

Verifying Short-Term Production Schedules using Truck-Shovel Simulation

Elmira Torkamani and Hooman Askari-Nasab
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

Abstract

Truck-and-shovel technology is widely used in open-pit mining operations. One of the major challenging issues in the current open-pit mining practices is to utilize these resources efficiently, because the operation of trucks and shovels has a significant contribution to the overall operational costs in a mine. An efficient truck-and-shovel system creates reduction in hauling, operating, and maintenance costs. 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 paper presents a methodology for developing and implementing a simulation model to analyze the truck-and-shovel haulage system in open-pit mining with a link to the short-term plans. This approach guarantees that the optimum Net Present Value (NPV) obtained in long-term scheduling and short-term scheduling phases will be followed in operational plans as well. Because of the stochastic nature of the truck-and-shovel system, a simulation approach is chosen to analyze the system and evaluate alternatives.

1. Introduction

The fundamental objective of any mining project is to maximize profit by extracting ore at the lowest possible cost over the life of the mine. This objective is the basis for decisions made in both strategic and operational levels. At the strategic planning level, this objective is achieved by implementing production scheduling that maximizes the Net Present Value (NPV) by generating optimal long-term and short-term plans. At the operational level, the objective is secured by effective usage of mining equipment, because mining equipment is one of the major capital investments of a mine.

Especially in open-pit mining where operations are highly capital intensive, acquiring the optimal production with minimum cost is an essential issue. Typical practices in open-pit mine planning try to decrease the costs associated with mine operations while satisfying production and grade targets. Since material handling and haulage systems are one of the main contributors to the overall operational cost in an open-pit mine environment, considering a simulation study has high potential to reduce costs such as hauling, operating, and maintenance costs.

Using Arena Software (Rockwell Automation, 2010) for modeling, this paper develops and implements a discrete-event simulation model to analyze the truck-and-shovel haulage system in open-pit mining linked to the short-term plans. This model imitates the complex truck-and-shovel system and considers the uncertainties associated with the operations of trucks and shovels. This approach guarantees that the operational plans will follow the strategic plan in place.

Truck-and-shovel systems have been used in open-pit mines since the 1930s and they are still the most common haulage systems in open-pit mining. Since open-pit mines are extremely large and fully mechanized nowadays and they have a huge variety and size of earth moving machinery, effective utilization of trucks and shovels is a complex task. Operation of trucks and shovels constitutes 50% to 60% of the overall operations' cost in open-pit mines (Ercelebi and Bascetin, 2009). Therefore, efficient utilization of the haulage system could result in savings and reducing the overall mining cost.

The most significant factors that make the analysis of a truck-and-shovel system complicated are the uncertainties in the operational parameters such as truck cycle time, load tonnage, and truck and shovel reliabilities. These factors affect the production of a mine. Ignoring such uncertainties in the operation of a mine could result in deviations from the optimal plans. Any deviation from the production plan because of operational uncertainties increases the overall cost. One of the solutions to prevent the risk of not meeting the production demand is to provide extra trucks and shovels which again imposes extra costs to the system. Because of this uncertain nature of a truck-and-shovel haulage system, evaluating the system requires accurate planning, development, and operation. Analyzing a truck-and-shovel system with the highest level of details can best be done by using simulation technology.

Over the last two to three decades, simulation has been one of the most admired operations research tools due to its ability to deal with complex models, flexibility, power, and ease of use. Simulation has been used in the mining industry throughout the world in both open-pit and underground mines, mostly in materials handling and haulage systems, mining operations, mine planning, and production scheduling. The first mine simulation studies date back to the 1950s (Raj et al., 2009). The Canadian mining industry has demonstrated an increasing interest in applications of discrete-event simulation in mining (Vagenas, 1999).

Besides simulation, other methods are presented in the literature to deal with the truck-and-shovel systems such as mathematical programming models, heuristic methods, models based on queuing theory, and stochastic approaches. In the past, the only methods used for truck allocation and dispatching problem were heuristic methods, overtime more rigorous methods such as mathematical programming have become more popular.

Some researches use the mathematical programming model alone such as Temeng et al. (1997) who used a transportation algorithm based on a non-preemptive goal programming model to formulate a real-time dispatching process, Topal and Ramazan (2010) who developed a mixed integer programming model to schedule a fixed fleet of trucks for a given operation with the objective of minimizing truck maintenance costs while considering constraints subject to production targets, and Gurgur et al. (2011) who developed an LP model to optimize truck allocation in open-pit mining. This model is implemented in association with a Mixed Integer Programming (MIP) model which generates short-term scheduling plans.

Others have used mathematical programming models in conjunction with simulation models. For example, Li (1990) developed a linear programming model to plan material flow, and employed simulation to find matching equipment and to determine how trucks should be assigned to the shovels. Yuriy and Vayenas (2008) combined a reliability assessment model which is based on genetic algorithm with a discrete-event simulation model to perform maintenance analysis on mining equipment. Fioroni et al. (2008) used a simulation model and optimization model to generate short-term planning schedules.

Mathematical programming models and heuristic methods have some shortcomings. Mathematical programming models usually cannot deal with the uncertainties associated with the operation of trucks and shovels. Heuristic methods generally do not consider the whole problem because they solve the problems by simplifying them. Therefore, heuristic methods provide a good solution that is not necessarily the optimal solution (Alarie and Gamache, 2002; Gurgur et al., 2011).

On the other hand, simulation approaches have the ability to analyze the truck-and-shovel system's behavior in detail while considering the uncertainties associated with the operation of trucks and shovels. Usually simulation is used to evaluate the effect of implementing a new method or a different policy on the system's behavior. Bonates and Lizotte (1988) developed a computer simulation model for open-pit mines to optimize the truck-shovel operations when applying different dispatching policies such as Fixed Truck Assignment, Maximizing Truck Use, Maximizing Shovel Use, and Match Factor. Wang et al. (2006) used simulation to evaluate a new real-time dispatching technique for open-pit mines under macroscopic control. Burt and Caccetta (2007) used simulation to evaluate using match factor (MF) as an indicator of a system's efficiency.

Simulation is also used to study specific real cases such as work done by Peng et al. (1988) who constructed a simulation model for an iron ore mine in Northeast China to match various types of equipment, and research performed by Forsman et al. (1993) who used the METAFORA discrete event simulation model to evaluate the truck-shovel system of a copper ore mine in northern Sweden. In one of the most recent simulation studies in a mine, Chanda and Gardiner (2010) compared the capability of computer simulation in estimating truck cycle time in open-pit mining with two other methods: artificial neural networks (NNs) and multiple regressions (MRs). The closest study to the one presented in this paper is the work done by Awuah-Offei et al. (2003) who used simulation techniques to forecast the truck and shovel requirements for a typical hard rock auriferous mine over a 4-year period.

