the shovel-agent receives all the proposals, it proceeds to evaluate them through the utilization of a utility function, subsequently dispatching an accept message to the corresponding truck-agent. Concurrently, it dispatches a reject message to the remaining contractors, thus informing them of its decision. Following this, the truck-agent that receives the acceptance message, along with the shovel-agent that instigated the negotiation, updates their schedules by incorporating the dispatching assignments that necessitate execution. Ultimately, the truck-agent undertakes the execution of the assignment and subsequently notifies the shovel-agent of the outcome (whether it be a failure or success) via an inform message [75]. Icarte Ahumada et al. proposed an MAS using the CNP in a manner that trucks, shovels, and unloading points as individual agents interact in a shared mine environment through exchanging their schedules in an attempt to accomplish production goals at the minimum cost [76]. Benchmarking the MAS model against a centralized system like DISPATCH® fed with actual data resulted in the transportation of the same amount of material, but with shorter travel time needed. The utility function developed advocates the proposals with on-time starting loading time and the least completion time required. However, the operability of large trucks remains unclear. In other words, when considering a heterogeneous fleet of trucks in a mining transportation system, smaller trucks are typically associated with shorter travel times. In certain scenarios, the utility function might prioritize smaller trucks over larger ones, even if the proposal originates from a large shovel that would ideally pair with a large truck. Later, their work was extended to allow for truck failures rescheduling [77]. In another effort, the MAS approach generated more efficient schedules and showed better uncertainty handling than Tabu Search [78]. Cohen and Coelho incorporated path finding within their MAS framework to reduce the number of agents while optimizing the selection process for assigning the most suitable agent to each dispatching task [74]. They evaluated the MAS model via comparing it with manual dispatching and a greedy algorithm on a web-based platform. The results were in favor of the MAS model in terms of fulfilling production targets and minimizing fuel costs. The negotiable scheduling configuration adopted in the aforementioned works opened a new door at mine FMSs; however, the communication overhead caused by negotiations for finding the best schedule leads to increased solving time as the truck fleet grows in number. To rephrase, MASs depend on the exchange of information and collaboration among individual agents in order to reach decisions. In the context of a truck dispatching system, the agents must engage in ongoing communication to share details regarding the location of trucks, their status, and assignments. This constant need for communication can result in delays and inefficiencies, particularly in extensive mining operations. However, this communication overhead is not that significant for agents in RL-based FMSs because communication, if any (it depends on the training scheme intended for the agents), exists in the training phase and agents act in real-time in the implementation phase.

In RL, an agent tries to find the best path to collect the highest reward. One can find a subtle analogy between the general approach and the route-finding problem in the mining industry. In fact, wherever an optimum path is required, RL comes forth, be it for block extraction sequence in production scheduling [79, 80] or fleet routing [6–8]. In a production scheduling problem, the RL agent engages with a simulated open pit environment and utilizes an algorithm such as Q-learning to optimize the net present value of the mining operation [79]. The agent's objective may encompass the maximization of production while simultaneously minimizing costs and adhering to safety constraints. Positive rewards can be attributed to desirable actions, such as extracting high-quality ore, achieving production targets, and demonstrating adherence to safety regulations. The range of possible actions includes decisions such as selecting the subsequent block for extraction or establishing the order of extraction, which shares a resemblance to the task of identifying the optimal route in the context of truck dispatching.

The application of RL in mine FMSs encompasses the resolution of a sequential decision-making problem, entailing the dynamic interaction of RL agents with the environment. To represent this problem, sequential models known as Markov Decision Processes (MDPs) are employed. MDPs offer the framework through which RL agents can evaluate the consequences of their actions, adapt their knowledge, and exercise informed decision-making in dynamic environments. The integration of RL and MDPs facilitates the formulation and resolution of the intricate sequential decision-making problem associated with truck dispatching in surface mines. The key components of MDPs in the context of RL are as follows [81]:

State (S): The state component comprises a collection of states that represent various potential configurations of the environment. These states contain all the pertinent information required to make decisions at a particular time step.

Action (A): MDPs establish a range of available actions that the agent can undertake in each state. These actions grant the agent the ability to shape the transitions between states, and thereby influence the subsequent state that will ensue.

Reward (R): This component encompasses a function that furnishes prompt feedback to the agent contingent upon its actions and the resultant states. This reward function quantifies the desirability of distinct states or actions by assigning numerical values, thereby serving as a guiding force in the agent's learning process.

Transition probability (P): It involves the specification of probabilities that govern the likelihood of transitioning from one state to another when a specific action is taken. These probabilities effectively encapsulate the inherent dynamics of the environment and are commonly denoted by a transition function $P(s'|s,a)$, where s and s' represent states and a denotes an action.

Policy (π): It delineates the conduct of the agent by outlining the mapping between states and corresponding actions. The primary objective is to acquire an optimal policy that maximizes the anticipated cumulative reward throughout the learning process.

Discount factor (γ): It is employed to express the agent's inclination towards immediate rewards relative to future rewards. This factor governs the balance between short-term gains and the accumulation of long-term rewards. A discount factor of 1 indicates equal significance attributed to both immediate and future rewards.

These components collaborate to establish the foundation of RL within the MDP framework. Through iterative interactions with the environment, the agent estimates the value of states or state-action pairs, and iteratively refines its policy. This progressive learning process enables the agent to make optimal decisions that result in attaining the highest possible long-term reward. In agent-based truck dispatching problems, trucks are considered individual agents interacting within the mining system to optimize a goal; therefore, the truck dispatching in surface mines is a multi-agent RL setup. In the realm of RL-based truck dispatching in surface mines, the term "environment" pertains to the operational context within which the agent functions. It encompasses a multitude of components, including the mine layout, truck fleet, loading areas, excavation sites, haul roads, traffic conditions, safety constraints, and other pertinent factors that exert influence on truck dispatching decisions. The environment in truck dispatching within surface mines is characterized by its dynamic nature and susceptibility to modifications over time. It reflects the real-world complexities and uncertainties inherent in mining operations, such as varying number of trucks, equipment failures, traffic congestion, and unexpected events. These environmental insights are embedded into a vector to be accessed by the agent over any time step. The process referred to as "state representation" entails determining the manner in which the current state of the system is represented. This may involve incorporating attributes such as the position and status of individual trucks, the position and loading status of shovels, traffic conditions, and any other pertinent information that affects dispatching decisions made based on a predefined action space. The action space involves all the dispatching decisions to or from different locations such as shovel stations, waste dumps, stockpiles, and processing plants. A correct dispatching decision (the optimal policy) in each state is learned by the agent as a result of reward signals that it receives as a feedback from the environment. A reward function is devised to encourage favorable assignments in truck dispatching. The reward function should dovetail with the established objectives and constraints. For instance, objectives may encompass minimizing operational expenses, minimizing truck idle time, maximizing productivity, and meeting the processing plant's requirements in terms of feed rate and grade quality. Positive rewards are assigned for proficient task completion, while negative rewards or penalties are imposed for delays, incorrect assignments, or undesirable outcomes. Having defined these fundamental components for the RL-based truck dispatching problem, one can now select an appropriate algorithm to train the agent. Model-based and model-free algorithms are two distinct approaches in the field of RL. Model-based algorithms depend on constructing or learning the transition functions that represent the environment's dynamics, while model-free algorithms directly acquire value functions or policies through experience, without necessitating knowledge of the underlying dynamics. This characteristic makes model-free algorithms well suited for addressing the truck dispatching problem in the dynamic and evolving mining environment. Model-free algorithms in RL can be further categorized into three main types: value-based, policy-based, and actor-critic algorithms. Value-based algorithms such as Deep Q-learning (DQN) [56] and Double DQN (DDQN) [82] aim to estimate the value function, which reflects the anticipated return or usefulness of being in a given state or executing a specific action. These algorithms directly evaluate and revise the values associated with states or state-action pairs. Policy-based algorithms such as deterministic policy gradients (DPG) [83] learn policies directly, which establish a relationship between states and actions, without explicitly estimating value functions. These algorithms explore various policies to find the one that maximizes the expected cumulative reward. Actor-critic algorithms such as advantage actor-critic (A3C) [84] merge aspects of value-based and policy-based methods, employing two key components: an actor responsible for policy learning and a critic responsible for value function estimation. The actor suggests actions based on the learned policy, while the critic evaluates the suggested actions by estimating their value. Selecting a suitable algorithm depends on the features of state and action spaces. In other words, in the truck dispatching problem typified by finite and discrete action spaces (the dispatching decisions are finite and discrete), value-based algorithms are preferred to the policy-based algorithms characterized with infinite and continuous action spaces. It stands to reason as to why a majority of the RL-based FMSs developed so far in the mining literature enjoy value-based algorithms (variants of DQN) in their architecture [6–8]. The RL agent undergoes training using the selected algorithm within a simulated environment, enabling it to engage and gain knowledge from numerous simulated truck dispatching scenarios. The simulation environment accurately represents the dynamics of the surface mine. Conventional offline simulation tools are typically used for this purpose; however, it could be a good initiative to leverage digital twins to realize online simulations in real-world scenarios [49].

