

# Truck-Shovel Simulation Reliability Analysis with Embedded Dispatch Optimizer

Ali Moradi Afrapoli, Mohammad Tabesh, and Hooman Askari-Nasab  
Mining Optimization Laboratory (MOL)  
University of Alberta, Edmonton, Canada

## Abstract

*Simulation has proven to be a powerful tool for assessing the performance of complicated uncertain systems with numerous interconnected parts with time-varying parameters. Simulation is especially useful where optimization methods fail to capture the complexity of real-world dynamic systems. A general reusable discrete-event simulation tool is developed and verified to analyze the behavior of open pit mining operations. The simulation tool imitates the truck-shovel operation and its interaction with the mining fleet management systems. The simulation model is linked to the mine production schedule. The developed simulation tool accurately monitors the system's major KPIs. The simulation model is run for predetermined number of replications over the desired planning time horizon to generate tight half-widths around the monthly and shift-based KPIs with high confidence level. The tool includes a thorough implementation of a dispatching logic which mimics real-world dispatching systems in allocating trucks to the neediest shovels on the shortest travel path. Moreover, a new algorithm is developed for truck allocation by MOL and was implemented in the system. Comparing the new algorithm with the common real-world dispatching systems on a case-study provides a 10% improvement in the production of the operation.*

## 1. Introduction

Mining projects, and more specifically surface mines, are capital intensive ventures with high operating costs. Approximately 50% of the operating costs in open pit mines (Alarie & Gamache, 2002) and even 60% in large open pit mines are allocated to haulage and materials handling (Ahangaran, Yasrebi, Wetherelt, & Foster, 2012; Akbari, Osanloo, & Shirazi, 2009; Alarie & Gamache, 2002; Oraee & Goodarzi, 2007). Therefore, optimization of the operational mine plans and the fleet management has a significant impact on operation efficiency.

Our research endeavors are focused on simulation and optimization of mine operational plans and its interaction with the extraction plants. The preliminary research (Tabesh, Azimi, & Askari-nasab, 2012) is geared towards integration of mine discrete event simulation and fleet management system to optimize the mining operation in one framework. The simulation and optimization tools work together towards generating a near-optimal and practical mine fleet management system working in presence of uncertainty. Correct implementation of the fleet management systems' logic in the integrated simulation and optimization framework is key to the success of this research. The dispatching logic integrated into the mine simulation needs to closely mimic the algorithms and logic implemented in today's industrial mine fleet management systems, such as DISPATCH® (Modular Mining Systems, 2016), Wencomine (Wenco Mining Systems, 2013), Jmineops (Leica

Geosystems, 2016), and CAT® MINESTAR™ FLEET (Caterpillar, 2016). As of majority of mines around the world and almost all of the active mines in north America are using DISPATCH® (Modular Mining Systems, 2016) we simulated a mine operation with embedded DISPATCH® in this paper as a benchmark model to verify reliability of MOL dispatching algorithm.

In the following sections, we first briefly go over the previous mining operation simulation studies. Then in the next section, we introduce some of the currently in use mining fleet management systems where subsections are providing mathematical background of the DISPATCH®. In section four, the system to be modeled, objectives to be achieved in this study, key performance indicators (KPIs), and flow diagram of the simulation model are presented followed by modeling approach in section five. Section six introduces an open pit mine as a case study. Before presenting conclusions in section eight, results of the simulation are presented and discussed in section seven.

## 2. Literature Review

The fleet management system mainly works based on two different setups: 1) fixed truck allocation and 2) flexible truck allocation. Transition of fleet management systems from fixed to flexible truck assignments has been investigated for more than 40 years. The first dispatching system applied in a limestone quarry operation in Germany showed a great improvement in the efficiency of the equipment (Bonates & Lizotte, 1988). Results of that implementation ended up introducing different dispatching packages with different optimization criteria to mining industry.

In fixed truck allocation setup, at the beginning of each shift a group of trucks is locked to each transportation route. The trucks allocated to the paths are to work on the same path over the shift based on several criteria, such as production requirement, availability of the trucks in the fleet, etc (Y. Lizotte, Bonates, & Leclerc, 1987; Yves Lizotte & Bonates, 1987). The paths to which trucks have been allocated will not change until a shovel breaks down or a critical event happens. Some efforts to modify this method have been seen in the literature. In flexible truck allocation, a number of available trucks in the fleet are assigned to a specific working shovel at the beginning of the shift. But these trucks, instead of being in the service of a single shovel or a single route during the shift, will receive a new assignment from the dispatch system every time after loading at the shovels and tipping at the dumping destinations. It has been shown that flexible truck allocation improves productivity of the operation by a high percentage.

First, Bogert (1964) suggested the use of radio communication between equipment operators and the mine control centre. In the late 1970s, Mueller (1977) introduced implementation of the dispatching boards installed in the control centre. This method of operation scheduling is the least productive method and from Kolonja and Mutmansky (1993) to Hashemi and Sattarvand (2015), it has been consistently used as a base method to study the performance of other algorithms and approaches. Kolonja and Mutmansky (1993) documented differences in production comparing fixed truck allocation and flexible truck allocation strategies. Furthermore, Hashemi and Sattarvand (2015) in a simulation study of the Sungun Copper mine operation showed that by implementing a flexible allocation strategy the productivity of the mine increased by 8% in comparison with the fixed allocation. Olson et al. (1993) reported a 13% increase in the production of the Bougainville Copper Mine using the flexible truck allocation. Also, a 10 to 15% improvement in the productivity of the Barrick Goldstrike Gold mine, a 10% growth in iron ore production at the LTV steel mining, and a 10% increase in the production of the Quintette Coal mine were reported by Olson et al. (1993). Therefore, we will review the literature on flexible truck allocation for the rest of this section.

In Bonates and Lizotte (1988) the authors evaluated application of a dispatching system using a computer simulation model. In the model, fleet management systems were categorized in 3 main groups including: Manual Dispatching, Semi-Automated Dispatching and Automated Dispatching.

The resulted model which was developed in FORTRAN, attempts to take into account the real features of the mine and optimize the utilization of the trucks and shovels as a Linear Programming (LP) objective function. Li (1990) introduced a methodology for optimum control of shovel and truck operation by defining an LP optimization model.

Soumis, Ethier, and Elbrond (1989) developed a nonlinear procedure to solve the mining truck dispatching problems. The algorithm proposed by them, was based on a nonlinear objective function with 3 main components including: deviation of shovels' operational excavation from the objective rate, deviation of trucks' real working hours from their scheduled operating hours, and penalties assigned to deviation from desired quality of input to the plant (Soumis, et al., 1989). Forsman, Rönkvist, and Vagenas (1993) developed a computer simulation model for Aitik open pit mine operation. In their simulation model graphical model of the mine was built implementing a discrete event modeling microcomputer called METAFORA. Optimum number of trucks required to achieve the production target is obtained from the simulation (Forsman, et al., 1993). Gove and Morgan (1994) worked on truck-shovel matching and the influential parameters using CAT's fleet production and cost (FPC) software (Gove & Morgan, 1994). Ataepour and Baafi (1999) worked on a simulation model for truck-shovel operation using Arena (Rockwell Automation, 2016) to assess both dispatching and non-dispatching mining operations. Their study can be divided into two major sections: The first step is to monitor the effect of number of trucks in system utilization, and the second step is to develop a dispatching rule based on minimizing truck waiting times. In the same year Basu (1999) proposed a dispatching strategy on the same logic base as developed by Ataepour and Baafi (1999).

