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Simulation-based optimization of truck-shovel material handling systems in multi-pit surface mines

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ABSTRACT

Truck and shovel are the most widely used equipment in the mining industry, and their performances are highly interdependent. When a problem occurs in one type of equipment, the productivity of the other type of equipment is also affected. That is to say, shovel waiting times, truck queues and bunches on the roads, and idle capacity problems in crushers are experienced in such a way as to result in direct or opportunity costs. In this paper, a two-stage dispatching system is proposed to maximize the utilization of truck-shovel systems. In the first stage, the truck and shovel fleets are divided into sub-fleets to work on the specific pit by a simulation-based optimization method which considers uncertainties in the mining operation. In the second stage, the trucks are simultaneously dispatched to the shovels in the pit by linear programming. Match factor is also tracked in the second stage as a measure of the compatibility of the fleets. In surface mines which consist of more than one pit, the trucks can be reassigned to another pit during the operation to manage high match factors for all pits. The proposed approach is tested in a mine. When the ore and waste production quantities of the previous dispatching system and the proposed framework were compared, the total quantity was increased with the proposed framework by 9.4% in a shift which corresponds to 6.0 K tonnes of material. The approach has great potential to increase the productivity of truck and shovel systems.

1. Introduction

Mining is a global industry, and commodity prices are set in the markets. Given low prices, many operations having high operating cost have recently striven to remain in the business. To challenge this problem, mining companies must always invest in the best engineering practices to increase the productivity and efficiency of the operations.

The material handling costs are a significant part of total operating costs [1, 2]. In the last decade, the hauling equipment capacities increased significantly to take advantages of economies of scale and decrease the unit cost of the operation. However, this capacity increase brings some risks as well as its benefits. When the trucks or shovels are idle, an opportunity cost has arisen in addition to their operating cost. Predictably, the opportunity cost of this large equipment is quite high. Therefore, the utilization of them should be kept as high as possible. An efficient truck dispatching can achieve this target.

Although many researchers investigated the truck dispatching problem [3-12], it is still a vivid research topic because (1) every mine is specific, (2) there are many uncertainties such as weather, cycle time, driver effect and so on, (3) new sensors technologies provide new opportunities to enhance the existing methods. Some commercial software companies have offered solutions. The most well-known of these companies are Modular Mining Systems, Jigsaw, RPMGlobal, Wenco International Mining Systems, Caterpillar,

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Leica Geosystems and Micromine. More information about the industrial mine fleet management systems in the market can be found at Afrapoli and Askari-Nasab [13].

The primary motivation to address truck dispatching problem is to improve productivity and efficiency. The problem can briefly be described as the decision of the next destination of a haul truck after dumping its material. Alarie and Gamache [1] have summarized the previous truck dispatching research in the mining industry. There are two main approaches to truck dispatching as the single stage and multi-stage system [1]. In single stage systems, the trucks are assigned to the shovels by dispatching criteria without considering production target or any constraints. The multi-stage systems divide the problem into subproblems. Generally, the production target for each shovel is defined in the first stage by mathematical optimization methods such as linear programming (LP) [6, 14, 15], non-linear programming [11], integer programming [12] and goal programming [16]. These optimization methods are also differentiated by the objectives which are also known as dispatching criteria as well as non-linearities in the objective function and/or the constraints. The dispatching criteria can be production maximization [8, 15], cost minimization [17, 18], truck waiting time minimization [19] or shovel idle time minimization [20]. In the second stage, the trucks are assigned to the shovels in real-time by some heuristics to minimize the deviation from the production target which is defined in the first stage. However, the heuristics are not mathematically proven and does not guarantee the optimal solution. The complex structure of a discrete mining system makes the heuristics popular in real-time truck dispatching decision.

The mathematical optimization methods used in the first stage are deterministic models. However, the mine operation environment is highly uncertain. For example, the available number of equipment may change due to unexpected failures. The cycle time of the trucks and loading time of the shovels depend on the operators, rock characteristics, weather and road conditions. These uncertainties fluctuate during the operation. These fluctuations cause deviations from the production targets. To consider the effect of the uncertain parameters in the optimization, a simulation-based optimization model is preferred to decide the production targets in the first stage.

Simulations imitate real-world systems and generate probable realizations. The mining and earthmoving operations are suitable to be modelled by discrete event simulation because the activities have discrete sequence of events [7, 21]. The simulation was previously used to material handling network in a coal mine for the solution of machinery scheduling and train loading problem [22], short-term mine planning [23], locating facilities in open-pit mines [24], modelling the mining supply chain from mine to port [25]. Furthermore, Jaoua, et al. [26] proposed a simulation framework for real-time fleet management to model the complex behaviour of internal haulage network in surface mines. As a result, the real-time truck fleet management was improved, and the internal traffic of the haulage networks are controlled. Moreover, real-time control formation based on simulation is applied to manage the truck system [27]. The formation includes fundamental characteristics of real-time implementations, simultaneity, reactiveness, and proper timing. The results proved the capability of the formation in the dynamic operating environment to achieve real-time truck dispatching. Moreover, the uncertain attributes such as traveling duration, waiting in queue and driver replacement can be considered in the model by simulation-based techniques [28].

Abovementioned approaches used in the second stage deal with one pit or one production face. The proposed approach extends multiple pits or production faces. Moreover, the approaches at the literature made the truck dispatching decision at the dump location based on the current conditions such as a truck queue, cycle time, shovel productivity, etc. However, these conditions may change until the truck arrives in the assigned shovel because of the dynamic mining operating environment. Also, the optimal shovel assignment for the truck may be different from these changes.

