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Published in:
International Journal of Mining Science and Technology

DOI:
10.1016/j.ijmst.2017.01.007

Published: 01/03/2017

Document Version
Publisher's PDF, also known as Version of record

International Journal of Mining Science and Technology 27 (2017) 229–236

Contents lists available at ScienceDirect

International Journal of Mining Science and Technology

journal homepage: www.elsevier.com/locate/ijmst

Digitalization of mine operations: Scenarios to benefit in real-time truck dispatching

Patarawan Chaowasakoo [a,*], Heikki Seppälä [b], Heikki Koivo [a], Quan Zhou [a]

[a] Department of Electrical Engineering and Automation, School of Electrical Engineering, Aalto University, Espoo, Finland
[b] Department of Mathematics and Systems Analysis, School of Science, Aalto University, Espoo, Finland

ARTICLE INFO

Article history:
Received 14 December 2015
Received in revised form 12 February 2016
Accepted 8 May 2016
Available online 27 January 2017

Keywords:
Discrete event simulation
GPS
Truck dispatching
Cycle time
Fleet management

ABSTRACT

One of the key factors in a profitable open-pit mine is the efficiency of the waste disposal system. Using GPS-technology, the truck-dispatching decisions can be made in real-time but the chosen strategy has a crucial role. Therefore, finding the optimal dispatching strategy for truck-shovel operations is extremely important. Dispatching strategies have been reported in the literature, but the comparison of these strategies is still missing. This paper illustrates the differences between the strategies by conducting a stochastic simulation study based on the data gathered from an actual mine. The findings underline the importance of the global vision in dispatching decisions.

1. Introduction

After another difficult year in 2014, the global thermal coal markets were faced with a backdrop of collapsing energy prices in 2015. Today, most mining companies attempt even harder to find intelligent services to improve the key areas of their operations [1–6]. General operational tasks of topsoil removal in open-pit mines include drilling and blasting, ore and waste loading, hauling and dumping, and various auxiliary services. The most important system, in terms of efficient material handling, is the truck-shovel operation. From the operational point of view, the crucial task is to decide how to allocate the truck-shovel resource in an efficient manner, since the large amounts of ore and waste must be delivered from the pit to their destinations through relatively long and steep haulage routes. Many prior research studies indicate that the transportation costs are relatively high, that is, 50–60% of the total operational cost of open-pit mines [7–12].

In the real world the system is complex: trucks must wait for the shovels to become available when the system is over-trucked and vice versa when the system is under-trucked. In most cases, operations require a high number of trucks to be assigned to shovels in order to maximize the production, and central dispatching approaches are typically used to minimize the queuing time. Previous research studies have addressed some problems of truck-shovel fleets in such a transportation system within different dispatching rules [2,8–11,13–23]. More recently, dynamic solutions to real-time fleets have been underlined. The use of the real-time fleet dispatching methods provides an advantage in the overall productivity of the mining system by ensuring the highest utilization of available trucks and shovels in the system at any given time. Many simulations with different algorithms for open-pit mining transportation systems are proposed to obtain the maximum efficiency of dispatching and routing [24–27]. Moreover, several areas that affect production are identified and these include: haul road conditions, the control systems, dispatching program, dispatching data management, as well as truck-shovel match factor techniques [28–29]. However, only few research papers on dispatching systems consider uncertainty [30–33], and there is no comparison to actual mine operations.

For more efficient real-time fleet management, it is important to take uncertainties into account. These uncertainties originate from, for instance, equipment faults or changing weather conditions, which cause variations in cycle times of truck-shovel operations. The objective of this work is to integrate a traffic simulation with uncertainties together with classical real-time truck dispatching strategies, that are widely used for solving fleet management problems in an open-pit mine. Based on extensive empirical data, collected from an open-pit mine, the empirical distributions of different activity times of truck-shovel cycle are used for finding a suitable parametric distribution for the simulation model as well as the right parameters. It is shown that the choice of the

* Corresponding author.
E-mail address: patarawan.chaowasakoo@aalto.fi (P. Chaowasakoo).

http://dx.doi.org/10.1016/j.ijmst.2017.01.007
2095-2686/

dispatching strategy has a significant impact on the performance of the mine. The simulation studies reveal that the differences in production figures under different dispatching strategies are remarkable.