At the beginning of the 21<sup>st</sup> century, Alarie and Gamache (2002) conducted a research on solution strategies used in truck dispatching systems for open pit mines. Based on their research, dispatching problem can be solved using two major approaches: single stage and multistage. The algorithms developed in a single stage approach send trucks to the needy shovels by solving one order of optimization problem while in a multistage approach an optimum production target is set for the operation using LP or heuristic methods. In the lower stages the assignments are handled in a way that the deviation of operational excavation from the targets, suggested by upper stage, are minimized. Wang, Zhang, Chen, and Xu (2006) studied truck real-time dispatching from a macroscopic point of view. They first defined internal nodes on each path and then evaluated the flow rates of the trucks on each route. Results illustrated that the proposed model shows better results in comparison with the conventional dynamic programming (DP) methods. Burt and Caccetta (2007) proposed another approach for the calculation of a match factor for heterogeneous fleets. Based on their method, if different cycle times are calculated for different truck types and shovel types, a match factor for the fleet is achievable. The proposed method is also capable of considering different haul road features. Krause and Musingwini (2007) used a machine repair analogy to analyze and determine truck fleet size for an open pit mine. They chose Arena (Rockwell Automation, 2016) for the simulation part "because it can be programmed with any number of probability distribution fitted to an unlimited number of cycle variables and is therefore a very flexible model for use in analyzing several variables in shovel-truck analysis".

Jaoua, Riopel, and Gamache (2009) developed a framework for realistic microscopic modeling of surface mining transportation systems. Advantages of the framework were highlighted as a library for the real-time allocation, an updater for the truck allocation, and a fuel controller.

He et al. (2010) implement a genetic algorithm to optimize truck dispatching problems in open pit mines. They tried to find a route and assign an upcoming truck to it based on minimized transportation and maintenance costs. In their model, it has been assumed that truck velocity in both loaded and empty conditions are the same, which is a drawback of their model. Although their major focus was on minimizing the costs, by assuming the same velocity for both loaded and unloaded trucks, they underestimated costs. Another major drawback, similar to almost all other models, is the assignment of trucks to routes rather than to shovel-destinations. Furthermore, they

assumed that truck maintenance costs become higher with the age of the truck by a constant coefficient, whereas Topal and Ramazan (2012) showed that maintenance cost behaves in a fluctuated manner during its life and it will decrease considerably after every overhaul.

Another model provided by Subtil et al. (2011) is used in the commercial package SmartMine® marketed by Devex SA (Devex, 2016). It uses LP, in the upper stage, to determine the maximum production capacity of the mine and the optimal size of the truck fleet required to meet the target production. The allocation planning stage completely remains to the planner. Moreover, the model does not take into consideration other desired characteristics such as grade blending and constant desired feed to plants. The dynamic allocation or the truck dispatching is achieved by adopting  $M$  trucks for  $N$  shovels strategy. Using  $M$  trucks, the best possible solutions based on undisclosed criteria are generated and each solution is simulated 50 times to achieve a desired confidence interval. The best solution is found using a multi-criteria optimization, which maximizes productivity of the transport fleet and minimizes queue time at shovels and idle time of shovels. A fuzzy logic expert system is then used to evaluate the solution and, if passed, dispatch the truck to the allocated shovel. The major drawback of the approach can be the cumbersome time consuming methodology adopted at the dynamic allocation stage, which requires real-time decisions. The authors of this study mention situations where fuzzy logic rejects the best solution and requires re-running of the entire model to obtain another solution. The alternate solution generated after rejecting the first one will be the second best solution, which may again get rejected, leading the method in a time-consuming loop.

Ahangaran et al. (2012) use a two stage model for truck dispatching, where the first stage uses a network analysis technique to determine the best routes between departure and destination points and second stage provides dynamic truck assignments. The second stage adopts a binary integer programming model to minimize the function of the total cost of loading and transportation. This dispatching model is significantly different compared to previous models in terms of the objective function and the mixed fleet considerations in the modeling equations. One of the major drawbacks of this model is that it does not consider traffic over the routes during the procedure to find the shortest path. Another drawback is that, although their objective function is to minimize total truck cycle time, they do not take into account truck spot time and truck waiting time at both shovels and crusher. They did not show the practicality of their model in at least one open-pit mine. As one of the latest studies in the field of open pit mining operation simulation, Que, Anani, and Awuah-Offei (2016) investigated the effects of implementing real-time correlated variables as non-correlated single input distribution on the final results of the simulation modeling. The results show the correlation exist in truck-shovel operations, although it depends on sensitivity of the results to the input variables as well as strength of the correlation.

### 3. Fleet Management Systems

There are many companies across the world providing mine fleet management systems. Some of the more popular ones are as follows: Modular Mining Systems, which is used in over 200 mines around the world (Modular Mining Systems, 2016), Jigsaw Software, which is installed in 130 mines (Leica Geosystems, 2016), and Wenco, which currently has 65 mine sites across the world (Wenco Mining Systems, 2013). TATA consultancy services has introduced Dynamine with a range of productivity improvement of 10% to 15% (TATA consultancy services, 2016). However, Micromine with Pitram system (Micromine, 2009) and Caterpillar with CAT® MINESTAR™ FLEET (Caterpillar, 2016) are the next leaders of mine fleet management systems.

The algorithms behind commercial mine fleet management systems are proprietary information, and therefore the companies do not disclose the logics. Consequently, a comparison of the optimality of the fleet management solutions is not feasible. However, in the 1980s and early 1990s, the Modular Mining System (Olson, et al., 1993; White & Olson, 1986) published their

models and algorithms, and based on these, the DISPATCH® (Modular Mining Systems, 2016) mine fleet management system has been developed. Thus, in this section we review the algorithms behind DISPATCH® (Modular Mining Systems, 2016) that were publically available.

Figure 1 and Figure 2 illustrate the procedure DISPATCH® (Modular Mining Systems, 2016) follows to find the solution and the algorithms implemented to complete the tasks, respectively. First, the data from the pit and manual assignment are input to DISPATCH® using forms. Then, the shortest paths to send material from loaders to the destinations are found using the Dijkstra algorithm. As the next step, an LP model is run to find the optimum material flow rate of each route. Finally, using DP, trucks in the available trucks list are assigned and all information is updated.