In previous research [29], a Petri-net simulation model was proposed to verify the feasibility of mine plans. The production quantity and quality were estimated by considering the uncertainties associated with activity times, fill factor, seasonal effect, road conditions, operator factor, etc. Also, the reliability of equipment and its relationship with fuel consumption were incorporated [29]. In this research, we take a further step and link the simulation model to an optimization framework for the real-time truck dispatching to improve the utilization of the mining equipment and increase the efficiency in production. In the proposed dispatching system, the truck and shovel fleets are divided into sub-fleets for pits by using simulation-based optimization technique in a way that the production will be maximized. As mining operating environment is highly dynamic and uncertain, simulation-based optimization is preferred to include the effect of uncertainties. When the trucks and shovels are grouped, the dispatching problem is divided into sub-problems. This significantly decreases the size of the complex dispatching problem. Then, the dispatching decision is made in the second stage by using linear programming instead of heuristics. In the current dispatching systems, the dispatching decision is made at the dump. However, the dispatching decision may not be optimum anymore when the truck reaches the shovel because of the dynamic mining operation environment. In this framework, the trucks move to their assigned pit after dumping, and the decision is made at the pit entrance. This minimizes the effect of uncertainties. Moreover, the conformity of the sub-fleets is measured by the match factor (MF) during the operation. If there is inefficiency, the system interrupts and change the assigned pit of a specific truck. This makes the dispatching system respond to the changes rapidly during the operation as an efficient dispatching system should have done.

The originality of this paper resides in: (1) a new simulation-based optimization approach is presented to minimize the lost time when trucks are traveling between pits, (2) the dispatching decision is made at the pit instead of the dump points by a mathematical optimization method, and (3) the MF values of the pits are tracked to increase the utilization of the mining equipment. Current mining practice does not consider the effects of uncertainties of mining events on dispatching decisions. They are also not able to react to unexpected realizations of unexpected events. The details of the proposed method will be described in the next section.

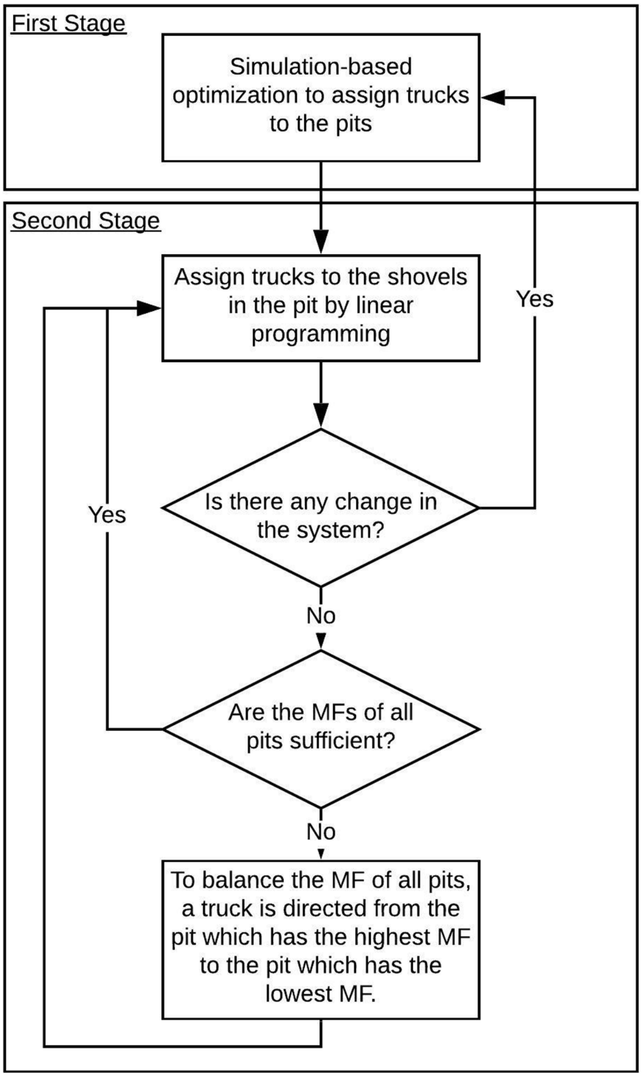

Fig. 1. The dispatching algorithm.

2. Research methodology

2.1. Discrete-event simulation and truck dispatching algorithm

Discrete-event simulation (DES) is a technique used to simulate a system containing a discrete succession of activities over time. It helps the decision maker to analyze system responses and bottlenecks within the system. DES method is commonly used in many sectors such as assembly lines in manufacturing, hospital procurement management, evaluation of capital investment decisions, personnel allocations in bank and call centers and traffic network simulations. In mining operations, it is mainly applied to materials handling systems because mining operations include a discrete sequence of time-ordered events such as drilling, blasting, loading, hauling and dumping.

The main purpose to use DES in this research is to assess the risks associated with uncertain parameters in the mining operations. Then, using system responses, the bottlenecks or deadlocks within this system are resolved. For example, the cycle time of the trucks is uncertain because of the dynamic change in the mine roads. If the mine roads are durable, the trucks can move faster; thus, the cycle times will be shorter. The reason for the change in mine roads may be caused by the change in weather condition and the effect of heavy vehicles. Also, the haul truck operators affect the cycle times of the trucks. Some operators are more confident and drive the haul truck faster while some of them drive slower. Similarly, the loading time of the shovels is also uncertain. Moreover, the load of the trucks is not the same in each cycle because of the fill factor and carry-back problem. Carry-backs are the material which sticks on the trucks' bucket in humid areas.

The algorithm of the proposed truck dispatching approach is summarized in Fig. 1. Initially, it divides the truck fleet to sub-fleets by assigning trucks to the pits to prevent time loss due to the truck movement among the pits. The method can be described in two stages. In the first stage, simulation-based optimization is used to assign the trucks to the pits. For this reason, 100 probable realizations are generated. In these realizations, the uncertainties in the mining operation are considered. The uncertain parameters are included in the model by sampling these parameters from distributions fitted to the historical data. Also, the operator effect is integrated into the simulation model as explained at Ozdemir and Kumral [30]. Since the agent-based models consider the uncertainties associated with the agent attributes, the accuracy of the results is further improved [31].

