Understanding Loading Practices in Trucks and Shovels in Open-Pit Mining Under Operation Uncertainties

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ABSTRACT

Material hauling and loading account for more than 50% of open-pit mining costs. This study aims to understand the efficiency of truck and shovel loading practices, evaluate them and develop a framework that can be implemented in short-term plans. The proposed methodology is evaluated by developing a simulation model using Haulsim software. Multiple scenarios (number of trucks, number of shovel passes and road rolling resistance) are simulated by formulating the problem in the software analysis terms: full truck (FT) and full bucket (FB). Based on the simulation results, the operation manager insights into the material handling system opportunities, deciding to switch between a FT (higher passes) and a FB (lower passes) based on the operation plan, match factor and production targets. Further outcomes are operation KPIs such as queuing time, number of trucks, trucks queue at the shovel, cycle time, production cost per ton, and initial total production for both FT and FB. Short-term production analysis and deep comparison between two loading strategies are checked, and elements that induce this dynamic change are studied and analyzed using suitable machine learning. Finally, it highlights all associated mining operation parameters that determine the potential sweet spot of the loading strategy.

1. Introduction

Mining and hauling are significant components of a mining project. Whether a mining project is based on surface or underground, loading and hauling still contribute to a significant proportion of the running operation costs ranging from 50-60% Upadhyay et al. (2021). Reducing these costs is a major factor in sustaining operation time and operating costs, whether through equipment technological enhancement, operator skill efficiency, complex dispatch systems, or even modern clouding systems and various loading strategies; operation enhancement is essential and valuable for any mining project in the upcoming time.

When considering loading strategies and practices in truck shovel loading and hauling material operations, investigating opportunities for enhancing and reducing these costs and productivity losses in the running operation, especially when operations run in unpredictable, uncertain conditions that cannot be determined or planned. This will pose tremendous pressure and risk on the operation and the available optional alternatives for fleet configuration and loading strategies. For example, when truck or shovel breakdown or their availability is reduced, and they are no longer serving the trucks due to various operating reasons, a decision should be interfered to enhance the operation (whether integrated into the dispatching system or not).

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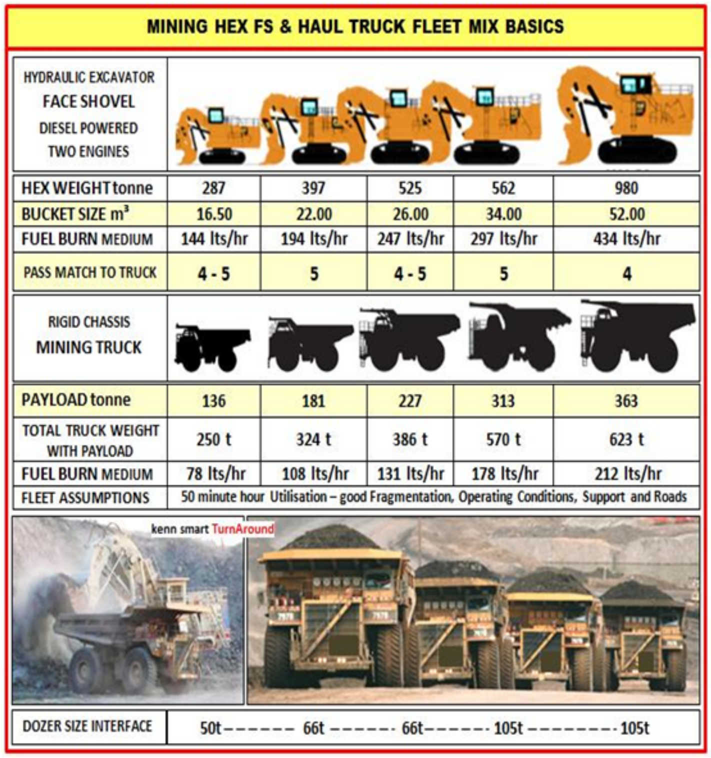
Uncertainty is not related to the equipment and fleet level alone. It expands to almost everything in the mining life; because high uncertainties with different magnitudes characterize mining. For example, commodity prices fluctuate from time to time due to various reasons that are related to supply and demand or due to unexpected events like COVID-19 and it is consequences, other factors like human factors (operators to the high management) and skills that will not be as planned to perform its role. Other significant uncertainties are related to the material in the mine (geological level), whether ore or waste and how it is extracted. This material has in place characteristics that differ when disturbed and dug up, inheriting the original characteristics with more voids (swelling) and less density per volume. In order to liberate this material from undisturbed to disturbed situations, blasting is a usual operation associated with extracting the material; uncertainties and efficiency of the conducted blasting are common things that change the final material fragment size, type, ore-waste mix, dilution, density, roundness and other factors. Consequently, when the shovel bucket encounters the material in the bench face, these uncertain parameters will affect the final material filled in the bucket; hence the final payload that is passed to the truck in a certain number of passes is also affected, especially the last pass.

Payload is another essential concept; the final payload affects and contributes to payload policy which will aid and determine whether the final truck load is good, under, over or even rejected in some cases, some systems use the conventional loading without any sensors monitoring the payload whether in shovel or truck other systems are evolving but with a marginal payload accuracy ~5%, newly systems are now emerging to monitor the dig, payload, material and send it to clouding system for further monitoring and analysis. It is also important to mention that the final payload affects the cycle time and is affected by operator skill. Moreover, the higher payload values will increase the maintenance costs of trucks and fuel consumption due to the high engine loading and mechanical fatigue frequency.

Truck shovel loading strategies have been a dilemma in loading payload and the number of passes; whether underloading or overloading the truck, each decision has its pros and cons and directly affects the efficiency. For instance, saturating a shovel to reach 100% efficiency or over will result in queuing conditions, and undersaturation of the shovel below 100% will result in higher costs.

Equipment matching is problematic as well; whether accounting for performance or production rate or operating costs or environmental impacts or operation constraints (grade, weather, accessibility, facilities matching), there will be a difference in the final results of the passes (decimal passes) and whether these passes will be rounded up or down, depending on the number of trucks and shovels, Figure 1 depicts this struggle and gives an example on the hydraulic shovel with various trucks configurations.



MINING HEX FS & HAUL TRUCK FLEET MIX BASICS					
HYDRAULIC EXCAVATOR FACE SHOVEL DIESEL POWERED TWO ENGINES					
HEX WEIGHT tonne	287	397	525	562	980
BUCKET SIZE m³	16.50	22.00	26.00	34.00	52.00
FUEL BURN MEDIUM	144 lts/hr	194 lts/hr	247 lts/hr	297 lts/hr	434 lts/hr
PASS MATCH TO TRUCK	4 - 5	5	4 - 5	5	4
RIGID CHASSIS MINING TRUCK					
PAYLOAD tonne	136	181	227	313	363
TOTAL TRUCK WEIGHT WITH PAYLOAD	250 t	324 t	386 t	570 t	623 t
FUEL BURN MEDIUM	78 lts/hr	108 lts/hr	131 lts/hr	178 lts/hr	212 lts/hr
FLEET ASSUMPTIONS	50 minute hour Utilisation – good Fragmentation, Operating Conditions, Support and Roads				
DOZER SIZE INTERFACE	50t------ 66t ------ 66t------ 105t -------- 105t				

Figure 1. Equipment and pass matching in a hydraulic shovel (Kenn Smart, 2011).

2. Literature Review

The literature summary aims to gain a more comprehensive understanding of earlier work on fleet simulation. Then delving into high-level focused literature relevant to the full truck (FT) and full bucket (FB), i.e., truck-shovel loading strategies and the associated KPIs in open-pit mining. The following sections discuss other interesting literature comparable to FT and FB loading strategies: starting with theoretical simulation history and methods. Then hands on the relevant and non-traditional methods, the discussion moves on to the software that uses Discrete Event Simulation (DES) and, later, a discussion on the literature related to fleet productivity and cost. Lastly, it highlights some literature on match factor and other related strategies. Finally, a conclusion of the related literature to the FT and FB.

2.1. Simulation Types and Techniques

This section discusses the concept of simulation that different researchers defined in addition to simulation purposes and the followed methodologies related to the mining fleet operation simulation. Banks and Nelson (2014) classified simulation models into static and dynamic models. A static simulation model represents a system at a particular point in time, while a dynamic simulation model represents a system that changes over time. It is further classified to:

- *Deterministic versus stochastic models*: a deterministic simulation model contains no random variables, e.g., a linear programming model, while a stochastic simulation model has one or more random variables as inputs and outputs, e.g., a queuing model.
- *Discrete versus continuous models*: a DES model represents a system in which the state variables change only at a discrete set of points in time. For example, a truck-shovel system is a typical discrete system. On the other hand, a continuous simulation model represents a system in which the state variables change continuously over time, such as a system associated with flowing fluids.

Bauer and Calder (1973) defined simulation as a concept. They defined simulation as a modelling technique that can predict the change in the performance of a system. They divided simulation into probabilistic Monte Carlo Simulation and standard using mathematical equations. Earlier methods of simulation techniques were by Sturgul and Harrison (1987). They discussed the use of simulation models using GPSS programming language to simulate various situations, including coal mine dispatching and mine fleet for uranium mine expansion. Ataeepour and Baafi (1999) implemented Arena software in simulation models, improving mine productivity. The status of mine simulations in Canada, including software and case studies, was addressed in an earlier study of the simulation literature by Vagenas (1999).

Then moving to robust and specialized approaches using MATLAB and other platforms, Askari-Nasab et al. (2007) implemented DES to capture random field processes in open-pit and material simulations using MATLAB. Shawki et al. (2015) implemented Arena software to improve excavator performance indices. Tabesh et al. (2016) implemented a simulation approach by incorporating truck shovel operations, road networks, stockpiles and other operations. They integrated the DES model into MATLAB, Excel and VBA to understand operation scenarios and uncertainties.