Some studies have applied the queuing theory in the analysis of the truck-and-shovel haulage system in open-pit mining. The very first application of queuing theory in a mining context was done by Koenigsberg (1958) and followed by other researchers. The latest investigations in the application of queuing theory in truck-and-shovel haulage systems were carried out by Alkass et al. (2003), Krause and Musingwini (2007), Ercelebi and Bascetin (2009), and Ta et al. (2010). There are a limited number of works on stochastic programming applied in the field of mining. An example is the work done by Ta et al. (2005) who developed a recourse-based stochastic programming model by defining a chance-constrained truck allocation problem to improve initial truck allocation.

The typical objective of the truck-and-shovel haulage system models presented in the literature is to maximize the mine's production utilizing the available trucks and shovels, or to minimize the number of trucks while considering the production target over an operational period. On the other hand, the main objective of mine planning is to maximize the Net Present Value (NPV) over the mine's life. With these definitions of objective functions, solutions obtained from truck-and-shovel models usually do not guarantee the optimal NPV.

To reach to the main objective of the mine plan, the decisions made in strategic and operational levels should be aligned to each other; therefore, truck-and-shovel models should be considered in conjunction with short-term and long-term plans. It is of great importance to analyze the behavior of truck-and-shovel systems as a component of a mine that is linked to short-term plans.

The model developed in this paper considers the optimal short-term schedule in simulation of a truck-and-shovel system while taking into consideration the uncertainties associated with the operation of trucks and shovels such as speed of empty and full trucks, movement speed of shovels, loading time, and dumping time. In the first stage of the proposed approach, various scenarios are generated with a different number of trucks and shovels and they are examined to determine the required number of each resource. In the second stage, using the resources determined in the previous stage, the system is analyzed in more detail and more key performance indicators (KPIs) of the truck-and-shovel system are evaluated. In both stages, short-term scheduling plans are the basis for building the model. The results verify the alignment of short-term plans with the operation

of trucks and shovels and show the effect of uncertainties on the performance of the proposed truck-and-shovel haulage system.

One of the main contributions of this work is a methodology that establishes the required number of trucks and shovels based on the short-term mine plan. This is derived from the overall mine plan requirements according to the economic and operational objectives, not only the shovel's requirements which is the common approach in the literature.

2. Problem definition

The following question drives this research: what is the proper size of the truck-shovel fleet for a mine to achieve the target production following an optimal monthly production schedule?

To answer this question we build a linkage between optimum short-term plans and a simulation model of a truck-and-shovel haulage system in open-pit mining. The developed truck-and-shovel haulage system in this research should follow the short-term plan schedules. The problem includes two sub-problems:

1. Making decisions about the required number of trucks and shovels, and;
2. Detailed analysis of the system's behavior and performance with the required number of trucks and shovels.

In the first sub-problem, the required numbers of trucks and shovels are determined at the beginning of the mine plan by evaluating different scenarios with different numbers of trucks and shovels. The decision on the number of trucks and shovels is made based on the performance and efficiency criteria of the truck-and-shovel system such as shovel utilization, truck utilization, and meeting production targets. The only constraint that should be satisfied in this sub-problem is the short-term schedules that specify the blocks to be extracted at each period and their respective destination.

The optimal short-term scheduling plan is the basis for building the simulation model. Short-term plans are obtained based on long-term plans. To perform long-term mine planning which maximizes the NPV of the mine over its life, a geological block model is used, then the ultimate pit limit is defined, and finally, the extraction sequence of blocks that should be mined are determined. Then using the solution from long-term mine planning, short-term mine planning is performed to execute the material movement in shorter time horizons. Therefore, short-term plans are based on the optimal block sequence obtained from long-term mine plans and they consider constraints similar to those considered in the long-term. In this paper short-term schedules obtained by Eivazy and Askari-Nasab (2012) is used in which the schedule is done based on mining-cuts rather than blocks.

Since the required number of trucks and shovels are determined in the first sub-problem, the system's behavior is further analyzed and its key performance indicators are evaluated in the second sub-problem to assess the system's overall performance. These uncertainties considered in the simulation model include the speed of trucks in a loaded state and unloaded state, movement speed of shovels, loading time, dump time, and load tonnage. The evaluation and analysis of the system's performance is done based on factors such as total ore tonnage dumped at each processing plant, total ore tonnage dumped at each stockpile, total waste tonnage, magnetic weight recovery (MWT grade) at each processing plant and stockpile, and resource utilizations. Phosphor percentage (S grade) and Sulphur percentage (P grade) are also monitored.

The extraction schedule which is the input to the simulation model consists of 12 periods (months). The extraction schedule provides information about the characteristics of the mining-cuts that should be extracted at each period such as mining-cuts' IDs to be extracted and their sequence of extraction, mining-cuts' material types, tonnages, coordinates, fraction of a mining-cut that is

extracted at each period, grades (P, S, and MWT), and the number of ramps through which material is transported to the exit point. Based on the material type of a mining-cut, the facility where that mining-cut is sent is also known. Eivazy and Askari-Nasab (2012) consider six possible destinations in their model: 2 waste dumps, 2 stockpiles, and 2 processing plants. They also provide data about the distances between each ramp and the exit point, between that exit point and each of the six destinations, and between stockpiles and processing plants.

A typical truck-and-shovel haulage system in an open-pit mine is considered in this paper. Based on the information of mining-cuts in each period, shovels are assigned to the mining-cuts which are ready to be extracted. It takes some time for a shovel to travel from its current location to the mining-cut it is assigned to. Simultaneously, a truck travels from the exit point in the pit to the mining-cut it is assigned to. The shovel starts to operate and extracts a portion of the mining-cut and loads it into the truck. The tonnage which the shovel can extract at each pass is not constant and follows a random distribution. The truck stays by the working shovel until it is fully loaded. Knowing the destination of the material which is extracted, the truck travels to either a processing plant, a stockpile, or a waste dump. At the same time, another truck travels to the shovel to be loaded. The shovel moves to the next mining-cut right after the current mining-cut is depleted.

There is no limit on the number of trucks which can dump concurrently at a waste dump, but there is a limitation on the number of trucks that can dump their material at a stockpile or a processing plant simultaneously. There is space for only one truck at each of the processing plants to dump at a time.