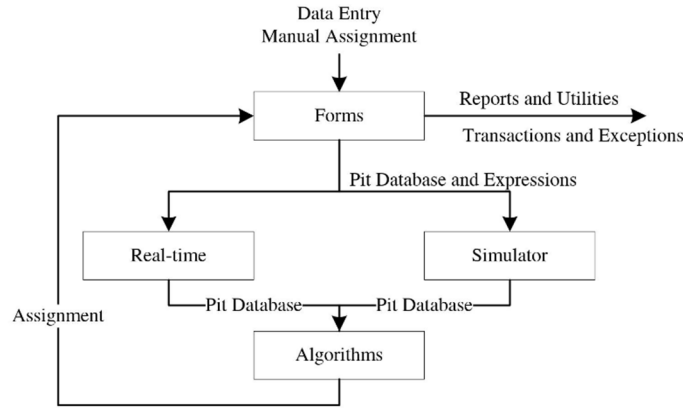


Figure 1: Schematic representation of DISPATCH® block diagram

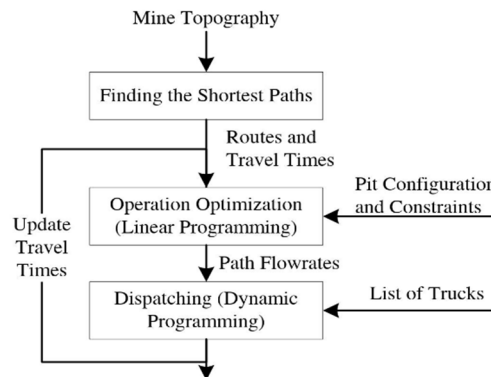


Figure 2: Procedure through with DISPATCH® assigns trucks

## 4. DISPATCH®

### 4.1. Finding the shortest path - DISPATCH®

In graph theory, the shortest path problem is the problem of finding a path between two vertices (or nodes) in a graph such that the sum of the weights of its constituent edges is minimized. To find the shortest path, DISPATCH® uses Dijkstra's algorithm with the objective of minimizing travel time between each pair of starting and ending points. After solving the shortest path problem in DISPATCH®, the following information is presented to the operation optimization model: 1) total minimum distance and travel time for each specific transport and 2) the nodes trucks must pass through to reach the destination.

## 4.2. Production optimization - DISPATCH®

DISPATCH® uses linear programming approach to optimize the production target within a specific time horizon by dividing it into two separate but weakly coupled models. The first one, Eq. (1), optimizes the total production of the operation, including mining, processing, and stockpiling, and the second part, Eq. (5), maximizes the fleet production by minimizing the total required volume to be handled. The second part generates a theoretical haulage master plan that considers production and operational constraints and is later used as a reference to generate real-time truck assignments. White and Olson (1986) and Olson et al. (1993) describe the model as follows:

$$\min C = \sum_{i=1}^{N_m} (C_m \times Q_i) + C_p \times (P_t - \sum_{i=1}^{N_m+N_s} Q_i) + \sum_{i=1}^{N_s} (C_s \times Q_i) + \sum_{i=1}^{N_m+N_s} \sum_{j=1}^{N_q} (L_j \times C_q \times X_{ij} \times Q_i) \quad (1)$$

Subject to:

$$0 \leq Q_i \leq R_i \quad (2)$$

$$P_t \geq \sum_{i=1}^{N_m+N_s} Q_i \quad (3)$$

$$X_j L \leq X_j A + \sum_{i=1}^{N_m+N_s} (X_{ij} - X_j A) \times Q_i \times T_c / (M_c / SG) \leq X_j U \quad (4)$$

Where:

$N_m$ , $N_s$ , and $N_q$	are the number of shovels at mining faces, the number of shovels working at stockpile, and the number of quality constraints
$C_m$ , $C_s$ , $C_q$ , and $C_p$	are the material transportation pseudo cost (hr/m <sup>3</sup> ), the stockpile material handling pseudo cost (hr/m <sup>3</sup> ), the quality pseudo cost (hr/m <sup>3</sup> ), and the pseudo cost of low feed to plant (hr/m <sup>3</sup> )
$Q_i$	is the material being transported per hour (m <sup>3</sup> /hr) that should be determined in the procedure
$L_j$	is the quality director: 1 for low crit and -1 for high crit
$X_{ij}$ , $X_j L$ , $X_j A$ , and $X_j U$	are the $j^{\text{th}}$ quality factor at $i^{\text{th}}$ shovel, the lower limit for quality factor $j$ , the running average value of quality factor $j$ , and the upper limit for quality factor $j$
$P_t$	is the target rate of plant feed
$R_i$	is the digging rate at $i^{\text{th}}$ shovel
$M_c$	is the 1 <sup>st</sup> in/1 <sup>st</sup> out average control mass, kg
$SG$	is the specific gravity
$T_c$	is the base control interval (hr)

All pseudo costs are chosen arbitrarily with respect to ( $C_m < C_q < C_s < C_p$ ).

As the second segment of the LP model, DISPATCH® tries to minimize total haulage capacity needed to meet shovel production coverage:

$$\min V = \sum_{i=1}^{N_p} (P_i \times T_i) + \sum_{j=1}^{N_d} (P_j \times D_j) + N_e \times T_s \quad (5)$$

Subject to:

$$\sum_{k=1}^{N_{pi}} P_k = \sum_{k=1}^{N_{po}} P_{k'} \quad (6)$$

$$R_j = \sum_{k=1}^{N_{po}} P_{k'} \quad \text{for mining shovels} \quad (7)$$

$$R_j \leq \sum_{k=1}^{N_{po}} P_{k'} \quad \text{for stockpiles} \quad (8)$$

$$P_j = Q_i \quad (9)$$

$$0 \leq P_i \quad (10)$$

Where:

- $V$  is the total mine haulage ( $\text{m}^3$ )
- $N_p$  is the number of feasible haul routes
- $P_i$  is the haulage on path  $i$  which should be determined ( $\text{m}^3/\text{hr}$ )
- $T_i$  is the path  $i$  travel time (hr)
- $N_d$  is the number of dumps for mine haulage
- $P_j$  is the net haulage input to dump  $j$  ( $\text{m}^3/\text{hr}$ )
- $D_j$  is the average dump time at dump  $j$  (hr)
- $N_e$  is the number of operating shovels
- $T_s$  is the fleet average truck size ( $\text{m}^3$ )
- $N_{pi}$  is the number of feasible input paths at node  $j$
- $N_{po}$  is the number of feasible output paths at node  $j$
- $P_k$  is the input path haulage ( $\text{m}^3/\text{hr}$ )
- $P_{k'}$  is the output path haulage ( $\text{m}^3/\text{hr}$ )
- $R_j$  is the limiting rate at node  $j$  ( $\text{m}^3/\text{hr}$ )