Price (2017) defined DES as "a modelling technique that is widely used to model complex systems". He also implied that comprehensive data from fleet management systems is rarely used to model fleets. The advantages include stochastic delays due to breakdowns and meal breaks, load and travel time, where some variables are random and dynamic, involving models that change with time. DES has been used extensively in different industries such as manufacturing, service providers, warehouse distribution, cashier checkout lanes market, department stores, airports, and mining. Price (2017) summarized the purposes of DES in mining as follows:

- Increase equipment utilization.
- Reduce waiting time and queuing.
- Study alternative investment ideas.
- Evaluate cost reduction ideas.
- Train operators in overall system operation.
- Support day-to-day decision-making.
- Minimize the effects of breakdowns.
- Understand the impact of mixed fleet interactions.

2.2. Fleet Different Simulation Approaches

Earthmoving operation literature is considered due to the lack of related literature in mining engineering, especially in the early stages and the similarities between construction operation trucks, off-road trucks and mining trucks. Earthmoving productivity calculation was conducted by Smith (1999), who estimated the productivity by regression analyses; his findings showed a relationship between operating conditions and productivity. However, his analysis overestimated the operation's productivity when resources were not well known.

Several researchers have developed a system of earthmoving selection using an expert system technique (Alkass and Harris, 1988; Amirkhanian and Baker, 1992; and Kirmanli and Ercelebi, 2009). Chanda and Gardiner (2010) compared three methods of cycle time analysis productivity. These methods are simulation, artificial neural networks, and multiple regression. They benchmarked the results with a monitoring system in a mine and found that simulation underestimated and overestimated the results, and the other proposed methods showed better results. However, their data was case specific.

Smith et al. (1995) customized higher-level DES models using a programming language. They developed a DES model that was translated into a computer program written in C programming language. Morley et al. (2013) utilized DES by developing quantitative formulas; they reached that a decrease in production does not directly correlate with an increase in cost. Cheng et al. (2010) implemented optimization and simulation using Perei net for equipment allocation, considering cost and other parameters in a dynamic constraint.

Alshibani and Moselhi (2012) integrated simulation with optimization using real-time GPS. Some researchers developed a framework using genetic algorithms for simulation-optimization of earthmoving operations (Marzouk et al., 2004; Shawki et al., 2009; and Hsiao et al., 2011). Neural network systems were developed by Shi (1999) and Chao (2001) for construction practitioners to forecast truck selection as well as earthmoving operations and performance.

In the field of simulation and optimization in mining engineering, Moradi Afrapoli et al. (2019) developed a simulation-optimization framework that optimizes haul fleet size by implying heterogeneous and homogeneous fleets of various sizes and recommending that equipment failures and maintenance should be evaluated for the optimal fleet size. Moradi Afrapoli and Askari-Nasab (2019) explained in a review that connecting the strategic part of the mine plan to the operational part is difficult. However, the operation should achieve both the long-term and short-term goals. They also emphasized technical and geological uncertainty that are crucial components in fleet systems management, and the shovel relocation to new mining cut associated losses should be understood well. A multi-optimization model was created by Mohtasham et al. (2021) that determines the optimal production plan for the shovels and allocates the mine fleet in an optimal production target, head grade and fuel consumption. Upadhyay et al. (2021) developed a simulation-based algorithm that estimates the productivity under technical uncertainties, giving a solution with higher accuracy and lower dependency on haulage distance.

2.3. Simulation Software

There are several simulation software tools that one can use to model a material loading and hauling in a mining operation. Some software programs involve learning the related programming language, while others have an interactive interface with pulldowns/command line. The simulation software, programs and models for truck shovel analysis can be summarized as follows:

- Iterative models that fit discrete empirical values to cycle variables, e.g.: machine repair model.
- Regressive models modify waiting time by using correction factors such as FPC ® by Caterpillar.
- Stochastic Monte Carlo models by fitting probability distributions to cycle variables, e.g.: Talpac ® and Haulsim ® by Runge Software.
- Stochastic graphic simulation following probability distributions within Monte Carlo simulation e.g.: Arena ® by Rockwell Software.
- General purpose simulation programming languages system (GPSS/H ®) by Wolverine Software and SIMAN.
- Simulation based on programming languages, C++ (C environments), Python and Java.

2.4. Cost, Production and Loading Times

In payload analysis, the literature reveals many different claims, findings and disagreements in balancing the payload, production, cycle time and passes loaded. Smith et al. (1995) concluded that the additionally loaded bucket is an advantage provided the truck is not overloaded. Furthermore, they figured out that spotting and loading time similarly affect production; hence reducing operation cycle times is important for achieving maximum production. They also discussed the interactions of four factors in earthmoving operations: production, match factor, passes per load and load pass time. They concluded that adding trucks would not increase production. According to Schexnayder et al. (1999) payload weight affects incremental production; they emphasized matching the number of bucket loads to fill a truck as an integer number. Hardy (2007) claimed that overloading trucks would increase productivity associated with increasing unit cost. Marinelli and Lambropoulos (2012) examined cost comparisons between loading and hauling. They came to a conclusion that, depending on the hauling distance and the volume of the last pass, a loading procedure could result in a significant cost decrease. Morley et al. (2013) concluded that the four to six passes rule is not applicable when dealing with real earthmoving applications due to equipment combinations such as smaller excavators and larger trucks. They also concluded that considering trends, trucks and excavators must be analyzed separately. They also implemented that using a loader to satisfy production requirements and then selecting trucks after will result in a higher per unit cost; consequently, this may result in a high production cost to keep the loader always utilized. Soofastaei et al. (2016) developed a DES model to investigate the payload variability on trucks in order to improve productivity and energy.

Carmichael and Mustaffa (2018) examined the loading policies and environmental impacts, including loading in zero waiting time and double loading. They concluded that the former had the least impact on the environment and optimal cost advantage while the latter had the highest environmental impacts and non-favourable costs.

2.5. Match Factor

The match factor (MF) is an important indicator of a mining operation's efficiency. Burt and Caccetta (2018) defined the match factor as a measure of the fleet productivity. It is a ratio that matches truck arrival rate to loader service rate. Their definition included over-trucking (MF>1) in which the loader is 100% efficient, and trucks are queued. In contrast, when loaders are waiting for trucks the MF is less than one. There is no queueing at the loader when the match factor equals 1; this is the optimal situation but not achievable realistically due to bunching and maintenance. Krause and Musingwini (2007) named terms as over-equipped when trucks are more than required and under-equipped when there are few trucks. The consequences of an over-equipped situation will increase the capital cost substantially while the whole under-equipped situation will not achieve the planned short-/long-term production. Dabbagh and Bagherpour (2019) examined the MF in their analysis using the ant colony algorithm; however, they state that it is not correct enough. They suggest using a detailed match factor which increased the production by ten percent.

2.6. Other Approaches to Evaluate Payload

Operators' score was suggested by Yaghini (2021), who presented an approach to characterize and evaluate the payload using the operator ranking systems. The score is calculated based on the truck, shovel and mine productivity indices. He concluded that the operator with the highest score would typically load trucks to a higher capacity with less cycle time and load passes. Furthermore, he suggested a term called dynamic target loading (DTL), which modifies the conventional 10:10:20 rule by reducing term passes loading practices and giving the operator a flexible load range; consequently, the loading cycle and queue are reduced. This analogy, reducing trim passes, is comparable in concept to the FB analysis adopted in this research. Production is also covered as a project KPI that provides feedback about bucket payloads and cycle time enhancement opportunities.

2.7. Related Research

Recently, Tapia et al. (2021) investigated loading methodologies in an open-pit mine. They used FT and FB scenarios by creating simulation models using Talpac software to understand cost and production analysis and how they relate to cycle and queuing time. They further adapted Activity Based Costing (ABC) models, "which are built on the concept that resources usage is not a function of the amount of the final product, but rather, resources are consumed by the elementary tasks and processes required to produce a unit of the final product" as defined by Botín and Vergara (2015). In order to calculate production per cost, Tapia et al. (2021) concluded that a decision must be made when a situation requires a change. They argue that mining projects will favour the FT strategy over the FB till a specific transition point at which the operating cost of the FB is favoured. Mustaffa (2021) investigated the impact of alternative loading practices on production and emission using Monte Carlo Simulation to compare these practices. The results showed that double-sided loading has the lowest effect on the environment. However, it is not always doable because it is limited to specific mining conditions, and cannot be generalized. In addition, filling one bucket more than the full load can result in greater overall productivity, lower emissions, and reduced truck cycle time, which may lead to a production increase. Other similar loading terminologies in earthmoving are fractional loading as in Mustaffa (2021) known as fractional loading practice, which indicates that each truck gets loaded to a minimum of passes. However, it could be filled to higher passes if additional time is allowed, the arrival of the next truck and varies between trucks. A similar term called multiplier loading practice assumes minimum passes are used, but there could be an extra pass depending on the loader's available time. This will yield higher payloads and production rates associated with fuel consumption increases due to longer cycle time and loading time.

2.8. Summary of Literature Review

Based on findings from the previous literature, a significant part of the research is covered by earthmoving trucks in simulation. However, there are many similarities between earthmoving trucks and mining trucks; a real mining equipment evaluation and simulation will add more realistic value to the FT and FB approach. Other literature was conducted using different simulation approaches, which could be time-consuming and not flexible.

The previous work also reveals some discrepancies when dealing with the costs, utilization and production, which could be due to the adapted simulation method or operation properties. Which is still not fully understood, and there is no comprehensive framework available to understand the operation more thoroughly in open-pit mining loading practices. It is vital to note that no research used a machine learning system to understand and anticipate the data from an FT and FB analysis utilizing Haulsim software. Furthermore, no literature offered any guidance or suggestions for modifying loading techniques in developing autonomous trucks and shovels and future level 5 mining.