Although RL-based truck dispatching research works in mine FMSs are scarce in quantity, a promising trend is inferred. Bastos et al. were one of the first employers of agent-based approaches in truck dispatching at mines, where they proposed a single-dependent agent approach based on time-dependent Markov decision processes [24]. Comparison of their model with two heuristics in a discrete event simulator showed a superiority in the amount of materials hauled. Although being primitive, this pioneering work was inspired by models that are more robust a decade later. Zhang et al. proposed an experience-sharing DQN network for dynamic truck allocation considering constraints such as truck capacity, expected wait time, total capacity of waiting trucks, activity time of delayed trucks, and capacity of delayed trucks [8]. The model was put to the test against two dispatching heuristics in an event-based simulator developed in SimPy™, resulting in above 5% increase in productivity. More precisely, the framework proposed consists of two main modules: the simulator and the neural network. The simulator provides the initial state of each truck for the network. If a truck needs to be dispatched, an action is randomly selected by the network and then executed in the simulator. This leads to a reward value and a new state signal both fed back from the simulated environment to the network. The reward function in this study was defined as the fraction of truck capacity by the time required to complete the dispatching action. This transition is stored in a replay memory as suggested by the first developers of the DQN algorithm [56]. Then, a memory-tailoring algorithm is called to remove the memories related to the problem of trucks cutting lines of others. This loop is repeated over a predefined number of iterations so that the trucks as agents accumulate an adequate amount of experiences. In the next step, a batch of transitions is repeatedly sampled from the replay memory to enable the agents to be trained using certain update formulas in Q-learning. The agents are trained in a centralized way, where all the agents are connected to a common network. This network takes in the observations from each individual agent and generates independent actions for each of them. During every training episode, the network's weights are adjusted, and this process continues until all the agents have gathered sufficient dispatching experiences. In real-world cases, this DQN-based FMS can be adequately trained prior to a working shift and then applied for real-time truck dispatching during the shift. Zhang et al. trained their network for 50 trucks, and then investigated the robustness of the model in case of truck failures or adding new trucks to the haulage fleet. Without retraining, the model demonstrated capability in handling the truck scalability up to a certain extent. In spite of all the creativity that their model enjoys, the impact of downstream units such as crushers or processing plants has been ignored. De Carvalho and Dimitrakopoulos integrated a discrete event simulation model with a DDQN algorithm for truck dispatching at mines with various configurations [7]. The simulator emulates operational interactions between shovels, trucks, and dumping locations to create a vector consisting of inputs such as queue sizes, availability, down times, crusher/plant requirements, and past experiences. These parameters together with a reward function are used to generate experiences, and to train the network for future truck assignments. The model outperformed two dispatching schemes at a copper–gold mining complex in terms of ore recovery, daily mill throughput, and queue sizes. Speaking of strengths, the model allowed for heterogeneous fleet (both shovels and trucks), machinery failures, capacities of plants, and geological uncertainties. However, changes in block sequence extraction, destinations, and fleet size require a 4-h retraining. Huo et al. applied an RL-powered intelligent dispatching system with the aim of greenhouse gas emissions minimization in open-pit mining operations [6]. They paid attention to scheduled and unscheduled maintenance in their multi-agent Q-learning algorithm. The model was benchmarked against two reference dispatching solutions (fixed allocation and fixed scheduling) in a simulator developed in the OpenAI™ framework. The RL-based dispatching scheme could reduce the emissions per unit production by over 30%. It also outperformed the fixed allocation solution by nearly one-third in fleet production and fuel efficiency. The model aims to maximize the number of accurate deliveries (transporting ore to the mill or waste to the dump), thereby minimizing greenhouse gas emissions consequently. The authors quantified the emissions per liter of the diesel fuel combusted in form of kgCO2 equivalent. The consumption rate of trucks is computed through some estimated values for three conditions: in transit full, in transit empty, or waiting. The Q-learning algorithm renders a dispatching decision on the next destination for the truck. Then, this action is executed in the simulator and the fuel consumed for this assignment is calculated and converted into kgCO2 equivalent. Seemingly, the fuel consumption is minimized as a result of more efficient dispatching decisions which itself originates from minimized incorrect hauling. Despite allowing for truck fuel consumption, the authors assumed the fleet to be homogenous and small-sized. Moreover, the state vector defined encompasses a small number of decision-making variables. That is why the classic Q-learning algorithm (known as tabular Q-learning) was utilized instead of a deep Q-learning algorithm. This decision affects the program solving time in larger-fleet cases. The involvement of processing plants was also neglected.

The x-shaped comparison matrix depicted in Fig. 2 draws a distinction among previously published highlighted works on MAS-based or intelligent FMSs in terms of those five technical feature classes developed earlier. In the context of the works based on the negotiable scheduling configuration, both studies conducted by Icarte Ahumada [77] and Cohen and Coelho [74] have explored similar features, with the exception of truck failures and shovel/truck fuel consumption, which are individually examined in each study. However, these two studies failed to incorporate even one feature of the destination feature class within their systems. On the positive side, both research works considered ore production target in their framework since negotiable-scheduling-based systems need to be essentially fed with the production plan in order to create the schedules required. While the RL-based works developed thus far have not addressed this particular aspect, they have focused on other types of features. Specifically, Huo et al. [6] paid attention to fuel consumption and scheduled maintenance, distinguishing themselves as the only RL-based work to address these two features. De Carvalho and Dimitrakopoulos [7] allowed for more unprecedented features including ore grade uncertainty, processing target, shovel failures, processing plant capacity, and crusher capacity, entitling their work as the system with the greatest number of technical features addressed, i.e., nine features. This figure is almost four times as great as the number for the work by Bastos et al. [24] as the system with the least number of features included. Despite negotiable-scheduling-based systems, scalability is an additional prominent feature that is frequently emphasized in RL-based works. Overall, a significant number of features developed earlier in the five feature echelle are disregarded in the intelligent FMSs proposed so far. The features neglected are enumerated as follows: production (stripping ratio, block precedence), shovel (scalability,