The model, Eq. (1), introduces the first segment of the operation optimization as a pseudo cost-based LP, which is established on the summation of costs in all four operational sectors of the mine. The solution of the first segment presents the shovels' production rates with respect to the maximum digging rate for a shovel, Eq. (2), the maximum capacity of the plant, Eq. (3), and the lower and upper bounds of the blending grade, Eq. (4). The second segment's LP maximizes the production of the operation by allocating a minimum number of trucks to each active route, Eq. (5) to meet the routes production rate. Eq. (6) makes sure that the input and output flow at each shovel and each dumping point are equal. Eq. (7) and (8) guarantee that the amount of material handled meets the grade requirements at the plant cannot exceed the amount produced by the mine and stockpile. Coupling segments of the operation plan is attained by constraining total production of all routes servicing a shovel to be greater or equal to the shovel production, Eq. (9). It should be mentioned here that both P and Q in Eq. (9) are vectors. Finally, Eq. (10) ensures that all haul rates in the mine are nonnegative. One benefit of the model is that it follows the current status of the mine by using real-time data. Another advantage of the model is that the optimum production rate of each route is based on the volume of material, not based on the number of trucks. That helps the dispatching step to send the proper truck to cover the shortage. A major drawback of the model is that it does not consider stripping ratio limitation in the operation. By limiting the lower bound of digging rates at each shovel to zero, they allowed the model to ignore a shovel operating at waste mining face. Another disadvantage of the model is that the plant head-grade requirement is

constrained to a range of grade between predefined upper and lower limits. It will cause an undeniable short-term influence on both plant output (final product) quantity and its input (utilization of some specific shovels which must be met up to the minute) (Temeng, Otuonye, & Friendewey, 1998). However, most of the drawbacks of DISPATCH® will arise in the real-time dispatching model that will be explained in more detail in the next section.

### 4.3. Real-time Dispatching - DISPATCH®

After solving the upper stage – operation optimization – LP problem by implementing the Simplex method (Dantzig, 1951), resulting in the optimum material flow rate on routes, White and Olson (1986) employ the dynamic programming (DP) (Bellman, 1954) approach to send trucks to the proper destination. To do so, two lists and three parameters are defined. A list of needy shovels or LP-selected paths and a list of trucks dumping material at discharge points or en-route from a loading point to a destination are provided. In addition, need-time, Eq.(11), which is defined as the expected time for each path's next truck requirement, is formulated as follows:

$$need - time_i = L_j + F_{ij} \times (A_j - R_j) / P_i \quad (11)$$

Where:

- $L_j$  is the time the last truck was allocated to the shovel  $j$
- $F_{ij}$  is flow rate of path  $i$  over the total flow rate into shovel  $j$
- $A_j$  is total haulage allocated by time  $L_j$  to shovel  $j$
- $R_j$  is haulage requirement of shovel  $j$
- $P_i$  is path flow rate (ton/hr or m<sup>3</sup>/hr)

So, the neediest path, which is on the top of the neediest shovels list, will be the one with the shortest need-time. Then lost-ton is defined and formulated as a criterion to find the best truck for the neediest path from the truck list with Eq.(12):

$$lost - ton = \frac{truck\ size \times total\ rate}{required\ trucks} \times (truck\ idle + excess\ travel) + shovel\ rate \times shovel\ idle \quad (12)$$

Where:

Truck size is the size of truck being assigned; Total rate is total digging rate of all shovels in the mine; Required trucks is total required trucks in the LP solution; Truck idle is expected truck idle time for this assignment; Excess travel is extra empty travel time to neediest shovel; Shovel rate is sum of all path rates into neediest shovel; And shovel idle is expected shovel idle time for this assignment.

Considering the lost-ton definition, the truck covering lost-ton of neediest shovel the most is the best truck. After the best truck is assigned to the neediest shovel, it is moved to the last position on the needy paths' list and the procedure is repeated for the second neediest until all trucks on the list are assigned.

Defining a rolling time horizon when a sequence of assignment is needed is a benefit of the model. The information of the mine status used in the model is always up to the minute. However, the model does not consider the effect of current truck assignment on the forthcoming truck matching, though all trucks previously sent to the shovels are considered. Another drawback of the model is that despite the authors' claim, the solution method is not a DP. It is a heuristic rule solving each sub-problem based on the best solution of previous sub problems. According to Alarie and Gamache (2002), the solution method's misnaming as a DP is perhaps because of the authors' misunderstanding of Bellman's principal of optimality. However, the DISPATCH® system has



been implemented in about 200 mines all around the world (Modular Mining Systems, 2016). Table 1 summarizes the procedure with which DISPATCH® solves a mine production problem.

Table 1: Summary of the models DISPATCH® uses in the fleet management systems

Category	Shortest Path	Allocation	Dispatch
Objective	Minimize travel time	Minimize total trucks required	Minimize lost-tons caused by the assignment
Constraints	Intermediate call points a truck should pass	Shovels' digging rate Dump area capacity Continuity at each loading and discharge point Total number of trucks available in the fleet Blending limits of grades Targets of material category blending	Proximity of truck that asks for an assignment to the destination
Solution Method	Dijkstra	Simplex	Dynamic Programming
Advantages	Algorithm often does not have to investigate all edges Dijkstra's algorithm has an order of $n^2$ so it is efficient enough to use for relatively large problems	Model is up to the minute Flowrate of each route is based on the volume of the material rather than number of trucks	Progressing time horizon when order of assignment is required Under-/Over-truck conditions considered
Disadvantages	Model is time consuming Failure in cases of negative edges Global information of the road network required	Appropriate when a few variables are at play Non-negative constraints for all variables	Definition of a progressing time horizon for an order of assignment Consideration of under-/over-truck conditions

## 5. MOL heuristic

The algorithm follows 1-truck-n-shovel approach addressed by Alarie and Gamache (2002). In this approach, the shovel need is updated when it moves to a new polygon and when a truck requests for a new assignment the algorithm runs and allocates the truck to a shovel based on a balance between shortest distance between the shovels and the truck location and the neediest shovel.

*Step 1:* Calculating required haulage capacity of shovel  $i$ .

*Step 2:* Determining allocated capacity to shovel  $i$  so far.

*Step 3:* Finding the shortest paths to the shovels from the current truck position.

*Step 4:* Calculating the normalized distances of the determined shortest paths.

*Step 5:* Sending the truck to the shovel with a minimum balance between its need and distance.

## 6. System Definition

### 6.1. System

In this paper, a whole mining operation is studied. The system includes one open-pit mine, haul network, two processing plants and one waste dump. At the beginning of the operation, trucks are assigned and travel to a shovel from the bay. Then the loading process is done by the shovel. Afterwards, loaded material is transported to one of the destinations. As the next step in the system,

the truck reaches the destination and backs up to the exact dumping location to dump the material. Here is the time dynamic programming part of DISPATCH finds the best truck among those just dumped their material into a dump and the trucks en route to a dumping point. At the same time, it finds the neediest shovel and matches the best truck with the neediest shovel. Then the truck travel to the shovel where dispatching system assigned it to. In the system with MOL heuristic, simulation model runs the MOL algorithm instead of DISPATCH when a truck dumps its load. Another major optimization component of the system is the linear programming segment of DISPATCH that runs every 30 minutes and whenever the system experiences a major change. Figure 3 illustrates the flow diagram of the operation.