3. Methodology

The theoretical framework of the proposed FT and FB simulation approach in both a holistic way in mining operation and a detailed approach will be discussed with a profound explanation, as well as further analysis of the simulation results, starting from the data which was imported as a schedule data from an external software that is used in Haulsim software. Then the equipment configured in Haulsim and the final DES results are interpreted and analyzed, and more analysis of the operation parameters and the results from simulated data is analyzed using Python programming language, where exploratory data analysis is conducted. Lastly, a machine learning classification model is created to predict the loading strategies based on the provided data that more understands the operation parameters and evaluates these parameters that trigger switching between loading strategies.

Locating the FT and FB in the broad frameworks, in the beginning, allows understanding where the research topic is focused as Figure 2 illustrates the general view of FT and FB loading in mining operation. When a shovel with force applied to the working bench excavates to scoop (tuck, engage, dig, release, swing and pass); the required material that has recently been blasted with characteristics reflecting the nature of that material; loose density, fragment size and excavatability, will affect the final bucket fill factor (BFF). This stage is performed by an operator with a scalable average efficiency and equipment; shovel with a known average utilization and availability. The following sections will discuss the material characteristics.

a. Shovel-Material Interaction

Because loading and hauling are the following processes after blasting, assessing post blasting of material in the mining operation is necessary when the distribution of fragmented material controls truck and shovel production rates, resulting from blasting. As the blasting efficiency increases, the final production increases. Blasting efficiency is increased by optimizing blasting design when the objective fragmentation size is determined. Fragmentation is affected by uncontrollable parameters, including the physical and geomechanical properties of the material. Coarser material led to higher energy consumption, increase in wear rates and a decrease in the loading and hauling productivity, final crusher and mills throughputs. In addition, fragmentation size affects fill factor and payloads. Dotto and Pourrahimian (2018) mentioned that poor fragmented material results in boulder sizes that are too big to handle and affects productivity negatively. Therefore, optimal fragmentation is essential for truck and shovel productivity.

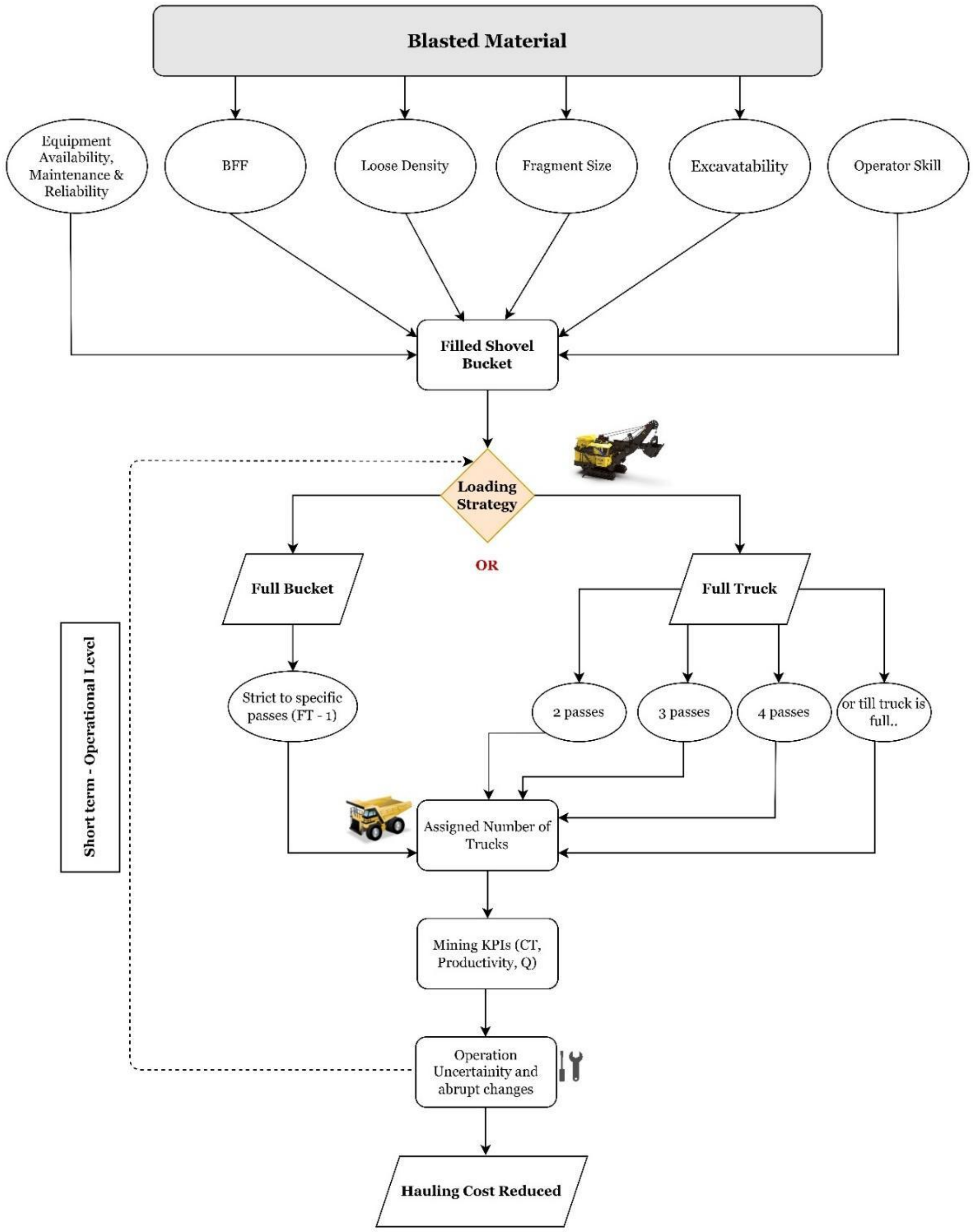


Figure 2. FT and FB flowchart in a mining operation.

Good fragmentation will result in a good heap in the bucket, while over fragmentation will make material flow more due to fines and no heaping will be formed in the bucket. Diggability which is a term used to describe how easily the material can be dug by the shovel, measured by specific dig energy. Loadsman et al. (2013) mentioned that as digging material gets harder, the payload decreases and the energy to fill increases.

Assessing the operational time in mining hauling and loading operation is important for measuring the operation's KPI. Figure 3 illustrates time usage model presented by Global Mining Guidelines Group (GMG) (2020).

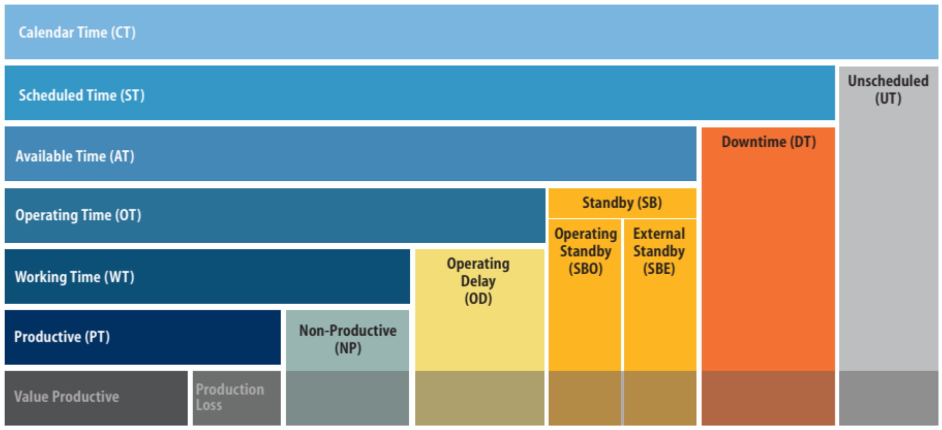


Figure 3. Time usage model (GMG - Time Usage Model, 2020).

b. Operator Skill and Efficiency

Khorzoughi and Hall (2016) studied the effect of operator skills and loading efficiency. They compared operators' KPIs in the loading and hauling operation, including passed payloads, productive cycle time, equivalent digging energy and loading rate. Yaghini (2021) emphasized that the operator role in truck shovel loading is important and greatly influences the operation's productivity and efficacy. Through operator skills and loading habits, he quantified and proposed a scoring system for evaluating the operator skills in the operation, taking into consideration the operator's payload, shovel's cycle time and other KPIs to finalize the operator rank from best to worst. All the previous performance indicators will affect the final payload in the shovel bucket, which has a specific capacity and range of filling material in the shovel bucket that will vary from struck to heaped as a filling percentage of 90 to 110% of the bucket capacity assuming average loading conditions.

c. Shovel Loading Truck (Digging and Filling)

After the bucket is filled by an operator from the shovel, the payload is passed to the truck with a set number of passes, depending on the passes required to fill the truck and the pass and equipment matching configuration. It is common in mining operations that hauling trucks are at least 100% loaded or exceeding 100% of their final load capacities depending on whether companies are strictly applying the loading policy or not and their actual compliance with these policies and skilled operators. In this step, the proposed loading strategies are involved and a proposed operational decision should be taken to proceed with the scenario of shovel's loading strategy as a FT or FB.