The paper is organized as follows: Section 2 contains the formulation of the problem and discusses the real-time truck dispatching strategies. The research methodology and conceptual model are presented in Section 3 and the results are shown in Section 4. Finally, the theoretical and practical implications of the research are given in the discussion and conclusion part in Section 5, where the limitations of the study are also presented, and the future research suggested.

2. Problem formulation

The aim of this work is to provide a simulation framework incorporating the dynamic assignment problem and its relationship to truck-shovel fleet management. Real-time truck dispatching strategies are simulated to address which approach is the most effective for assigning truck-shovel pairs in order to maximize the productivity when uncertainties are taken into account.

2.1. Truck dispatching strategies

The purpose of optimizing a dispatching system is to maximize the productivity. The dispatching methods considered in this paper are partly based on minimizing the queuing time of trucks when waiting to be served by shovels. Consequently, if the lost time in queue is reduced, the utilization of trucks will increase. The above policy uses the concept of real-time truck dispatching strategies described below, for further details see References [11,31,33].

(1) The 1-truck-for-n-shovels approach (Greedy heuristic), illustrated by Fig. 1, is the strategy which is most commonly used in mining operations. A truck operator asks for a new assignment and n possible shovels where the truck could be sent are considered. The choice of the shovel which the truck is assigned for depends on the skills or logical operating procedure of a dispatcher, who typically follows one of the heuristic methods presented in Table 1. The truck is sent to the shovel which offers the highest potential. Typically this strategy is implemented based on the single-stage approach.

(2) The m-trucks-for-1-shovel method is based on the multi-stage approach: truck dispatching decisions will be made by taking into account the m next trucks to dispatch, considering one shovel at a time. More specifically, the shovels are first sorted according to a priority scheme based on how much they are behind their production schedule. Subsequently, the dispatcher assigns the best truck (under the chosen measure) to the shovel that is first on the priority list, see Fig. 1.

(3) The m-trucks-for-n-shovels method is based on the multi-stage approach: the dispatcher simultaneously considers m forthcoming trucks and n shovels, and the requesting truck is assigned for the most suitable shovel, based on forecasted availability of trucks and shovels. Only the truck that has submitted the request is assigned. This is illustrated in the rightmost panel of Fig. 1. In this strategy m should be greater than or equal to n.

2.2. Process properties

The study is carried out at PT. Kitadin Tandung Mayang's East Kalimantan production site based on a concession of mine rated at up to three million tonnes of coal per annum with a total movement of overburden of fifty million bank cubic meter (bcm) using a fleet of 115 machines. The production of the mine varies significantly from month to month and the production rate between shifts fluctuates independent of the working day even if the quantity of trucks and shovels remain the same. It is of great interest to determine which truck dispatching strategy gives the maximal

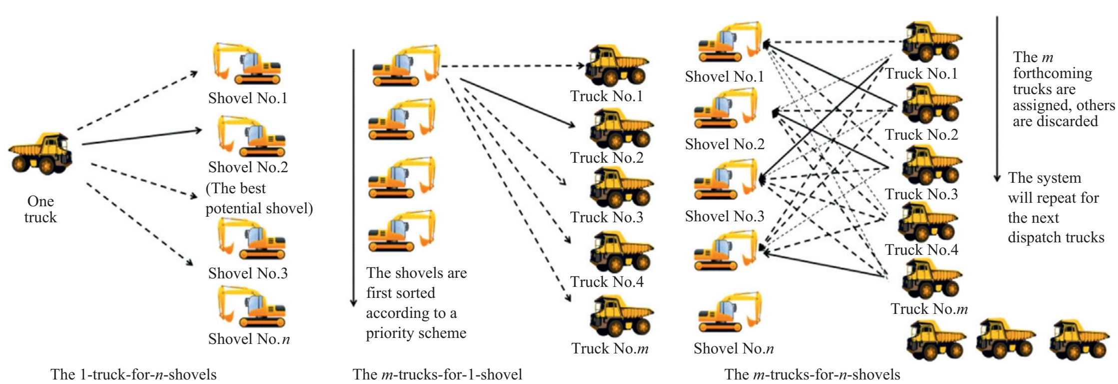

Fig. 1. Real-time truck dispatching strategies.

