Analyzing Trends and Challenges in Artificial-Intelligence-Based Fleet Management Systems for Open Pit Mines through Literature Review and Strategic Examinations

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ABSTRACT

Embracing the principles of Mining 4.0, transportation fleets, integral to open pit operations, recognize the importance of adopting autonomy, interoperability, virtualization, visualization, and interconnectivity. However, any novel transformation needs to be justified theoretically and strategically. To conform to the principle, the present work investigated into the limitations of conventional fleet management systems (FMSs) to establish the need for intelligent solutions. Following that, artificial-intelligence-based FMSs developed up to the present time were explored to track the latest status of this technological trend within the mining industry. Then, these frameworks were compared in terms of seven categories of features to pinpoint potential gaps and research directions. The popular SWOT analysis method was leveraged to outline the strengths, weaknesses, opportunities and threats associated with the advent of these smart controlling setups in mines of future. By and large, advantages outweighed disadvantages. Temporary obstacles are believed to be tackled by increasing pace of technological breakthroughs and propagation of the paradigm of cognitive management systems.

1. Introduction

Owing to extended operational lifecycles, substantial capital outlays, computational constraints (Upadhyay, 2017), mine planning tasks are categorized into three primary segments: strategic (encompassing long-term and medium-term planning), tactical (pertaining to short-term planning), and operational planning (involving fleet distribution and dispatching). The latter spans a time frame from seconds to a day, aligned with the designated planning horizon (Moradi Afrapoli and Askari-Nasab, 2020). Slightly over 50% of operational expenses, almost 30% of overall energy consumption, and approximately 10% of worldwide energy-linked greenhouse gas emissions are attributed to mining operations (Ahangaran et al., 2012; Siami-Irdemoosa and Dindarloo, 2015; Yokoi et al., 2022). These statistics highlight the significance of operational fleet management systems (FMSs), where even minor modifications result in significant economic and ecological advantages. In a mining setting, an FMS focuses on optimizing the loading-haulage process by making informed allocation and dispatch choices using computer algorithms, striving to function autonomously while bridging strategic plans with real-time production activities. The task of dynamically assigning vacant trucks is denoted as the dispatching issue. Dispatching mechanisms are categorized into three main types: manual, semi-automated, and fully automated. Manual dispatching adheres to a fixed or inflexible protocol, where a specific number of trucks are designated to a particular shovel for the entire work shift. The key contrast between the other two

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approaches lies in the requirement for human engagement within the semi-automated framework (Lizotte and Bonates, 1987). Contrary to the fixed allocation, flexible truck allocation involves trucks receiving fresh assignments from the dispatching system instead of being dedicated to a single shovel. This shift results in a productivity enhancement of around 10-15% (White et al., 1993). Literatures chiefly show 1-truck-for-n-shovels, m-trucks-for-1-shovel, and m-trucks-for-n-shovels assignment strategies (Alarie and Gamache, 2002). Truck allocation occurs through two primary systematic approaches: single-stage or multistage. In the single-stage method, assignments are made solely based on one or multiple heuristic rules (also known as dispatching criteria), without taking production requirements into account, namely fixed allocation (Lizotte and Bonates, 1987), minimizing the number of trucks (Munirathinam and Yingling, 1994), minimizing shovels' waiting time, minimizing trucks' cycle time, minimizing trucks' waiting time, minimizing shovel saturation (Kolonja et al., 1993). 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 (Moradi Afrapoli and Askari-Nasab, 2019). The multistage approach gains an advantage by addressing diverse constraints at the higher level, leading to enhanced efficiency in making dispatching decisions at the lower level.