Using the truck combinations generated by simulation-based optimization, an average production rate for each truck combination per pit is calculated. The combination which gives the highest rate is selected. Also, the simulation model provides the production targets for each shovel for a specified period. The specified period can be a shift if it is the beginning of the shift. It can also be the rest of the shift after a change in the mine such as equipment breakdown, priority change, etc.

In the second stage, the trucks are individually assigned to a specific shovel in the pit by another LP model. If there is any change in the system, the algorithm comes back to the first stage and the simulation-based model is rerun to distribute the trucks into the pits and maximize the production at the rest of the shift. The operation continues with new truck assignments. On the other hand, if there is no change in the system, the MF of each pit is calculated and compared during the operation. Higher MF means higher efficiency in production. Hence, the trucks can be moved among the pits to increase the MF. For example, the MF of Pit 1 is 1.3 which is the maximum, and the MF of Pit 3 is 0.6 which is the minimum among all pits. In this case, one truck is moved from Pit 1 to Pit 3 to decrease the MF of Pit 1 and increase the MF of Pit 3. Hence, a better match between the trucks and shovels is obtained in each pit. While the production in Pit 3 is increased, the queuing time in Pit 1 is decreased. The better match means less waiting time for trucks and less idle time for shovels, which end with a more efficient hauling cycle.

2.2. Simulation-based optimization to divide trucks in sub-fleets

The simulation model is given in Fig. 2. The trucks, which previously divided into the sub-fleets for each pit, come to the pit station. Here, the dispatching decision is made and direct the truck to a specific shovel in the pit. When the truck reaches the shovel pad, it seizes the shovel. The attributes (such as maneuvering time, loading time, fill factor, load tonnage, carry-backs, destination, etc.) are assigned to the truck entity. These attributes are sampled from the probability distributions fitted to the historical field data. Since the fragmentation size affects the hauling efficiency [32], it is included in the model via fill factor. The operator competency is inputted when an operator starts using the assigned equipment at the beginning of the shift. Then, the truck releases the shovel and moves to its destination. The route time is uncertain because of the changes in weather, road conditions, operator competency, etc. When the truck reaches its destination, it dumps the material to the dump location which can be crusher or waste dump. The tonnage and grade attributes are recorded at the dump location. After the truck dumps its material, it will move back to the pit station to complete another haul cycle. If the assigned pit changes after dumping, the truck will proceed to the assigned pit. More information about simulation modelling can be found at Ozdemir and Kumral [29] and Rossetti [33].

The simulation-based optimization model is solved in OptQuest® for Arena® Simulation Software. The specific optimization target in the paper is to maximize total material (ore and waste) production under constraints of operational equipment capacities and time limitations. The objective function is evaluated by black box optimizers which are context-independent procedures. These optimizers find as good as a possible value for a function within predefined limits. Since they are context-independent, they do not benefit from the problem's specific structure [34]. Black box optimizer uses Scatter search method coupled with tabu search strategies to solve the problem with a simulation model. This problem is dividing trucks into sub-fleets at the first stage. It is a population-based metaheuristic and can be applied to problems which have continues or discrete variables. The framework of scatter search is given below [34]. More information about scatter search can be found at Laguna and Martí [35].

```
while (stopping criterion is not satisfied) {
        reference set update
        while (new reference solution) {
                subset generation
                Combination
                improvement
                reference set update
        }
        Rebuild the reference set
}
```

In the optimization model, m is the material moved from shovel j in time t. m is a function of n_p which is the number of trucks assigned to the pit p. n_p is the decision variable in the optimization model. The number of trucks assigned to each pit is changed in combinations and each combination was run 100 times. The average total production is recorded for each combination. The objective is to decide on a combination which provides the highest production amount. Thus, the production will be maximized by applying the selected combination. The summation of trucks assigned to the pits should be equal to the total number of available trucks. Furthermore, shovels have minimum production requirements. These are included as constraints in the model. The simulation-based optimization algorithm can be modelled as given below.

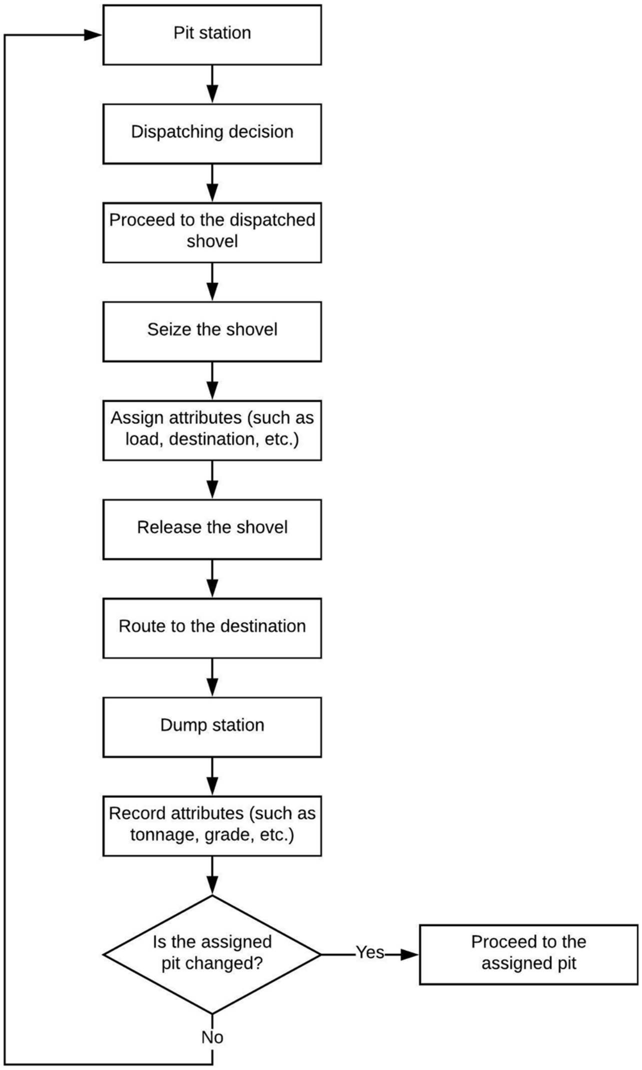

Fig. 2. The simulation model.