## **6.2. Objective of the simulation**

The main goal here is to analyze and verify the reliability of the MOL dispatching algorithm with respect to DISPATCH® in simulation modeling of mining operation. To achieve this goal, we use the Gol-E-Gohar open pit mining system as a case study.

## **6.3. Key Performance Indicators**

We have to define major Key Performance Indicators (KPIs) in order to compare the two systems and assess the reliability of our algorithm. Here in this specific project what we are considering as KPIs are: total material input to each processing plant, tonnage of ore and waste material transported, stripping ratio, total amount of material transported, Loading time, Spot time, Dump time, Backing time, Empty and Loaded velocity of the trucks, and the utilization of the shovels.

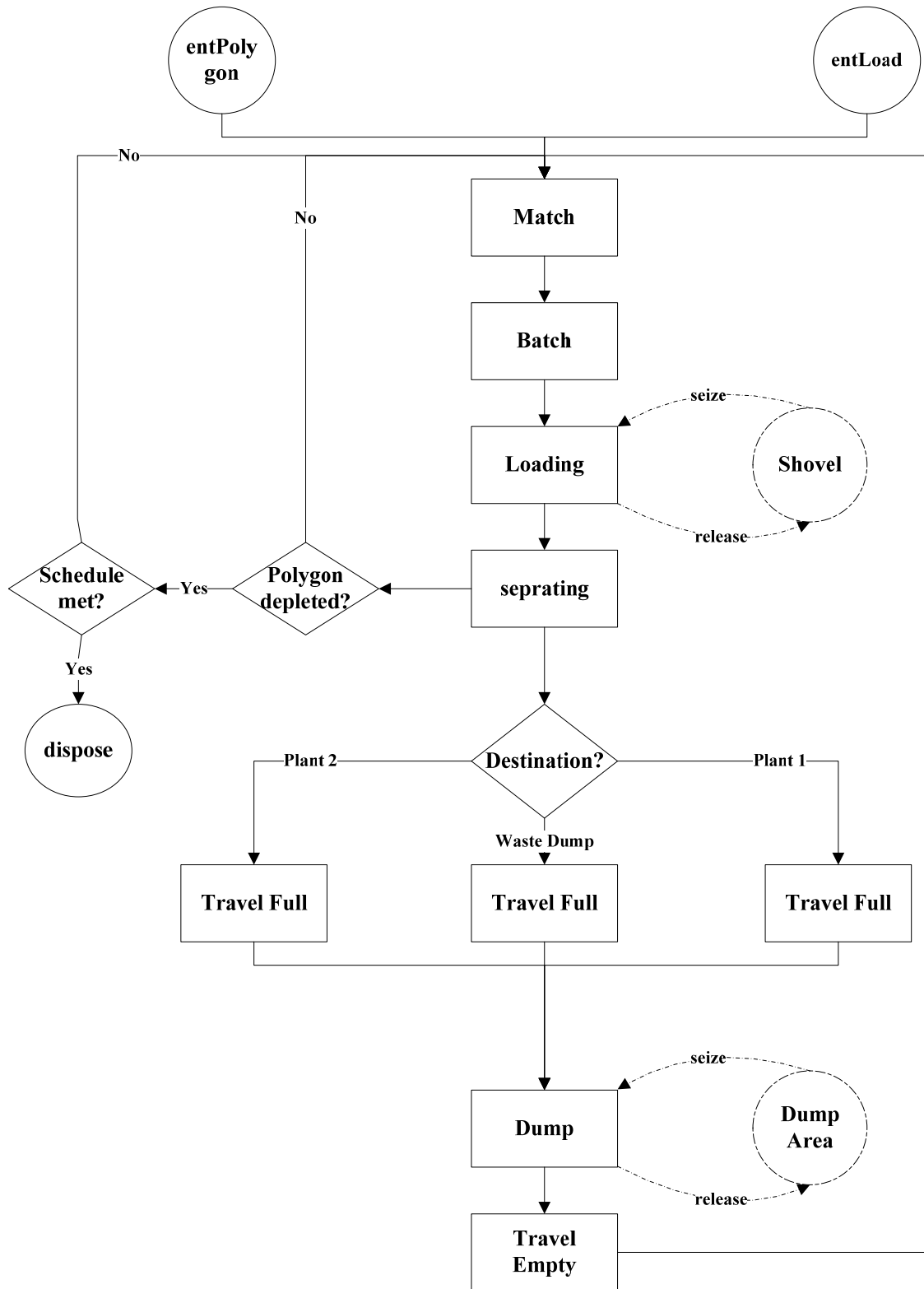


Figure 3: Flow Diagram of the Mining Operation Simulation Model

## 7. Case Study – Gol-E-Gohar Iron Ore Mine

### 7.1. Mine Location and Its Operation Fleet

Gol-E-Gohar iron ore mine is located in Kerman Province of Iran. The project lies in southwest of the province, approximately 50 km southeast of the city of Sirjan (Figure 4). Mining operation in Gol-E-Gohar is being handled by a truck shovel system. The operating fleet consists of Hitachi EX2500 and Hitachi EX5500 excavators and rigid frame rear dump Cat 785C and 793C trucks. There are three main dumping points for the loaded trucks including two processing plants and one waste dump each of which has two hoppers (or dumping point in the case of waste dump). Figure 5 shows the location of loading and dumping points as well as the road network for the year 11 of the operation. Furthermore, Table 2 presents general specifications of the operating system. It is also worth noting that the mine operates for a single 12-hour shift a day for 340 days a year.