Reinforcement Learning

Ore grade		Scalability, Maintenance, Failure, Fuel	Huo et al. (2023)	Route finding		6
Ore grade, Processing target	Failure, Heterogeneity	Failure, Heterogeneity, Scalability	De Carvalho and Dimitrakopoulos (2021)		Plant capacity, Crusher capacity	9
		Failure, Heterogeneity, Scalability	Zhang et al. (2020)			3
	Heterogeneity	Heterogeneity	Bastos et al. (2011)			2
Production	**Shovel**	**Truck**	**<Feature Class>**	**Operation**	**Destination**	**No. of features addressed**
Production target	Heterogeneity	Failure, Heterogeneity	Icarte et al. (2021)	Route finding		5
Production target	Heterogeneity, Fuel	Heterogeneity, Fuel	Cohen and Coelho (2021)	Route finding		6

Negotiable scheduling

Fig. 2 Comparison matrix of some highlighted mine intelligent FMSs in terms of the technical features addressed movement time, scheduled maintenance), operation (bunching, weather conditions, drilling/blasting), and destination (processing plant head grade, stockpile capacity, and grade requirements). Interestingly, all the characteristics embedded within the truck feature class are collectively addressed across the published works. Realistically, nearly half of the desirable features are ignored, highlighting the necessity for more efforts in the field of intelligent FMSs to come up with frameworks that are more robust. Nevertheless, there arises the question of the extent to which it is feasible to develop and deploy such intelligent FMSs? In the forthcoming section, we endeavor to address this inquiry by employing a strategic methodology, seeking to find a suitable response.

3 The Strategic Analysis

Although nearly obscure in origin and unspecified in the time developed [85], the SWOT analysis is a popular mechanism for assessing intrinsic (controllable, strengths and weaknesses) and extrinsic (uncontrollable, opportunities and threats) factors affecting an organization with the aid of a strategic matrix in an attempt to follow a methodical approach for decision-making occasions [86]. SWOT combines internal and external factors contributing in the efficiency of an industry, a company, individuals or even a new transformation in a system. Strengths determine what areas an organization excels in and what differentiates it from its competitors. Weaknesses cause the organization not to function in the most optimal way possible; thus, their amendment is of great importance to stay in the market. Opportunities are those external factors that can create a competitive advantage for the organization to seize or invest in them. Threats are a group of external factors that can harm the organization and jeopardize its success. These four elements are visualized on a 2×2 grid to explicitly outline the pros and cons of a project. The SWOT diagram for the analysis of intelligent FMSs is depicted in Fig. 3. Each of those components is expounded as follows:

Strengths The main supremacy of RL algorithms lies in their capability to address the dynamicity involved in a mining site. The adaptive decision-making in real-time is necessitated by the dynamic characteristics of open pit mines, exemplified by fluctuations in truck availability and uncertainties in ore grades. The RL agent, adequately trained through trial and error, can swiftly cope with these changes in the environment, preparing it for real-time rerouting and rescheduling. In fact, the agent is trained over 10,000 episodes for example, thereby gaining experience in handling different types of uncertainties. We can exemplify the framework developed by Zhang et al., where they demonstrated the truck scalability handling ability of their RL-based dispatching system in cases with 10% changes in the truck fleet size [8]. Another example of dynamicity handling is the work by Huo et al., where they allowed for ore grade uncertainties in the training process of the RL agent [6]. Another strength is their ability to surmount large-scale problems compared to conventional methods. In other words, based on the problem-solving methodology alone, they reduce

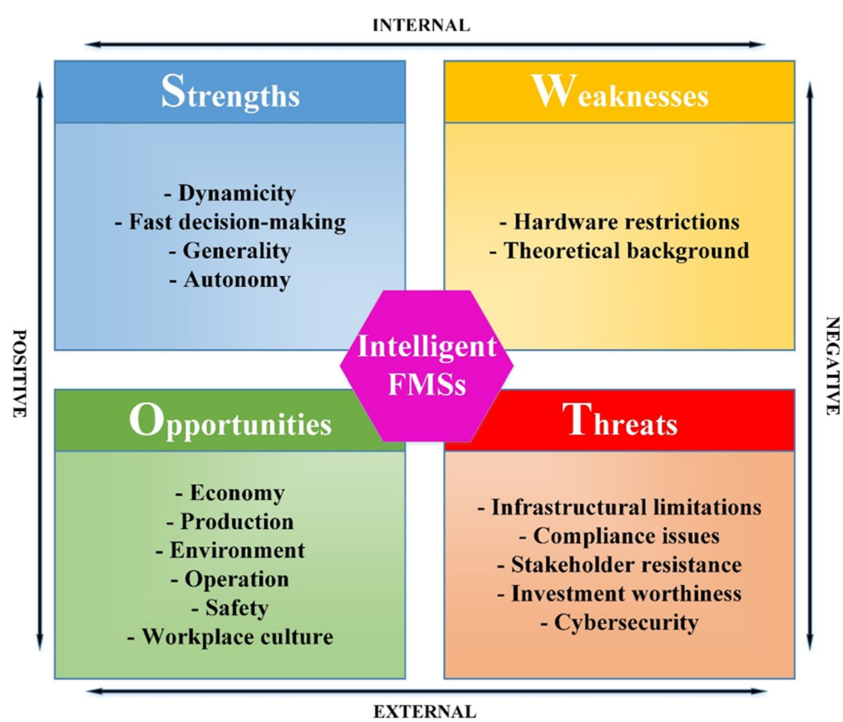

Fig. 3 The SWOT analysis diagram for intelligent fleet management systems (FMSs) in open pit mines

computational complexity and runtime by seeking near-optimal solutions. An additional noteworthy problem-solving aspect pertains to the ability of these intelligent algorithms to sustain their dispatching operations without necessitating the complete reiteration of the entire model solely due to minor alterations in the mine environment [7]. This stands in contrast to conventional methods that require resolving of the model for every single operational change. In fact, within an RL setting, the agent assumes the role of an intelligent decision-maker characterized by its self-awareness. Thus, it can cope with abrupt changes in the mine environment up to a large extent. This algorithmic strength is usually referred to as "generality" in some RL texts [87]. In addition to the aforementioned strengths, RL agents exhibit an impressive level of autonomy when it comes to truck dispatching in open pit mines. These agents possess the capability to acquire knowledge from their surroundings and autonomously make decisions, devoid of explicit instructions or continuous human intervention. Through the utilization of past experiences and trial-and-error exploration, they can generate optimized dispatching decisions without relying on fleet operators contrary to manual dispatching systems. Overall, RL can contribute to dynamicity handling, fast decision-making (or reduced runtime), generality, and autonomy in mine FMSs.

