Truck-Shovel Operational Planning using Simulation in Open Pit Mines

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Abstract

One of the primary problems in open-pit mining is the efficient use of loading and hauling fleet, in order to obtain the maximum efficiency and minimum cost. Shovels and trucks are the most commonly used loading and hauling equipment in open-pit mining throughout the world. The problem is challenging, because truck-and-shovel systems are complicated due to the uncertainties associated with truck-and-shovel operations and the vast number of parameters and resulting interactions involved in the problem. This paper develops and implements a stochastic discrete-event simulation model to design and analyze the behavior of a truck-and-shovel haulage system in open-pit mining in conjunction with short-term plans. This model imitates the complex truck-and-shovel system, and considers the uncertainties associated with the operations of trucks and shovels. It guarantees that the operational plans will honor the optimum net present value obtained in the scheduling phase. Two main sub-problems are considered in this research. First is the equipment selection problem, in which the numbers of trucks and shovels are determined. In the second sub-problem, using the resources determined in the previous stage, the key performance indicators of the truck-and-shovel system are evaluated. In both stages, the optimal short-term production schedule is the basic input in the model. The proposed simulation model is developed using Arena simulation software and it is applied on a real open-pit iron ore mine.

1. Introduction

The fundamental objective of any mine plan is to maximize the mine profit by extracting ore at the lowest possible cost over the mine life. Especially in open-pit mining, acquiring the optimal production with minimum cost is an essential issue, because open-pit mining operations are highly capital intensive. To achieve this goal, production scheduling is done at the strategic planning level to maximize the net present value (NPV) while considering the extraction sequence of blocks that have to be mined. At the operational planning level, one of the most challenging practices is to use the mining equipment effectively because mining equipment is one of the most expensive necessities of a mine.

Truck-and-shovel system has been the most commonly used material handling and haulage system in open-pit mining throughout the world since the 1930s (Raj et al., 2009). Since the operation of

Askari-Nasab, Hooman (2013), Mining Optimization Laboratory (MOL) – Report Five, © MOL, University of Alberta, Edmonton, Canada, Pages 230, ISBN: 978-1-55195-327-4, pp. 123-136.

Paper presented at APCOM 2013 Brazil

trucks and shovels is one of the main contributors to the overall mining costs, it is critical to utilize these resources efficiently, because an efficient truck-and-shovel system creates reductions in hauling, operating, and maintenance costs. Decisions about truck-and-shovel systems should be consistent with those made in the production scheduling phase which is an important aspect of mine planning and design.

Different methods for modeling truck-and-shovel systems are reported in literature. Some of these methods rely on empirical rules and some are highly mathematical, requiring significant computational effort. None of these methods can comprehensively consider all aspects of truck-and-shovel systems. Most approaches usually ignore the stochastic nature of the truck-and-shovel operations. Mathematical programming and stochastic methods such as queuing theory are examples of the commonly used approaches in the literature.

Although mathematical programming-based models have been developed for truck-and-shovel systems since the 1970s, most have some shortcomings. They do not take into account the stochastic nature of the truck-and-shovel systems, the economic parameters, and the multi-time-period nature of the mining operations (Gurgur et al., 2011), so they are usually combined with simulation models or other stochastic approaches, as seen in studies by Temeng et al. (1997), Fioroni et al. (2008), and Yuriy and Vayenas (2008). Some other studies have developed models based on mathematical programming approaches to optimize production scheduling and truck dispatching problems in the same framework, such as works by Yan and Lai (2007), Yan et al. (2008), and Gurgur et al. (2011).

Some studies have applied the queuing theory to analyze truck-and-shovel haulage systems in open-pit mining. The first application of queuing theory in mining context was done by Koenigsberg (1958). His work is followed by Carmichael (1986; 1987), Kappas and Yegulalp (1991), Muduli and Yegulalp (1996), Czaplicki (1999), Trivedi et al. (1999), Alkass et al. (2003), Krause and Musingwini (2007), Ercelebi and Bascetin (2009), and Ta et al. (2010).

Among current operations research (OR) methods, simulation is widely accepted as a way to assess the performance of mining operations, because it makes it possible to incorporate the system's inherent variability and complexity. The widespread use of simulation techniques is explained by the fact that the models usually are easier to understand. Also compared to other OR techniques, simulation requires less complex mathematical modeling and formulation. Simulation has become even more popular as computers have become more powerful and inexpensive. Simulation studies about truck-and-shovel systems are mostly implemented for specific cases. Each of these studies tries to apply the simulation modeling for a real mine such as models developed by Sturgul and Eharrison (1987) for a surface mine in Australia, Peng et al. (1988) for an iron ore mine in northeast China, Forsman et al. (1993) for a copper ore mine in northern Sweden, and Awuah-Offei et al. (2003) for a typical hard rock auriferous mine in Ghana. The majority of these simulation studies, such as those by Wang et al. (2006) and Burt and Caccetta (2007), are only evaluating truck dispatching rules, while others, such as Karami et al. (1996) and Awuah-Offei et al. (2003), try to also consider the operations involved in the truck-and-shovel system.

Because of the stochastic nature of the truck-and-shovel systems that makes the studying of these systems difficult and time consuming, a simulation approach is chosen in this study to represent the truck-and-shovel operations in detail. Using Arena (Rockwell Automation, 2010) simulation software, this paper develops and implements a discrete-event simulation model to analyze the truck-and-shovel haulage system in open-pit mining with a linkage to the short-term plans. It is of great importance to analyze the behavior of truck-and-shovel systems as a component of a mine that has the high potential to create savings, in conjunction with short-term plans. This approach guarantees that the optimum NPV obtained in short-term schedule planning will be followed in operational plans as well. The proposed model imitates the complex truck-and-shovel system and considers the uncertainties associated with the operations of trucks and shovels. These uncertainties include truck velocity during day and night shifts, shovel velocity, shovel's bucket capacity, dump time, and failures of fleets and facilities. With a larger view to the problem, these factors have an impact on overall mine production. Ignoring such uncertainties in mine operations could result in deviations from the optimal plans. Any deviation from the production targets because of operational uncertainties increases the overall cost.