The proposed simulation model also considers reclaiming material from stockpiles to processing plants. It is assumed that each stockpile can feed just one specific processing plant. Loaders and trucks are employed for the reclamation process from stockpiles. The number of loaders and trucks needed at the stockpiles are also determined through a simulation model with the same approach used for shovels and dump trucks. The performance and utilization of loaders and trucks are assessed in the model.

3. Methodology

The simulation model developed in this study is a dynamic, discrete, and stochastic model. In the truck-and-shovel system under consideration, the state of the system changes at discrete points in time, and there are random and uncertain parameters in the system's inputs. ARENA simulation software is used in this paper to model a truck-and-shovel haulage system. The system is designed for an open pit considered by Eivazy and Askari-Nasab (2012) which is an iron ore open-pit mine located in southern Iran. Shovels extract material, and trucks haul them to a unique exit point through one of 34 ramp access points, and from the exit point to one of the 6 destinations. After dumping, trucks travel back to the exit point of the pit. The possibility of reclaiming material from each stockpile to a specific process plant is also considered.

In the model proposed by this paper, an entity is defined as a mining-cut portion extracted at each period and sent to a definite destination. Trucks, shovels, and loaders are modeled as resources. The model reads all the required data and random distributions directly from excel sheets. At the beginning of the model, entities are introduced to the system and attributes are assigned to them, consisting of the entity's number, ID, coordinates of x, y and z, mining-cut tonnage, fraction mined, destination, distance to destination, and grades. Each entity's tonnage is calculated using Eq.(1).

$$\text{entity tonnage} = \text{origin block tonnage} \cdot \text{fraction} \quad (1)$$

At this stage, variables such as total waste tonnage and ore tonnage entering the system are calculated and the initial coordinates of the shovels' locations, processes, stockpiles, and waste dumps locations are defined. Entities entering the system wait in a queue to seize a shovel and a

truck as resources. Once they seize a shovel and a truck, the shovel and the truck travel from their current locations to the mining-cut's location, so there is a queue of both entities and trucks at the shovels. Since distance through each ramp to the exit point and the distance between the exit point and each of the destinations are known, the distance between each mining-cut and its destination is calculated. Knowing the speed of trucks in both unloaded and loaded states, the time that it takes for the truck to travel from a mining-cut to a destination or travel back from a destination to a mining-cut is obtained using general physics formula Eq.(2).

$$time(\text{minute}) = \frac{distance(\text{meter})}{speed(\text{meter/minute})} \quad (2)$$

Movement speeds of the shovels and the trucks follow Normal distributions with different parameters and all with small variances. Beside travel times, other processes also follow random distributions such as loading time, dumping time, and tonnage loaded to a truck at each pass. All these random distributions are presented in Table 1.

Table 1. Random distributions of uncertain elements

Uncertain Element	Random Distribution	Parameters	Units
Shovel Movement Speed	Normal	(100 , 10)	meter/minute
Loaded Truck Movement Speed	Normal	(600 , 50)	meter/minute
Unloaded Truck Movement Speed	Triangular	(300 , 50)	meter/minute
Load Time	Triangular	(0.2 , 0.25 , 0.30)	minute
Dump Time	Triangular	(0.17 , 0.2 , 0.25)	minute
Pass Tonnage	Triangular	(30 , 35 , 40)	tonne

Once both truck and shovel reach the block, the extraction begins. The truck's nominal capacity is 120 tonnes and the shovel has the nominal bucket capacity of 40 tonnes. A shovel can load the truck in 3 passes. After each pass, the model checks if the remaining tonnage of the entity is less than 40 tonnes, then the remaining amount will be loaded to the truck. After each load, three variables are updated: (1) the remaining entity tonnage, (2) the number of passes of the current truck, and (3) the tonnage loaded to the truck. In this part of the model three different situations could occur and each of these situations require a different action:

- If a mining-cut is completely extracted, the shovel working at that mining-cut is released and the truck working with the shovel travels to its destination. When a shovel is released it moves from its current location, which is the same as the extracted mining-cut's coordinates, to the next mining-cut's location, and new coordinates are assigned to the shovel.
- If a mining-cut is not completely extracted but the truck is fully loaded, the model duplicates the entity to 2 entities: mining-cut and load. The mining-cut entity which keeps the shovel and seizes a new truck, and the load entity representing the full truck travels to its destination.
- If a mining-cut is not completely extracted and the truck is not fully loaded, the shovel and the truck remain at their current locations and continue the extraction and loading process.

A truck which is loaded leaves the mining-cut and travels to the mining-cut's assigned destination. There is no limit on the number of trucks that can dump at the waste dumps at the same time, but no more than one truck can dump at one stockpile or process plant at the same time. The traveling time of the truck is based on the destination, the truck's speed when it is loaded, and the ramp through which material is moved. After dumping, the truck returns to the shovel and both the truck and the shovel are seized by the next mining-cut in the queue.

A sub-model is defined in the simulation to model the operations of reclamation from stockpiles. In this study stockpile 1 only feeds processing plant 1 and stockpile 2 feeds only processing plant 2.