Emerging as an idea at a German exhibition in 2011 and formally commencing its era in 2015, Industry 4.0 represents a transformative departure from conventional manufacturing methods. This evolution is founded on principles of interconnection, automation, autonomy, machine learning, and real-time data utilization (Munirathinam, 2020). Mining 4.0 can be defined as a digital revolution aimed at infusing intelligence into conventional mining activities. The objective is to establish robust and intelligent systems capable of adeptly managing dynamism, fostering interoperability, exhibiting autonomy, enabling monitoring, optimizing processes, predicting outcomes, making informed decisions, and providing virtualization and visualization. This transformation relies on foundational technologies like the Internet of Things, cloud computing, digital twins, artificial intelligence, and augmented reality. Given that load-and-haul machinery serves as the backbone of open pit mining operations, it necessitates a transformation in terms of embedded devices and management systems. This requirement arises not only from the overarching Mining 4.0 framework but also from various factors such as escalating operational intricacies and costs within and between value chains. However, the driving forces behind this change must initially be illuminated from both theoretical and strategic perspectives. This constitutes the primary objective pursued by the present paper. In other words, the article undertakes a literary examination to chart the attributes of conventional FMSs and their associated limitations, while highlighting the demand for alternative models. Subsequently, the study delves into intelligent FMSs developed within mining literature, aiming to provide a comprehensive overview of the prevailing trend and its current state by conducting a comparative analysis based on distinctive characteristics among previously published works. This analysis is envisioned to serve as a navigational guide for future research trajectories within the realm of mining FMSs. In order to conduct a strategic assessment, the widely recognized SWOT analysis technique is harnessed. This approach is employed to delineate the strengths, weaknesses, opportunities, and threats that warrant consideration in the practical implementation of such intelligent systems within open pit mining operations.

2. The Literary Analysis

Broken into two subsections, the literary analysis attempts to elicit the underlying need for move from conventional towards intelligent FMSs. In addition to the review of non-intelligent models, their main features addressed including contributing factors, parameters, and optimization goals are itemized to gain a deeper insight into these systems before bringing them under criticism. Upon establishing the need for change, intelligent FMSs are examined to draw the latest trajectory in the mining scope as well as comparing features of the models proposed to date as a means to pinpoint research gaps for building up further works with the least amount of flaws possible.

2.1. Conventional FMSs

Conventional mine operational planning has mainly witnessed four approaches: operations research (OR), heuristics, queuing theory and simulation. Dijkstra is the most prevalent method in finding the shortest path in mining systems due to its simplicity (Dijkstra, 1959), and seen in commercial packages like DISPATCH®. Regarding the upper stage, Ercelebi and Bascetin (2009) created a truck allocation model capable of approximating the number of trucks, equipment idle time, and the processing plant's feed (Ercelebi and Bascetin, 2009). Nevertheless, the model assumes Markovian behavior for all uncertain parameters. Most of the thus far developed FMSs implement linear programming (LP) and mixed-integer linear programming (MILP) approach to solve the upper stage problem. White and Olson (1986) introduced a two-segment LP model to make optimal decisions on production requirements (White and Olson, 1986). While the first segment tries to ascertain shovels' digging rates, the second part allocates a minimum number of trucks to each active route to meet the routes' productivity rate. Bonates and Lizotte (1988) assumed a linear relation between shovels' production and the number of trucks in their LP model, which poses a problem in heterogeneous fleet (Bonates and Lizotte, 1988). Zhang et al. (1990) proposed another LP model for the optimal allocation of the flow of trucks in an open pit, yet the capacities of truck fleet were ignored (Zhang et al., 1990). With the aim of minimizing the total number of trucks required to meet the production schedule, Ta et al. (2013) developed an MILP model to solve the upper stage problem (Ta et al., 2013). In contrast, Chang et al. (2015) took transportation revenue into account for their MILP model tailored for a homogeneous fleet only (Chang et al., 2015). A pitfall of LP-based models is that to consider the limitations of the operation, such as the stripping ratio and required feed grade, the models have to define an acceptable range, pushing the operation far behind optimality (Moradi Afrapoli and Askari-Nasab, 2019). Elbrond and Soumis (1987), and Munirathinam and Yingling (1994) argue that the use of a nonlinear model at the upper stage instead of a linear one is preferable since truck waiting time does not follow a linear function, and NLP models search for the optimum solution over the entire feasible region instead of corners merely (Elbrond and Soumis, 1987; Munirathinam and Yingling, 1994). Temeng et al. (1998) formulated a goal programming model to enhance shovel production considering ore grade, shovel dig rate, dumping capacity and stripping ratio requirement (Temeng et al., 1998). They also allowed for fleet heterogeneity, but ignored other notable goals such as equipment movement costs. Anaraki and Afrapoli (2023) introduced a bi-objective mathematical model that integrates carbon emission reduction with allocation optimization. The model accounts for various factors influencing truck allocation decisions, including fleet size, truck velocity, and age groups. Through case studies in iron and copper mines with varying equipment quantities, the study demonstrated that the proposed model effectively improved production and emissions.