Before proceeding with these terms, there should be a definition for them, which could be defined as the following: shovel that loads in a fully bucket; the truck requires less than a FB load to reach its payload. Therefore truck will travel underloaded, and the additional pass time is not wasted (Haulsim, 2022). Another definition by Tapia et al. (2021) defines it as saving the additional pass of the loading equipment. While FT loading assumes the loader always tries to fill the truck, even if the last pass only requires a small portion of a bucket load. Therefore this additional pass will consume more time in shovel loading and queuing conditions will occur (Haulsim, 2022).

d. Assigned Trucks

The assigned trucks are based on MF as a reference; the usual value for MF in mining operation is 1, which means 100% efficiency. However, MF is uncertain and varies through short-term operation due to various uncertainties. Therefore, in this paper multiple trucks (1 to 30) are analyzed to determine MF values with shovel configurations. Then FB and FT loading strategies are evaluated based on the selected fleet.

e. Operation Parameters

A set of operating configurations is usually prepared before running the simulation. This includes the hauled material, mining and hauling equipment data (capital costs, operating costs, operating data), shifts configuration as scheduled and unscheduled operating and non-operating time and rolling resistance.

f. Operation Uncertainty

Generally, the mining operation is classified as considerably uncertain and unpredictable with time. In the mining equipment arena, the uncertainty and unpredictability of equipment are common, especially when equipment is getting older, this includes short and long delays, stoppages and breakdowns due to various reasons, whether related to the smallest scale mining operation or to the largest scale market situation that effect mining decision or any other reason. This research approach demonstrates shovel breakdown as an example of fleet uncertainty. Other reasons can be crusher reduced efficiency, stoppage, blasting efficiency, or variability in the material in mine. It is also known that any accident or unplanned incident will affect the operation, and a feasible option is available when adapting a modified loading strategy. Further focusing on the scheduled and unscheduled delays.

These various uncertainties in mining operation will affect the continuity of production rate and operation cost. In this research assumption, one of the shovels is stopped, or its availability is decreased for a particular time due to various reasons, as discussed previously.

g. Match Factor

In the research, the MF is calculated as a normal operation running assumption, with a set number of trucks assigned to the shovel to understand the effect of changing the number of trucks, which reflects on the final MF. However, when the shovel breaks down, MF surges to 1.5, accompanied by an increase in the number of trucks reassigned to the remaining working shovel Figure 4.

After the equipment matching for operation is done, a short-term mining operation schedule for a specific period for the operation is imported into the software. This schedule includes the sources (shovels) and destination in addition to material quantities and time steps. Next, running the operation at a MF of one, assuming two shovels are running the operation. There are assigned trucks to each shovel that are homogeneous and dependent (same trucks type and assigned to the same shovel) but with a similar destination target, the crusher.

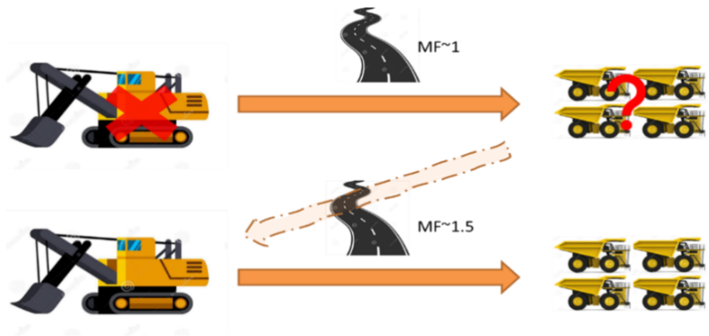


Figure 4. Reassigning trucks assumption in research methodology.

The varying number of trucks to mimic the operation uncertainty and shovel stoppage changes the MF when operation uncertainty is encountered. Here in our assumption, the second shovel is no longer operating for a specific period of time due to major mechanical failure. As discussed previously, other operation uncertainty could affect the fleet haulage. Based on the unutilized trucks, these trucks are redirected to the first shovel (the working shovel), and the match factor will increase to 1.50. In this stage, a decision should be made to switch between the loading strategy from FT to the FB; the obtained operation KPIs control this switch, mining roads cycle times and the reduced costs associated with this switch.

Figure 5 illustrates the methodology and the approach followed in comparing FT and FB.

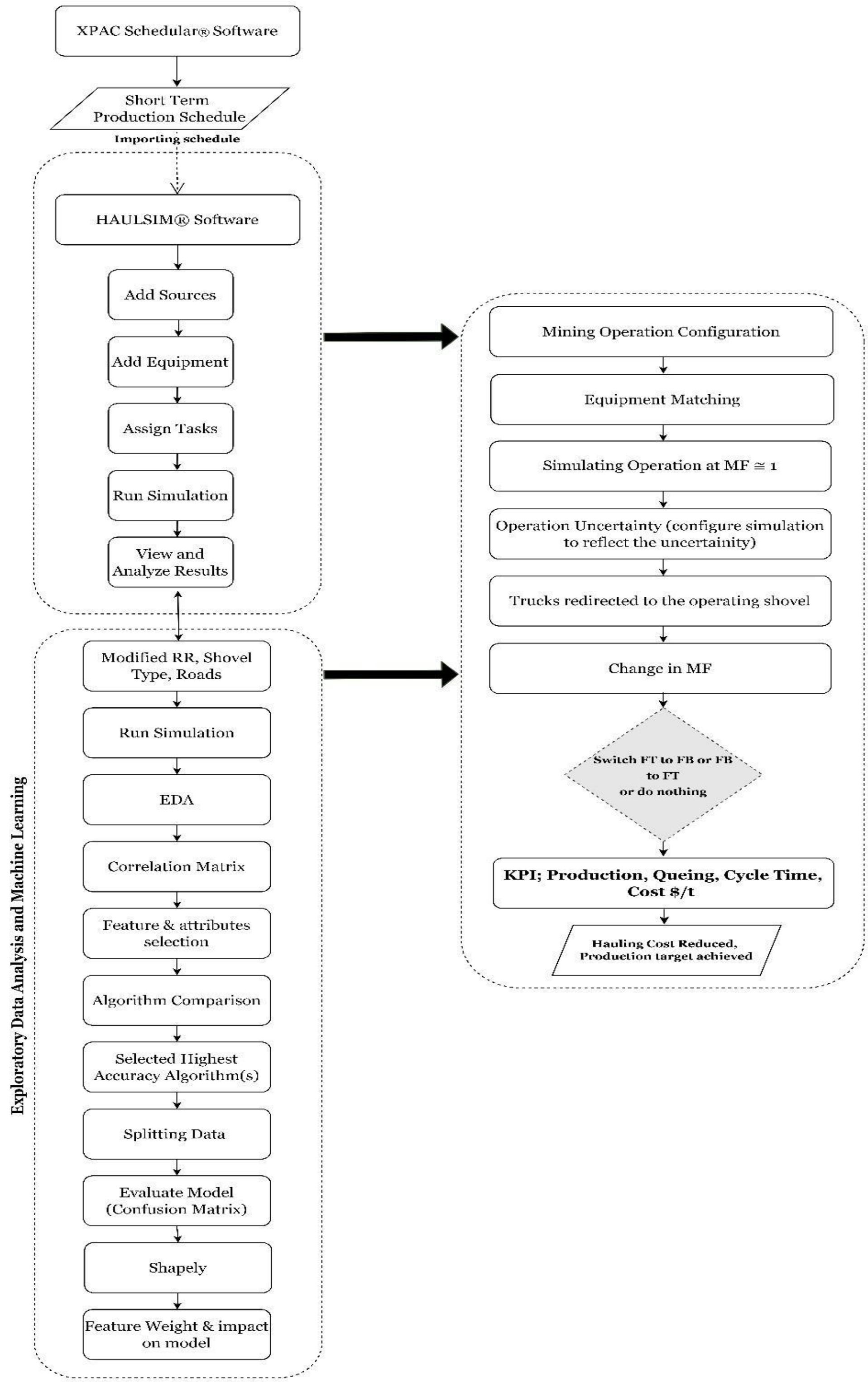


Figure 5. Detailed framework in FT and FB.

4. Case Study

Scheduling data for a gold mine was exported from a scheduling software OPMS and imported to the Haulsim.

a. Material characteristics

The selected material in simulation is high-grade sulphide (HGSx). Table 1 summarizes the material's characteristics.

Table 1. Hauled material characteristics.

Material Characteristics		Unit
In-situ Bank Density	2.4	t/m^3
Swell Factor	1.25	-
Loose Density	1.92	t/m^3
BFF-Heaped	97.5	%
BFF-Struck	97.5	%

b. Equipment Data

Operating and costing data for the mining fleet are included in the simulation for both shovels and trucks. The shovels used in the simulation are P&H 2800 XPC and the trucks are CAT 793 F. Table 2 presents shovel configuration data. Table 3 presents the configuration of the truck CAT 793 F.

Table 2. P&H 2800 XPC shovel used data in simulation.

Shovel P&H 2800 XPC			
Operating Data	Capacity	32.78	m^3
	Bucket Cycle Time	40	sec
	Filled Capacity	31.96	lcm
	Filled Payload	61.49	t
	Maximum Production Rate	5533.95	t/h
Costing Data	Purchase price	19,714,300	$
	Life	20	years
	Owning Cost	101.27	$/hour
	Operating Cost	129.95	$/hour

Figure 6 illustrates the distributions used for the shovel's loading time and bucket payload. For shovel loading time, the mean value is 40 seconds, and the distribution is skewed to the right. At the same time, the payload factor is one and skewed to the left. Figure 7 illustrates the distributions used for trucks. For truck dump time, the mean value is 30 seconds. Moreover, for the truck's load and carry time, the estimated mean of the value of which there is a 50% probability of occurrence, the mean value here is 40 seconds.

Table 3. CAT 793 truck data used in the simulation.