Table 1
Heuristic truck dispatching methods.

Method	Key objectives	Assignment
Minimizing shovel waiting time (MSWT)	To maximize the utilization of both trucks and shovels	An empty truck is assigned to the shovel with the longest idle time or to the shovel that is expected to be idle first
Minimizing truck cycle time (MTCT)	To maximize the total tonnage productivity	An empty truck is assigned to the shovel that allows the shortest truck cycle time
Minimizing truck waiting time (MTWT)	To maximize the utilization of a shovel by minimizing truck waiting time	An empty truck is assigned to the shovel in which the loading operation starts first
Minimizing shovel saturation and coverage (MSC)	To minimize a shovel operating waiting time	An empty truck is assigned to shovel at equal time intervals to keep shovels non-idle

production. The problem is solved by setting up a discrete event simulation model. Sets of statistical data gathered from the mine are the inputs of the simulation model. First, the truck-shovel activity time data between June-October 2014 is observed and collected using the global positioning system (GPS). The collected data is sufficient to allow for statistically significant analysis.

After that, the distributions of activity times of trucks and shovels are analyzed to find a suitable parametric distribution. A log-normal distribution is chosen because it fits to the empirical distribution of activity times better than many other parametric distributions, such as the exponential distribution. The fitting is based on the sample mean and the sample variance calculated from the corresponding data set. The implementation of the proposed model is carried out using MATLAB®.

2.2.1. A cyclic operation of truck and shovel

The collected data is categorized on a monthly basis and divided based on the capacity of truck types (small size 23 bcm, large size 41.5 bcm) and shovel types (small size 7 m^3 and large size 14 m^3). In order to understand and analyze the bottlenecks in the system, a number of activity terms needs to be determined and constructed. Fig. 2 illustrates a cyclic operation of truck and shovel activity. Activity times are calculated based on GPS data by determining the time the truck spends on a given area. These activities are defined as follows:

(1) Travelling refers to the time the empty truck travels to a shovel at the loading point area.
(2) Waiting in terms of trucks refers to the time the truck waits at a shovel. On the other hand, in terms of shovels it refers to the time from the moment when the previous truck leaves the loading area until the moment the next truck takes the position for loading.
(3) Spotting refers to the time the truck positions itself for loading.
(4) Loading in terms of trucks refers to the time the shovel loads the truck. This is the time the truck spends on the loading area. In terms of shovels it refers to the time between the moment when the first material is loaded into the truck, and the moment when the truck leaves the loading area.
(5) Hauling refers to the time the truck hauls to a dump point.
(6) Queued refers to the time the truck waits at the dump point.
(7) Backing refers to the time the truck spends on taking the position for dumping.
(8) Tipping refers to the time the truck dumps material.

2.2.2. Mine uncertainties

(1) Hauling distance

First, the truck receives a dispatching order and then travels to the assigned shovel. After that, the material is loaded onto the truck and the truck hauls the material to the dump point. Finally, the truck waits for a new dispatching order. This procedure is repeated until the end of the shift. In the mine operation under consideration, there are three shifts; (i) shift ‘A’ operating from 7:15–15:15, (ii) shift ‘B’ operating from 15:15–23:15, and (iii) shift ‘C’ operating from 23:15–7:15. Hauling distance is the crucial uncertainty in the open-pit mine operation, because the distances can vary significantly depending on (i) available trucks and shovels, and (ii) dispatching orders. Fig. 3 presents the collected hauling distance data, which is categorized by the shift and the capacity of trucks. There are several outliers that exceed the mean by more than 100%, which makes the system highly unpredictable. In addition, the standard deviation varies significantly from month to month, and the standard deviation is in most cases about 20–50% of the mean.