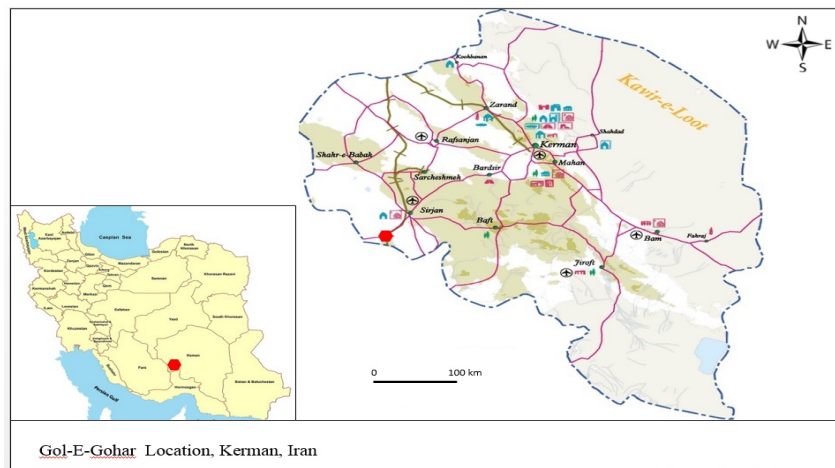


Figure 4: Location of the Gol-E-Gohar Project in Kerman Province of Iran

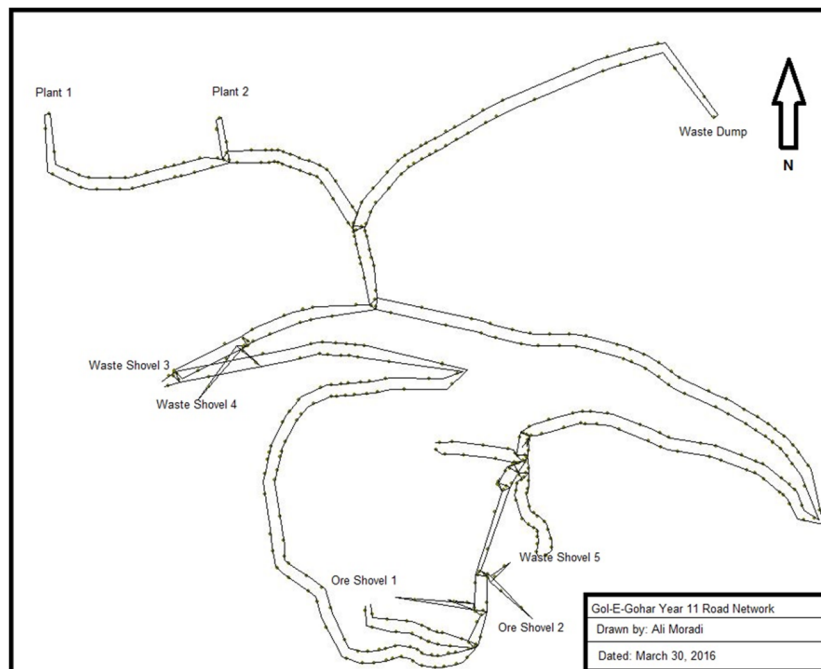


Figure 5: Gol-E-Gohar Iron Ore Mine Year 11 Road Network and loading and dumping locations

Table 2: General specifications of the operation fleet

No.	Loading Point	Destination	Starting Distance (m)	Loader	Hauler
1	Shovel 1	Plant 1	4129	Hitachi EX2500	Cat 785C & Cat 793C
		Plant 2	3626		
2	Shovel 2	Plant 1	4196	Hitachi EX2500	Cat 785C & Cat 793C
		Plant 2	3693		
3	Shovel 3	Waste Dump	1930	Hitachi EX5500	Cat 785C & Cat 793C
4	Shovel 4	Waste Dump	1850	Hitachi EX5500	Cat 785C & Cat 793C
5	Shovel 5	Waste Dump	4295	Hitachi EX2500	Cat 785C & Cat 793C

## 7.2. Input parameters into the simulation model

Input parameters are required to run the simulation model. However, these required input parameters are uncertain due to their nature. To account for the uncertainty of the parameters different distributions were fitted. Using Kolmogorov-Smirnov and Chi Square tests, the best function with the least square error from the empirical data was selected for each parameter. Figure 6 represents the best fitted distributions on the dump time for both types of truck in the fleet tested by aforementioned tests. The main input parameter to be used in simulation model are: trucks spot time at each shovel, varies based on truck type and shovel type combination and mainly following Lognormal probability density function (PDF); number of passes required to load each truck type with a specific shovel type; loading cycle time for each shovel type loading a truck type, which changes based on types of equipment as well as change in season; amount of material each shovel type loads to a specific truck type in a single loading cycle; velocity of trucks in the mine road network when they are carrying material varying based on truck type; velocity of empty trucks, which varies based on truck type as well; duration of each truck type backing up at dumping points; and the time it takes for the trucks to dump their material into a dumping point varying based on truck type. Table 3 introduces the best fitted models on some of the aforementioned parameters to be used in the simulation.

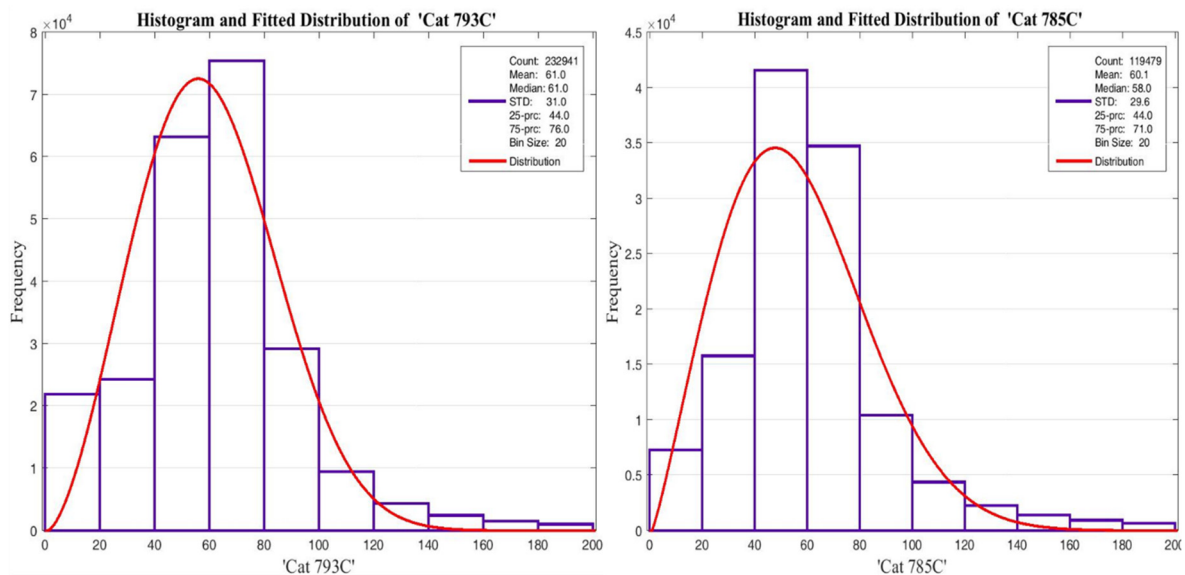


Figure 6: Best fitted distributions on dump time to be used as input parameter in simulation: a) time (seconds) it takes Cat 785C to dump its loaded material; b) Cat 793C dump time (seconds)