Truck Cat 793 F			
Operating Data	Capacity	175	m^3
	Actual Capacity	117.89	lcm
	Payload	226.8	t
	Dump Time	60	sec
	Spot Time @ Loading	24	sec
	Spot Time @ Dump	18	sec
Costing Data	Purchase price	3,568,900	$
	Life	15	years
	Owning Cost	24.44	$/hour
	Operating Cost	435.28	$/hour

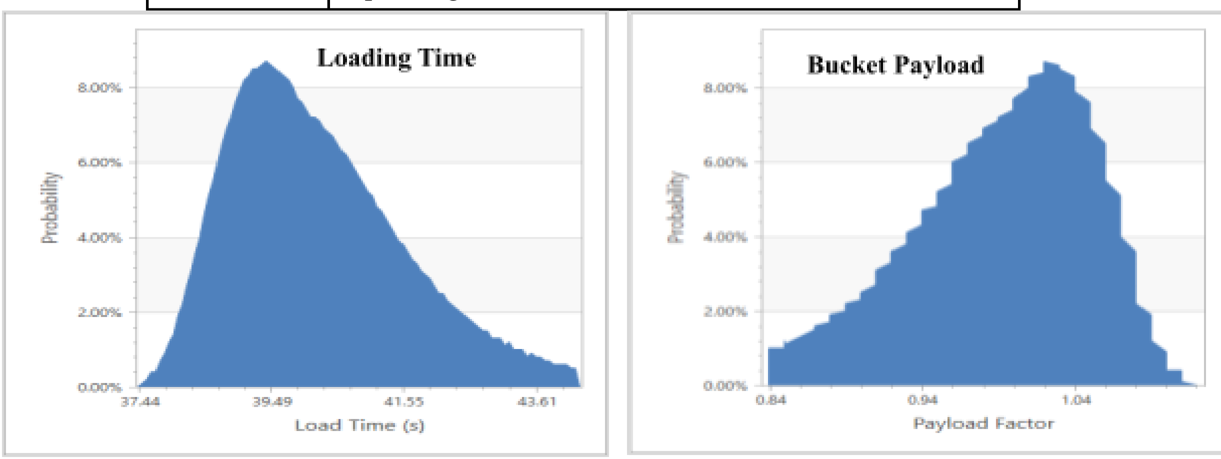


Figure 6. Distribution data for P&H 2800 XPC.

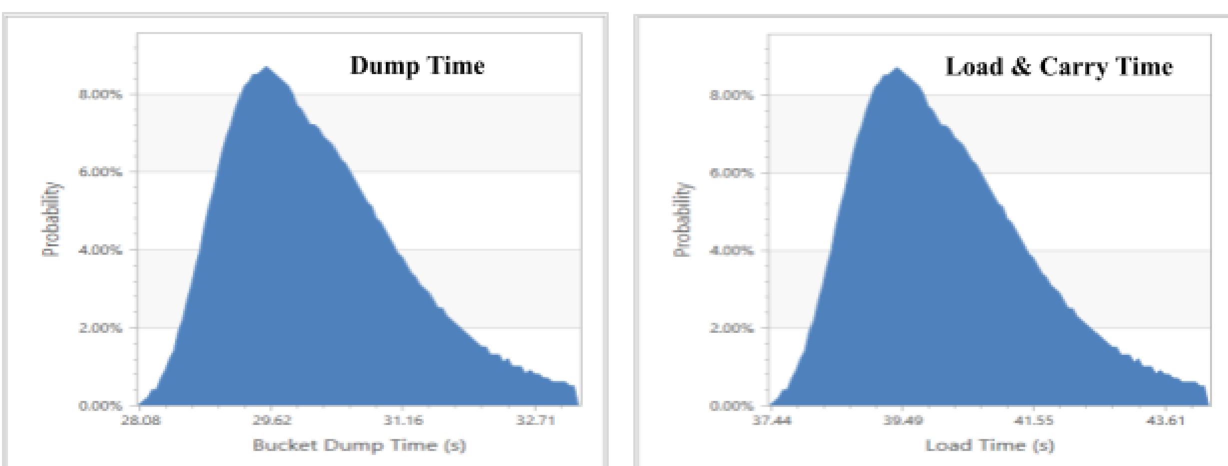


Figure 7. Distribution data for CAT 793 F.

c. Shifts and Working Times

Table 4 represents the time model used in the simulation. The non-operating shift delays are 30 min and the operating delays are 60 min in each shift; therefore, the actual working time in a shift will be 6.5 hours. Shovel and truck availability is assumed to be 85%.

Table 4. Shifts data and effective working times.

Working Time		
Mon-Fri	5	days/week
Shift Duration	8	hours
Non-Operating Shift Delays	0.5	hour
Shift Operating Time	7.5	hours
Operating Shift Delays	1	hour
Shift Working Time	6.5	hours
Shovel Availability	85	%
Truck Availability	85	%

d. Roads and Cycle Time Analysis

Two mining haul roads were implemented for simulation (denoted as R1 and R2) as in Figure 8. Each road begins in a bench face and ends in the crusher. Both working benches have high-grade sulphide (HGSx). The length of haul road 1 (R1) is 3.46 km and haul road 2 (R2) is 2.65 km. The maximum grades in R1 is 10.6 %, and in R2 8.76 %. Both road has a rolling resistance of 2%. Each haul road segment's final cycle time is different due to varying distances and the accompanied cornering speeds.

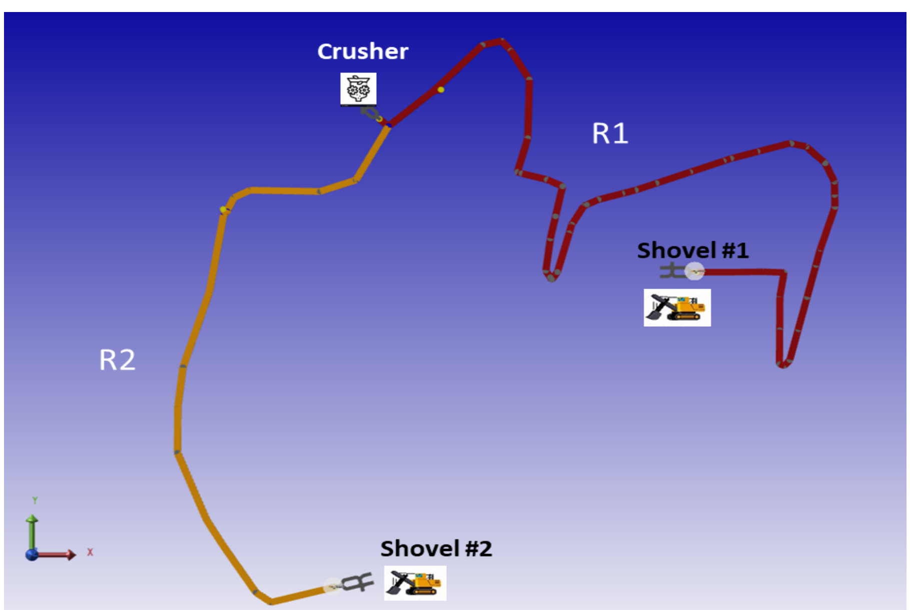


Figure 8. Haul roads layout.

The cycle time analysis was done for one truck only and one shovel to understand and analyze the differences between the haul roads. Table 5 presents the results for both the FT and FB scenarios in haul road 1 and haul road 2. Results show that cycle time with a FB loading strategy takes less cycle time (including truck travel times) than FT. This is due to the fact that the trucks have a less payload in FB scenario and consequently they travel uphill faster. In haul road 1, the cycle time in FT loading strategy is 23.42 min while in FB loading strategy is 21.68 min. There is a 7.4% difference between two loading strategies. FT travelling time also has a 8.7% difference because of the same reason explained for the cycle time. The reverse time has no differences between the loading strategies because the trucks are empty and travel on the same road in both scenarios. Analyzing haul road 2 cycle time shows FT and FB a 6.83% difference between the loading strategies. Travelling time has the same case as road 1 with a difference of 1.25%. The lesser difference can be interpreted as haul road 2 has less distance, almost 40% than haul road 1. Another reason for the difference is the rise and run and grades that are higher in road 1 over frequent segments; this affects the cycle time and travel time.

Table 5. Cycle time analysis for haul roads within loading strategies.

	Haul Road 1		Haul Road 2		
	Shovel	**Truck**	**Shovel**	**Truck**	**Unit**
	P&H 2800 XPC	Cat 793 F	P&H 2800 XPC	Cat 793 F	HGSx
FT Loading	Distance	3463.57	Distance	2064.89	m
	Travel Time	0:12:16	Travel Time	0:04:17	hh:mm:ss
	Reverse Travel Time	0:07:17	Reverse Travel Time	0:03:44	hh:mm:ss
	Total Distance	6927.13	Total Distance	4129.79	m
	Total Travel Time	0:19:33	Total Travel Time	0:08:01	hh:mm:ss
	Total Cycle Time	0:23:25	Total Cycle Time	0:11:53	hh:mm:ss
	Payload	226.80	Payload	226.80	tonne
FB Loading	Distance	3463.57	Distance	2064.89	m
	Travel Time	0:11:12	Travel Time	0:04:11	hh:mm:ss
	Reverse Travel Time	0:07:17	Reverse Travel Time	0:03:44	hh:mm:ss
	Total Distance	6927.13	Total Distance	4129.79	m
	Total Travel Time	0:18:29	Total Travel Time	0:07:55	hh:mm:ss
	Total Cycle Time	0:21:41	Total Cycle Time	0:11:07	hh:mm:ss
	Payload	184.17	Payload	184.17	tonne

One of the important results in cycle time analysis is the average payload for both FT and FB. Due to the higher loaded pass tendency in the FT, the calculated average payload in cycle time analysis is 226.8 tonnes. In contrast, in FB, the average payload was 184.1 tonnes. The difference in final payload between loading strategies is 18%. Considering the payloads, the productivity per truck in haul road 1 is higher in the FT at a rate of 581.15 t/h while in FB, 509.55 t/h with a difference of 12.32%. Other parameters, such as Tonne Kilometres per Hour (TKPH) (which is an essential expression of the working capacity of a tire representing the load capacity in relation to heat generation) are lower in the FT with a value of 947.35, while in the FB, the value is 978.57. Loading truck full affects the TKPH negatively and reduces the tires life and equipment reliability with time, with the general understanding that lower TKPH means lower heat resistance which is not recommended for truck hauling and higher TKPH means higher heat resistance which means better truck hauling conditions. However, the lower TKPH has a higher cut and wear resistance. Additionally, the total fuel consumed is higher by 8% in FT (36.23 litre/trip) than in FB (33.47 litre/trip). The reason is the higher payload, which requires more engine power to move the truck hence more fuel consumption.

e. Match Factor Analysis

To understand the operation correctly, match factor criteria were selected as 1 and 1.5; the latter was selected because of increasing trucks and the availability of only one shovel in operation.