(2) Time of cyclic truck and shovel operation

The truck-shovel operation time depends on the hauling distance, the speed of the truck, capacities of trucks and shovels, and the length of the queue. The time span of the truck-shovel operation is uncertain and the problem is stochastic. For example, the travel time of a truck between the same specific loading and dumping points are not the same over the whole shift and can be modeled by a random variable. The log-normal distribution fits sufficiently well to the data and is used for modeling activity times.

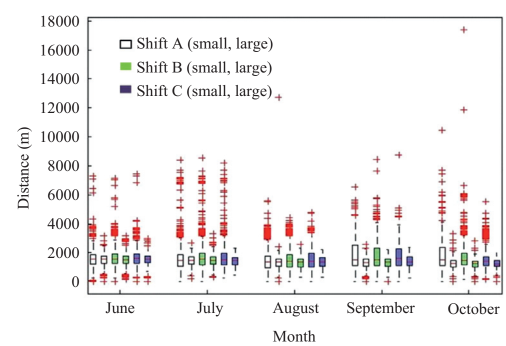

Fig. 3. Hauling distance of shift A, B, and C.

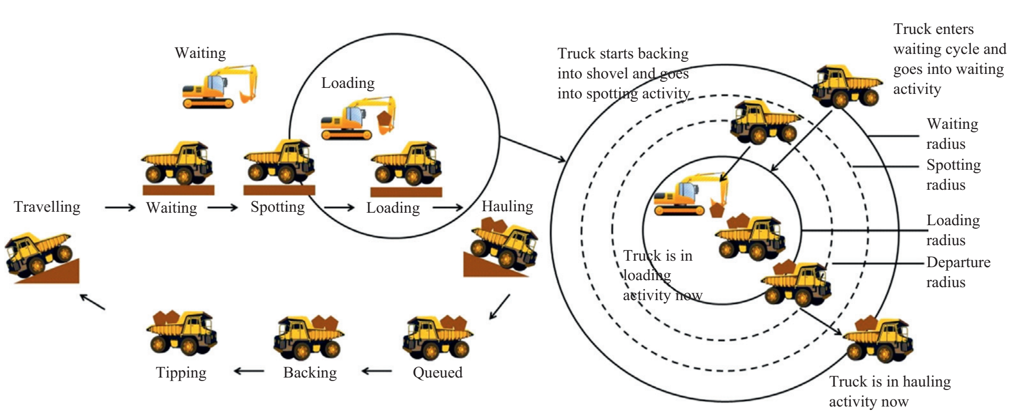

Fig. 2. A cyclic operation of truck and shovel.

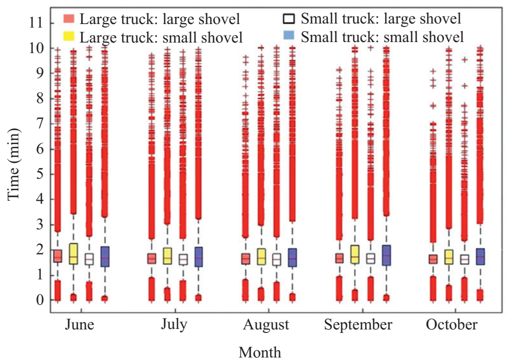

Fig. 4. Loading time of matched truck and shovel.

From the practical perspective it is convenient that the means and the variances of all activities are quite stable between months. Namely, the means and the variances of the previous month's activities can be used as a bench-mark when simulating the future production. In particular, one can write a program that makes the optimal decision using Bayesian approach, where the time distributions are in the beginning of the month based on those of the previous month and update the distributions when more data is gathered.

(3) Loading time of matched truck and shovel

In a heterogeneous fleet, the loading time of a shovel is different for each type of trucks. The collected loading time data of matched truck and shovel is presented in Fig. 4. It shows that both the mean and the variance are relatively stable from month to month. The variance is 39–46% of the mean for small shovels and 29–39% for large shovels. However, Fig. 4 illustrates that the tails of the distributions are long and it is not exceptional that loading time exceeds the average loading time by more than 100%. The statistical data of loading times can identify the efficiency of the truck and shovel fleet and in some cases has been used to determine the shovel service rate.