Table 3: Summary of some of the input parameters best fitted distribution

Data set	Truck & Shovel combination	Best fitted distribution
Spot time(s)	Hitachi EX2500 & Cat 785C	LOGN(32.7, 26.5)
	Hitachi EX2500 & Cat 793C	LOGN(42.4, 41.4)
	Hitachi EX5500 & Cat 785C	LOGN(69.7, 94.6)
	Hitachi EX5500 & Cat 793C	LOGN(79, 114)
Winter loading cycle time(s)	Hitachi EX2500 & Cat 785C	NORM(17.1, 0.526)
	Hitachi EX2500 & Cat 793C	TRIA(16.6, 18, 18)
	Hitachi EX5500 & Cat 785C	NORM(16.5, 0.99)
	Hitachi EX5500 & Cat 793C	16.6 + ERLA(0.254, 3)
Loaded velocity (km/hr)	Cat 785C	3.6 + GAMM(10.04, 22.79)
	Cat 793C	1.06 + LOGN(18.64, 7.56)
Dumping time(s)	Cat 785C	NORM(60.1, 27.9)
	Cat 793C	NORM(62.7, 28.7)

## 8. Results

In this paper, we have built two simulation models to investigate the DISPATCH optimization algorithms (i.e. upper stage LP algorithm and lower stage DP algorithm) and compare it against a heuristic algorithm developed in MOL based on some modifications on DISPATCH. We have used historical mining data to create random distributions for various input parameters and built the models in Arena simulation package. The two models and the verification process are explained in the following sections.

### 8.1. Input parameters' distribution

As the first section of the reliability analysis, we look at the random distribution functions fitted on historical data and compare them against the historical. We ran the simulation model with the fitted distributions and compared the sampled values against historical values by plotting histograms of the two sets of data, a quantile-quantile plot and a box-plot of the simulated values. As examples, we present empty velocity of Cat 793C trucks, loaded velocity of Cat 793C trucks, backing time of the same truck types, loader bucket tonnage when a Hitachi EX2500 shovel loads a Cat 785C truck, time it takes Cat 793C trucks to dump their load into a dumping point, loading cycle time for Hitachi EX2500 loading Cat 785C trucks, and spotting time when a Hitachi EX2500 loads a Cat 793C are illustrated in Figure 7 to Figure 13, respectively. Looking at these figures we can conclude that the random distributions fitted on historical data are verified to a good extent and we can move forward to running the models and obtaining simulation results for the two models.

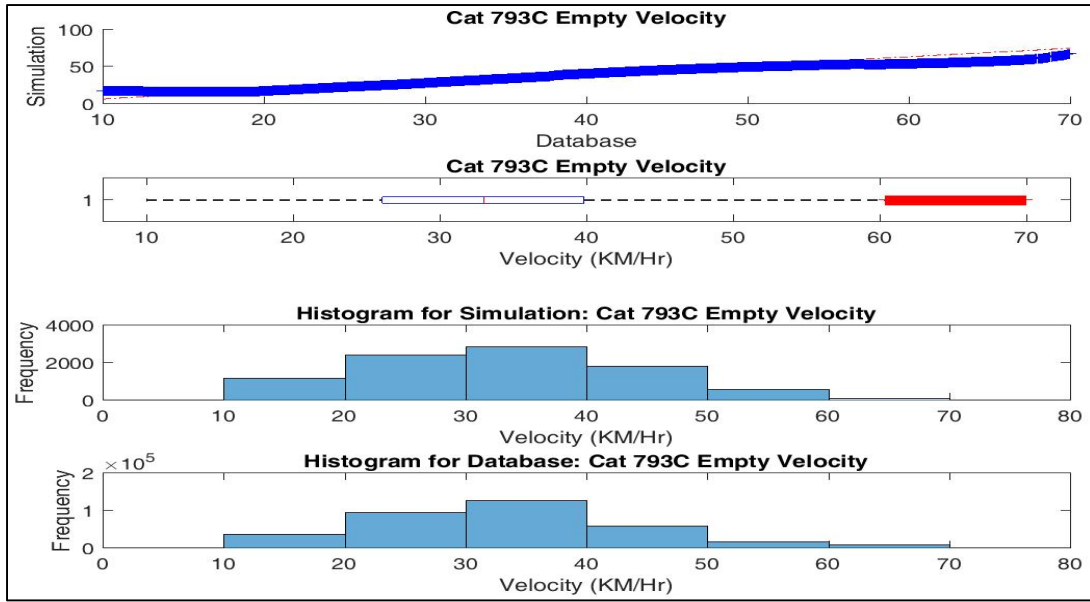


Figure 7: Truck type Cat 793C empty velocity: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

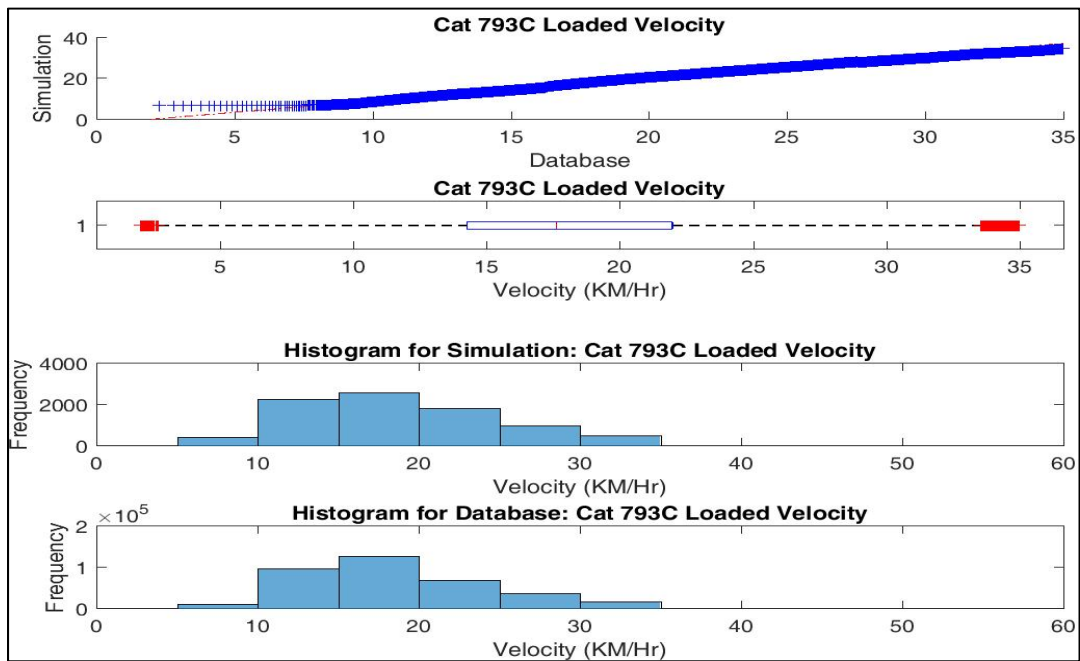


Figure 8: Truck type Cat 793C loaded velocity: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