The normal hauling mining operation usually runs at MF equals 1. In the case study, this resulted in 10 trucks when the loading strategy was FT. With changing the loading strategy to FB, the proper number of trucks (at MF=1) was 12. This difference in the number of trucks is due to lower passes affecting the MF formula.

f. Production-Cost-Fleet Curves

The simulation model was run for a different number of trucks to capture the effect of MF change from 1 to 1.5 in FB and FT loading strategies. Figure 9 and Figure 10 show the cost-production fleet curves for the FT and FB, respectively.

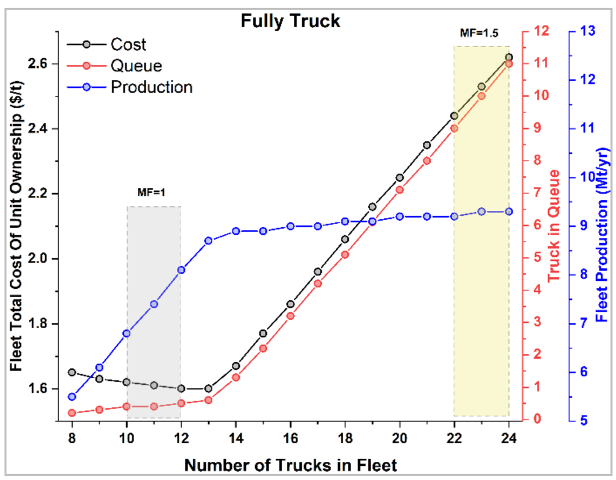


Figure 9. Cost-Production fleet curves for FT loading strategy.

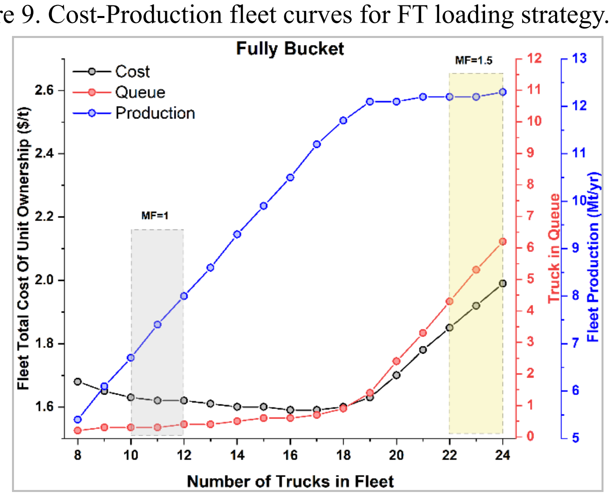


Figure 10. Cost-Production fleet curves for FB loading strategy.

In the FT loading strategy (Figure 9), with increasing the number of trucks in the fleet, the production increases until the number of the truck is equal to 13; after this point, the production slightly increases until the number of trucks in the fleet reaches to 24. In the FB loading strategy (Figure 10) the fleet production has a similar trend to the FT strategy, but the production still increases till the fleet size is equal to 19. Moving to the cost curve, in Figure 9 the cost decreases with the increased number of trucks until number 13; then it increases steadily until the last truck. The cost of the FB loading strategy decreases until the number of trucks equals 18, increasing afterwards. The increase in cost occurs earlier in the FT loading strategy. Finally, a comparison of the number of trucks in queue shows that at the beginning, there is a slight increase in both loading strategies. In the FT strategy, the number of trucks in the queue is insignificant until the fleet size is equal to 13; after this point, the number of trucks in the queue increases steadily until the fleet size is equal to 24. The FB strategy has the same behaviour, but the prominent increase in the number of trucks in the queue is stated after fleet size 18.

In Figure 9 and Figure 10, areas with MF of 1 and 1.5 has been highlighted. For MF of 1, the sufficient number of trucks is between 10 and 12. For this area, in the FT strategy, the total cost for hauling is between 1.60 and 1.62 $/t, while in the FB strategy, it is between 1.62 and 1.63 $/t, which is a small significant difference. Fleet production is the same case, 6.8 to 8.1 Mt/yr in FT and 6.7 to 8.0 Mt/yr in FB. Also, there is a negligible difference in queuing conditions between FT and FB strategies. Therefore, considering the cost, production, and number of trucks in the queue, the FT loading strategy is suitable when the MF is 1.

In contrast, when the MF increases to 1.5, the FB strategy works much better. This increase in the MF happens because of the uncertainty and unplanned equipment breakdowns or any operation stoppage or unplanned queueing that significantly affects the operation. This paper assumed that one of the shovels broke down for a time, and the trucks were sent to the other available shovel. When the MF is in 1.5, the shovel controls the operation. In this situation, the cost of FB strategy is much lesser than FT, ranging from 1.85 to 2.0 $/t, while in FT strategy, it varies between 2.45 and 2.65 $/t with a difference equal % 25. In addition, the production of FB strategy (12.25 Mt/yr) is much higher than the FT strategy. Another advantage for the FB when the MF is 1.5 is the number of trucks waiting for the shovel. The number of trucks in the queue for the FT strategy is double that for the FB strategy.

g. Machine Learning-Controlling Parameters in Loading Strategies

i. Data Preparation

In order to run machine learning properly and evaluate the model, the data should be cleaned and reflect the real situation of hauling operations in a mine. For this purpose, the raw data obtained from simulation for MF of 0.75 and greater were selected. The data for MF<1 was selected to understand the behaviour of operation parameters even with lower efficiency (MF<1) in the hauling operation.

ii. Exploratory Data Analysis (EDA)

An EDA using python programming language was conducted to understand and illustrate the resulting simulation data. Plus, the relationships between the input parameters in the hauling and loading operation and the parameters that control the switch between FT and FB strategies in the simulated loading and hauling operation. Starting from the original dataset containing 750 records with 22 attributes that resulted from Haulsim simulation and filtered out based on MF of 0.75, each entry represents the adapted loading strategy and the associated input data from simulation in the EDA.

A correlation matrix was generated to examine these relationships between operation loading strategies and selected parameters for the correlation approach Figure 11. Some input parameters are linearly correlated, such as cycle time and fleet size, the number of trucks queued, cost and fleet size. In contrast, other parameters, such as loader utilization, are reversely correlated with MF, such as loader utilization, especially when queuing condition occurs, it is reversely correlated but less strong with other operating parameters.

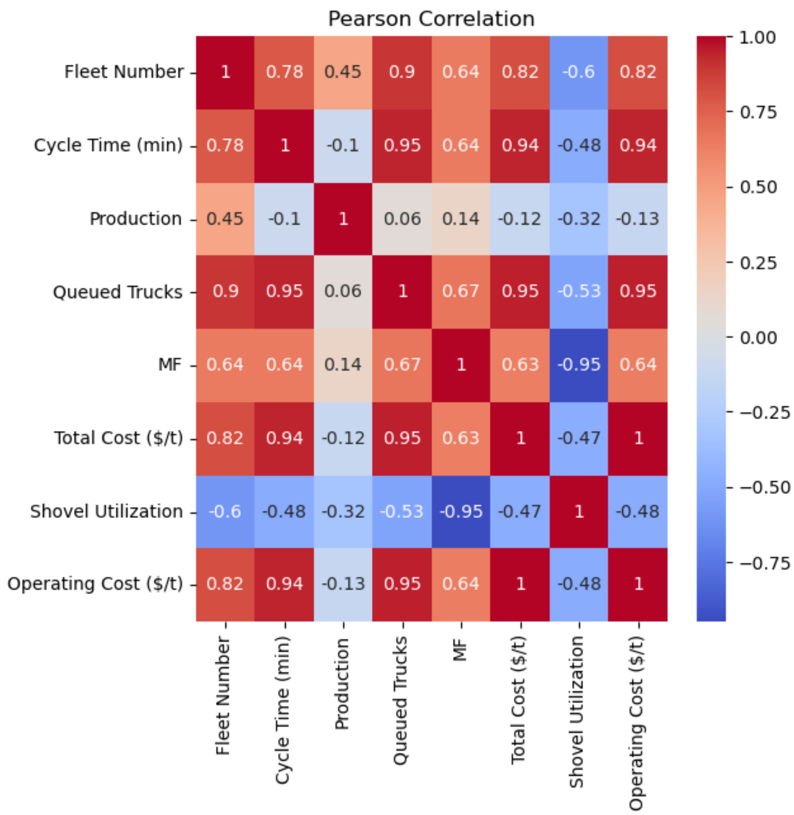


Figure 11. Correlation matrix for simulated data.

iii. Multiple Machine Learning Algorithms

In order to observe the best results of what could be simulated in operation, a set of models was prepared to examine the best recall results for various machine learning algorithms. Each model enters into train and test data. Figure 12 illustrates the comparison of the algorithms generated. These models are selected from the supervised machine learning under classification and regression models because the data set is labelled and training is possible for further prediction. The selected models are:

1) *Linear Discriminant Analysis (LDA)*

   LDA is a linear model for classification and dimensionality reduction that is used for feature extraction in pattern classification problems.

2) *K Neighbors Classifier (KNN)*

   KNN is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions of data.

3) *Decision Tree Classifier (CART)*

CART is a predictive model explains how an outcome variable's values can be predicted based on other values.

4) *Gaussian NB (NB)*

NB is a type of Naïve Bayes classifier algorithm used when the features have continuous values assuming all features have a gaussian normal distribution.