3. Modeling

Mines are dynamic systems and hence information changes over time. Simulation models are often based on historical information provided by the GPS technology. The concept of real-time truck dispatching strategies has been used for modeling systems. The fundamental concept of this model is developed for truck allocation based on three uncertain parameters; the truck cycle time, the loading time of matched truck and shovel, and inactive times of trucks and shovels.

The process (Fig. 5) starts with the collection of historical mine data. The mine data is analyzed and converted into the input data for the simulation model, which is based on the real-time truck dispatching strategies. The main idea of the simulation model reflects how much waste can be produced if dispatching rules are changed. The procedure of optimization models involves a number of steps listed below.

3.1. The 1-Truck-for-n-shovels (single-stage approach)

3.1.1. Initialization

First, the arrival times, which are the sums of simulated travelling and spotting times, are sorted ascendingly. Then the simulated return times (hauling + backing + tipping + spotting) and loading times are sorted, and finally trucks and shovels are matched based on chosen heuristic methods.

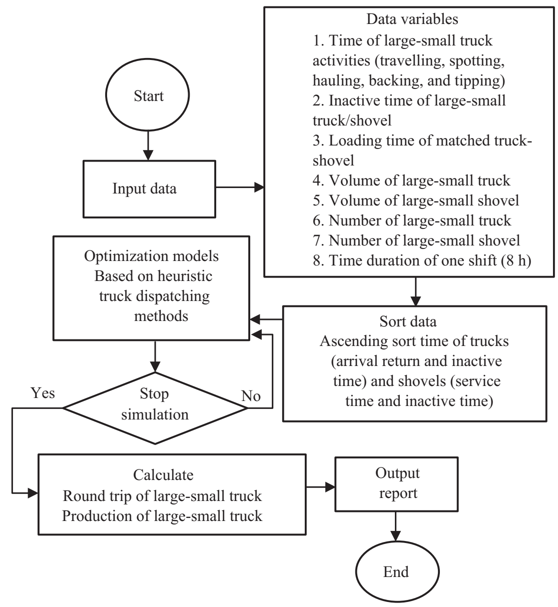

Fig. 5. Conceptual model of the real-time truck dispatching strategies.

Step 1. Assign an empty truck based on one of the following strategies:

(1) Minimizing Shovel Waiting Time (MSWT): an empty truck (large/small) is randomly assigned to a shovel that is expected to be idle first. Run the simulation loop until the total time (arrival + loading service + return) of the truck is 8 h.
(2) Minimizing Truck Cycle Time (MTCT): an empty truck (large/small) with minimal cycle time (arrival time + return time) is assigned to a shovel that is expected to have the shortest loading service. Run the simulation loop until the total time (arrival + loading service + return) of the truck is 8 h.
(3) Minimizing Truck Waiting Time (MTWT): an empty truck (large/small) is randomly assigned to a shovel in which the loading operation starts first. Run the simulation loop until the total time (arrival + loading service + return) of the truck is 8 h.
(4) Minimizing Shovel Saturation and Coverage (MSC): an empty truck (large/small) with minimal cycle time (arrival time + return time) is assigned to a shovel at equal time intervals to keep shovels busy. Run the simulation loop until the total time (arrival + loading service + return) of the truck is 8 h.

3.2. The m-trucks-for-1-shovel (multi-stage approach)

3.2.1. Initialization

First, the arrival times, which are the sums of simulated travelling and spotting times, are sorted ascendingly. Then the simulated return times (hauling + backing + tipping + spotting) and loading times are sorted, and finally trucks and shovels are matched based on chosen heuristic methods.

Step 1. The time of loading service based on matching truck and shovel is obtained by categorizing the service time by

(1) Small truck with small shovel and small truck with large shovel.
(2) Large truck with small shovel and large truck with large shovel.

Finally, the loading times of shovels are sorted according to the time priority.

Step 2. The shovel that is expected to have the shortest loading service is the first in priority order and is assigned with an empty truck (large/small), which is selected such that it has the lowest minimum cycle time (arrival time + return time). Run the simulation loop until the total time (arrival + loading service + return) of the truck is 8 h.