- **Step 1:** Create the simulation model of the mine by including the uncertainties of the mining operation.
- **Step 2:** Formulate the optimization model with constraints. The objective of the optimization is to maximize the total hauled ore and waste material from shovels in all realizations.

The constraints of the model are:

1 The numbers of trucks assigned to the pits should be integer numbers.

$$n_p \in \mathbb{Z}^+ \tag{1}$$

2 There are minimum ($n_{p,\min}$) and maximum ($n_{p,\max}$) limits for the numbers of trucks assigned to the pits.

$$n_{p,\,\min} \le n_p \le n_{p,\,\max} \tag{2}$$

3 The summation of the number of trucks assigned to the pits is equal to the total number of available trucks (N).

$$\sum_{p=1}^{P} n_p = N \tag{3}$$

4 The simulation time is the time left in the current shift.

$$t \leq 12 \text{ hours} \tag{4}$$

5 The production of each shovel should be equal to or larger than the minimum production requirement of the shovel (M_j) decided according to the short-term mine plan.

$$m_j \geq M_j \tag{5}$$

- **Step 3:** Input the initial values for the truck-pit combination.
- **Step 4:** Run the simulation model 100 times with the current combinations for the pits and record the total productions.
- **Step 5:** Compare the average total production of the new and previous combination. If the total production with the new combination is larger than the production with the previous combination, keep the new combination and discard the old one. Otherwise, keep the old combination and discard the new one.
- **Step 6:** Produce a new combination for trucks and pits by considering the constraints.
- **Step 7:** Return to Step 3 and repeat the cycle until all the possible combinations are tried.

The proposed method is specifically beneficial for the mines which have multiple pits as it prevents the lost time during the truck travel between the pits. It categorizes the shovels and trucks as sub-fleets to minimize the time loss; hence, the production will be maximized.

2.3. Real-time truck assignment

When the truck-shovel fleet is divided into sub-fleets for each pit, the dimension of the dispatching problem becomes smaller. Thus, it can be solved in real-time by using mathematical optimization techniques. The truck dispatching decision is made in the pit based on the truck queues at the loading points and the production targets of each shovel. The grade variable can be added to the model if there is a need. The target grade is obtained by blending before secondary crushing.

The previous research proposed that the truck dispatching decision is made at the dump location [1, 36, 37]. This decision is based on different variables such as truck queues, shovel production, etc. However, these variables may change during the truck moves from the dump location to the assigned shovel. It is hard to estimate route time because of uncertain events happening during the operation. In this research, the trucks are already assigned to a pit; hence, they move back to the pit after dumping. The dispatching decision is made in real-time by using LP when the truck reaches to the pit entrance. LP was previously used in truck allocation problem [14], making decisions on the destination of extracted block [38] and short and long-term mine planning [39].

The LP algorithm chooses the shovel which has the minimum waiting time for the trucks. The waiting time of the shovel is equal to the multiplication of the current number of the truck in the queue and the average of last four loading time of the shovel. The production target of each shovel is already defined in the first stage as shown in Eq. (5). Moreover, the production of each shovel is tracked in the framework during the shift. By using this production information, the ratio of the remaining production to target production can be calculated. This enables the program to understand how much the shovels are behind their specific target. In the case of same waiting time for two or more shovels, these ratios are compared, and the truck is dispatched to the highest ratio.

2.4. Match factor integration

MF is a ratio to measure the compatibility of a truck-shovel fleet. The roots of the MF rests on the equation proposed in Douglas [40]. The equation is the ratio of the shovel productivity to truck productivity, and used to determine the optimum number of trucks for one shovel. The productivity in the formula is defined as the amount of the produced material in a specified time period. Later, Morgan and Peterson [41] first named the MF and formulated it as follows:

$$Match\ Factor = \frac{(number\ of\ trucks) \times (loading\ time)}{(number\ of\ loaders) \times (cycle\ time)} \tag{6}$$

However, the equation is only valid for homogeneous truck-shovel fleets. Since most of the mining equipment fleets are mixed, Burt and Caccetta [42] developed the MF equation for heterogeneous truck-shovel fleets as given in Eq. (7). As seen, it is a function of the number of trucks, the cycle times of the trucks, the number of shovels and the loading times of the shovels. If the MF is equal to 1.0, it indicates a perfect match between trucks and loaders. There is no waiting time for trucks or idle time for shovels. If it is higher than 1.0, the system has more trucks than needed. Truck lines are observed to get loaded by a shovel. If the MF is lower than 1.0, the number of trucks is not enough to keep shovels productive. In this case, shovel idle times are observed.

$$Match\ Factor = \frac{(number\ of\ trucks)}{\left(\sum_j \frac{(number\ of\ loaders)_j}{(loading\ time)_j}\right)\left(\sum_i [(trucks)_i \times (truck\ cycletime)_i]\right)} \tag{7}$$

where i and j are the indices for the trucks and shovels, respectively. MF is considered as a single static value in the literature to