Weaknesses The utilization of RL for truck dispatching in open pit mines can be impeded by hardware restrictions encompassing limited computational resources, memory capacity, communication latency, and environmental constraints. These restrictions have the potential to curtail the optimal functioning of RL algorithms. Notably, RL algorithms necessitate considerable computational power, particularly when confronted with expansive state and action spaces. In the context of open pit mines, the magnitude of operations and the intricacies associated with truck dispatching can overwhelm the available hardware resources. In addition, some abrupt changes in the dynamics of the mine environment might entail the immediate retraining of the dispatching algorithm in less than a minute for instance. In such cases, the necessity of high computational capabilities is highlighted. An avenue to address this predicament entails optimizing the implementation of RL algorithms to augment their computational efficiency. Techniques such as parallelization [88] and distribution [89] can be employed to alleviate the computational burden. Furthermore, the utilization of cloud computing or specialized hardware such as graphics processing units (GPUs) holds the potential to enhance performance. RL algorithms frequently entail computationally demanding matrix operations, and GPUs demonstrate exceptional proficiency in parallel processing, rendering them well suited for accommodating RL workloads. Fundamentally, the hardware requirements for RL depend on the specific problem targeted and the desired performance objectives, compelling the need for a thoughtful evaluation of the computational demands intrinsic to the problem under study in order to determine the most suitable hardware configuration. A suitable laptop for RL operations is usually equipped with the following hardware configuration [90]: operating system (Windows 10 or 11 64-bit), GPU (NVIDIA GeForce RTX™ 2080 Ti 11 GB), CPU (Eighth Gen Intel® Core™ i7, 6 Core, 4.1 GHz), storage (512GB SSD), and RAM (32 GB). The storage and updating of value functions, policies, and experience replay buffers impose substantial memory requirements on RL algorithms. However, in the context of large truck dispatching problems, the limited memory capacity presents challenges in maintaining a comprehensive memory of past experiences. A viable solution entails the utilization of memory-efficient data structures and algorithms. For instance, implementing prioritized experience replay [91] enables the storage and sampling of valuable experiences with greater frequency, thereby alleviating the constraints imposed by limited memory. Within open pit mines, substantial delays in communication between the RL agent and trucks can arise due to the vast distance separating the control center and the trucks. Such latency can detrimentally affect the real-time decision-making process and diminish the efficacy of RL algorithms. To mitigate the effects of communication latency, a decentralized RL approach [92] can be implemented. Rather than relying on a central agent for decision-making, individual trucks can function as autonomous RL agents, making localized decisions grounded in their immediate surroundings. These local agents can intermittently communicate with a central server to synchronize their knowledge and update global information. By adopting this approach, the adverse impact of latency is lessened, thereby facilitating more prompt and timely decision-making. Open pit mines can impose distinctive environmental limitations that exert influence over hardware utilization. Extreme temperatures, dust, vibrations, and various other factors serve as examples of elements that can compromise the reliability and durability of hardware components. Accordingly, it becomes imperative to devise hardware systems capable of withstanding harsh environmental conditions.

In addition to the hardware issues, the theoretical background for artificial intelligence, particularly RL, is not mature in terms of sample efficiency, hyperparameter tuning, and convergence guarantees [87]. The adoption of effective policies in RL algorithms typically necessitates a substantial volume of interactions with the environment. This pronounced sample complexity can pose a hindrance, particularly in complex environments. To mitigate sample inefficiency, an approach worth considering is transfer learning [93], wherein prior knowledge or pre-training on tasks related to the target problem is leveraged. Due to the extensive range of potential hyperparameter values, the process of hyperparameter tuning and subsequent agent training is typically time-consuming. A good solution for this issue might be the consultation with adroit experts. The theoretical comprehension regarding the convergence guarantees of RL algorithms is still in a state of evolution. Ensuring the reliable convergence of RL algorithms to optimal policies holds significant importance. Further investigation is necessary to establish convergence guarantees that encompass a broader range of conditions and more intricate RL settings. Although there exist several achievements in the theoretical backgrounds, there are many rooms for improvement. All the weaknesses mentioned here might seem significant in number; nonetheless, they are tractable through the advancements in technology and academic texts.

Opportunities In open pit mines, intelligent methods offer several opportunities for improving FMSs from many aspects including economy, production, environment, operation, safety, and workspace culture. Beginning with the economy aspect, intelligent FMSs have the potential to reduce costs through enhancement of operational efficiency and production levels. Thus, the economy aspect has an intertwined relationship with the production and operation aspects. Through the utilization of intelligent algorithms, dispatching decisions can be made to maximize the efficiency of truck operations. RL agents, by taking into account various factors such as truck locations, load capacities, traffic conditions, and material availability, possess the capability to make real-time intelligent decisions. As a result, this facilitates the creation of optimized truck routes, decreased waiting times, and an overall improvement in operational efficiency, ultimately leading to cost savings. An intelligent system for truck dispatching in open-pit mines is said to be capable of nearly 17% decrease in truck costs [77]. By implementing intelligent techniques in mine FMSs, fuel consumption can be effectively reduced. This optimization of dispatching strategies and decision-making processes can lead to substantial savings in fuel usage, thereby effectively reducing the overall operating costs for the mining operation. This fuel-saving advantage not only contributes to cost reduction but also aligns with environmental sustainability efforts by minimizing the carbon footprint associated with truck fleet operations. RL-aided dispatching could diminish the greenhouse gas emissions per unit production by 30% in an open pit mine with a fleet size of fifteen trucks [6]. Another opportunity is that maintenance schedules for trucks can be optimized, resulting in cost savings. By scrutinizing sensor data and historical maintenance records, intelligent algorithms possess the capability to forecast the most favorable intervals for maintenance for each truck. This proactive methodology aids in the prevention of breakdowns, diminishes instances of unplanned downtime, and consequently minimizes the expenses associated with maintenance activities. This advanced approach to maintenance scheduling ensures the smooth operation of the truck fleet, maximizes operational efficiency, and contributes to overall cost reduction for the mine. However, scheduled maintenance as one of the features included in the five-feature echelle is neglected in the works reviewed earlier. The bright side is that the truck failure feature has been captured by the most of the works reviewed. Through the implementation of intelligent FMSs, the allocation of resources can be optimized. RL agents have the capability to make informed decisions regarding resource allocation by assimilating knowledge from experiences and real-time data. This prudent approach guarantees the efficient utilization of resources, thereby curtailing avoidable expenses and enhancing overall productivity. By leveraging the power of intelligent systems, mining operations can achieve a streamlined and effective resource allocation process, leading to cost savings and improved operational efficiency. Huo et al. showed that the correct delivery of ore and waste improves the overall production of a fleet with the size of fifteen trucks by 30% [6]. Leveraging intelligent FMSs can aid in the minimization of idle times and waiting times for trucks, resulting in decreased downtime. By dynamically adapting truck routes, optimizing dispatch decisions, and taking real-time conditions into account, intelligent algorithms possess the ability to significantly reduce the duration that trucks spend waiting for loading or unloading tasks. It not only enhances operational efficiency but also brings about cost reduction by mitigating the expenses associated with downtime. Having employed their DDQN methodology, De Carvalho and Dimitrakopoulos report the formation of smaller queues at the mill [7]. Another opportunity is related to the capacity of intelligent FMSs to boost the productivity of the entire mining operation thanks to informed decision-making, reduced inefficiencies, maximized utilization, and optimized operational processes. This improvement manifests in enhanced throughput, increased material movement, and ultimately an elevated level of productivity and revenue generation for the mine. The research works reviewed earlier from Huo et al., De Carvalho and Dimitrakopoulos, and Zhang et al. report an average production increase of 5 to 30% due to the application of RL-based FMSs in open pit mining [6–8]. Overall, direct benefits of intelligent systems include minimization of fuel, idling, and maintenance costs, as well as reducing vehicle and employee working hours. Additionally, indirect asset management benefits, such as equipment tracking, security, utilization, predictive maintenance, and extended vehicle lifespan through timely repairs, should also be noted. Another opportunity is ascribed to the operational efficiency manifested by technical features and Mining 4.0 requirements. The five feature echelle developed earlier attempts to highlight the most essential technical features required in a mine FMS. In other words, this echelle can serve as a benchmark to evaluate the technical and operational capability of the intelligent frameworks developed so far and those that are about to be developed. Thus, this echelle can demonstrate the technical potentials that an intelligent FMS can bring in its train. Mining 4.0 operational requirements such as autonomy and self-awareness are realized through intelligent FMSs. All the intelligent frameworks reviewed earlier serve as brilliant examples of rendering dispatching decisions without human intervention. In addition to the abovementioned opportunities, intelligizing the mine FMSs enables the development of decision-making models that assign paramount importance to safety in truck dispatching. These systems possess the capacity to acquire knowledge concerning safety-related aspects (e.g., the proximity to other vehicles, driver's behavior, road conditions, weather conditions, and potential defects in vehicles) during the process of making dispatch decisions. This integration of safety considerations facilitates the reduction of potential risks associated with accidents and injuries within open pit mines. A useful safety-related aspect of these systems is that they advocate professional documentation and reduced paperwork. For instance, in some underdeveloped mines, the onus of tracking the cycle of trucks and their load quality rests upon an in-field human controller, which is not only dangerous (in terms of occupational hazards, respiratory diseases, etc.) in the task itself but also erroneous in data, especially in inclement weathers. Another opportunity that warrants attention is workplace culture. The less human interactions exist in a jobsite, the less conflicts will occur. For instance, a truck driver could become involved in an altercation with a foreman over discharging the load in the wrong location; however, it might not be the case in an intelligent framework where the ore destination path is displayed on a compact monitor installed at the driver's fingertips. Therefore, intelligent FMSs hold the potential to foster a positive workplace culture through its capacity to optimize work processes, alleviate employee stress, and facilitate enhanced communication and collaboration across different teams. Overall, by harnessing the potentials of intelligent FMSs, mining operations can achieve enhanced efficiency in a variety of aspects, positioning themselves for sustained success in the industry.