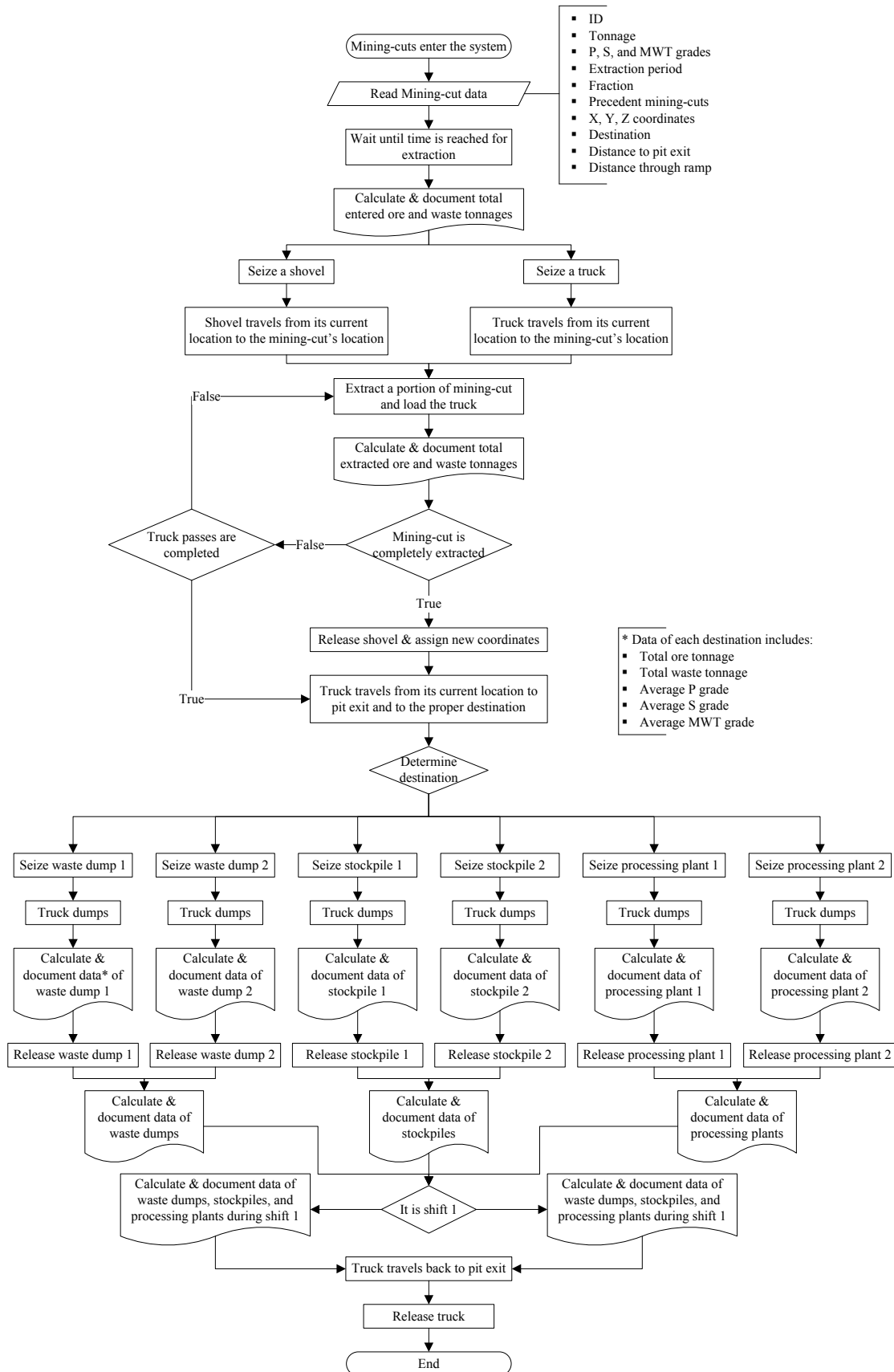


Fig.1. Flowchart of the model.

Based on the input data, if in a month material is sent to the stockpile, in the next month that material is reclaimed from that stockpile. The distance between each processing plant and the feeding stockpile is known. A loader and a truck are allocated for the process of getting material from the stockpile and hauling it to the processing plant. This sub-model uses the same logic as the basic model. The model keeps track of reclaimed tonnage and grades from a stockpile to a processing plant monthly.

The model keeps track of many variables of interest during each month. These variables consist of ore tonnage at each of the processing plants, ore tonnage at each of the stockpiles, waste tonnage at each of the waste dumps, average P, S, and MWT grades at each of the processing plants, average P, S, and MWT grades delivered to each of the stockpiles, average P, S, and MWT grades at each of the waste dumps, average shovel utilization, and average truck utilization.

It is assumed that the mine is working 24 hours a day, 360 days a year. Two 12-hour shifts are considered as day shifts and night shifts. All the statistics mentioned above are also collected for each shift during different months. For this purpose, a logic is used to determine the shift and the month during the whole run. At the end of the simulation time the model creates a dummy entity to record all these variables and write them to an output EXCEL file. Fig. 1 shows the flowchart of the basic model.

4. Implementation and results

As described in the previous sections, the open-pit mine presented by Eivazy and Askari-Nasab (2012) is considered in this paper. The optimal short-term schedules generated by these researchers are chosen as the input scheduling data. The input data include mining-cut tonnage, mining-cut fraction extracted, destination, coordinates, P grade, S grade, MWT grade, distance to pit exit point, distance from pit exit point to each of the 6 destinations, and random distributions which the simulation model reads directly from the Excel file. The entire time horizon consists of 12 months.

Different scenarios are generated with a different number of trucks and shovels to assess the delivered tonnages, average truck utilization, and average shovel utilization through the whole year. ARENA Process Analyzer is used to run the scenarios and the results are demonstrated in Table 2.

Table 2. Results of different scenarios considering whole year

Scenario ID	Number of Shovels	Number of Trucks	Delivered ore (thousand tonnes)	Extracted Waste (thousand tonnes)	Shovel Util.	Truck Util.
1	1	3	3455.2	7307.6	0.6897	0.9627
2	1	4	4634.3	8997.1	0.8792	0.9196
3	1	5	5230.8	10068.0	0.9831	0.8227
4	1	6	5420.0	10075.0	0.9997	0.6961
5	1	7	5420.0	10078.2	1	0.5968
6	2	4	4747.1	9919.7	0.4934	0.9908
7	2	5	5952.1	12202.2	0.6057	0.982
8	2	6	7231.8	14243.6	0.713	0.9709
9	2	7	7992.7	16711.7	0.8122	0.9554
10	2	8	7992.7	17007.5	0.8108	0.8415
11	2	9	7992.7	17007.5	0.8053	0.7474
12	3	6	7262.0	14320.2	0.5112	0.9929
13	3	7	7992.7	16868.6	0.5743	0.9728
14	3	8	7992.7	17007.5	0.57	0.8525
15	3	9	7992.7	17007.5	0.564	0.7562

Starting with 1 shovel and 3 trucks, the delivered ore and waste tonnage during the year do not meet the production target. By increasing the number of trucks, the deviation from the production target decreases but then stabilizes at that level. After this point, further increasing the number of trucks not only does not reduce the deviation, it also reduces utilization of resources. It is inferred that the number of shovels must increase. Scenario number 10 with 2 shovels and 8 trucks seems to be the best in which the production target is met and the resources are utilized efficiently. After this point, increasing the number of trucks or shovels is not required (see Fig. 2).