Despite the tremendous published models on the upper stage, the share of the lower stage has been limited. Noteworthy early works are enumerated as White and Olson (1986), Soumis et al. (1989), Li (1990), and Temeng et al. (1997) (White and Olson, 1986; Soumis et al., 1989; Li, 1990; Temeng et al., 1997). Then, the problem remained unattended for nearly two decades. Ahangaran et al. (2012) used a network analysis technique for routes finding and an MILP model for dynamic truck assignments by minimizing the total cost of loading and transportation in their two-stage algorithm (Ahangaran et al., 2012). They ignored traffic over the routes, though. Moradi-Afrapoli (2019) compared a benchmark model used in DISPATCH® with three simulation-integrated models for real-time dispatching, namely a multiple objective goal programming model, a stochastic mixed integer linear programming model, and a fuzzy linear programming model (Moradi Afrapoli, 2019). Results demonstrated that the developed models needed an average of 16.5% fewer trucks to meet production requirements. Afrapoli et al. (2018) presented a mixed integer linear programming solution for the surface mine truck dispatching problem. They recognized the uncertainty in input parameters and employed a fuzzy approach to tackle it. Applying their model to a case study, they demonstrated its superiority over a benchmark model, requiring fewer trucks to meet production requirements. Moradi Afrapoli et al. (2022) proposed a nested fleet management system (N-FMS) for open-pit mining, connecting operations with strategic plans through shovel allocation and feed optimization. The N-FMS optimizes shovel and truck fleet efficiency using nested multiple-objective models. Application to a metal mining case revealed a substantial 14.6% increase in required truck fleet capacity for meeting production targets, surpassing locked-in approaches. Mirzaei-Nasirabad et al. (2023) addressed real-time truck dispatching in open-pit mining through a two-stage approach. They proposed a scenario-based method to estimate optimal truck sizes and introduced a multi-objective model to dynamically allocate trucks, minimizing waiting times and production deviations. The study evaluated their model using three heuristics and a copper ore mine simulation for comparison. Another fraction of authors has resorted to evolutionary algorithms and heuristics in an attempt to expedite the runtime of real-time dispatching models (He et al., 2010; Souza et al., 2010; Dabbagh and Bagherpour, 2019; Dabbagh and Bagherpour, 2019; Dabbagh and Bagherpour, 2019; Zhang et al., 2021; Pirmoradian et al., 2022).

Discrete-event simulation (DES) paradigm is applicable in material handling systems since they possess a discrete sequence of time-ordered events (loading, hauling, and dumping) (Blouin et al., 2007). Moradi-Afrapoli and Askari-Nasab (2022) proposed the need for constructing a simulation and optimization framework for mines, wherein the simulation component emulates operational processes, while the optimization facet replicates decision-making instruments. The credit for the first simulation in truck management in an open pit mine is given to Madge (1964) (Madge, 1964). In the 1970s, a slow computer language named Fortran was primarily used. In the next decade, more efficient simulation languages including GPSS and SLAM emerged and were endorsed by authors such as Sturgul and Harrison (1987) (Sturgul and Harrison, 1987), and Castillo and Cochran (1987) (Castillo and Cochran, 1987). In the 1990s, animation-based simulation found its way into fleet optimization frameworks by researchers, namely Forsman et al. (1993) (Forsman et al., 1993) and Jacobsen et al. (1995) (Jacobsen et al., 1995). In the third millennium, the most noticeable innovation has been the combination of simulation with optimization techniques. Askari-Nasab et al. (2014) applied a mixed integer linear goal programming to optimize four different goals (Askari-Nasab et al., 2014). Moreover, a DES model was developed to investigate the behavior of a truck-shovel haulage system in the presence of uncertainty within mining operations. Tabesh et al. (2016) proposed a complete dynamic package by incorporation of truck-shovel operations, road networks, processing plants, stockpiles, equipment failures, maintenance and capacity changes into a DES model (Tabesh et al., 2016). Moradi-Afrapoli et al. (2019) benchmarked their multiple objective mixed integer linear programming model against Modular Mining DISPATCH®, resulting in 13% reduction in the required truck fleet size (Moradi Afrapoli et al., 2019). Later, they made use of a fuzzy linear programming method, leading to a smaller fleet size of trucks to meet production targets (Moradi Afrapoli et al., 2021). A mixed-integer-linear goal programming model was formulated by Mohtasham et al. (2021) for fleet allocation, aiming at four major goals incorporating production, head grade, tonnage to the ore destinations, and fuel consumption of mining trucks (Mohtasham et al., 2021).