2. Methodology

The proposed simulation model is developed for an open-pit iron ore mine, Gol-E-Gohar, in the south of Iran. The mine under study has a large pit with a unique pit-exit point. Extracted material is hauled to the pit-exit point through two ramps, before being sent to final destinations. There are six different destinations in the mine: two waste dumps, two stockpiles, and two processing plants. It is assumed that stockpile 1 feeds only crusher 1 and stockpile 2 feeds only crusher 2. Figure 1 shows the schematic view of the mine and the distances between the pit-exit point and different destinations, as well as the distances between the processing plants and the corresponding stockpiles.

The total mining capacity of the mine is approximately 2.2 million tonnes per month. The rehandling capacity at the stockpiles is independent of the mining capacity. The upper and lower bounds on the monthly material delivered to each crusher can vary between 0.32 million tonnes and 0.4 million tonnes per month. There is no limit on the capacities of stockpiles and waste dumps. The main element of interest in the deposit is iron, for which magnetic weight recovery (MWT) is measured, and phosphor and sulfur are the contaminants. The upper and lower bounds on the element grades at processing plants and stockpiles are represented in Table 1. There are no grade bounds for material delivered to waste dumps. It is assumed that only 1 truck can dump at each of the processing plants or each of the stockpiles at the same time. There is room for only 3 trucks at each of the waste dumps.

The proposed simulation model is linked to the mine's optimal short-term production schedule which is produced by Eivazy & Askari-Nasab (2012) for a time horizon of one year, with monthly resolutions. They have used a mixed integer linear programming (MILP) model to generate the optimal short-term production schedule. They have also applied a hierarchical clustering algorithm to aggregate blocks into scheduling mining units, referred to as mining-cuts. The schedule is shown in Figure 2.

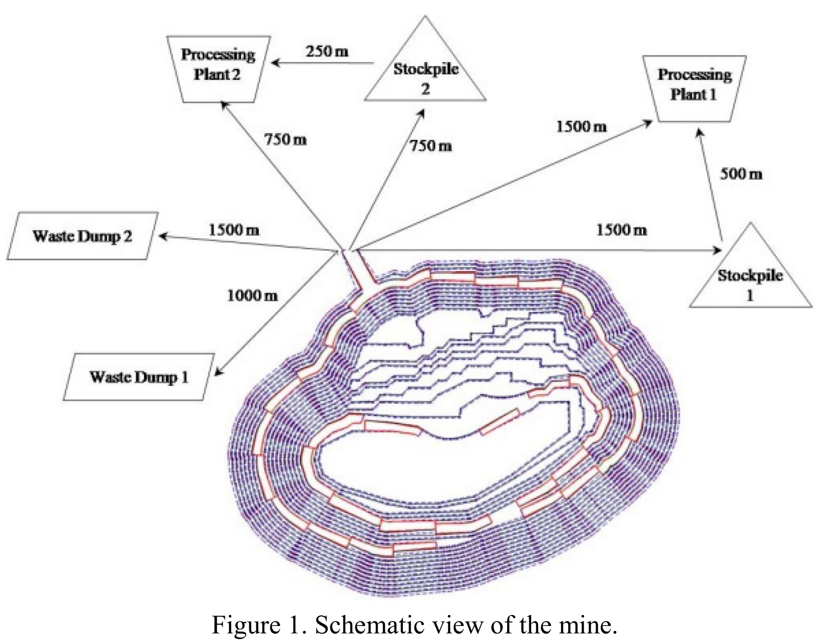

Figure 1. Schematic view of the mine.

Table 1. Upper and lower limits of grades at destinations

Destination	Element	Lower Grade (%)	Upper Grade (%)	Output Grade (%)
Processing Plant 1	MWT	73	78	-
	Phosphor	0	0.3	-
	Sulfur	0	2	-
Processing Plant 2	MWT	78	82	-
	Phosphor	0	0.3	-
	Sulfur	0	2	-
Stockpile 1	MWT	71	74	72.5
	Phosphor	0	0.3	0.15
	Sulfur	0	3	.5
Stockpile 2	MWT	75	77	76
	Phosphor	0	0.35	0.17
	Sulfur	0	2	1

The mine employs CAT 785D mining trucks and CAT 7295 HD electric rope shovels. The truck's nominal payload capacity is about 120 tonnes and the shovel's nominal dipper payload capacity is about 40 tonnes. So, a truck is fully loaded by 3 load-passes. The equipment works 24 hours a day: one day shift and one night shift. Based on the information provided by the short-term schedule about each period, a shovel travels to the location of a mining-cut which is available to be extracted. It takes some time for the shovel to travel from its current location to the mining-cut's location. Simultaneously, a truck travels from its current location to the same mining-cut location as the shovel. The shovel starts its work to extract a portion of the mining-cut and load it into the truck. The truck stays by the working shovel until it is fully loaded. If the material type of a truck's load is ore, it will be delivered to a stockpile or a processing plant.

If it is waste, it will be delivered to one of the waste dumps. Classification of material as ore, stockpile, and waste material, as well as the material's respective destination, is based on the optimal short-term schedule. At the same time, another truck travels to the shovel to be loaded. The shovel moves to another mining-cut's location right after the current mining-cut is completely depleted. Regarding the rehandling process, a loader and a truck are used to reclaim material from stockpiles. In the simulation model, trucks, shovels, waste dumps, stockpiles, and crushers are modeled as resources of the truck-and-shovel operations.