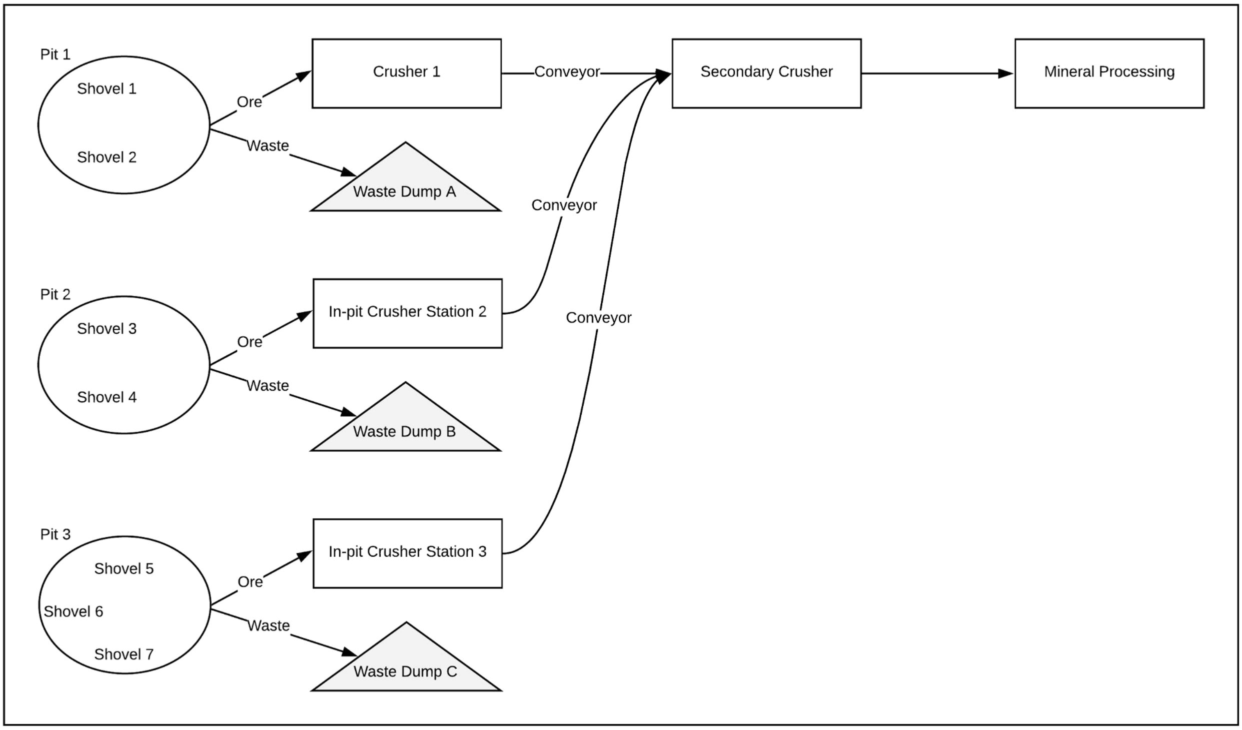

Fig. 3. Mine Model.

evaluate the efficiency of the truck-shovel fleet based on average loading time, cycle time and the number of equipment in the fleet. It ignores the variations over time; however, the mine operation environment is dynamic. Thus, Ozdemir and Kumral [43] discussed the dynamic usage of MF which considers the change in the available number of equipment during the operation due to the unexpected failures. Additionally, the cycle times of the trucks and loading time of the shovels are variable because of the uncertainties caused by road conditions, weather and operator competency. Chaowasakoo et al. [44] explained the benefits of using MF in fleet management.

3. Results and discussion

3.1. Mine model

A case study was conducted to a hard rock mine which is visualized in Fig. 3. The mine has seven shovels working in three pits. Shovel 1 and 2 are in Pit 1, Shovel 3 and 4 are in Pit 2, and Shovel 5, 6 and 7 are located in Pit 3. The ore extracted from Pit 1, Pit 2 and Pit 3 is hauled by haul trucks to Crusher 1, Crusher Station 2 and Crusher Station 3, respectively. Crusher 1 is a stationary ex-pit crusher. Crusher 2 and Crusher 3 are stationary in-pit crushers. The ore is first crushed in these crushers; then, it is moved to the secondary crusher by conveyors. When the ore passes through the secondary crusher, it is blended and continues to the mineral processing. The waste material extracted in Pit 1, Pit 2 and Pit 3 is hauled by haul trucks to the Waste Dump A, Waste Dump B and Waste Dump C, respectively. The mine works 24 hours/day in two 12-hour shift.

Table 1
The values of the parameters used in the case study.

Parameter	Value
Number of trucks	36
Capacity of trucks	240 t
Working hours/shift	12 h
Minimum production requirement/shovel	6000 t/shift
Minimum number of the truck in a pit ($n_{p,\ min}$)	6
Maximum number of the truck in a pit ($n_{p,\ max}$)	16
Fill factor (Min, Most likely, Max)	PERT (85, 90, 95) %
Loading time (Min, Most likely, Max)	PERT (2.5, 4, 6) min
Dumping time (Min, Most likely, Max)	PERT (0.5, 1, 2) min

Table 2
The hauling times (minutes) from shovels to the destinations.