Threats Introducing intelligence into mine FMSs contributes to the opportunities discussed earlier. Nonetheless, this integration brings about some threats. In this analysis, the word "Threat" means all the external factors hindering the successful implementation of an intelligent FMS. Beginning with infrastructural limitations, challenges arise from limited connectivity, outdated technology, or inadequate sensor networks. An example of this hindrance is insufficient network coverage, which disrupts real-time communication between trucks and the dispatching system, causing delays and inaccuracies in decision-making. One possible solution is to enhance the mining site infrastructure by implementing reliable wireless networks or adopting Internet of Things technologies. This upgrade enables smooth data exchange between trucks, sensors, and the dispatching system, thereby facilitating the integration of intelligent frameworks. Insufficient or low-quality data can pose another threat. Inadequate data regarding truck movements, road conditions, or equipment status can affect the efficacy of learning algorithms. For instance, inconsistent or outdated data on truck locations and load capacities can lead to less-than-optimal dispatching decisions. A solution to this issue is to implement strong data collection methods utilizing sensors, GPS tracking, or telematics devices to acquire precise and timely information about trucks, routes, and environmental conditions. Furthermore, employing data cleansing techniques can increase the accuracy of the collected data. Incorporating intelligent systems can face another threat in the form of compliance issues. This refers to the challenges posed by breaching safety regulations and legal requirements. Stringent regulations concerning equipment operation, worker safety, and environmental protection must be taken into account. For instance, the RL algorithm may propose dispatching decisions that violate specific regulations, resulting in legal complications or safety issues. A feasible resort lies in fostering collaboration with regulatory authorities and legal experts to comprehend and integrate pertinent safety and compliance guidelines into the intelligent system. Another threat is in the form of stakeholder resistance, including shareholders, managers, and mine workers, which can impede progress. Concerns over job security, a lack of trust in automation, and misunderstandings about technology replacing human workers can hinder acceptance. Workers, for instance, may exhibit reluctance towards adopting these cutting-edge systems due to fears of potential job losses or reduced control over operations. A potential solution lies in raising awareness regarding the opportunities offered by intelligent FMSs and highlighting their capacity to enhance human capabilities rather than supersede workers. Conducting the Porter's value chain analysis [94] can also prove beneficial in shedding light on the added value that such systems can bring to shareholders and managers. This is where another threat as investment worthiness or profitability comes to the fore. The financial implications and the ambiguity surrounding the return on investment can impede the integration of intelligence. Significant initial costs, constrained budget allocations, and uncertain cost-saving benefits can present obstacles. The upfront investment necessary for the implementation of intelligent FMSs, encompassing hardware, software, and training, may surpass the available budget, thereby discouraging the adoption. One plausible solution involves conducting a comprehensive cost-benefit analysis to illustrate the medium-to-long-term financial benefits associated with intelligent FMSs. The last but not least significant threat lies in the vulnerability of intelligent systems to cyberattacks, resulting in disruptions, compromise of sensitive data, and potential harm to personnel and equipment. For instance, an intruder could embed malware into the FMS to compromise its functionality. Cybercriminals may also gain unauthorized access to sensitive information, including truck routes, production rates, or personnel data, thereby causing privacy breaches. Additionally, social engineering tactics could deceive employees into divulging sensitive information or granting illicit access to the system. Lastly, dissatisfied employees might exploit their authorized access to sabotage operations or manipulate sensitive data such as the ore tonnage hauled by the trucks of a contractor. To effectively combat these cyber threats, it is imperative to establish a robust cybersecurity framework and adhere to industry best practices. This entails conducting regular security assessments, implementing continuous monitoring, formulating comprehensive incident response plans, and ensuring timely software updates to address emerging threats and vulnerabilities. Most crucial threats regarding intelligent FMSs were dissected and provided with solutions in this section. Thorough evaluation and resolution of these external factors are of utmost importance during the planning and implementation phases of integrating intelligent FMSs into open pit mines. Successful navigation through these obstacles necessitates robust collaboration among mining companies, technology providers, regulators, and stakeholders.

Figure 3 depicts the components of the SWOT analysis in the two general classifications: internal/external and positive/negative. Internal factors (strengths and weaknesses) are correlated to intrinsic features of intelligent systems (e.g., algorithm and hardware), whereas external factors (opportunities and threats) consider constructive and destructive forces imposed extrinsically. The count of internal and external factors amounts to 6 and 11, respectively, indicating that the adoption of intelligent FMSs is predominantly governed by external factors. Threats and opportunities are nearly similar in terms of the items included; however, the threats are tractable using the solutions recommended earlier. From another perspective, these four components can be categorized into negative (weaknesses and threats) and positive (strengths and opportunities) groups. The negative and positive groups reach 7 and 10 in number, respectively, indicating that the diagram is on the positive side. The number of items in the strengths part is twice as great as the number for the items in the weaknesses part. Hardware restrictions and immature theoretical backgrounds were provided with some solutions earlier. By and large, the advantages outweigh the disadvantages when it comes to incorporating intelligent FMSs into open pit operations.

The opportunities presented in the context of applying intelligent FMSs in open pit mines can serve as countermeasures against the identified threats. The financial advantages gained through optimized truck dispatching and increased production can generate revenue streams, which can be strategically employed to overcome infrastructural limitations and concerns regarding investment worthiness. In fact, companies can allocate resources to upgrade their hardware infrastructure, invest in essential network connectivity, and ensure sustainable profitability. Improvements in operational efficiency play a pivotal role in addressing doubts surrounding investment worthiness. By streamlining processes, reducing waiting times, and maximizing equipment utilization, companies become more inclined to embrace intelligent FMSs. These innovative systems offer the potential to reduce emissions and enhance safety, effectively addressing compliance issues associated with environmental and safety standards. This is achieved through demonstrating a dedicated commitment to environmental protection and adopting a proactive approach to accident prevention. Moreover, the establishment of a positive workplace culture resulting from enhanced operational efficiency can significantly alleviate the stakeholder resistance. By promoting an environment that fosters productivity, collaboration, and job satisfaction, companies can win the trust of various stakeholders. All in all, seizing the opportunities presented by intelligent FMSs, companies can effectively counteract the threats they face.