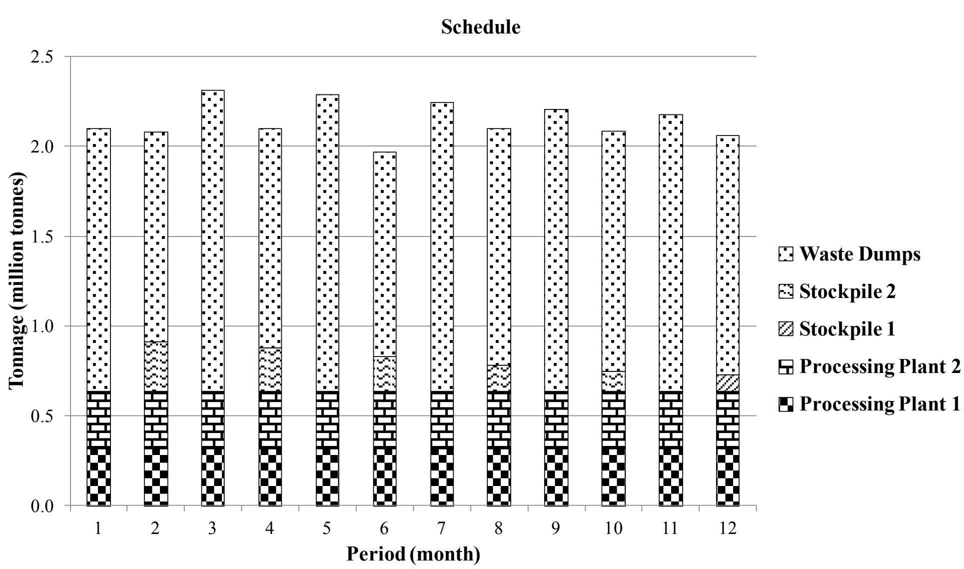

Figure 2. Optimal short-term schedule developed by Eivazy and Askari-Nasab (2012)

The simulation model deals with the uncertainties associated with the operations of trucks and shovels. Each stochastic variable is represented with a probability density function. Most of the probability density functions are obtained by performing data analysis on historical dispatching data gathered from a Jigsaw dispatching database. To fit the best probability density function, Arena Input Analyzer (Rockwell Automation, 2010) is used. Two main sub-problems are considered in the simulation model. First is the equipment selection problem, in which the numbers of trucks and shovels are determined. In the first stage of the proposed approach, different scenarios are generated with alternative number of trucks and shovels and they are examined to determine the required number of each resource. The only constraint considered in this part is meeting the short-term extraction schedule in each period. Therefore, the decision on the number of trucks and shovels is made based on the criterion known as production level.

The second is the behavior of the designed system with the selected amount of equipment. Using defined key performance indicators (KPIs), the efficiency of the system is measured. One of the most important KPIs is the truck cycle time. Since a typical truck-and-shovel system is considered, a truck cycle time is comprised of the time it takes the truck to travel to the mining-cut location, be loaded by the shovel, travel to the destination facility, dump, and travel back to the pit-exit point. This research goes beyond the existing short-term plan and considers the ability to send ore to stockpiles when a crusher is down. The truck-and-shovel system performance is assessed under this new assumption as well. Table 2 illustrates the random variables used in the simulation model, including the mean time between failures (MTBF) and mean time to repair (MTTR).

Table 2. Stochastic variables and their representative probability density functions

Stochastic Variable	Probability Density Function
Loaded Truck Velocity During Day Shift (km/h)	Normal (18, 3)
Loaded Truck Velocity During Night Shift (km/h)	Triangular (15, 15, 18)
Empty Truck Velocity During Day Shift (km/h)	Normal (36, 3)
Empty Truck Velocity During Night Shift (km/h)	Triangular (30, 30, 33)
Shovel Velocity During Day Shift (km/h)	Normal (6, 0.6)
Shovel Velocity During Night Shift (km/h)	Triangular (5.1, 5.1, 5.7)
Load Time (s)	Triangular (12, 15, 18)
Dump Time (s)	Triangular (10.2, 12, 15)
Load-pass Tonnage (tonnes)	Triangular (30, 35, 40)
MTBF for Truck Minor Failure (h)	Weibull (27, 200)
MTTR for Truck Minor Failure (h)	Gamma (1.4, 1.5)
MTBF for Truck Major Failure (h)	Weibull (65, 200)
MTTR for Truck Major Failure (h)	Gamma (0.25, 24)
MTBFfor Shovel Failure (h)	Weibull (32, 216)
MTTRfor Shovel Failure (h)	Gamma (1.4, 1.5)
MTBF for Crusher Failure (h)	Weibull (90, 200)
MTTR for Crusher Failure (h)	Gamma (0.25, 24)

3. Results and discussion

To solve the first sub-problem which is to determine the required numbers of trucks and shovels, different scenarios are generated using Arena Process Analyzer (Rockwell Automation, 2010). The procedure starts to build scenarios with small numbers of trucks and shovels, and increases them in the consecutive scenarios. In this sub-problem, the variable under control is the numbers of trucks and shovels, which differs depending on the scenario. The criterion used to evaluate each scenario is the production level. Scenarios in which the production target is met are considered feasible scenarios. The best scenario is a feasible scenario with the smallest number of trucks and shovels. The production target is met in the best scenario with the resulted numbers of trucks and shovels, so purchasing more trucks or shovels is not economically reasonable.

As shown in Figure 3 and Table 3, scenario generation starts with 2 shovels and 4 trucks, and increases to 4 shovels and 12 trucks. As the number of trucks increases, the deviation from the production target decreases but then stabilizes. After this point, further increasing the number of trucks will not result in much higher production. In the best scenario (scenario 18), with 3 shovels and 11 trucks, the production target is met. The average shovel utilization is about 89% and the average truck utilization is about 67% in this scenario (see Figure 4).