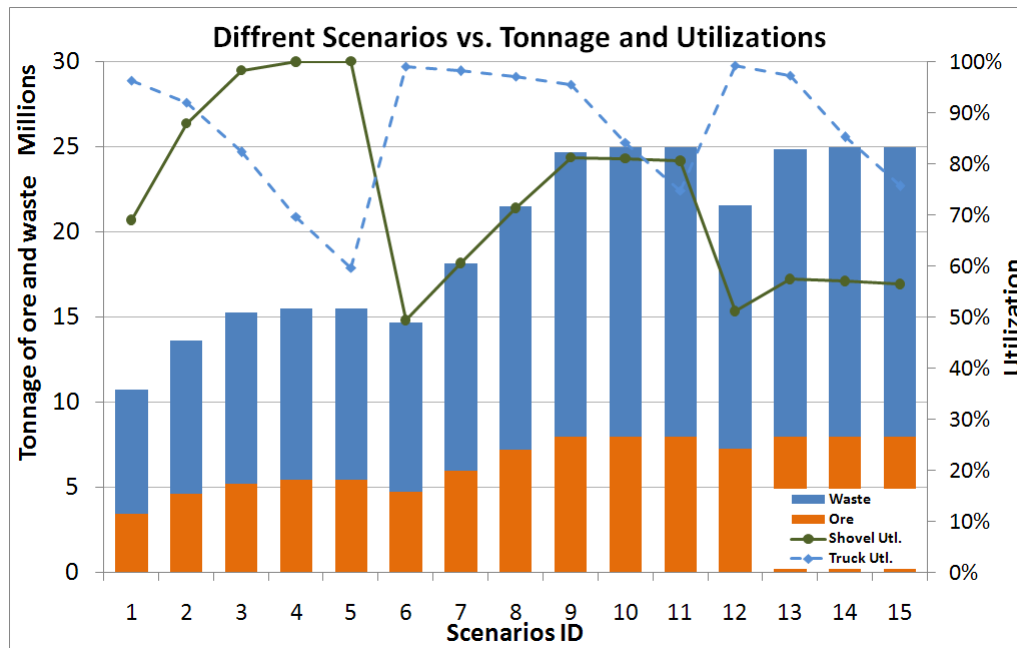


Fig.2. Illustrative results of different scenarios.

In the second stage, the available number of trucks and shovels are set to the quantities resulting from the previous stage. The truck-and-shovel system's performance is further studied during the second stage and the efficiency of the system is evaluated during the day shifts and night shifts. These uncertainties include the variations in speed of loaded truck, speed of unloaded truck, speed of shovel, loading time, dump time, and extraction tonnage. These uncertain parameters result in variations in outputs for different shifts. The model is run for ten, 360-day replications.

Fig. 3 shows ore tonnage and waste tonnage delivered to process 1, process2, stockpile 1, stockpile 2, waste dump 1, and waste dump 2, and reclaimed from stockpile 2 to process 2 at each month. Average shovel utilization and truck utilization are reported for each month (Fig. 4).

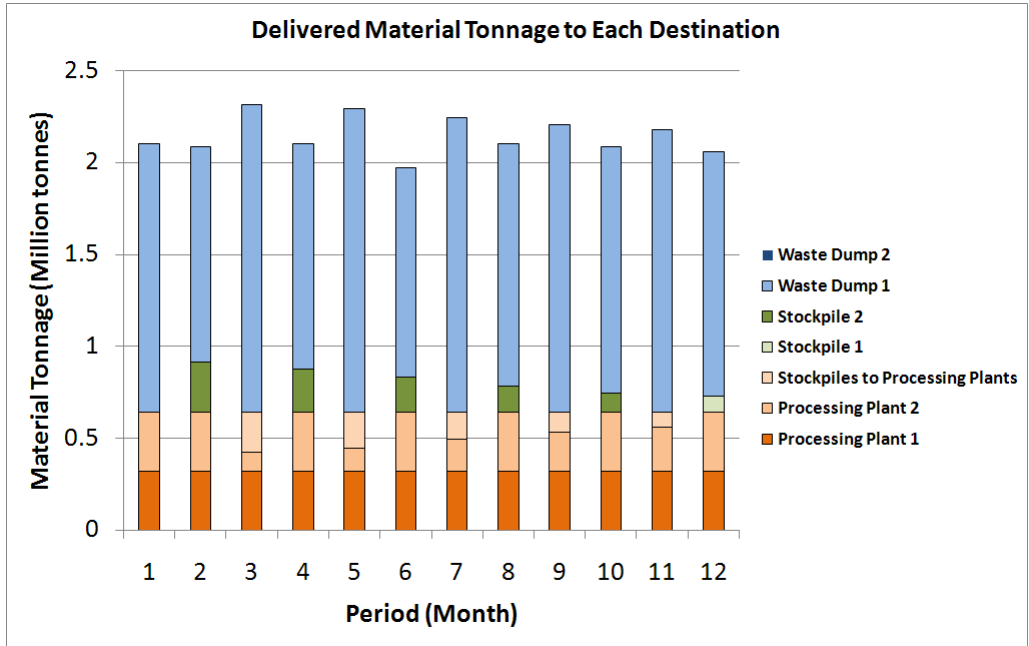


Fig.3. Tonnages delivered to each destination and reclaimed from stockpiles (monthly).

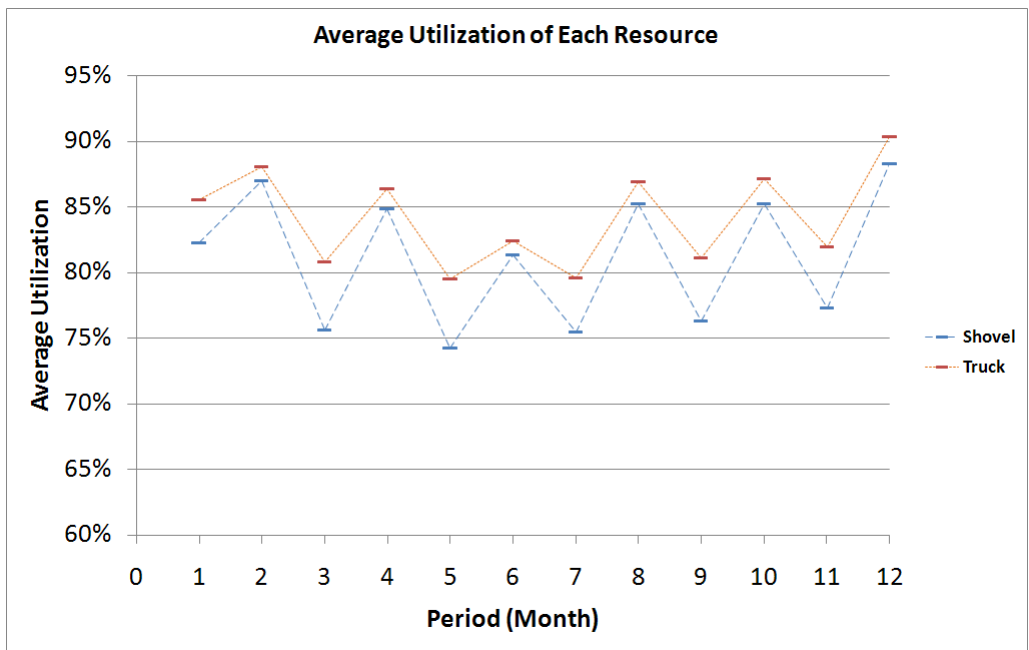


Fig.4. Average truck and shovel utilizations (monthly).