Main contributing factors, parameters, and optimization goals noticed in the previous non-intelligent fleet management works are categorized and listed in Table 1 for deeper insights. The selection of factors and parameters has a lot to do with the goal(s) targeted. Despite having sculpted a large fraction of research works, conventional methods are encountered with several drawbacks, and thereby requiring much attention. Speaking of OR, these methods pose a problem for large-size production scheduling in terms of complexity and runtime. Exact and numerical methods fall already short in present simplified problems, let alone in future cases, where more characteristics and sensory data must be taken into account. Another major ignored feature is stochasticity on account of inherent uncertainties present in most real-world problems. Deterministic approaches often lead to non-optimal results, and this pitfall is magnified excessively in equipment dispatching. Queuing theory runs into trouble in uncertain and complex problems, and it also has a limited scope (Gurgur et al., 2011). Metaheuristics are exploited to alleviate the severity of the mentioned downsides, yet they are not perfect. There are more than 40 metaheuristic algorithms nowadays (Tilahun and Ong, 2015). The enormity in number baffles practitioners every so often as which method is more congruous with their need. Moreover, each method has some hyper-parameters needing sufficient tuning to act efficiently, and their adjustment is usually carried out by trial and error. Last but not least, they are problem-specific, and often yield excellent results for the problem they have been designed for, but they are not readily applicable to other variants of the same problem (Lamghari, 2017). As a whole, these disadvantages entail researchers to seek other potential tools. AI as a fast-growing field in all industries has the merit to peer through for its promising solutions. Utilizing AI-powered FMSs can offer a substantial boost to operational effectiveness by promptly making decisions informed by complex data analysis. This, in turn, can optimize routes for vehicles and curtails periods of inactivity. To elaborate, AI leverages ML algorithms to examine historical data and foresee maintenance needs, allowing for timely servicing that minimizes downtime. Furthermore, these systems heighten safety measures by utilizing predictive analytics to anticipate potential accidents, as well as by facilitating remote monitoring to avert personnel exposure to risky zones. To exemplify, the incorporation of AI into an FMS for an open pit mine enables the dynamic allocation of haul trucks, considering real-time variables like traffic congestion, weather conditions, and equipment status. The outcome is a smoother traffic flow, decreased fuel consumption, and a more secure operational environment.

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

No.	Items	Components
1	Contributing 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.

2.2. Intelligent FMSs

Artificial Intelligence (AI) involves the exploration of enabling computers to perform tasks that currently humans excel at (Rich, 1983). Machine Learning (ML), a significant component of AI, employs input data to accomplish a specific objective without explicit programming (hard coding). In other words, the algorithm autonomously adjusts its structure to advance its proficiency in achieving the desired task (El Naqa and Murphy, 2015). ML is divided into three primary learning approaches: supervised learning (SL), unsupervised learning (USL), and reinforcement learning (RL). In SL, both training and testing data are accessible, allowing the model to learn from labeled data for tasks such as regression or classification. Conversely, USL involves training a model using unlabeled data to identify patterns or associations. Unlike the first two strategies, where models learn from datasets, RL relies on trial and error or experiential learning. In other words, an agent engages with an environment to determine the best policy through a system of 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. Deep Learning (DL), categorized separately within Artificial Neural Networks (ANNs), holds a distinct position owing to its importance. Unlike conventional scenarios, human intervention doesn't directly influence the process of extracting features from input data. DL draws inspiration from the intricate structure of the human nervous system, and its formation is based on a complex network of neurons that interact across input, hidden, and output layers. DL experienced a period of twenty years marked by limited progress, primarily due to inadequate availability of substantial datasets and suitable software/hardware. However, its resurgence commenced with renewed vigor during the ImageNet challenge of 2012. Since then, this field of study has undergone remarkable and rapid evolution. Notably, in 2017, Gartner forecasted that the domains of DL and ML would advance significantly within a span of 2 to 5 years, reaching a point of high productivity (Gartner Inc., 2017). During the second decade of the 21st century, SVM and DL are recognized as the prevailing methods, while RL is progressively expanding its presence within the mining sector (Jung and Choi, 2021; Noriega and Pourrahimian, 2022). During the mining exploitation phase, ML applications can primarily be categorized into production scheduling, drilling/blasting, and equipment management.