4 Discussion and Conclusion

FMSs have played a crucial role in revolutionizing the operational quality of open pit mines. Throughout the course of history, notable strides have been made in the development of these systems, affording mining companies the capability to maximize fleet utilization, streamline workflows, and boost overall productivity. In the earlier stages, the supervision of mining fleets heavily relied upon labor-intensive tracking and communication methods, engendering inefficiencies and untimely interruptions. To handle these issues, the second generation of mine FMSs known as conventional systems starting from the 1980s came into effect to take advantage of the computer power for the purpose of allocation and dispatching using operations research techniques, metaheuristics, and offline simulation. Although having taken the center stage for nearly four decades, conventional FMSs with all of their relative maturity feel the necessity to give way to their third generation rival, intelligent FMSs, in the 2020s. Two contributing factors are detectable in this transformative paradigm shift: (1) the Mining 4.0 requirements regarding autonomy, dynamism handling, and decision-making on all operational levels; and (2) structural shortcomings inherent in conventional models as mentioned earlier. Intelligent FMSs, particularly those that integrate RL, possess an impressive capability to manage and adapt to dynamicity. Through extensive training over numerous iterations, RL algorithms familiarize the agents with diverse uncertainties and dynamic scenarios, equipping them with an enhanced ability to effectively address dynamic environments. This dynamicity manifests itself across various factors, encompassing fluctuations in truck numbers, varying ore grades, shifting production targets, changes in processing plant feed rate and head grade, fluctuating weather conditions, road conditions including traffic, and more. In contrast to conventional systems, agents trained within RL algorithms demonstrate adeptness in navigating through these ever-changing dynamics, historically regarded as challenging. As a result, the proficiency of intelligent FMSs in handling dynamicity brings about a paradigm shift, elevating operational efficiency within open pit mines and prompting transformative alterations in existing practices within the industry. A few but growing number of researchers have strived to introduce intelligence into mine FMSs through leveraging SL techniques and MASs. The SL techniques have been mostly applied for prediction of the traveling time of trucks; however, they pale in comparison with MASs due to their lack of capability in dynamism handling as explained earlier. The MAS paradigm has been applied in negotiable scheduling or RL configurations. The constant requirement for communication within negotiable-scheduling-based methodologies can give rise to delays and inefficiencies, particularly in vast mining operations. This drawback has consequently led to the endorsement of RL algorithms. An RL problem is formulated using MDP, the key components of which in mine FMSs were adequately defined and explained earlier. These components include agent (trucks), environment (mine site), action space (dispatching decisions), state space (state representation vector), reward function (minimizing operational costs, minimizing truck idle time, and maximizing productivity), transition probability, policy, and discount factor. The research works conducted on MASs suffer from some technical faults related to allocation and dispatching features. To highlight these faults, we developed a five feature echelle inspired from investigating conventional FMSs. Overlaying this echelle on the previously developed FMSs via negotiable scheduling or RL algorithms demonstrated that nearly half of the desirable features in the echelle are neglected in these frameworks. It draws a research line for developing more robust intelligent FMSs in the future so that they can address the neglected features as much as possible. The features neglected include production (stripping ratio, block precedence), shovel (scalability, movement time, scheduled maintenance), operation (bunching, weather conditions, drilling/blasting), and destination (processing plant head grade, stockpile capacity, and grade requirements). In addition to this bottom-up analysis, we adopted a top-down approach to depict a broad picture about the implementation feasibility of intelligent FMSs. The SWOT analysis generated strengths (dynamicity, fast decision-making, generality, and autonomy), weaknesses (hardware restrictions and theoretical backgrounds), opportunities (economy, production, environment, operation, safety, and workspace culture), and threats (infrastructural limitations, compliance issues, stakeholder resistance, investment worthiness, and cybersecurity) associated with introducing intelligence into mining FMSs. The SWOT analysis revealed key opportunities for the integration of intelligent FMSs into mining operations, despite some notable challenges. The weaknesses and threats were found to be temporary and tractable through the solutions provided. By emphasizing the potential opportunities that intelligent setups can offer, the underlying threats are mitigated. Mining companies can achieve the financial and attitudinal motivations required to counteract the potential challenges and risks that may emerge through tapping into the powerful capabilities of intelligent systems. Overall, the balance of positive factors leans more in favor of intelligent FMSs in the SWOT diagram. To recap, this study confirmed the need for intelligent FMSs in open pit mines through both the technical review and the strategic analysis.

Author Contributions Arman Hazrathosseini: conceptualization, methodology, data curation, investigation, writing original draft. Ali Moradi Afrapoli: supervision, conceptualization, and manuscript review, editing and submission.

Declarations

Conflict of Interest The authors declare no competing interests.

References

1. Ali D, Frimpong S (2021) DeepHaul: a deep learning and reinforcement learning-based smart automation framework for dump trucks. Progr Artif Intell 10(2):157–180
2. Moradi Afrapoli A, Askari-Nasab H (2020) A stochastic integrated simulation and mixed integer linear programming optimisation framework for truck dispatching problem in surface mines. Int J Mining Min Eng 11(4):257–284
3. Ahangaran DK, Yasrebi AB, Wetherelt A, Foster P (2012) Real–time dispatching modelling for trucks with different capacities in open pit mines. Arch Min Sci 57:1
4. Siami-Irdemoosa E, Dindarloo SR (2015) Prediction of fuel consumption of mining dump trucks: a neural networks approach. Appl Energy 151:77–84
5. Yokoi R, Watari T, Motoshita M (2022) Future greenhouse gas emissions from metal production: gaps and opportunities towards climate goals. Energy Environ Sci 15(1):146–157
6. Huo D, Sari YA, Kealey R, Zhang Q (2023) Reinforcement learning-based fleet dispatching for greenhouse gas emission reduction in open-pit mining operations. Resour Conserv Recycl 188:106664