5) *Random Forest Classifier (RF)*

RF is a classification algorithm consisting of many decision trees.

6) *Support Vector Machine (SVM)*

SVM is a supervised machine learning model that uses classification algorithms for two classification problems.

Most algorithms showed a high accuracy median value except for the Gaussian NB algorithm, valued at 0.57. The LR showed the highest recall value at 0.9, followed by CART and the RF with accuracy values of 0.83 and 0.795, respectively. Therefore, machine learning implementation was done based on LR method due to its higher accuracy and the tendency of categorical values.

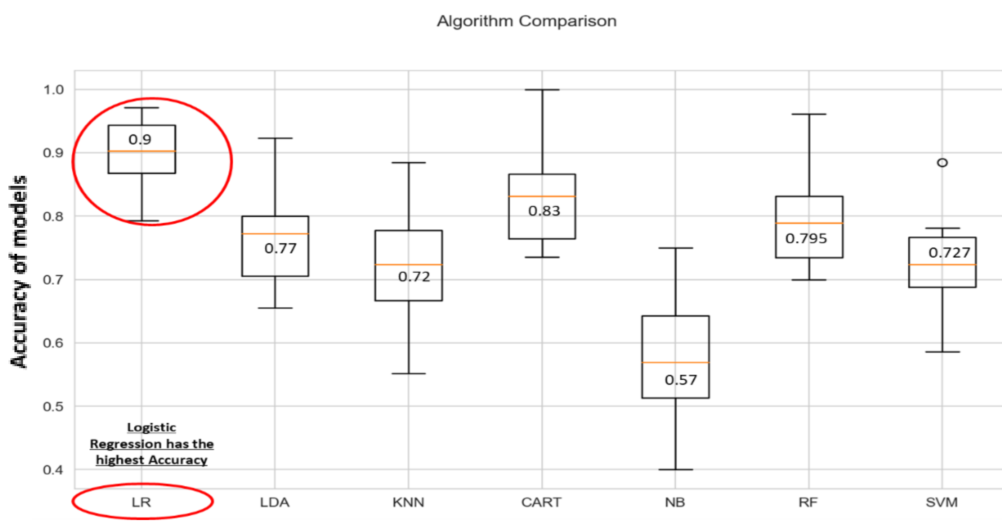


Figure 12. Analysis and comparison of multiple algorithms.

iv. Logistic Regression

The simulated data from various scenarios were implemented into the LR model to understand the effecting factors in the operation and to predict the loading strategy based on the selected data features. The training data feature included hauler fleet size, cycle time, trucks in the queue, MF and rolling resistance. The testing was based on 20% of the simulated data in 750 records, the confusion matrix illustrated in Figure 13 shows more than 90% accuracy in predicting the loading strategies.

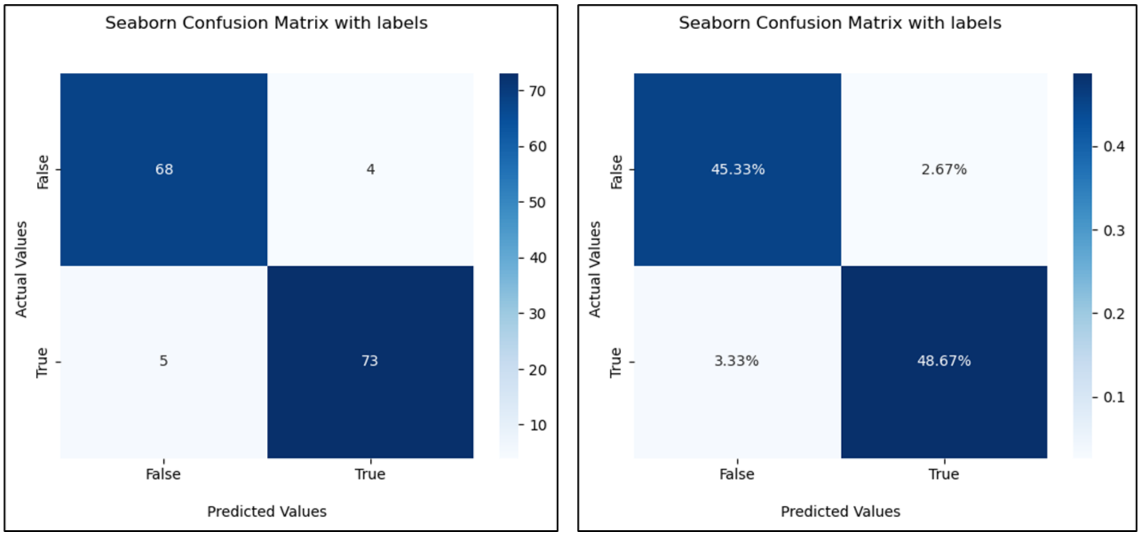


Figure 13. Confusion matrix for the logistic regression model.

v. Shap Values

Shap values (**SH**apley **A**dditive ex**P**lanations) is a cooperative game theory method used to increase the transparency and interpretability of machine learning methods. In Figure 14, the order of columns represents the amount of information accountable for in LR prediction, colour reflects the real data, and the x-axis represents the shap value impact on the model categorical decision (FT or FB). Each dot corresponds to an individual loading strategy in the simulation. The dot's position on the x-axis shows the feature's impact on the model's prediction for that strategy. When multiple dots land at the same x position, they pile up to show density.

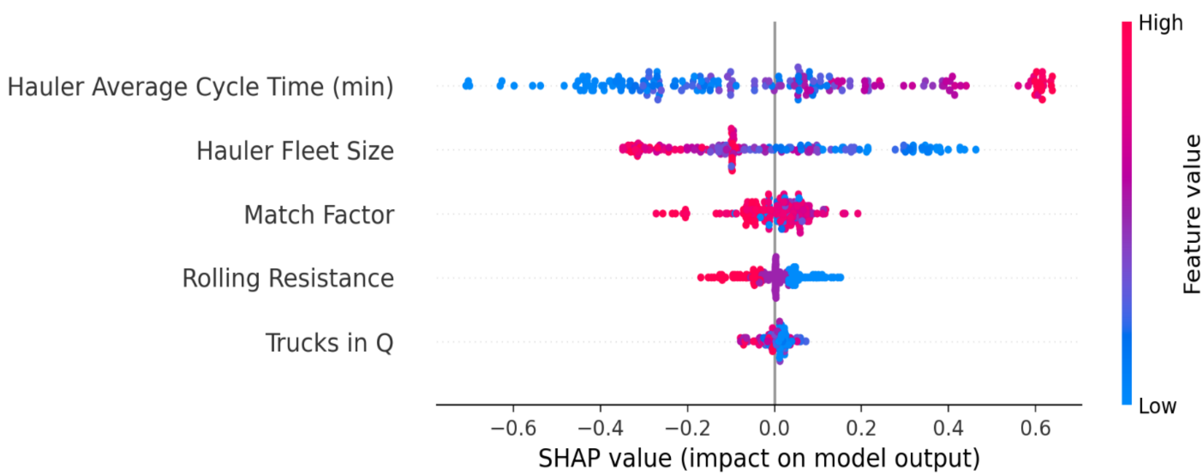


Figure 14. Set of bee swarm plots (revise) for the machine learning model.

Similarly, plotting the data in a different method, the cycle time contributes the most to the model prediction, followed by a fleet number as in Figure 15.

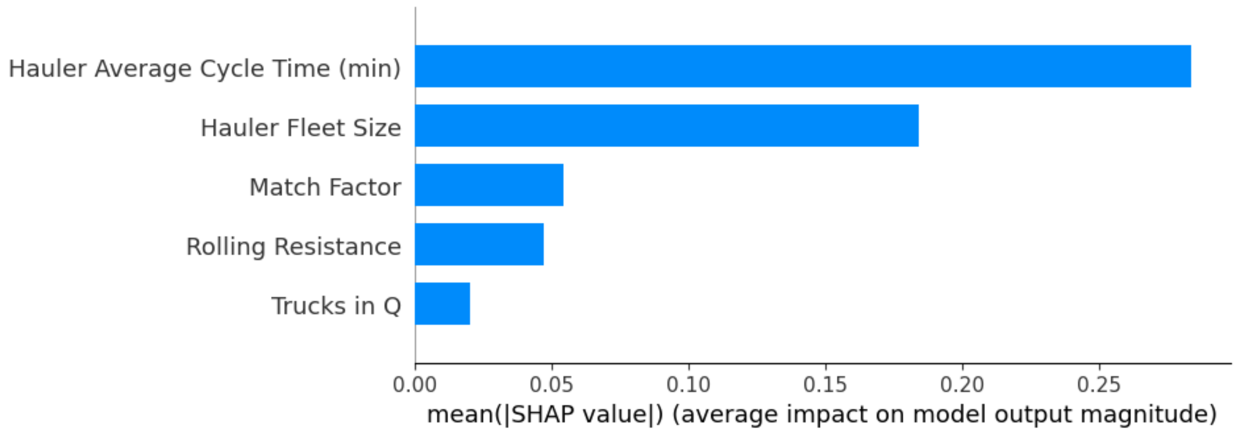


Figure 15. Bar plot Shapley feature importance in predicting model.

5. Conclusions and Discussion

The MF is equal one or averaged to one; the recommended loading strategy is FT based on balanced equipment and cycle times. When operation uncertainty is profound, there should be a consideration for changing the loading strategies in the fleet in order (i) to reduce the hauling costs (ii) to increase production and (iii) to decrease the number of trucks in the queue. In this situation, with switching from FT to FB strategy, the utilization of the shovel increases. The machine learning model showed that cycle time significantly contributes to the loading strategies in the mining operation. Autonomous trucks are promising areas in adapting this framework because they can decide more than the conventional operator. Also, linking the truck and shovel with clouding systems that evaluate the material will prioritize the loading strategy based on the current operation level conditions. These analyses showed that there is an opportunity that advantages the FB over the FT based on changing the match factor in operation, which is directly related to the shovel-truck loading time in a specific number of passes and number.