Various Machine Learning approaches become apparent when considering equipment management. Wang et al. (2019) juxtaposed four ML techniques to construct a driving style identification model for open-pit mine truck drivers, and reduce diesel consumption, where RF was found to be the most effective tool (Wang et al., 2019). Choi et al. (2021) compared six ML techniques for predicting ore production through truck haulage using Internet of Things (IoT) as a data collector, with the SVM model exhibiting the most superior performance (Choi et al., 2021). In another study, they predicted the performance of a truck-haulage system in the ore transportation process in open-pit mines using a combination of Harris hawks optimization and SVM before comparing it with RF and ANNs (Choi et al., 2022). Choudhury and Naik (2022) made a comparison among three models i.e., SVM, kNN and RF to predict the travelling time of trucks, thereby minimizing the cycle time and allocating an optimized number of dumpers to one shovel

(Choudhury and Naik, 2022). RF was recognized as the most suitable algorithm with least errors. Then, a linear programming model was developed to minimize the total number of trucks. The model is inclusive of constraints such as time-related attributes, truck condition, driver experience, atmospheric condition, and route profiles. These same algorithms were employed by Sun et al. (2018) for prediction of the real-time link travel time of open-pit trucks, where SVM and RF resembled in accuracy (Sun et al., 2018). To optimize the type of loader and the number of trucks required to meet the processing plant's throughput, Nobahar et al. (2022) compared five algorithms including linear regression, decision tree, kNN, RF, and gradient boosting algorithm, with the latter being indicated as the most precise (Nobahar et al., 2022).

However, SL is incapable to capture and model real-time changes (Lin et al., 2018), especially in mining environments, where high-dimensional dynamic and stochastic events govern. On the other hand, an RL agent strives to discover the optimal route that yields the greatest reward. An intriguing parallel can be drawn between this overarching concept and the challenge of route optimization encountered in the mining sector. Indeed, wherever the quest for an optimal pathway emerges – whether it pertains to determining the sequence for block extraction in production scheduling or mapping out the most efficient routes for the mining fleet – RL emerges as a suitable methodology. In scenarios involving agent-based truck dispatching dilemmas, each truck functions as an individual agent that collaborates within the mining system, all aimed at optimizing a specific objective. Bastos et al. (2011) 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 (Bastos et al., 2011). Comparison of their model with two heuristics in a DES simulator showed a superiority in the amount of materials hauled. Icarte Ahumada et al. (2020) utilized a negotiation mechanism for task sharing called the Contract Net Protocol, under the supervision of which 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 (Icarte Ahumada et al., 2020). Benchmarking the model against a heuristic brought about 18% decline in expenses. However, the scheduling process requires up to 16 minutes computational time on a standard device. Later, their work was extended to allow for truck failures rescheduling (Icarte Ahumada et al., 2021). Zhang et al. (2020) proposed an experience-sharing deep Q-learning 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 (Zhang et al., 2020). Sharing the same network, trucks are able to be added or removed readily. To speed up the training, they only eliminated learning-complicating experiences. Additionally, a memory-tailoring algorithm was scripted to cope with the problem of trucks cutting lines of others. Finally, 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. 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 (2021) integrated a discrete event simulation (DES) model with a deep double Q-learning network for truck dispatching at mines with various configurations (De Carvalho and Dimitrakopoulos, 2021). 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-hour retraining. Huo et al. (2023) applied an AI-powered intelligent dispatching system with the aim of greenhouse gas emissions minimization in open-pit mining operations (Huo et al., 2023). They paid attention to constraints including payload, traffic, queueing, and maintenance conditions in their multi-agent Q-learning algorithm. The model was benchmarked by 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. However, they assumed the fleet to be homogenous and small-sized. That's why the Q-table was utilized instead of a deep Q-learning network, and this decision affects the program solving time in larger-fleet cases. Processing plants' role was left out, too. Due to significant injuries and fatalities of mining trucks, the idea of autonomous trucks has also been addressed in literature. Ali and Frimpong (2021) developed a framework named DeepHaul consisting of two major components: first, inducing an object recognition ability using CNNs, and second, an RL-based algorithm for the steering action decision-making ability (Ali and Frimpong, 2021). The algorithm allegedly exhibited a remarkable accuracy score regarding safety, haulage efficiency and overall effectiveness.