7. De Carvalho JP, Dimitrakopoulos R (2021) Integrating production planning with truck-dispatching decisions through reinforcement learning while managing uncertainty. Minerals 11(6):587
8. Zhang C, Odonkor P, Zheng S, Khorasgani H, Serita S, Gupta C, Wang H (2020) Dynamic dispatching for large-scale heterogeneous fleet via multi-agent deep reinforcement learning. In: 2020 IEEE International Conference on Big Data (Big Data). IEEE, pp 1436–1441
9. White JW, Olson J, Vohnout S (1993) On improving truck/shovel productivity in open pit mines. CIM Bull 86(973):43–49
10. Alarie S, Gamache M (2002) Overview of solution strategies used in truck dispatching systems for open pit mines. Int J Surf Min Reclam Environ 16(1):59–76
11. Chaowasakoo P, Seppälä H, Koivo H, Zhou Q (2017) Digitalization of mine operations: scenarios to benefit in real-time truck dispatching. Int J Min Sci Technol 27(2):229–236
12. Moradi Afrapoli A, Askari-Nasab H (2019) Mining fleet management systems: a review of models and algorithms. Int J Min Reclam Environ 33(1):42–60
13. Zeng W (2018) A simulation model for truck-shovel operation. . Ph.D. Thesis,. School of Civil, Mining and Environmental Engineering, University of Wollongong, Wollongong, Australia
14. Lizotte Y, Bonates E, Leclerc A (1987) A design and implementation of a semi-automated truck/shovel dispatching system. In: Proceedings of the twentieth international symposium on the application of computers and mathematics in the mineral industries, vol. 1, pp. 377–387
15. Lizotte Y, Bonates E (1987) Truck and shovel dispatching rules assessment using simulation. Min Sci Technol 5(1):45–58
16. Munirathinam S (2020) Industry 4.0: industrial internet of things (IIOT). Adv Comput 117:129–164
17. TIMining Co. (2023). TIMining Aware solution. https://www.timining.com/ (accessed 01 May 2023).
18. Petra Co. (2023). FORESTALL online predictive and prescriptive maintenance solution. https://www.petradatascience.com/ (accessed 01 May 2023).
19. Rio Tinto Inc. (2023). http://www.riotinto.com/ (accessed 01 May 2023).
20. Sener E, Iseley DT (2009) Construction equipment fleet management using telematics technology: research and resultant educational perspectives. In: 2009 Annual Conference & Exposition, pp 1–14.362
21. Bogert J (1964) Electronic eyes and ears monitor pit operations. Met Min Process: 42–45
22. White JW, Olson JP (1986) Computer-based dispatching in mines with concurrent operating objectives. Min Eng-Littleton 38 (11):1045–1054
23. Koenigsberg E (1960) Finite queues and cyclic queues. Oper Res 8(2):246–253
24. Bastos GS, Souza LE, Ramos FT, Ribeiro CH (2011) A single-dependent agent approach for stochastic time-dependent truck dispatching in open-pit mining. In: 2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC). IEEE, pp 1057–1062
25. Dallaire R, Laplante A, Elbrond J (1978) Humphrey's spiral tolerance to feed variations. Canad Mining Metallurg Bull 71(796):128–134
26. Alkass S, El-Moslmani K, AlHussein M (2003) A computer model for selecting equipment for earthmoving operations using queuing theory. CIB Rep 284:1
27. Kappas G, Yegulalp TM (1991) An application of closed queueing networks theory in truck-shovel systems. Int J Surf Min Reclam Environ 5(1):45–51
28. Upadhyay SP (2017) Simulation optimization of mine operations for uncertainty based short term and operational planning in open pit mines. Doctoral thesis,. University of Alberta, Canada
29. Ercelebi SG, Bascetin A (2009) Optimization of shovel-truck system for surface mining. J South Afr Inst Min Metall 109(7):433–439
30. Mohtasham M, Mirzaei-Nasirabad H, Askari-Nasab H, Alizadeh B (2021) A multi-objective model for fleet allocation schedule in open-pit mines considering the impact of prioritising objectives on transportation system performance. Int J Min Reclam Environ 35(10):709–727
31. Moradi Afrapoli A, Upadhyay S, Askari-Nasab H (2021) Truck dispatching in surface mines-Application of fuzzy linear programming. J South Afr Inst Min Metall 121(9):505–512
32. Temeng VA, Otuonye FO, Frendewey JO (1998) A nonpreemptive goal programming approach to truck dispatching in open pit mines. Miner Resour Eng 7(02):59–67
33. Soumis F, Ethier J, Elbrond J (1989) Evaluation of the new truck dispatching in the mount wright mine. Application of Computers and Operations Research in the Mineral Industry, 21st APCOM Proceedings, pp 674–682
34. Ta CH, Kresta JV, Forbes JF, Marquez HJ (2005) A stochastic optimization approach to mine truck allocation. Int J Surf Min Reclam Environ 19(3):162–175
35. Moradi Afrapoli A, Tabesh M, Askari-Nasab H (2019) A multiple objective transportation problem approach to dynamic truck dispatching in surface mines. Eur J Oper Res 276(1):331–342
36. Afrapoli AM, Upadhyay SP, Askari-Nasab H (2022) A nested multiple-objective optimization algorithm for managing production fleets in surface mines. Eng Optim, pp. 1–14. https://doi.org/10.1080/0305215x.2022.2153840
37. Madge D (1964) Simulation of truck movement in an open pit mining operation. Canad Operat Res Soc 11:32–41
38. Awuah-Offei K, Temeng V, Al-Hassan S (2003) Predicting equipment requirements using SIMAN simulation-a case study. Min Technol 112(3):180–184
39. Yuriy G, Vayenas N (2008) Discrete-event simulation of mine equipment systems combined with a reliability assessment model based on genetic algorithms. Int J Min Reclam Environ 22(1):70–83
40. Askari-Nasab H, Upadhyay S, Torkamani E, Tabesh M, Badiozamani M (2014) Simulation optimisation of mine operational plans. Orebody Modelling and Strategic Mine Planning Symposium, Perth, WA Australia
41. Afrapoli AM, Askari-Nasab H (2019) Simulation and optimization framework for evaluating the mining operations. In: Mining goes Digital: Proceedings of the 39th International Symposium Application of Computers and Operations Research in the Mineral Industry'(APCOM 2019), June 4-6, 2019, Wroclaw, Poland, CRC Press, p 393
42. Nageshwaraniyer SS, Son Y-J, Dessureault S (2013) Simulation-based robust optimization for complex truck-shovel systems in surface coal mines. In: 2013 Winter Simulations Conference (WSC). IEEE, pp 3522–3532
43. Ozdemir B, Kumral M (2019) Simulation-based optimization of truck-shovel material handling systems in multi-pit surface mines. Simul Model Pract Theory 95:36–48
44. Upadhyay SP, Askari-Nasab H (2018) Simulation and optimization approach for uncertainty-based short-term planning in open pit mines. Int J Min Sci Technol 28(2):153–166
45. Bissiri Y, Dunbar WS, Hall A (2002) Swarm–based truck-shovel dispatching system in open pit mine operations. Ph. D. Thesis. Mining and mineral process tengineering, University of
46. He M-X, Wei J-C, Lu X-M, Huang B-X (2010) The genetic algorithm for truck dispatching problems in surface mine. Inf Technol J 9(4):710–714
47. Dabbagh A, Bagherpour R (2019) Investigating the applicability of imperialist competitive algorithm in the problem of allocating truck to the open pit mine. Rudarsko-geološko-naftni zbornik 34:2