6. References

[1] Alkass, S., & Harris, F. (1988). *Expert system for earthmoving equipment selection in road construction*.

[2] Alshibani, A., & Moselhi, O. (2012). Fleet selection for earthmoving projects using optimization-based simulation. *Canadian Journal of Civil Engineering*, *39*(6), 619–630. https://doi.org/10.1139/L2012-042

[3] Amirkhanian, S. N., & Baker, N. J. (1992). *Expert system for equipment selection for earth-moving operations*.

[4] Askari-Nasab, H., Frimpong, S., & Szymanski, J. (2007). Modelling open pit dynamics using discrete simulation. *International Journal of Mining, Reclamation and Environment*, *21*(1), 35–49. https://doi.org/10.1080/17480930600720206

[5] Ataeepour, N., & Baafi, E. Y. (1999). ARENA simulation model for truck-shovel operation in despatching and non-despatching modes. *International Journal of Surface Mining, Reclamation and Environment*, *13*(3), 125–129. https://doi.org/10.1080/09208119908944228

[6] Banks, J., & Nelson, N. (2014). *Discrete-event system simulation.* (5th ed.).

[7] Bauer, A. D., & Calder, P. N. (1973). *Planning Open Pit Mining Operations Using Simulation*.

[8] Botín, J. A., & Vergara, M. A. (2015). A cost management model for economic sustainability and continuos improvement of mining operations. *Resources Policy*, *46*, 212–218. https://doi.org/10.1016/j.resourpol.2015.10.004

[9] Burt, C. N., & Caccetta, L. (2018). *Erratum to: Equipment Selection for Mining: With Case Studies* (pp. E1–E1). https://doi.org/10.1007/978-3-319-76255-5_11

[10] Carmichael, D. G., & Mustaffa, N. K. (2018). Emissions and production penalties/bonuses associated with non-standard earthmoving loading policies. *Construction Innovation*, *18*(2). https://doi.org/10.1108/CI-05-2017-0047

[11] Chanda, E. K., & Gardiner, S. (2010). A comparative study of truck cycle time prediction methods in open-pit mining. *Engineering, Construction and Architectural Management*, *17*(5), 446–460. https://doi.org/10.1108/09699981011074556

[12] Chao, L.-C. (2001). Assessing Earth-Moving Operation Capacity by Neural Network-Based Simulation with Physical Factors. In *Computer-Aided Civil and Infrastructure Engineering* (Vol. 16).

[13] Cheng, F., Wang, Y., & Ling, X. (2010). *Multi-Objective Dynamic Simulation-Optimization for Equipment Allocation of Earthmoving Operations*.

[14] Dabbagh, A., & Bagherpour, R. (2019). Development of a Match Factor and Comparison of Its Applicability with Ant-Colony Algorithm in a Heterogeneous Transportation Fleet in an Open-Pit Mine. *Journal of Mining Science*, *55*(1), 45–56. https://doi.org/10.1134/S1062739119015287

[15] Dotto, M. S., & Pourrahimian, Y. (2018). *Effects of Fragmentation Size Distribution on Truck-Shovel Productivity*.

[16] GMG - Time Usage Model. (2020). *A standardized time classification framework for mobile equipment in surface mining: operational definitions, time usage model, and key performance indicators*. http://www.gmggroup.org

[17] Hardy, R. J. (2007). *Selection Criteria For Loading and Hauling Equipment-Open Pit Mining*.

[18] Haulsim. (2022). *RPM Global Haulsim Tutorials 3.6* (3.6). RPM Global.

[19] Hsiao, W.-T., Lin, C.-T., Wu, H.-T., & Cheng, T.-M. (2011). *A Hybrid Optimization Mechanism Used to Generate Truck Fleet to Perform Earthmoving Operations*.

[20] Kenn Smart. (2011). *Basics of earthmoving mining equipment* (3.1).

[21] Khorzoughi, M. B., & Hall, R. (2016). A study of digging productivity of an electric rope shovel for different operators. *Minerals*, *6*(2). https://doi.org/10.3390/min6020048

[22] Kirmanli, C., & Ercelebi, S. (2009). An expert system for hydraulic excavator and truck selection in surface mining. *The Journal of The Southern African Institute of Mining and Metallurgy*, *109*.

[23] Krause, A., & Musingwini, C. (2007). *Modelling open pit shovel-truck systems using the Machine Repair Model*.

[24] Loadsman, S., Lumley, G., Seviour, L., & Fan, A. (2013). *Truck and Loader Dictionary Second Edition 2013* (2nd ed.). pwc. www.pwc.com.au

[25] Marinelli, M., & Lambropoulos, S. (2012). Earth Loading and Hauling Optimal Trade-Off. *Procedia - Social and Behavioral Sciences*, *48*, 2325–2335. https://doi.org/10.1016/j.sbspro.2012.06.1204

[26] Marzouk, M., Moselhi, O., & Asce, F. (2004). *Multiobjective Optimization of Earthmoving Operations*. https://doi.org/10.1061/ASCE0733-93642004130:1105

[27] Mohtasham, M., Mirzaei-Nasirabad, H., Askari-Nasab, H., & Alizadeh, B. (2021). A multi-objective model for fleet allocation schedule in open-pit mines considering the impact

of prioritising objectives on transportation system performance. *International Journal of Mining, Reclamation and Environment*, *35*(10), 709–727. https://doi.org/10.1080/17480930.2021.1949861

[28] Moradi Afrapoli, A., & Askari-Nasab, H. (2019). Mining fleet management systems: a review of models and algorithms. *International Journal of Mining, Reclamation and Environment*, *33*(1), 42–60. https://doi.org/10.1080/17480930.2017.1336607

[29] Moradi Afrapoli, A., Tabesh, M., & Askari-Nasab, H. (2019). A stochastic hybrid simulation-optimization approach towards haul fleet sizing in surface mines. *Mining Technology: Transactions of the Institute of Mining and Metallurgy*, *128*(1), 9–20. https://doi.org/10.1080/25726668.2018.1473314

[30] Morley, D., Joseph, T., & Lu, M. (2013). *In search of the ideal truck-excavator combination*.

[31] Morley, D., Lu, M., & Abourizk, S. (2013). Utilizing simulation derived quantitative formulas for accurate excavator hauler fleet selection. *Proceedings of the 2013 Winter Simulation Conference - Simulation: Making Decisions in a Complex World, WSC 2013*, 3018–3029. https://doi.org/10.1109/WSC.2013.6721669

[32] Mustaffa, N. K. (2021). *Alternative Configurations of Earthmoving Loading Practices toward Emissions Reduction*. https://doi.org/10.1061/(ASCE)CO.1943

[33] Price, A. (2017). *Making better decisions with reduced uncertainty*. www.rpmglobal.com

[34] Schexnayder, C., Weber, S. L., & Brooks, B. T. (1999). Effect of truck payload weight on production. *JOURNAL OF CONSTRUCTION ENGINEERING AND MANAGEMENT*, *125*(1), 1–7.

[35] Shawki, K., Abd El-Razek, M., & Abdulla, N. (2009). Earthmoving productivity estimation using genetic algorithm. *Journal of Engineering Sciences*, *37*(3), 593–604.

[36] Shawki, K. M., Kilani, K., & Gomaa, M. A. (2015). Analysis of earth-moving systems using discrete-event simulation. *Alexandria Engineering Journal*, *54*(3), 533–540. https://doi.org/10.1016/j.aej.2015.03.034

[37] Shi, J. J. (1999). A neural network based system for predicting earthmoving production. *Construction Management and Economics*, *17*(4), 463–471. https://doi.org/10.1080/014461999371385

[38] Smith, S. D. (1999). *Earthmoving productivity estimation using linear regression techniques*.

[39] Smith, S. D., Osborne, J. R., & Forde, M. C. (1995). *Analysis of earth-moving systems using discrete-event simulation*.

[40] Soofastaei, A., Aminossadati, S. M., Kizil, M. S., & Knights, P. (2016). A discrete-event model to simulate the effect of truck bunching due to payload variance on cycle time, hauled mine materials and fuel consumption. *International Journal of Mining Science and Technology*, *26*(5), 745–752. https://doi.org/10.1016/j.ijmst.2016.05.047

[41] Sturgul, J. R., & Harrison, J. F. (1987). Simulation models for surface mines. *International Journal of Surface Mining, Reclamation and Environment*, *1*(3), 187–189. https://doi.org/10.1080/09208118708944118

[42] Tabesh, M., Upadhyay, S. P., & Askari-Nasab, H. (2016). *Discrete Event Simulation of Truck-Shovel Operations in Open Pit Mines 1*.

[43] Tapia, E., Salazar Araya, A., Saavedra, N., Nehring, M., & Mora, J. (2021). An analysis of full truck versus full bucket strategies in open pit mining loading and hauling operations. *International Journal of Mining, Reclamation and Environment*, *35*(1), 1–11. https://doi.org/10.1080/17480930.2020.1712639

[44] Upadhyay, S. P., Tabesh, M., Badiozamani, M. M., Moradi Afrapoli, A., & Askari-Nasab, H. (2021). A simulation-based algorithm for solving surface mines' equipment selection and

sizing problem under uncertainty. *CIM Journal*, *12*(1), 36–46. https://doi.org/10.1080/19236026.2021.1872995

[45] Vagenas, N. (1999). Applications of discrete-event simulation in Canadian mining operations in the nineties. In *International Journal of Surface Mining, Reclamation and Environment* (Vol. 13, Issue 2, pp. 77–78). A.A. Balkema. https://doi.org/10.1080/09208119908944213

[46] Yaghini, A. (2021). *Electric Rope Shovel Operation Enhancements, Understanding and Modelling the Impact of The*.