From	To					
	Crusher 1	Waste dump A	Station 2	Waste dump B	Station 3	Waste dump C
Shovel 1	LG (17.3,1.5)	WB (10.3, 13.8)	–	–	–	–
Shovel 2	WB (17.5,15.6)	LG (14.0,1.33)	–	–	–	–
Shovel 3	–	–	WB (11.2,19.6)	NR (15.8,1.7)	–	–
Shovel 4	–	–	NR (17,8,1.7)	LG (14.9,1.5)	–	–
Shovel 5	–	–	–	–	NR (12.3,1.4)	LG (13.5,1.7)
Shovel 6	–	–	–	–	LG (13.2, 1.3)	WB (10.0, 15.1)
Shovel 7	–	–	–	–	LG (13.9, 1.5)	NR (14.5, 1.3)

3.2. Results of simulation-based optimization

The parameters and their values used in the case study are provided in Table 1. The mine model was created in Arena® Simulation Software [45]. The realizations of uncertain parameters are sampled from a probability distribution based on the previous observations. Since the distance between the pits and the dumping points are constant, the 1-year travelling time data between these points are used in the analysis. However, the travelling times from shovels to the pit entrance changes as mine progresses. Therefore, the time period for this data is one month. Undoubtedly, more observations in a longer time horizon mean a more accurate estimation of the uncertain parameter. Normal (NR), lognormal (LG) and Weibull (WB) distributions were tested for the uncertain parameters in the mine model such as fill factor, loading time, hauling time, dumping time and empty travel time. The goodness-of-fit between the distribution and the previous observations are tested by the Akaike information criterion (AIC), Hannan-Quinn information criterion (HQIC) and the Schwarz information criterion (SIC). The distribution which provides the best fit for the previous observations was selected for each parameter. Moreover, the program evaluation and review technique (PERT) distribution is used for the fill factor and, loading and dumping times as their historical data generate the best fit for these variables according to goodness-of-fit tests. PERT is a smooth version of triangular distribution and widely used to model expert data. It is defined by minimum, most likely and maximum values that the variable can take [46]. The hauling times and empty traveling times between the locations are given in Tables 2–4. These values represent the characteristics of the mine. These characteristics or the needs of the operation may change in time. Therefore, they should be updated as mine advances. Furthermore, since every mine is unique, the simulation model and the parameters must be updated before applying to a different mine.

The traveling time of the trucks is changing depending on the operator's competency and performance. Operator coefficients can be calculated based on a machine learning scoring technique as mentioned in Othman [47] and Ozdemir and Kumral [30]. In this research, the operator coefficients are randomly assumed as given in Fig. 4. For example, the score of Operator 4 is 1.26. The cycle time of the truck which Operator 4 drives will be multiplied with this coefficient. Hence, the cycle time will be 1.26 times longer while Operator 4 drives the truck. These coefficients are updated regularly.

OptQuest® solved the optimization problem by changing the number of trucks assigned to the pits. The optimization engine tries all possible combinations for the truck assignments and simulates the system 100 times for a 12-hour shift. It compares the results of the average total production of 100 realizations. The combination which gives the maximum total production was chosen. Table 5 denotes the combinations and average total production in a shift for each combination. To achieve the maximum production which is 67,418 tonnes, the number of trucks assigned to the Pit 1, Pit 2 and Pit 3 should be 10, 11 and 15, respectively. This maximum production value can be achieved and increased by real-time dispatching of the trucks to the shovels.

The production targets of each shovel for the shift were also determined in the simulation-based optimization. These production targets are used in the real-time truck dispatching. Table 6 provides the specific target of each shovel.

3.3. Real-time truck assignments

The real-time decision is made by LP based on trucks waiting time and shovel's production target as explained in Section 2.4.

Table 3
The empty traveling time (minutes) from the dumping points to the pit entrance.

From	To		
	Pit 1	Pit 2	Pit 3
Crusher 1	WB (14.6,15.5)	–	–
Waste dump A	NR (10.0,0.78)	–	–
Station 2	–	NR (14.9, 1.9)	–
Waste dump B	–	NR (12.0, 1.1)	–
Station 3	–	–	WB (14.4,10.4)
Waste dump C	–	–	LG (10.1, 0.7)

Table 4
The empty travelling time (minutes) from the pit entrance to the shovels.

From	To						
	Shovel 1	Shovel 2	Shovel 3	Shovel 4	Shovel 5	Shovel 6	Shovel 7
Pit 1	LG (3.2,0.6)	NR (3.3,0.7)	–	–	–	–	–
Pit 2	–	–	WB (8.4, 4.1)	LG (3.0, 0.4)	–	–	–
Pit 3	–	–	–	–	WB (4.2, 2.4)	LG (3.2, 0.6)	WB (8.6, 3.1)

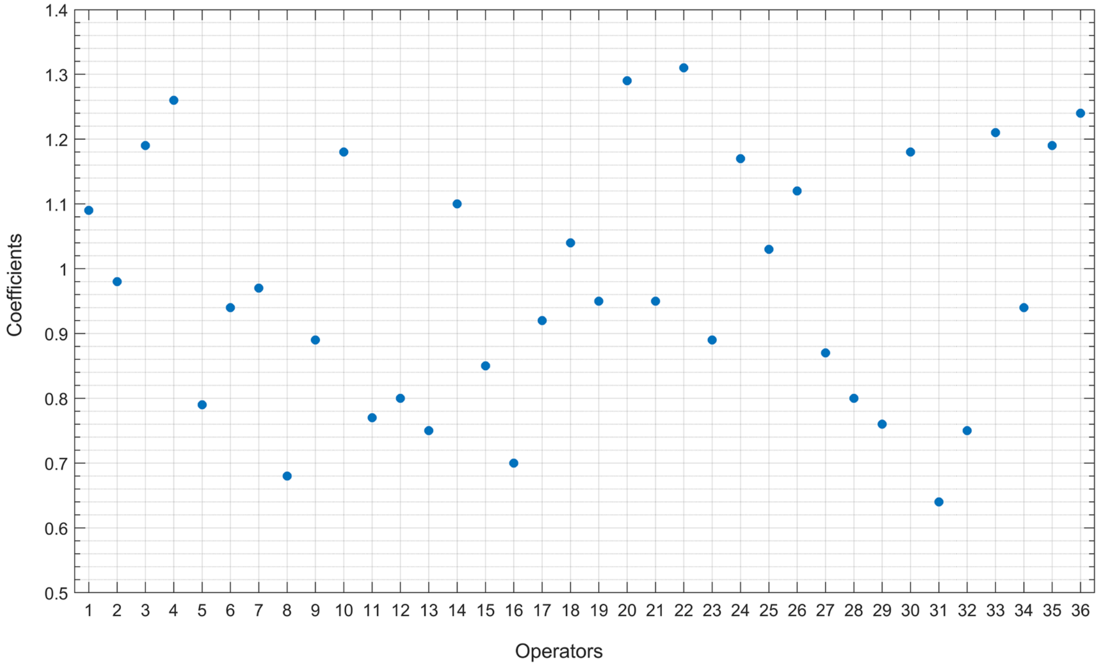

Fig. 4. The operators' coefficients.