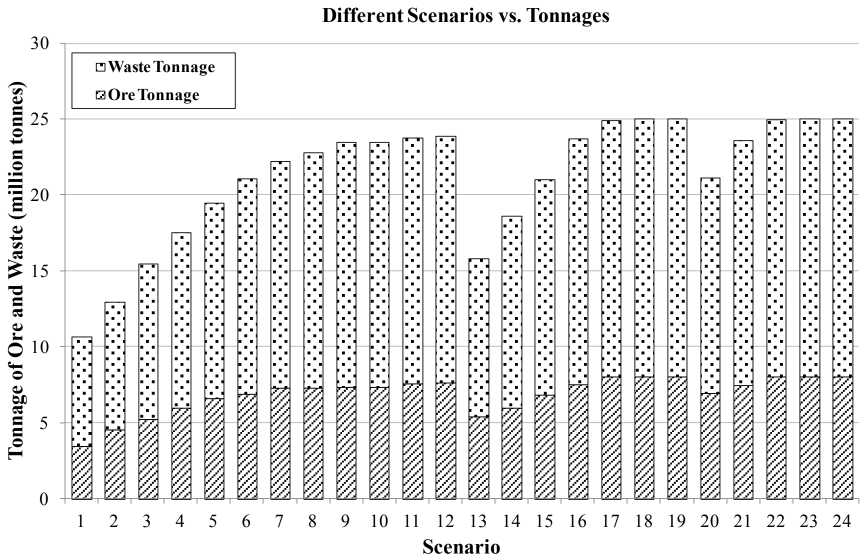

Figure 3. Delivered material tonnage in a year.

Table 3. Delivered material tonnage in a year

Scenario	Number of Shovels	Number of Trucks	Delivered Ore Tonnage (million tonnes)	Delivered Waste Tonnage (million tonnes)
1	2	4	3.43	7.19
2	2	5	4.54	8.36
3	2	6	5.22	10.22
4	2	7	5.95	11.54
5	2	8	6.56	12.89
6	2	9	6.84	14.19
7	2	10	7.26	14.92
8	2	11	7.26	15.52
9	2	12	7.34	16.08
10	2	13	7.35	16.08
11	2	14	7.57	16.19
12	2	15	7.61	16.24
13	3	6	5.36	10.44
14	3	7	5.95	12.63
15	3	8	6.78	14.19
16	3	9	7.50	16.16
17	3	10	7.99	16.90
18	3	11	7.99	17.01
19	3	12	7.99	17.01
20	4	8	6.93	14.20
21	4	9	7.44	16.15
22	4	10	7.99	16.93
23	4	11	7.99	17.01
24	4	12	7.99	17.01

The average truck and shovel utilizations during each month are monitored based on the pre-set numbers of 11 trucks and 3 shovels. As presented in Figure 4, the average truck and shovel utilizations in the odd months (1, 3, 5, 7, 9, and 11) are almost less than those in the even months (2, 4, 6, 8, 10, and 12). This is because during odd months less material has been delivered directly from the mine to the processing plants. Instead, some material is reclaimed from stockpiles during these months. In order to study the possibility of employing less equipment in odd months, another scenario analysis is implemented with the focus on odd months. In all scenarios, 3 shovels and 11 trucks are fixed for even months. The numbers of trucks and shovels for the odd months differs from one scenario to another. As presented in Figure 5 and Table 4, Scenario 15 with 3 shovels and 10 trucks is the best scenario. This means that the mine employs 3 shovels and 11 trucks during the year, but in odd months it does not use one of the trucks because of scheduled maintenance.

The resulting average monthly truck and shovel utilizations are shown in Figure 6. Compared to the previous scenario which uses fixed numbers of trucks and shovels throughout the year, the new scenario results in steadier equipment utilization.

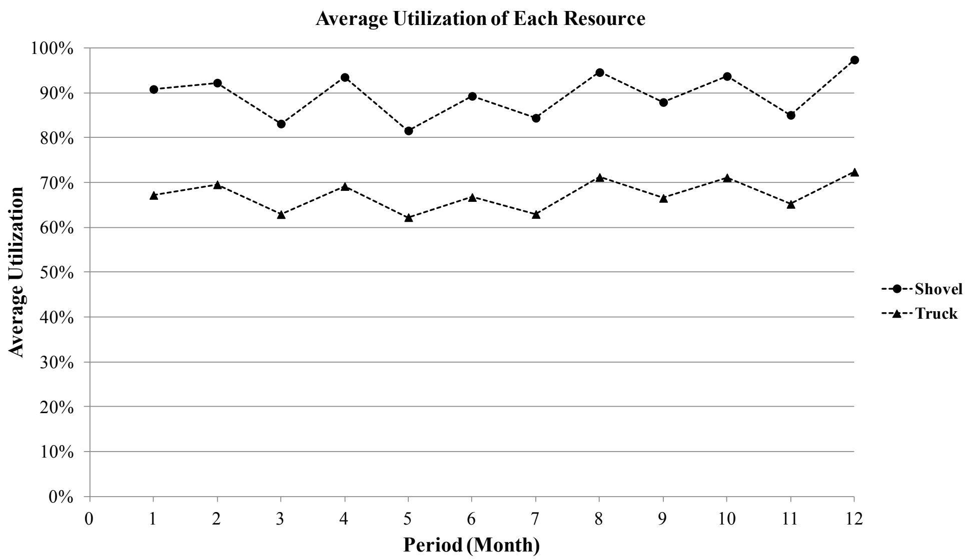

Figure 4. Average utilizations of resources with 3 shovels and 11 trucks.