3.3. The m-trucks-for-n-shovels (multi-stage approach)

3.3.1. Initialization of MSWT and MTWT

First, the arrival times, which are the sums of simulated travelling and spotting times, are sorted ascendingly. Then the simulated return times (hauling + backing + tipping + spotting) and loading times are sorted, and finally trucks and shovels are matched based on chosen heuristic methods.

Step 1. Compare the arrival times of all small/large trucks, then select the shortest arrival time. The selected trucks are assigned to the shovels that are expected to have the longest idle time if the method is MSWT. If the method is MTWT, the shovels which start the loading operation first are assigned. In this way, the first round of the selected truck and shovel is chosen and operated.
Step 2. Check the return time to the starting point of the selected truck. Compare arrival times between idle small/large trucks and the selected trucks that go to loading service on the first round and choose the one with the shortest arrival time. After that, assign the truck with the shortest arrival time to the shovels according to MSWT or MTWT method.
Step 3. Run the simulation loop until the total time (arrival + loading service + return) of the trucks is 8 h.

3.3.2. Initialization of MTCT and MSC

Same as initialization of MSWT and MTWT methods above.

Step 1. Compare the cycle times of all small/large trucks, then select the shortest cycle time. The selected trucks are assigned to the shovels that are expected to have the shortest loading time, if the method is MTCT. If the method is MSC, the arrival time and cycle time have to be compared and the best time is selected. Finally, the selected trucks are matched to the shovel at equal time intervals to keep shovel busy. The operation is started at the first round.
Step 2. Check the time when the selected truck will arrive at the starting point. Compare the arrival time and the cycle time between idle small/large trucks and the selected trucks, and choose the one with the shortest time. After that, assign the trucks to the shovels with the shortest loading time in MTCT method. For MSC method, only the cycle time is required.

Step 3. Run the simulation loop until the total operational time of the trucks is 8 h.

3.4. Model fit

The performance of the log normal model is illustrated by Fig. 6, which shows the comparison of simulations by (i) re-sampling from the real activity time data, and (ii) the fitted log-normal distributions, using "the *m*-trucks-for-1-shovel" approach. The results obtained from the re-sampling are almost identical to the results obtained from the log-normal distribution, which confirms that the log-normal model is sufficiently accurate for modeling activity times, in order to get realistic results for simulated production.

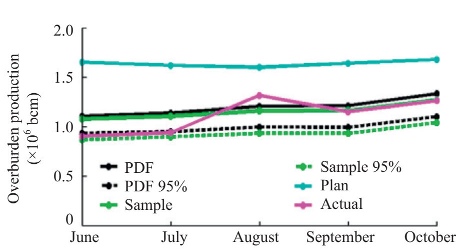

Fig. 6. Simulated production of the fitted model.

4. Results

The simulation study is conducted in order to compare the real-time truck dispatching strategies, and to demonstrate the effect of changing conditions in the mine operation. The experiment is considered based on the number and types of trucks and shovels, which operates in the mine. The fleet consists of 32 small trucks (23 bcm), 36 large trucks (41.5 bcm), 16 small shovels (7 m^3), and 4 large shovels (14 m^3). The length of the period is one month, with 8 h per shift. One thousand samples for each shift are simulated. The average production of simulated scenarios for all truck dispatching approaches are calculated and compared to the plan and the actual production of the mine.

4.1. The 1-truck-for-n-shovels

Under the 1-truck-for-*n*-shovels model, the simulated average production in each month using MSWT and MTWT methods are relatively close to the plan, while MTCT and MSC methods give results that are somewhat close to the actual production, see Fig. 7. The 95% figures are the values that are exceeded in 95% of simulated paths, that is, the production exceeds this with 95% probability. Table 2 illustrates the index values of the simulated production of each method. This clearly shows that the change of heuristic truck dispatching method reveals the differences in production. The simulated result of MTWT and MSWT yield high production in each month, while MTCT and MSC are equivalent and yield equal production. It is noteworthy that the actual productions in June and July are close to the 95%-limits of the simulated MTCT and MSC methods, while in August-October the actual production is close to the average production of the simulated MTCT and MSC methods.