48. Zhang X, Guo A, Ai Y, Tian B, Chen L (2022) Real-time scheduling of autonomous mining trucks via flow allocation-accelerated tabu search. IEEE Trans Intell Vehicles 7(3):466–479
49. Hazrathosseini A, Moradi Afrapoli A (2023) The advent of digital twins in surface mining: Its time has finally arrived. Res Policy 80:103155
50. Newman AM, Rubio E, Caro R, Weintraub A, Eurek K (2010) A review of operations research in mine planning. Interfaces 40(3):222–245
51. Gurgur CZ, Dagdelen K, Artittong S (2011) Optimisation of a real-time multi-period truck dispatching system in mining operations. Int J Appl Decis Sci 4(1):57–79
52. Lamghari A (2017) Mine planning and oil field development: a survey and research potentials. Math Geosci 49(3):395–437
53. Icarte Ahumada G, Riveros E, Herzog O (2020) An agent-based system for truck dispatching in open-pit mines. ICAART 1:73–81
54. Dhamija P, Bag S (2020) Role of artificial intelligence in operations environment: a review and bibliometric analysis. The TQM J 32(4):869–896
55. Rich E (1983) Artificial intelligence. McGraw-Hill, Inc
56. Mnih V, Kavukcuoglu K, Silver D, Rusu AA, Veness J, Bellemare MG, Graves A, Riedmiller M, Fidjeland AK, Ostrovski G (2015) Human-level control through deep reinforcement learning. Nature 518:529–533
57. Chen MK, Liu X, Sun Y, Tsai DP (2022) Artificial intelligence in meta-optics. Chem Rev 122(19):15356–15413
58. El Naqa I, Murphy MJ (2015) What is machine learning? Springer
59. McCulloch WS, Pitts W (1943) A logical calculus of the ideas immanent in nervous activity. Bull Math Biophys 5(4):115–133
60. Rosenblatt F (1958) The perceptron: a probabilistic model for information storage and organization in the brain. Psychol Rev 65(6):386
61. Rumelhart DE, Hinton GE, Williams RJ (1985) Learning internal representations by error propagation. California Univ San Diego La Jolla Inst for Cognitive Science
62. LeCun Y, Boser B, Denker JS, Henderson D, Howard RE, Hubbard W, Jackel LD (1989) Backpropagation applied to handwritten zip code recognition. Neural Comput 1(4):541–551
63. Gartner Inc. (2017). Gartner hype cycle for emerging technologies in 2017. https://www.gartner.com/ (accessed 01 April 2023).
64. Jung D, Choi Y (2021) Systematic review of machine learning applications in mining: Exploration, exploitation, and reclamation. Minerals 11(2):148
65. Noriega R, Pourrahimian Y (2022) A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning. Res Policy 77:102727
66. Choi Y, Nguyen H, Bui X-N, Nguyen-Thoi T, Park S (2021) Estimating ore production in open-pit mines using various machine learning algorithms based on a truck-haulage system and support of internet of things. Nat Resour Res 30(2):1141–1173
67. Choi Y, Nguyen H, Bui X-N, Nguyen-Thoi T (2022) Optimization of haulage-truck system performance for ore production in open-pit mines using big data and machine learning-based methods. Res Policy 75:102522
68. Choudhury S, Naik H (2022) Use of machine learning algorithm models to optimize the fleet management system in opencast mines. In: 2022 IEEE 7th International conference for Convergence in Technology (I2CT). IEEE, pp 1–8
69. Sun X, Zhang H, Tian F, Yang L (2018) The use of a machine learning method to predict the real-time link travel time of open-pit trucks. Math Probl Eng 2018. https://doi.org/10.1155/2018/4368045
70. Nobahar P, Pourrahimian Y, Mollaei Koshki F (2022) Optimum fleet selection using machine learning algorithms—case study: Zenouz Kaolin mine. Mining 2(3):528–541
71. Lin K, Zhao R, Xu Z, Zhou J (2018) Efficient large-scale fleet management via multi-agent deep reinforcement learning. In: Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp 1774–1783
72. Abbas HA, Shaheen SI, Amin MH (2015) Organization of multi-agent systems: an overview. J Intell Inform Syst 4(3):46–57. https://doi.org/10.11648/j.ijiis.20150403.11
73. Dorri A, Kanhere SS, Jurdak R (2018) Multi-agent systems: a survey. IEEE Access 6:28573–28593
74. Cohen MW, Coelho VN (2021) Open-pit mining operational planning using multi agent systems. Procedia Comp Sci 192:1677–1686
75. Smith RG (1980) The contract net protocol: High-level communication and control in a distributed problem solver. IEEE Trans Comput 29(12):1104–1113
76. Icarte Ahumada G, Berrios P, Castillo R, Herzog O (2020) A multiagent system for truck dispatching in open-pit mines. In: International Conference on Dynamics in Logistics. Springer, pp 363–373
77. Icarte Ahumada G, Diaz Pinto J, Herzog O (2021) A dynamic scheduling multiagent system for truck dispatching in open-pit mines. In: International Conference on Agents and Artificial Intelligence. Springer, pp 132–148
78. Ahumada GI, Herzog O (2021) Application of multiagent system and tabu search for truck dispatching in open-pit mines. ICAART 1:160–170
79. Askari-Nasab H, Szymanski J (2007) Open pit production scheduling using reinforcement learning. Cell 780(717):2987
80. Kumar A, Dimitrakopoulos R (2021) Production scheduling in industrial mining complexes with incoming new information using tree search and deep reinforcement learning. Appl Soft Comput 110:107644
81. Sutton RS, Barto AG (2018) Reinforcement learning: an introduction (2nd ed.). The MIT Press, pp 50–60
82. Van Hasselt H, Guez A, Silver D (2016) Deep reinforcement learning with double q-learning. In: Proceedings of the AAAI conference on artificial intelligence (vol. 30, no. 1)
83. Silver D, Lever G, Heess N, Degris T, Wierstra D, Riedmiller M (2014) Deterministic Policy gradient algorithms. Proceedings of the 31st Intern conference machine learning, in proceedings of Mach Learn Res 32(1):387–395. https://proceedings.mlr.press/v32/silver14.html
84. Mnih V, Badia AP, Mirza M, Graves A, Lillicrap T, Harley T, Silver D, Kavukcuoglu K (2016) Asynchronous methods for deep reinforcement learning. Proceedings of the 33rd international conference machine learning, in proceedings of Mach Learn Res 48:1928–1937. https://proceedings.mlr.press/v48/mniha16.html
85. Helms MM, Nixon J (2010) Exploring SWOT analysis–where are we now? A review of academic research from the last decade. J Strat Manag 3(3):215–251
86. Ghazinoory S, Abdi M, Azadegan-Mehr M (2011) SWOT methodology: a state-of-the-art review for the past, a framework for the future. J Bus Econ Manag 12(1):24–48
87. Farazi NP, Zou B, Ahamed T, Barua L (2021) Deep reinforcement learning in transportation research: a review. Trans Res Interdiscip Perspec 11:100425
88. Lv Z, Li J, Xu Z, Wang Y, Li H (2021) Parallel computing of spatio-temporal model based on deep reinforcement learning. In: Wireless Algorithms, Systems, and Applications: 16th International Conference, WASA 2021, Nanjing, China, June 25–27, 2021, Proceedings Part I. Springer, pp 391–403
89. Liang E, Liaw R, Nishihara R, Moritz P, Fox R, Goldberg K, Gonzalez J, Jordan M, Stoica I (2018) RLlib: abstractions for distributed reinforcement learning. Proceedings of the 35th international conference on machine learning, in Proceedings of Mach Learn Res 80:3053–3062. https://proceedings.mlr.press/v80/liang18b.html

90. Edureka (2023). The best laptop for machine learning. Accessed on 25/06/2023. http://www.edureka.co.
91. Schaul T, Quan J, Antonoglou I, Silver D (2015) Prioritized experience replay. arXiv preprint arXiv:1511.05952. Published at International Conference on Learning Representations (ICLR) 2016
92. Zhang K, Yang Z, Liu H, Zhang T, Basar T (2018) Fully decentralized multi-agent reinforcement learning with networked agents. Proceedings of the 35th international conference on machine learning, in Proceedings of Mach Learn Res 80:5872–5881. https://proceedings.mlr.press/v80/zhang18n.html
93. Isele D, Cosgun A (2017) Transferring autonomous driving knowledge on simulated and real intersections. arXiv preprint arXiv:1712.01106. https://doi.org/10.48550/arXiv.1712.01106
94. Porter ME (1985) Competitive strategy: creating and sustaining superior performance. The free, New York