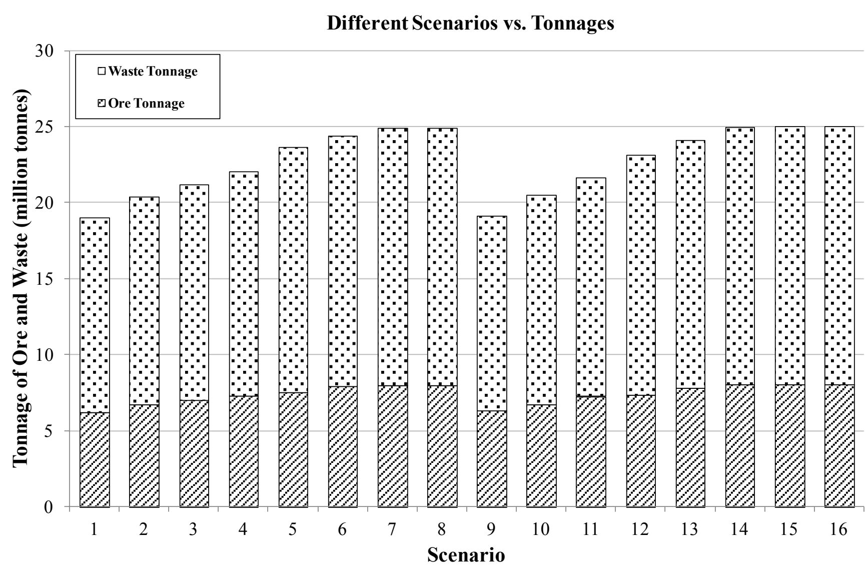

Figure 5. Delivered material tonnage in a year in second scenario.

Table 4. Delivered material tonnage in a year in second scenario

Scenario	In odd months		Delivered Ore Tonnage (million tonnes)	Delivered Waste Tonnage (million tonnes)
	Number of Shovels	Number of Trucks		
1	2	4	6.20	12.80
2	2	5	6.70	13.68
3	2	6	7.00	14.19
4	2	7	7.26	14.77
5	2	8	7.49	16.14
6	2	9	7.89	16.46
7	2	10	7.97	16.90
8	2	11	7.98	16.93
9	3	4	6.30	12.80
10	3	5	6.70	13.77
11	3	6	7.26	14.34
12	3	7	7.32	15.77
13	3	8	7.77	16.32
14	3	9	7.99	16.96
15	3	10	7.99	17.01
16	3	11	7.99	17.01

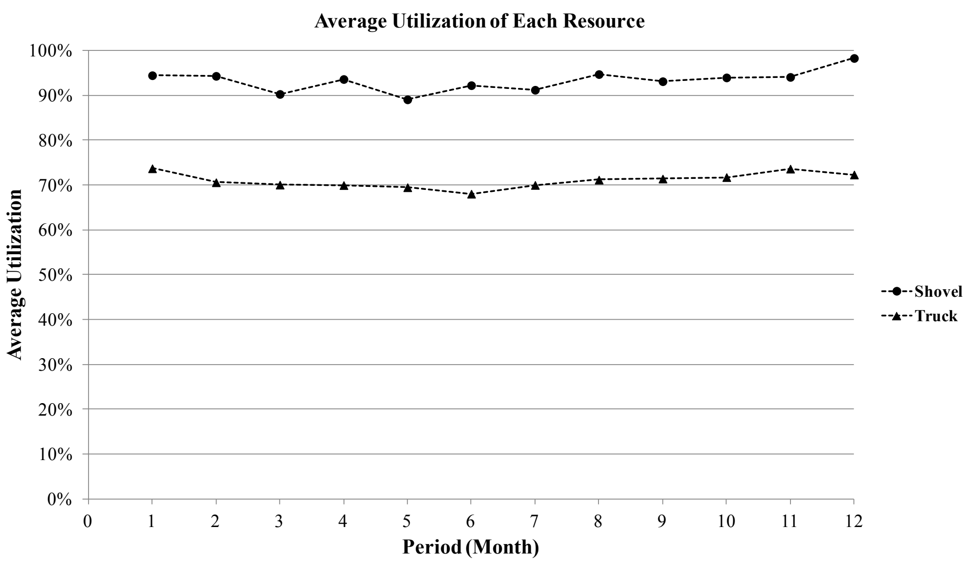

Figure 6. Average utilizations of resources considering maintenance schedule.

To deal with the second sub-problem, the simulation model is run for 50 replications. One of the most important KPIs is the average utilizations of trucks and shovels. Because of stochastic variables taken into account in the model, each replication gives a different average utilization of equipment. To show the results clearly, box plots are used in this study. The box plots of the average utilization of shovels and trucks and the corresponding statistics are shown in Figure 7, and Figure 8.

Delivered material tonnage is another significant KPI which is also used to verify the model. Total delivered material tonnage to different destinations should follow the optimal short-term production schedule.

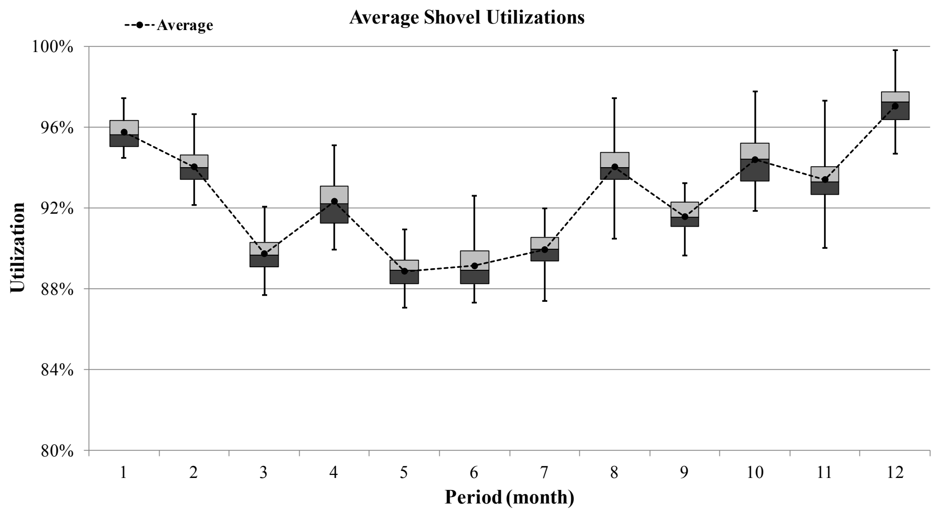

Figure 7. Box plot of average shovel utilization during each period.