4.2. The m-trucks-for-1-shovel

In this approach, the decision is made by taking into account the *m* next trucks to dispatch in the near future, but only considering one shovel at a time. More specifically, the priority of shovels is based on ascendingly sorted times. The results of simulated

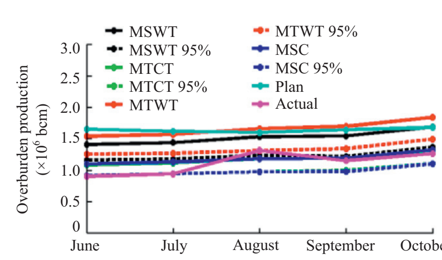

Fig. 7. Simulated production of the 1-truck-for-*n*-shovels.

Table 2
Index production of the 1-truck-for-n-shovels (%).

Methods	June	July	August	September	October
MSWT	85	89	96	94	101
MTCT	66	69	74	72	78
MTWT	93	97	104	103	110
MSC	66	70	74	72	79
Plan	100	100	100	100	100
Actual	55	58	82	70	75

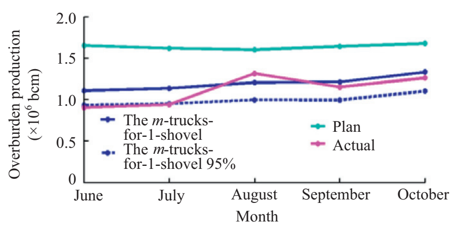

Fig. 8. Simulated production of the m-trucks-for-1-shovel.

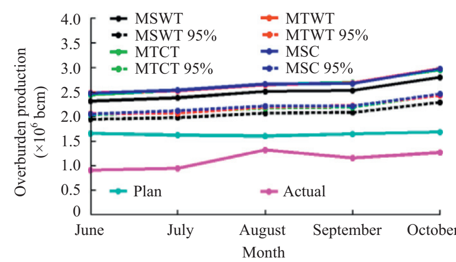

Fig. 9. Simulated production of the m-trucks-for-n-shovels under ideal operation.

production are presented in Fig. 8. Also, using this approach, the average production is close to the actual production in August-October, while the actual production in June and July is nearly equal to the 95%-limit of simulated production. Table 3 illustrates that the performance of this approach appears to be 27% lower than the target plan, while it is close to the actual production.

4.3. The m-trucks-for-n-shovels

For the m-trucks-for-n-shovels approach two scenarios are considered: the first scenario assumes the ideal operating condition, while the second scenario involves an unexpected event which occurs from equipment faults or poor weather.

4.3.1. Scenario 1

Fig. 9 shows the production when all n shovels are operating, and when the running of m trucks dispatching decisions are made based on a global vision, that is, by choosing the shovel to which the next truck is dispatched by optimizing over m next trucks and all n shovels. For the optimal solution, the aim is to minimize the total time in the system. Table 4 shows the results of MTCT, MTWT and MSC methods, which are equivalent and yield equal production, while the performance of MSWT is about 6% lower. However, all these methods give results that on average exceed the actual production by 90–270%. Even the 95%-limits are 57–125% higher than the actual production. The m-trucks-for-n-shovels approach yields a production that clearly exceeds the planned production regardless which method is used.

4.3.2. Scenario 2

Fig. 10 shows the simulated production, when m trucks and n shovels are operated with increased uncertainty. That is, unexpected events slowing down the production are added to the simulation model. For example, in the event of the breakdown of shovels or trucks, the system works with reduced capacity. The data related to unexpected events at the mine was collected with GPS technology, the average inactive time of small trucks, large trucks, small shovels, and large shovels in each month is 57, 58, 185, and 146 h, respectively. The simulation model is the same as in Scenario 1, but inactive time is included in the simulation model for all methods. The production is reduced compared to Scenario 1, but it is still on average higher than the planned production and almost double compared to the actual production. The 95%-limits are quite close to the planned production. Table 5 illustrates the results affected by unexpected events, the capability of the fleets prescribed lower production by approximately 36% compared to Scenario 1.

Table 4
Index production of the m-trucks-for-n-shovels under ideal operation (%).