Fig. 5 through Fig. 7, respectively, show the monthly average P grade, average S grade, and average MWT grade at processes and stockpiles. Fig. 8 through Fig. 12 demonstrates the same statistics in the same order over shift by shift periods.

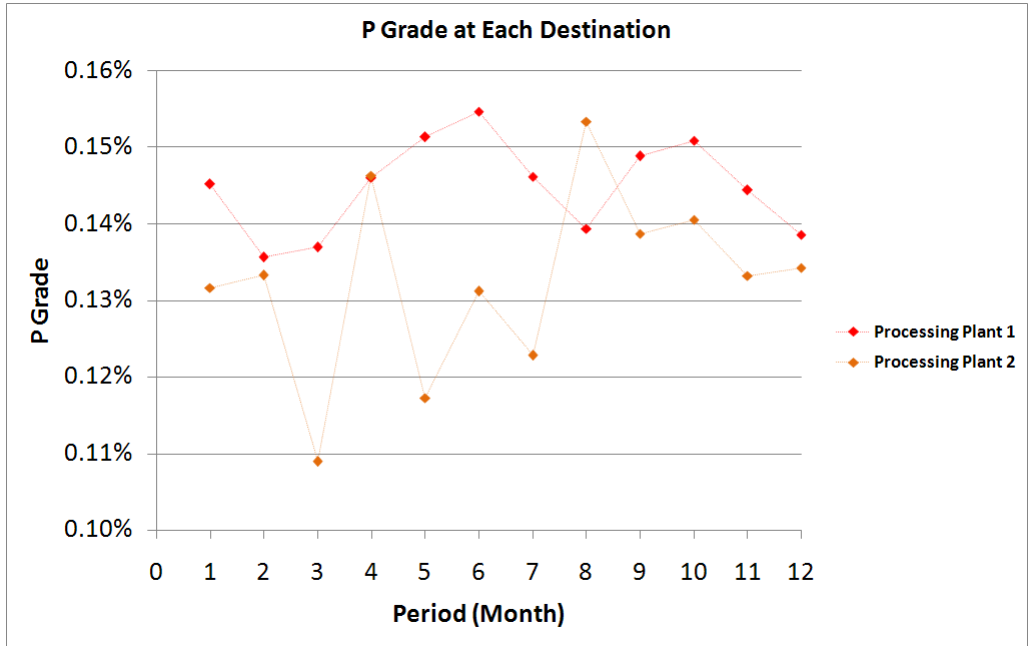


Fig.5. Average P grade of material delivered to each destination (monthly).

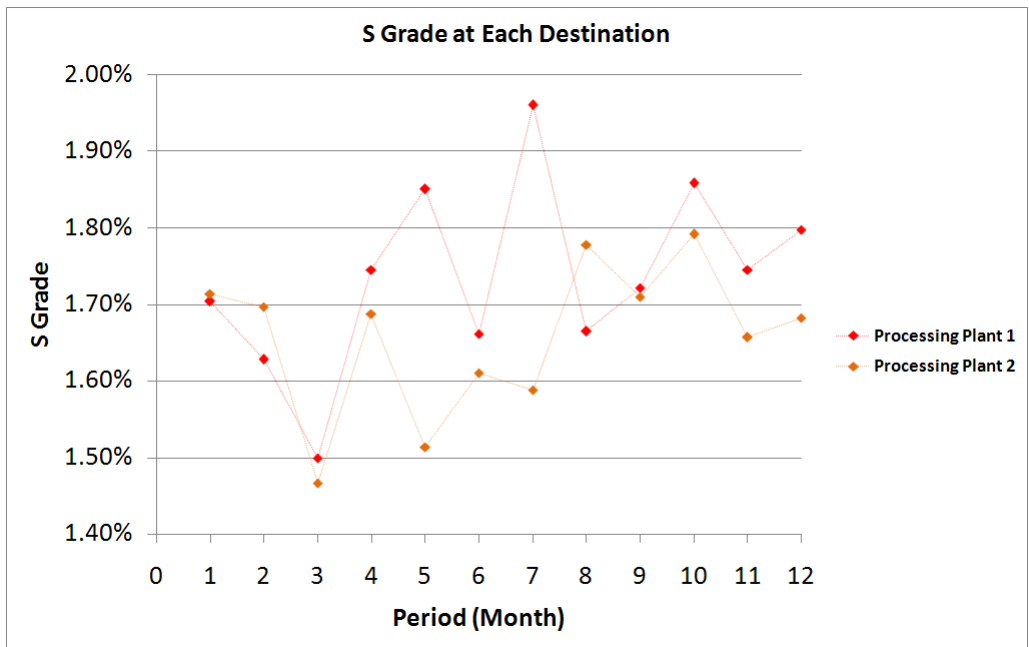


Fig.6. Average S grade of material delivered to each destination (monthly).