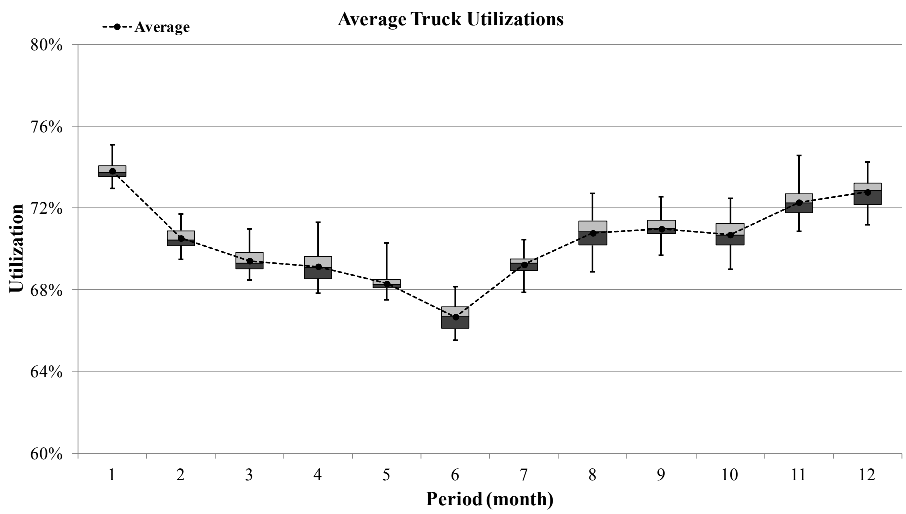

Figure 8. Box plot of average truck utilization during each period.

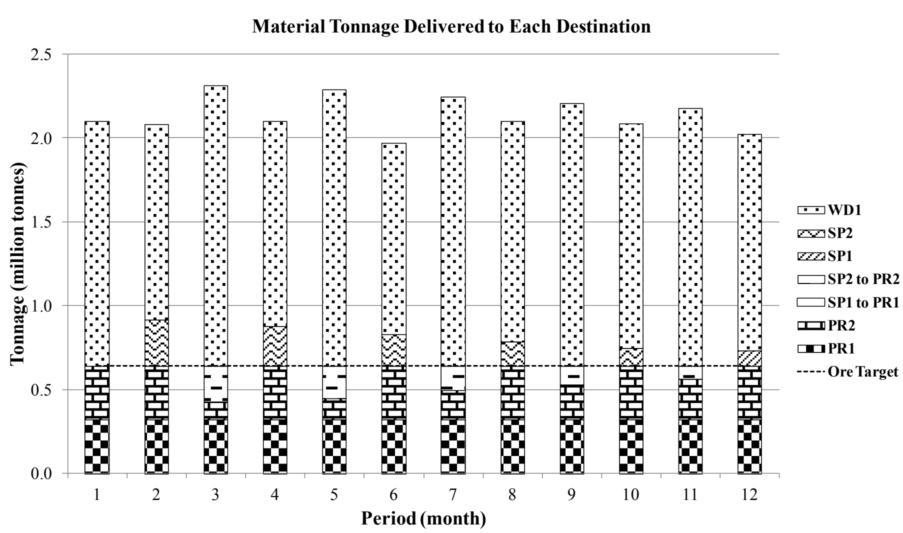

Figure 9. Delivered material tonnage to different destinations.

Having an invariable feed of material at the end of a period in different replications occurs because the numbers of trucks and shovels has been determined in such a way as to meet the production target (see Figure 9). As explained before, grade of elements such as iron is taken into consideration. Figure 10 and Table 5 show the weighted average grade of iron delivered to each processing plant. Although there are some variations from one period to another, all grades are between the predetermined boundaries. This further confirms that the model is working accurately.

The truck waiting time at different destinations is one of the main KPIs that shows how effectively the trucks are used. The destination facility may be unavailable due to two reasons: 1) other trucks are dumping at the destination and there is no room for the truck to dump its load and 2) the destination facility has failed. As can be seen from Figure 11, trucks wait an average of 2.25 minutes at processing plant 1 and an average of 2.32 minutes at processing plant 2. To improve the system by reducing truck waiting times, it is recommended that if a crusher has failed, no trucks should travel to that processing plant. Instead, trucks should be redirected to the corresponding stockpile. The resulting average waiting time at processing plant 1 and 2 are reduced by more than 99% Table 6.

Any improvement in truck waiting time would impact the truck queue length and truck cycle time and, thus, improve the system’s total efficiency. Truck cycle time is another critical KPI that is addressed in this section. In the new scenario, because the truck waiting time is decreased, the expectation is that there will be lower truck cycle times. Figure 12 and Table 7 compares the average truck cycle time during day and night shifts in basic scenario to those in the new scenario. In both scenarios, truck cycle time during day shifts is less than that during night shifts because trucks and shovels travel faster during day shifts.