Scrutinizing the components described in Table 1 unveils the fact that all the factors and parameters are reducible to seven chief features: (1) Rock mass (e.g., grade, production rate, stripping ratio, block precedence), (2) Shovel (e.g., capacity, digging rate, number, loading time, movement time), (3) Truck (e.g., capacity, velocity, loading time, hauling time, spotting time, number), (4) Operational (e.g., heterogeneity, scalability, failures, traffic jam, weather condition), (5) Processing plants (e.g., head grade, feed rate, capacity), (6) Stockpiles and waste dumps (capacities and grade requirements), (7) Linkage to strategic plans. Table 2 draws a distinction among previously-published works in RL-based fleet systems in terms of these features. As it is obvious, codes 5, 6 and 7 are the least addressed features. Rock mass and operational features are partially paid attention to in the literature. These bottlenecks highlight the necessity for more probe into the artificial world in the hope of bridging the research gap as much as possible. However, one should be cognizant of the fact that an ideal intelligent FMS incorporating all viable features might not be in the realm of possibility, at least at the moment due to hardware or software restrictions. On the other hand, rapid advancements in technology, especially quantum computing, are tantamount to an encouragement for practitioners to pass the ideality milestone in the foreseeable future.

Table 2. Salient RL-based proposed FMSs in the literature and features addressed.

No.	Authors	Features
1	Bastos et al. (2011)	1(production rate), 2,3, 4 (heterogeneity)
2	Icarte Ahumada et al. (2020)	1(production rate), 2, 3
3	Icarte Ahumada et al. (2021)	1(production rate), 2, 3, 4 (failures)
4	Zhang et al. (2020)	1(production rate), 2, 3, 4 (failures, scalability, heterogeneity)
5	De Carvalho and Dimitrakopoulos (2021)	1(production rate, grade), 2, 3, 4 (heterogeneity, failures), 5 (capacity)

6	Huo et al. (2023)	1(production rate, grade), 2, 3, 4 (failures, scalability)

3. The SWOT Analysis

Despite its unclear origins and lack of specific development timeframe (Helms and Nixon, 2010), the SWOT analysis method has gained widespread recognition for evaluating both internal (controllable: strengths and weaknesses) and external (uncontrollable: opportunities and threats) aspects influencing an entity. It employs a strategic matrix to systematically analyze these factors, aiding decision-making processes (Ghazinoory et al., 2011). SWOT integrates both internal and external factors that contribute to the effectiveness of an industry, a company, individuals, or even a new system transformation. Strengths identify the areas where an organization excels and what sets it apart from its rivals. Weaknesses, conversely, hinder the organization from operating optimally; hence, addressing them becomes crucial to maintain market presence. Opportunities encompass external factors that can provide the organization with a competitive edge to capitalize on or invest in. In contrast, threats encompass external elements that could potentially harm the organization and jeopardize its success. The SWOT diagram for the analysis of intelligent FMSs is illustrated in Fig. 1. Each of these components is elaborated upon as follows:

Strengths: The main supremacy of RL algorithms lies in their capability to address the dynamicity involved in a mining site. The RL agent is trained by trial and error to immediately acclimate to timely-changes in the environment as a way to be prepared for real-time rerouting and rescheduling. Another strength point relates to their ability for surmounting large-sized problems relatively to conventional methods. In other words, judging on the mere solving methodology, they alleviate the computational complexity and runtime by looking for near optimal solutions. This feature should not be confused with the temporary hardware-processing-power-restriction defect commented by some critics. The next significant merit is autonomy and self-awareness, thus reducing human interventions and mistakes.

Weaknesses: RL-based systems are suffering from a few temporary impediments. Firstly, hardware restrictions pose a problem in extremely high-dimensional environments unless the quantum-computing technology emerges rapidly with affordable costs. Secondly, the theoretical background for artificial intelligence, particularly RL is both obscure and deficient in maturity. A significant variety of algorithms comes to notice in the literature with increasing complexity. Furthermore, the effective design of an RL framework has a lot to do with the developer's knowledge, experience and hardware. Nonetheless, these barriers are tractable through the advancements in technology and academic texts.