Table 5
Average total production in a shift for sample combinations of pits and the number of trucks.

Combination	Number of trucks in Pit 1	Number of trucks in Pit 2	Number of trucks in Pit 3	Average Production of 100 realizations (tonnes)
1	10	11	15	67,418
2	10	10	16	66,950
3	14	13	9	66,874
4	12	13	11	65,994
5	15	14	7	65,950
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
82	16	6	14	60,529

Thus, the opportunity cost associated with trucks' waiting time is minimized.

An example of a specific case is presented from Pit 3 in the middle of the shift. The average loading time of last four loading activity and a number of trucks in the queue for each shovel is known at a certain time. There are 6 hours left in this shift. The production target of each shovel at the beginning of the shift is given. The production amounts of each shovel in the first 6 hours of the shift is also known. With these targets and current productions, the completed percentage of the production is simultaneously calculated. These percentages are used to define the priorities of the shovels. If a truck has similar waiting times for two or more shovels, the shovel with lower completed production percentage is preferred. Moreover, ore quality constraints can be considered at this stage as the fluctuations in material characteristics lead to additional costs in mineral processing [48]. Since the ore blending in this case study is achieved after the primary crusher, it was ignored. When a truck arrives in Pit 3, the system runs the algorithm with the current parameters and come up with a decision. The parameters of the example for the specific case is given in Table 7. When the algorithm was run, the truck is dispatched to Shovel 5.

Table 6
Production targets of shovels for the shift.

Shovel	Production target (tonnes)
1	11,520
2	11,699
3	12,427
4	11,738
5	6622
6	7127
7	6284
Total	67,418

Table 7
Dispatching decision data for the first truck in Pit 3.

Parameters	Shovel 5	Shovel 6	Shovel 7
Average loading time (minutes)	4	3.5	4.2
Number of the trucks in the queue	1	2	1
Average waiting time (minutes)	4	7	4.2
The production target for the shift (tonnes)	6622	7127	6284
Production in the shift (tonnes)	3852	5236	4027
Production completed (%)	58.2	73.5	64.1
Decision	1	0	0

If another truck arrives in the same pit right after the truck is dispatched to Shovel 5, the system reruns algorithm. This time the number in the queue for Shovel 5 increased by one because the previous truck is dispatched to Shovel 5. Consequently, the second truck arriving in Pit 3 is dispatched to Shovel 7. Table 8 provides the details of the dispatching parameters for this situation.

3.4. Effect of match factor

While the dispatching decisions are made as described, the system tracks the MF of each pit over time. If the trucks were not reassigned to the pits during the shift, the MF change of the pits would be as given in Fig. 5a. As seen from the figure, the MF of Pit 3 is mostly higher than 1.0, which means that truck queues are observed in the shovels' pad. On the other hand, the MF of the other pit is lower, the shovel idle times are observed. When the trucks are reassigned among the pits during the shift, the changes in the MF of the pits are visualized as given in Fig. 5b. Thus, the truck queues in Pit 3 are diminished and the shovel idle times observed in the other pits are decreased. Hence, the opportunity costs associated with the waiting times of mining equipment are decreased and the production is increased.

The proposed framework was validated by benchmarking the ore and waste material production of the framework and the current practice. The justification of the proposed model can be summarized in Fig. 6. The dividing truck fleet into sub-fleets increases the production by 7.7% which corresponds to 4.8 K tonnes. Furthermore, the production is increased another 1.7% which is 1.2 K tonnes when the MF is integrated with the dispatching system. These production values are for a 12-h shift. When a larger time interval is considered, the numbers become larger and end up with thousands of tonnes of extra production. The proposed model increases equipment utilization by decreasing opportunity costs associated with queuing and waiting times. Therefore, the benefit of an increase in production will surpass the cost increase of more equipment utilization.

4. Conclusions

The profitability of mining operations can be increased by improving the utilization of the mining equipment which has a quite high operating and opportunity costs. This objective can be managed through an efficient truck-shovel allocation and dispatching

Table 8
Dispatching decision data for the second truck in Pit 3.

Parameters	Shovel 5	Shovel 6	Shovel 7
Average loading time (minutes)	4	3.5	4.2
Number of the trucks in the queue	**2**	2	1
Average waiting time (minutes)	**8**	7	4.2
The production target for the shift (tonnes)	6622	7127	6284
Production in the shift (tonnes)	3852	5236	4027
Production completed (%)	58.2	73.5	64.1
Decision	0	0	**1**