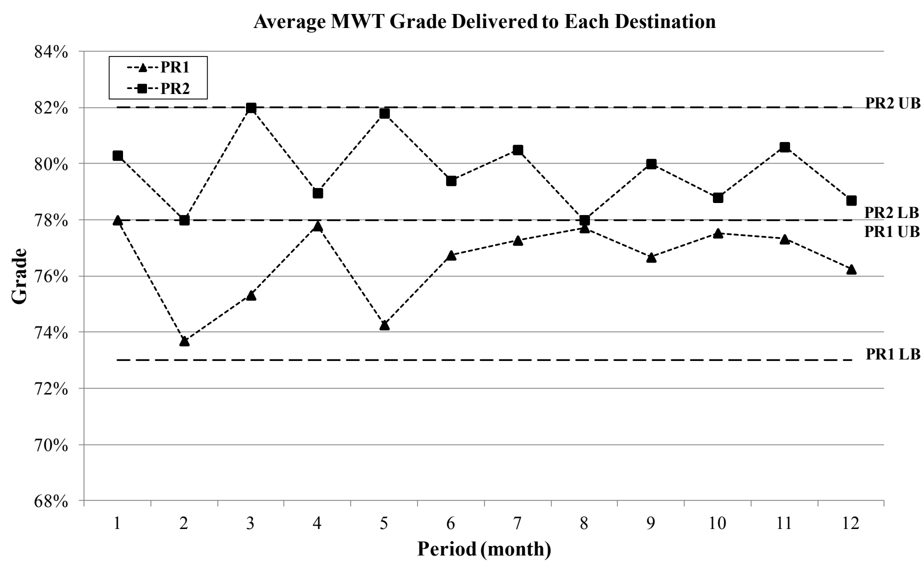

Figure 10. Average MWT grade of material delivered to each processing plant.

Table 5. Average MWT grade of material delivered to each processing plant

Month	1	2	3	5	6	7	8	9	10	11	12
PR1	78.00	73.70	75.32	77.79	74.27	76.75	77.28	77.72	76.67	77.53	77.32
PR2	80.30	78.00	82.00	78.96	81.80	79.40	80.50	78.00	80.00	78.80	80.60

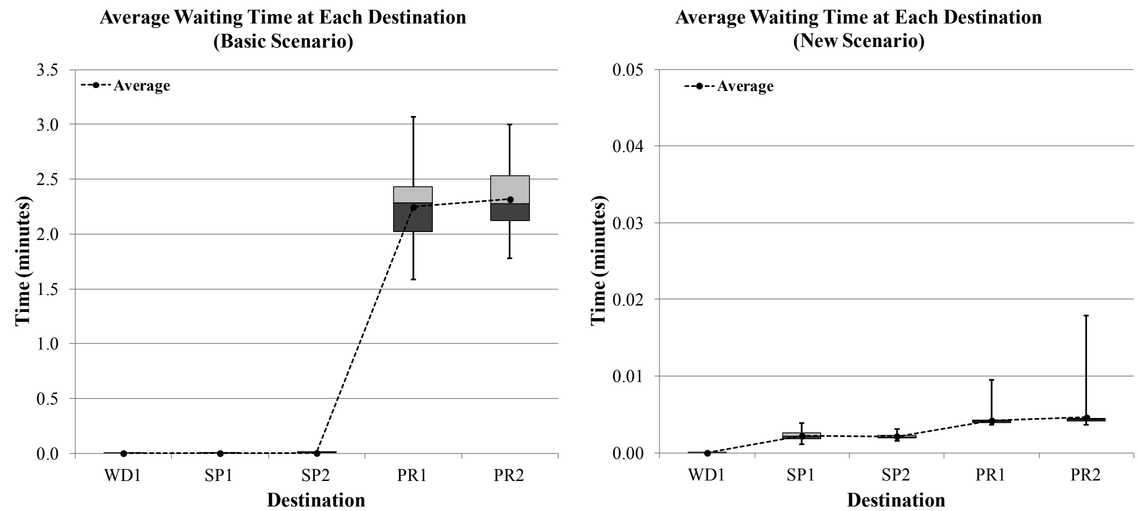

Figure 11. Box plot of average truck waiting time at each destination in basic and new scenarios.

Table 6. Improvement percentages in waiting times at processing plants

Destination	Average Waiting time (minute)		Improvement
	Basic Scenario	New Scenario	
PR1	2.25	0.004	99.81%
PR2	2.32	0.005	99.80%

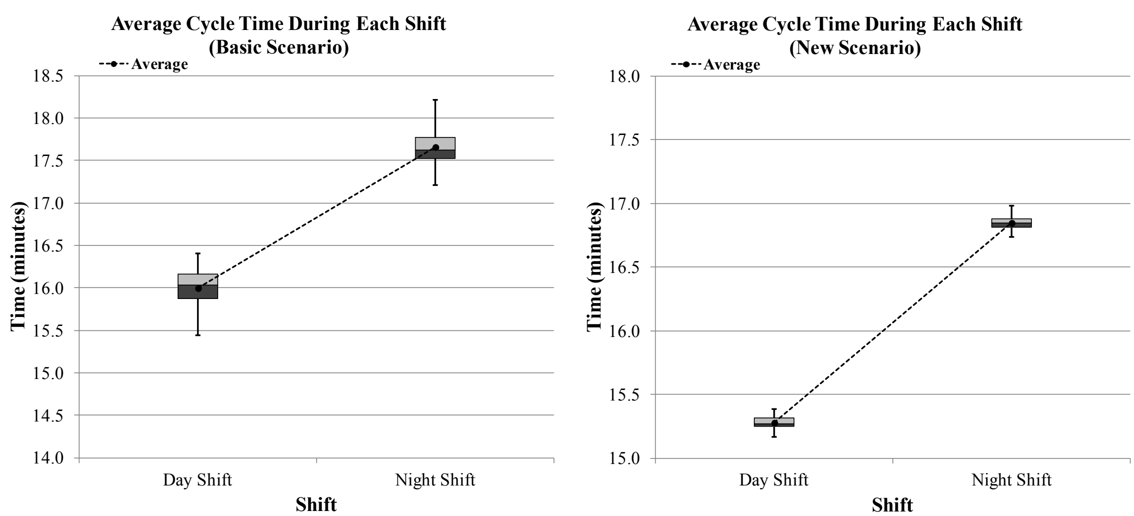

Figure 12. Box plot of average truck cycle time during each shift in basic and new scenarios.