Opportunities: Research works report an average productivity increase of 5 to 30% as a result of a smart FMS application (Zhang et al., 2020; De Carvalho and Dimitrakopoulos, 2021; Huo et al., 2023). An agent-based system for truck dispatching in open-pit mines is said to be capable of nearly 17% decrease in truck costs (Icarte Ahumada et al., 2021). Minimization of fuel, idling and maintenance costs as well as working hours of vehicles and employees are merely the direct benefits of intelligent systems, not to mention of indirect asset-management merits including equipment tracking, security, utilization, predictive maintenance, and life extension of vehicles via timely repairs. Another strength is ascribed to operational efficiency, specifically agile dispatching, proficient rescheduling induced by failures, weather conditions, or change in ore destinations, as well as bringing an organized procedure and smooth implementation, automation, autonomy and self-awareness. Regarding environmental aspects, RL-aided dispatching could diminish the greenhouse gas emissions per unit production by one-third in a three-shovel mine (Huo et al., 2023). Safety and health practices can be upgraded to higher standards through road conditions monitoring, traffic accidents prevention, driver's behavior surveillance (e.g., speeding or sleeping), and analysis of received sensory data for finding potential defects in vehicles. Professional documentation and data reporting (e.g., 3D visualization by HoloLens), and less paperwork are also promised. 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 laborious in the task itself but also erroneous in data, especially in inclement weathers. Another dimension worth attention is culture. The less human interactions exist in a jobsite, the less conflicts will occur. That is to say, a truck driver may became involved in an altercation with a foreman over discharging the load in a wrong dump; 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.

Threats: In this analysis, the word Threat means all the external factors hindering the successful implementation of an intelligent FMS. First of all, the capital investment required for intelligent systems is significant due to their need for infrastructure and speedy hardware, and the restricted knowledge behind these solutions. Another threat seems to be the persuasion of shareholders regarding the added value of such systems and the return promised over a medium-to-long run. A cost-benefit analysis is thus proposed to be conducted in such occasions for catching a deeper insight into this transformation. Governmental policies can also stand in the way, especially in countries with restrictive communication rules, which overshadows telematics. Last but not least, hackers might gain unauthorized access to the fleet control unit. However, the cybersecurity science has evolved proportionally by introducing up-to-the-minute firewalls.

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. In another perspective, these four components are itemized as negative (weaknesses and threats) and positive (strengths and opportunities) classes. Fig. 1 illustrates that the diagram is on the positive side, implying that the advantages outweigh the disadvantages when it comes to incorporating intelligent FMSs into open pit mining operations.