Methods	June	July	August	September	October
MSWT	140	147	157	154	166
MTCT	148	156	166	164	176
MTWT	150	155	165	163	177
MSC	150	156	166	163	177
Plan	100	100	100	100	100
Actual	55	58	82	70	75

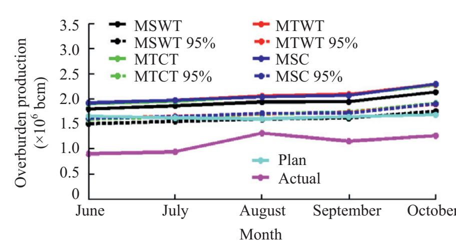

Fig. 10. Simulated production of the m-trucks-for-n-shovels under unexpected event.

Table 3
Index production of the m-trucks-for-1-shovel (%).

Methods	June	July	August	September	October
m-trucks-for-1-shovel	67	70	75	74	79
Plan	100	100	100	100	100
Actual	55	58	82	70	75

Table 5
Index production of the *m*-trucks-for-*n*-shovels under unexpected event (%).

Methods	June	July	August	September	October
MSWT	109	115	121	118	127
MTCT	115	121	128	127	136
MTWT	116	122	128	127	136
MSC	116	122	127	126	137
Plan	100	100	100	100	100
Actual	55	58	82	70	75

Table 6
Average production of simulation models.

	Average production of June-October 2014 (bcm)					
	1-truck-for-*n*-shovels	*m*-trucks-for-1-shovel	*m*-trucks-for-*n*-shovels		Plan	Actual
			Scenario 1	Scenario 2		
MSWT	1,521,324		2,501,568	1,932,280		
MTCT	1,175,004		2,651,868	2,052,703		
MTWT	1,661,652		2,656,512	2,063,946		
MSC	1,182,636		2,658,168	2,057,400		
m-trucks-for-1-shovel		1,198,224				
Plan					1,638,132	
Actual						1,113,811

Table 6 presents the average production of the simulation models compares to the plan and the actual production. The results of simulation model in each method illustrate that 'the *m*-trucks-for-*n*-shovels' is clearly the best allocation approach for real-time truck dispatching. On the other hand, the MSC method, which is the best method for 'the *m*-trucks-for-*n*-shovels' approach, is inefficient when 'the 1-truck-for-*n*-shovels' approach is used. Consequently, it appears that using the global vision for the truck-shovel dispatching allocation clearly increases the production compared to typically used approaches, where decisions are made only considering one shovel or one truck at the time.

5. Discussion and conclusions

Mines are dynamic systems, the cycle travelling time of each truck is short compared to the length of the shift and the timing demands at each loading point are frequently high. Hence the use of GPS tracking is an important tool for monitoring and improving the performance of the mine. Using this modern technology, it is possible to dynamically update the travel time data in order to make optimal dispatching decisions.

The experiments of this paper illustrate how the choice of the dispatching approach impacts on the production. The simulations based on a class of heuristic methods show that dispatching decisions made according to a global vision outperforms, in terms of production, the commonly used methods, where only one truck or one shovel is taken into account in each dispatching decision. The simulations based on fitted log-normal distributions of activity times yield similar results as the actual production when "the 1-truck-for-*n*-shovels" or "the *m*-trucks-for-1-shovel" approach is used. On the other hand, the simulations based on "the *m*-trucks-for-*n*-shovels" provide significantly higher production even when unpredictable events are included in the model. Obviously it is likely that in practice one faces problems that are not included in the simulation model, but the improvement is so pronounced that it is likely that the use of this more sophisticated approach would yield more significant improvement in the mine production than one would expect.

Truck dispatching problems do not occur only in mining operations, but also in many other industries, such as shipping, taxis, and the package delivery, that face similar dispatching problems in the fleet management. The simulation study conducted in this paper could give guidelines of the volumes of improvement also for other industries if more sophisticated methods are employed.

In order to create high yield and high efficiency mining production, it is important to develop digital mine techniques rapidly as these techniques can provide more precise real-time information. The next step for research is to find methods for optimizing fleet size and structure under realistic conditions, such as the operating cost of equipment and coal blending constraints.

Acknowledgments

The authors would like to thank Banpu Public Company Limited for their valuable support throughout this study and for providing the data used in the experiments.

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