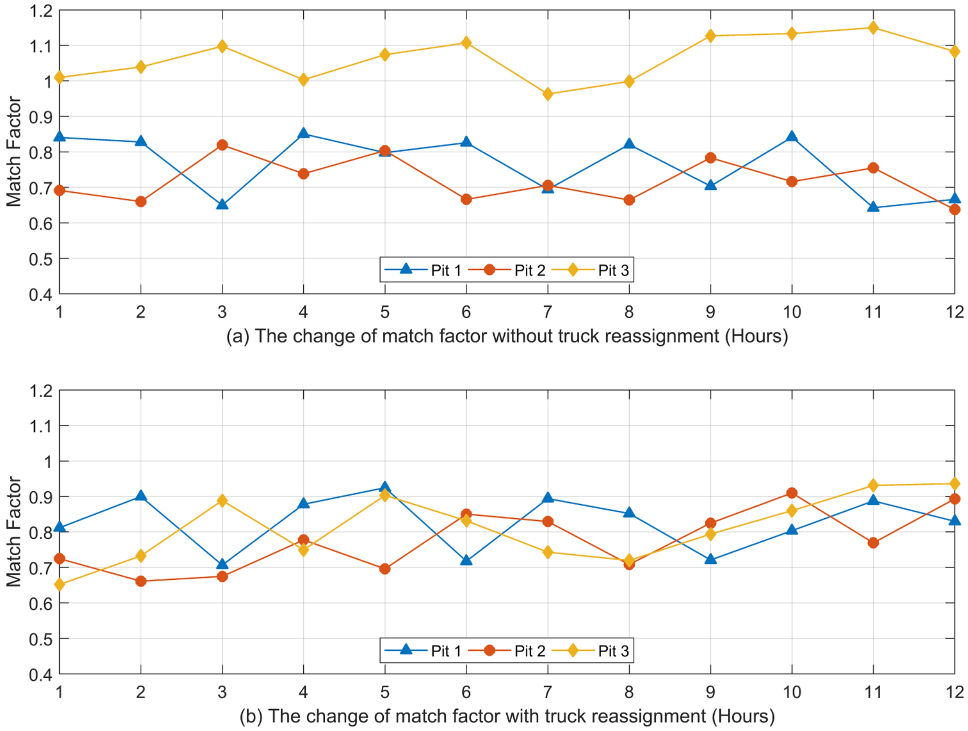

Fig. 5. The change of MF during the shift without (a) and with (b) interruptions.

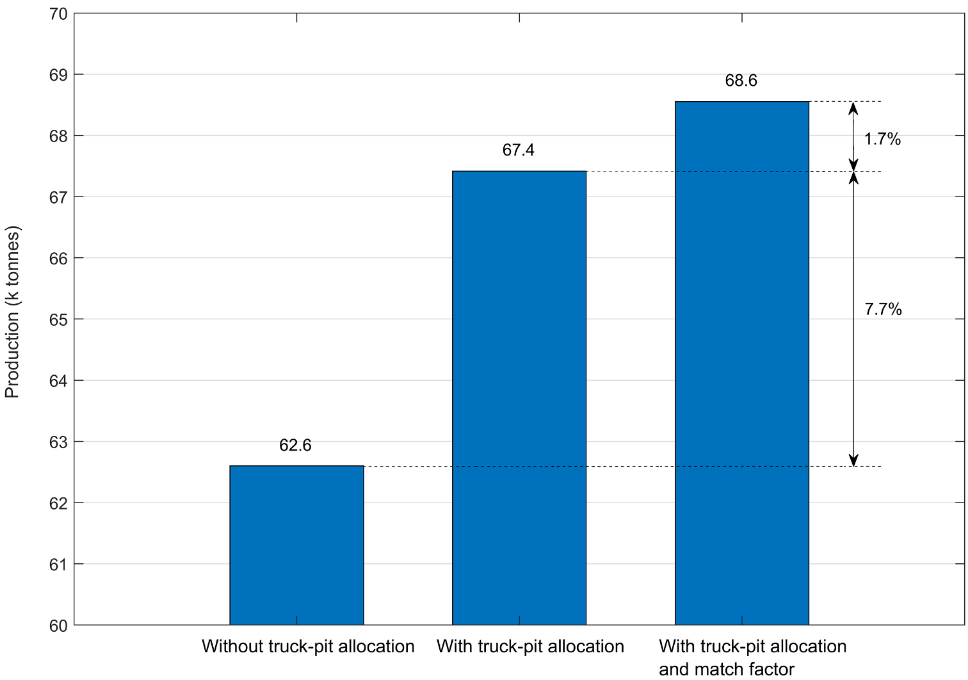

Fig. 6. The benchmark of the production.

approach. However, this is a complex problem due to uncertain mining operating conditions. In mining operations, the loading time of the shovels, the cycle time of the trucks, the number of available equipment are uncertain parameters. These variables might change with the effect of unexpected equipment failures, weather and road conditions, and operator effect. Hence, the solution approaches based on deterministic models are insufficient.

This paper proposes a novel truck dispatching approach for surface mining operations to increase the utilization of the mining equipment; so, the production quantities. In the first stage, the trucks are distributed to the pits by using a simulation-based optimization model in a way that the production is maximized. The simulation-based model helps to analyze the effect of uncertain parameters in the operation. For example, operator effect and carry-backs are considered in the simulation-based optimization model. This consideration provides a closer estimation of the actual production. Also, the production target of each shovel is decided in this stage. In the second stage, the trucks are simultaneously dispatched to the shovels in their assigned pit by LP. The objective is to minimize the waiting time of the trucks by meeting the production targets decided in the first stage. The results of the case study generated a 7.7% increase in production quantity with the proposed technique. Moreover, the MF of each pit is tracked in the second stage. If required, some of the trucks are reassigned to another pit to have a better match between truck and shovel fleet and increase the production. By this way, the dispatching system can respond to the changes rapidly during the operation. When the trucks were reassigned to the pits according to the MF, another 1.7% increase was observed in the production. In total, the production quantity increased 6.0 K tonnes per shift which corresponds to 9.4%.

The proposed truck dispatching approach increases equipment utilization and the productivity in surface mines; especially for the surface mining operations which have more than one pit or production face. It can also be applied in large-scale open-cast mines as well as earthmoving and construction industry which includes heavy equipment. In the case study, the ore quality was not considered since there were only one or two ore shovels in a pit. If the number of ore shovels in a pit increases, the ore quality can be integrated into the model in the future. Moreover, the reliability of the trucks can be considered in the truck dispatching system.

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