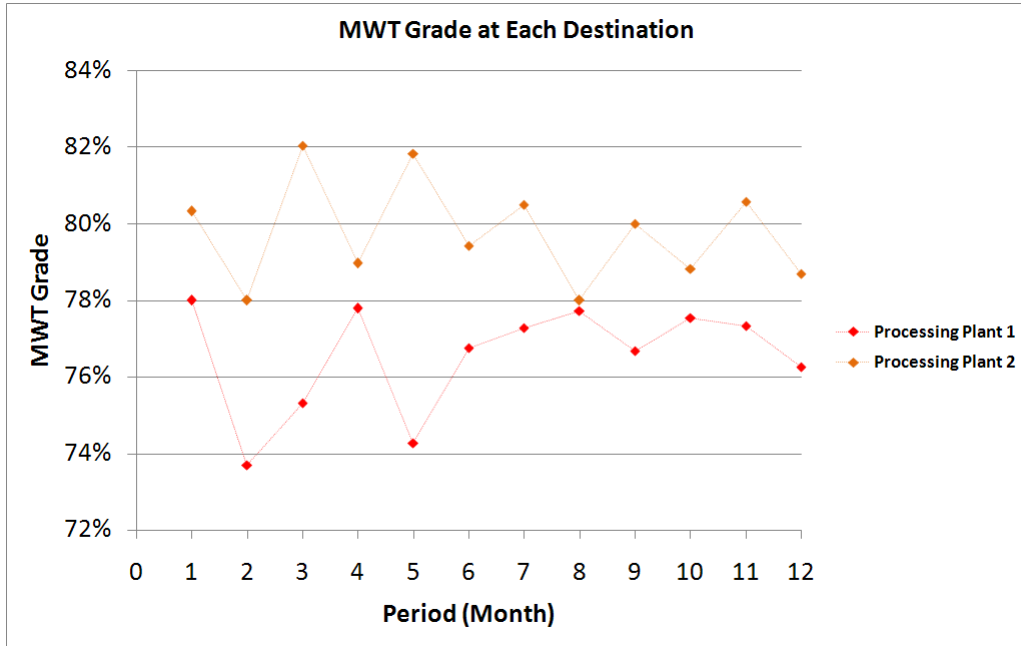


Fig.7. Average MWT grade of material delivered to each destination (monthly).

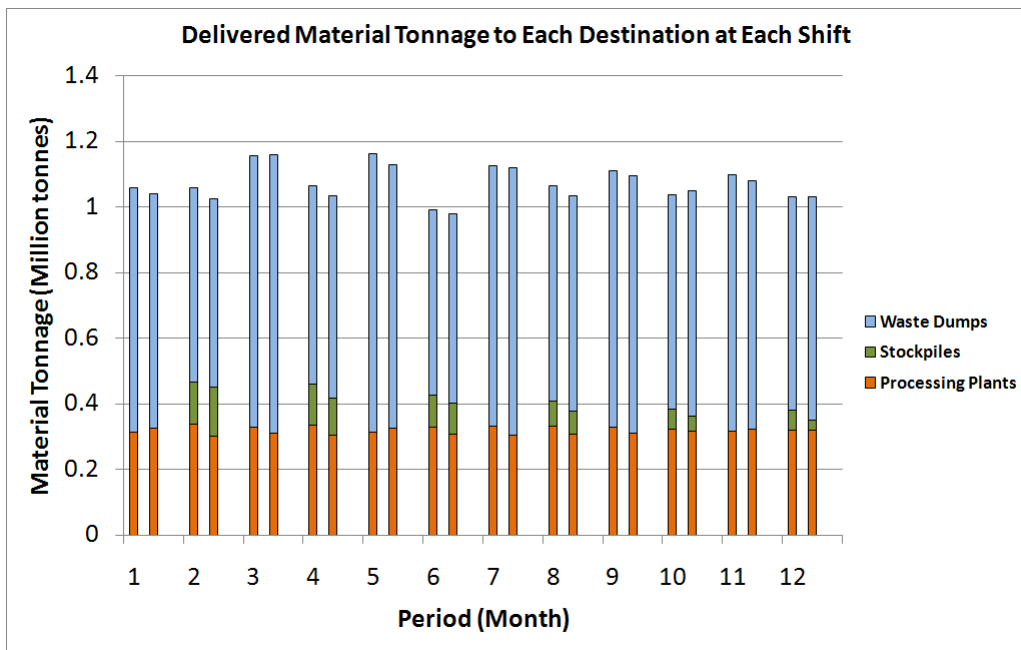


Fig.8. Tonnages delivered to each destination and reclaimed from stockpiles (shift by shift).

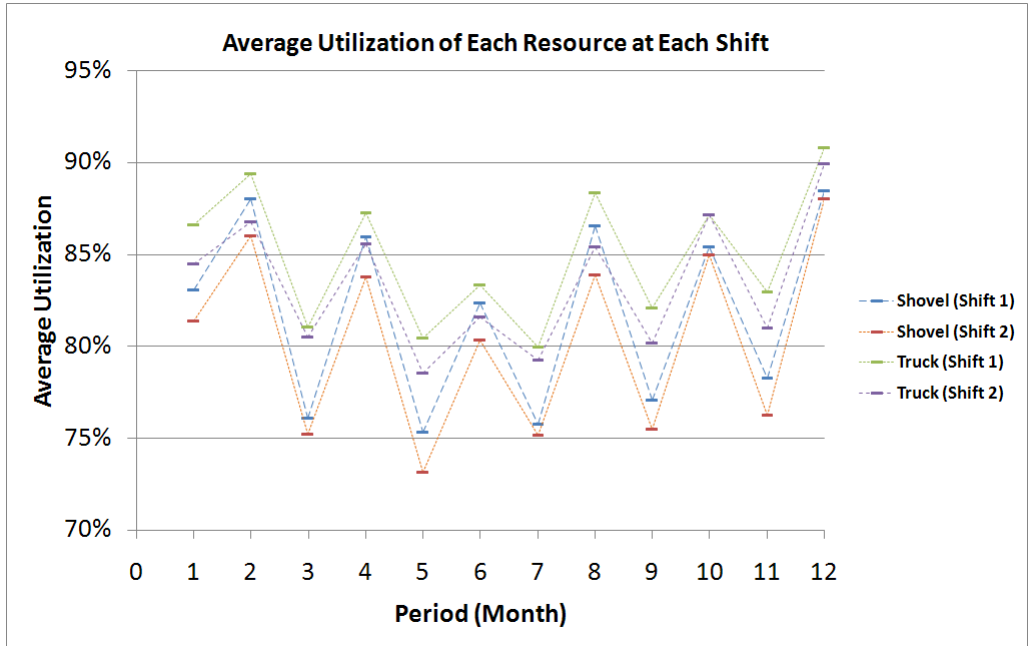


Fig.9. Average truck and shovel utilizations (shift by shift).