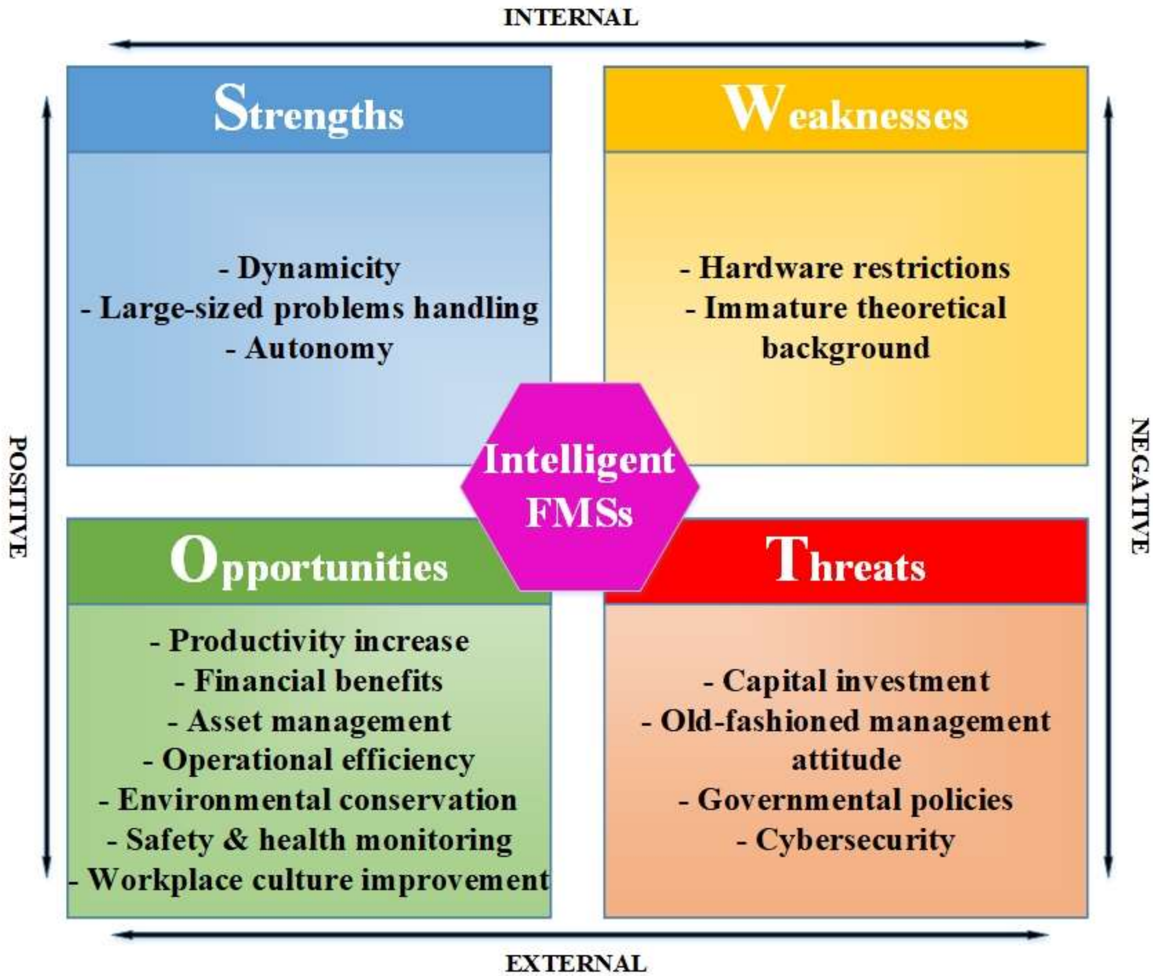

Fig. 1. The SWOT analysis diagram for intelligent fleet management systems (FMSs) in open pit mining.

4. Discussion and Conclusion

In mining publications, fleet management is traceable in diverse equipment-related aspects such as production optimization, dispatching, maintenance, fuel conservation, environmental impacts, weather conditions, the vehicle's operator monitoring, and health/safety aspects. The most prevalent algorithms applied are classifiable as conventional and intelligent. A variety of factors, parameters and goals has been attended to in conventional texts to capture dispatching and fleet-related issues. Nevertheless, the absence of scalability and dynamicity is noticed in real-life implementation of such models, entailing a quest for alternative solutions, which seems not to be a demanding task, with the Industry 4.0 ideology prevailing ubiquitously. Its translation into the mining context known as Mining 4.0 highlights the need for dynamism, one of the main tools of which in fleet routing is RL. This agent-based method has a rosy future ahead as hardware obstacles vanish. The trace of RL in mining FMSs literature is noticeable from the year 2011. Since then, RL has witnessed new developments in terms of underlying algorithms, and continues its evolutionary trajectory similarly to any new phenomenon.

RL empowers systems to acquire insights from their interactions with the environment, gradually streamlining decision-making processes for enhanced results. This innovation holds significant potential for elevating fleet management protocols, enabling systems to dynamically adjust and optimize operations in response to real-time circumstances. For instance, the realm of truck dispatching, where RL algorithms can develop proficiency in making optimal choices by scrutinizing a spectrum of variables including shovel availability, traffic patterns, haul road conditions, and ore demand. These algorithms continuously fine-tune dispatching strategies, thereby curtailing wait times, minimizing unproductive runs, and refining overall truck deployment efficiency. In the larger scheme, the integration of RL into fleet management bears the potential for a myriad of advantages. Augmented production efficiency and reduced operational expenses stem directly from optimized dispatching and maintenance, which concurrently extend the functional longevity of equipment. Moreover, through dynamic adjustments to evolving conditions and drawing insights from historical data, RL-driven fleet management systems can bolster safety protocols by preemptively detecting and mitigating potential hazards. As the technology advances and mining enterprises harness its capabilities, prospects for advanced applications are foreseeable, culminating in heightened productivity, more effective resource utilization, and the promotion of sustainable mining practices within surface mining operations. The characteristics-based comparison revealed the status quo and research directions for addressing more features, especially processing plants, ore/waste dumps, and linkage to strategic plans. Now, RL programmers are challenged into developing holistic algorithms capable of satisfying all the requirements in the scope of mining FMSs. After proving theoretically the underlying need for intelligent systems, a strategic mechanism was needed to uncover all the related aspects of this type of transition. Herein, the SWOT analysis generated strengths (dynamicity, large-sized problem handling, autonomy), weaknesses (hardware restrictions and immature theoretical backgrounds), opportunities (productivity, finance, environment, safety and culture) and threats (investment, persuasion of shareholders, governmental deterrents and cybersecurity) associated with introducing intelligence into mining FMSs. These weaknesses appear to be tractable as time goes on. The required capital investment and outdated attitudinal issues are manageable by elaborating on the potential opportunities that intelligent setups can open up for shareholders. Overall, the plate for positive factors weighs more in favor of smart fleet systems. To recapitulate, the present study corroborated the need for intelligent FMSs using literary and SWOT analyses.

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