Table 7. Improvement percentages in cycle times during day and night shifts

Shift	Average Cycle time (minute)		Improvement
	Basic Scenario	New Scenario	
Day	16.00	15.28	4.50
Night	17.66	16.85	4.59

In the new scenario, some material that was supposed to go the processing plants is delivered to stockpiles because of a crusher failure. Because a crusher failure is a stochastic variable, the material delivered to the processing plants and stockpiles varies in different replications. In this scenario, in addition to scheduled reclamation from stockpiles, extra reclamation should be done to meet the production target. Therefore, there are variations in reclaimed material tonnage as well. The unplanned flow of material from each period is reclaimed during the subsequent period. Figure 13 shows the average material tonnage delivered to each destination in the new scenario. The total ore tonnage delivered to processing plant, both directly delivered and reclaimed, deviates from the optimal target. Figure 14 presents these deviations in terms of percentages of the optimal ore production target.

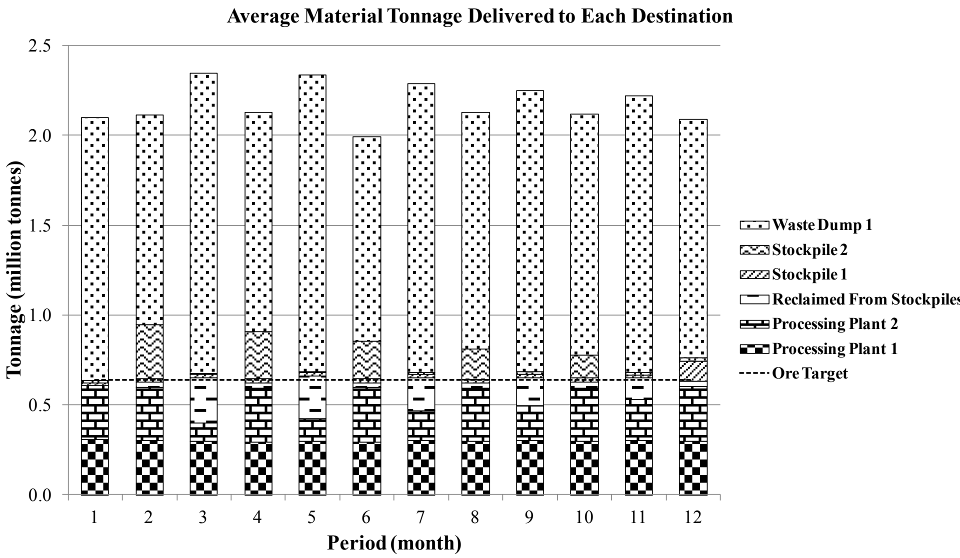

Figure 13. Average material tonnage delivered to each destination in the new scenario.

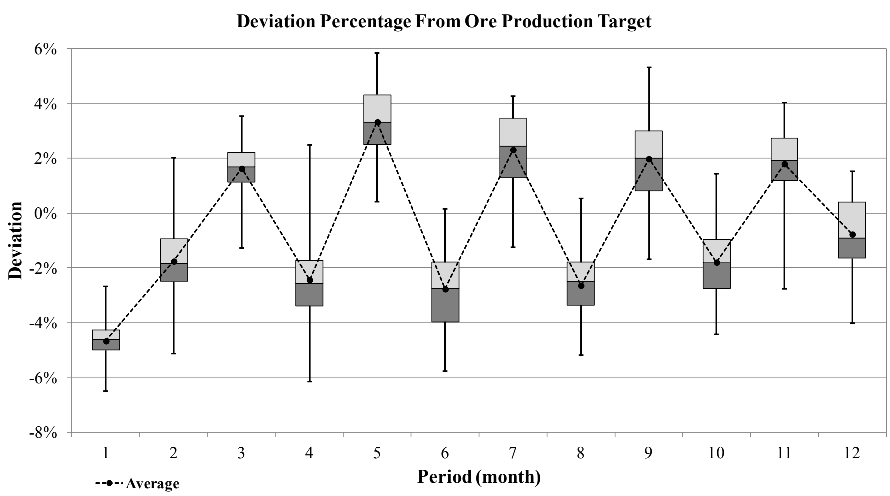

Figure 14. Box plot of the percentage of average delivered ore that has deviated from the production target.

4. Conclusions

Using Arena (Rockwell Automation, 2010) simulation software, a stochastic discrete-event simulation model is developed and implemented in this paper to analyze the behavior of a truck-and-shovel haulage system in open-pit mining in conjunction with the optimal short-term plan. In such a system, material is extracted by shovels and hauled by trucks to different destinations that include waste dumps, processing plants, and stockpiles. The proposed model takes into account the stochastic variables of the system, determines the required numbers of trucks and shovels, evaluates the possibility of building a maintenance schedule, assesses the system's KPIs, and improves the system. The main scientific contribution of this paper on the body of knowledge is the development and implementation of a simulation model with a link to optimal short-term schedule, which is derived from the overall mine plan requirements according to the economic and operational objectives, not only the shovels' requirements which is the common approach in the literature. Another main contribution is considering the mining-cut extraction sequences in the simulation model.

5. References

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