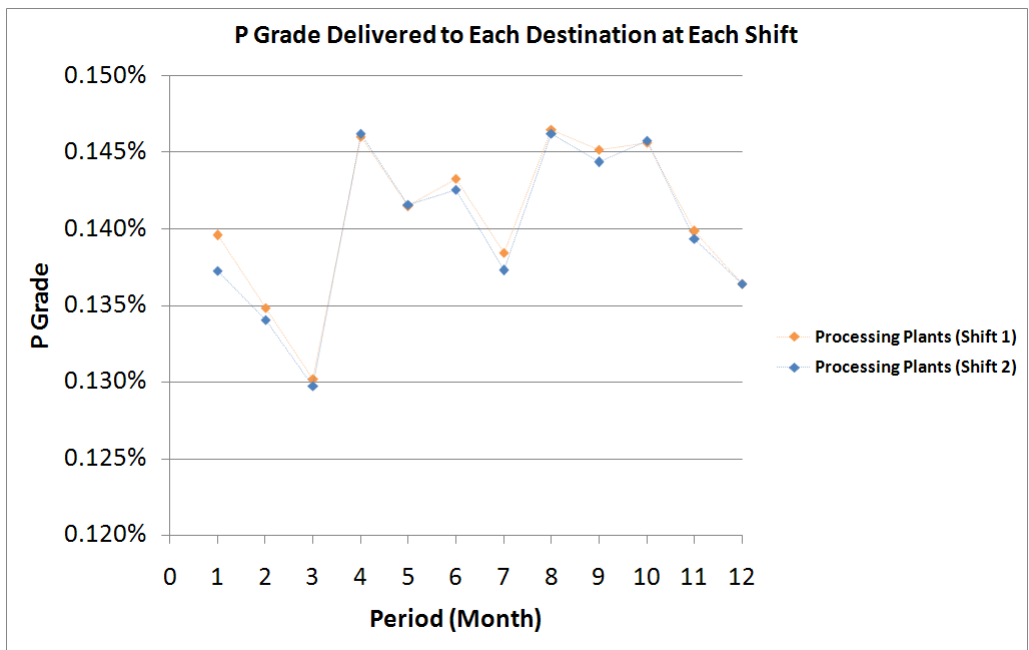


Fig.10. Average P grade of material delivered to each destination (shift by shift).

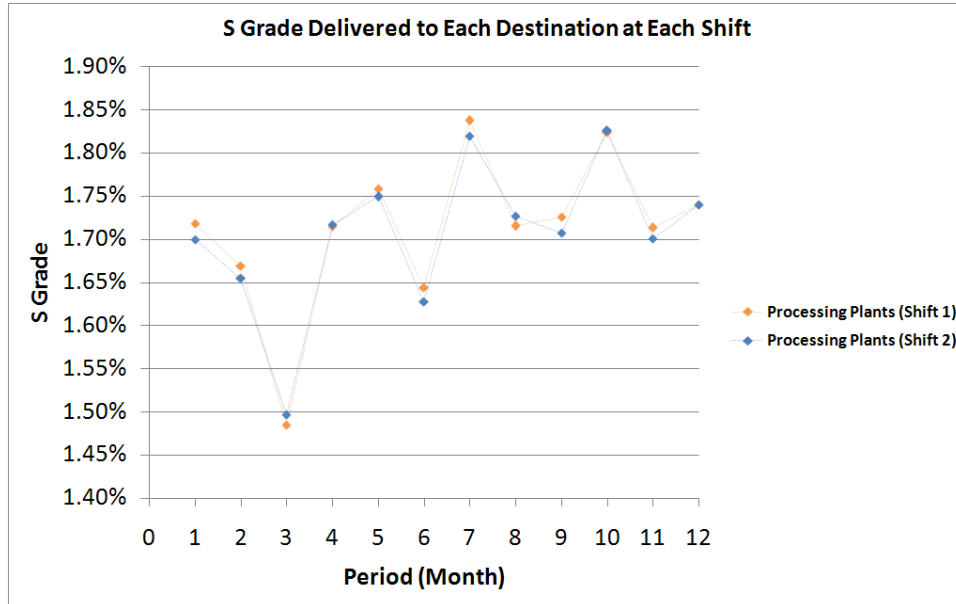


Fig.11. Average S grade of material delivered to each destination (shift by shift).

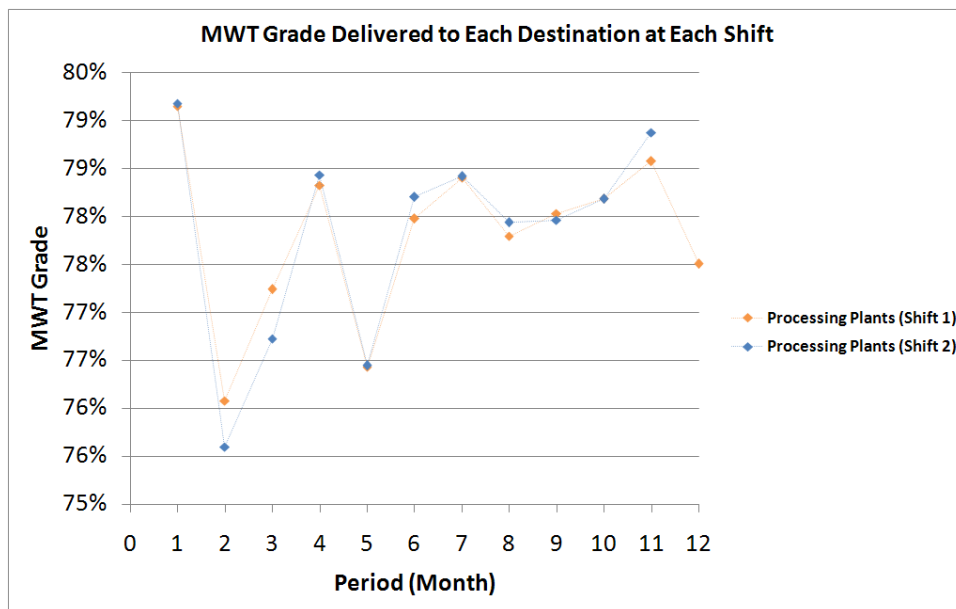


Fig.12. Average MWT grade of material delivered to each destination (shift by shift).

5. Conclusion and future work

This paper presented a simulation model to evaluate the truck-and-shovel haulage system in an open-pit mine by taking into account the uncertainties associated with the operation of trucks and shovels and considering short-term production schedules. This approach ensures that the optimum NPV obtained in long-term schedule planning and short-term schedule planning phases will be followed in operational plans as well. The proposed model could further be developed by considering the exact sequence of mining-cut extraction within each period. Planned and unplanned failures of resources such as trucks, shovels, and crushers and repairing processes could be added to the model to generate a more accurate assessment of the system.

6. References

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