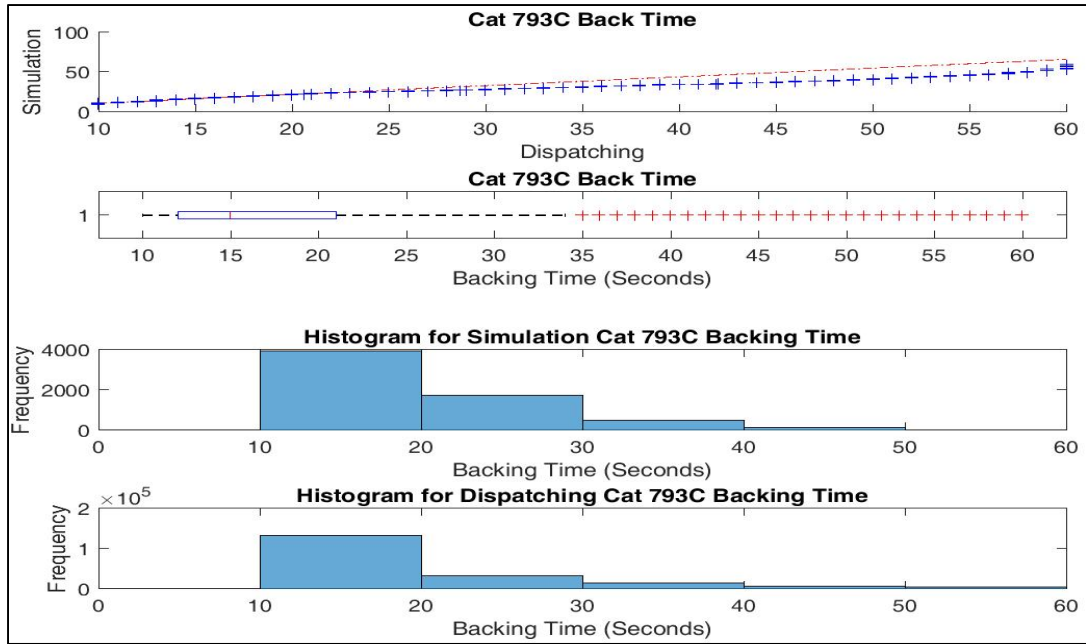


Figure 9: Truck type Cat 793C backing time: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

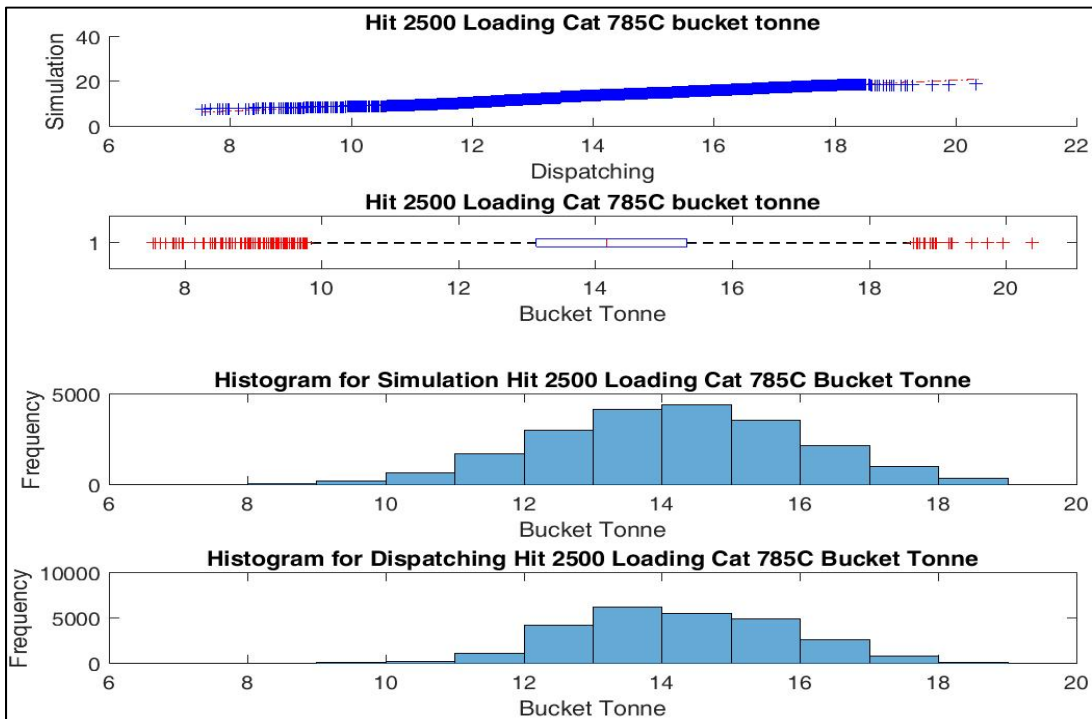


Figure 10: Shovel type Hitachi EX2500 loads truck type Cat 785C bucket tonnage: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.



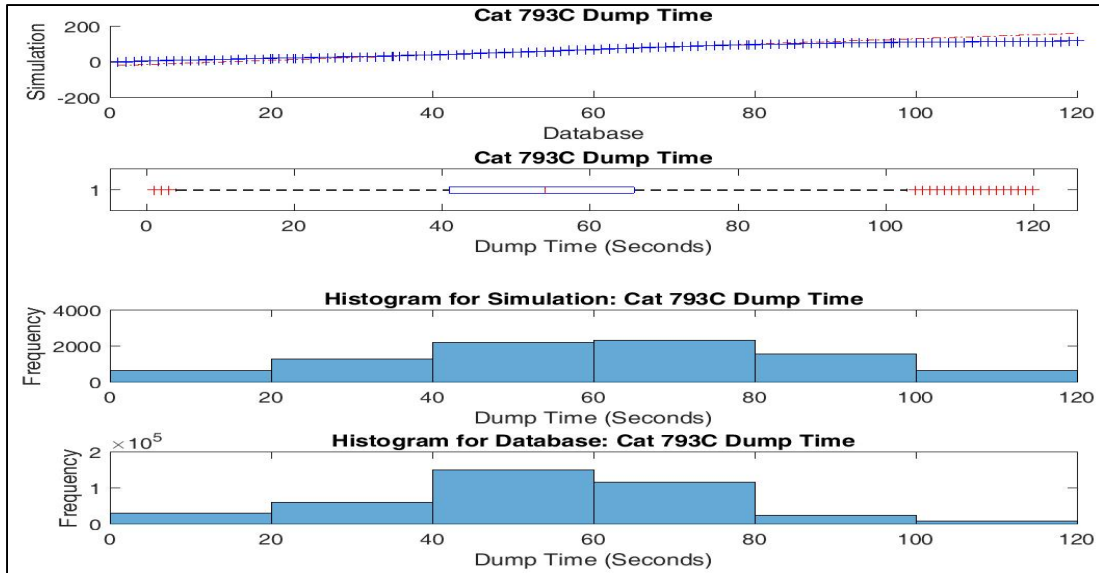


Figure 11: Truck type Cat 793C dump time: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

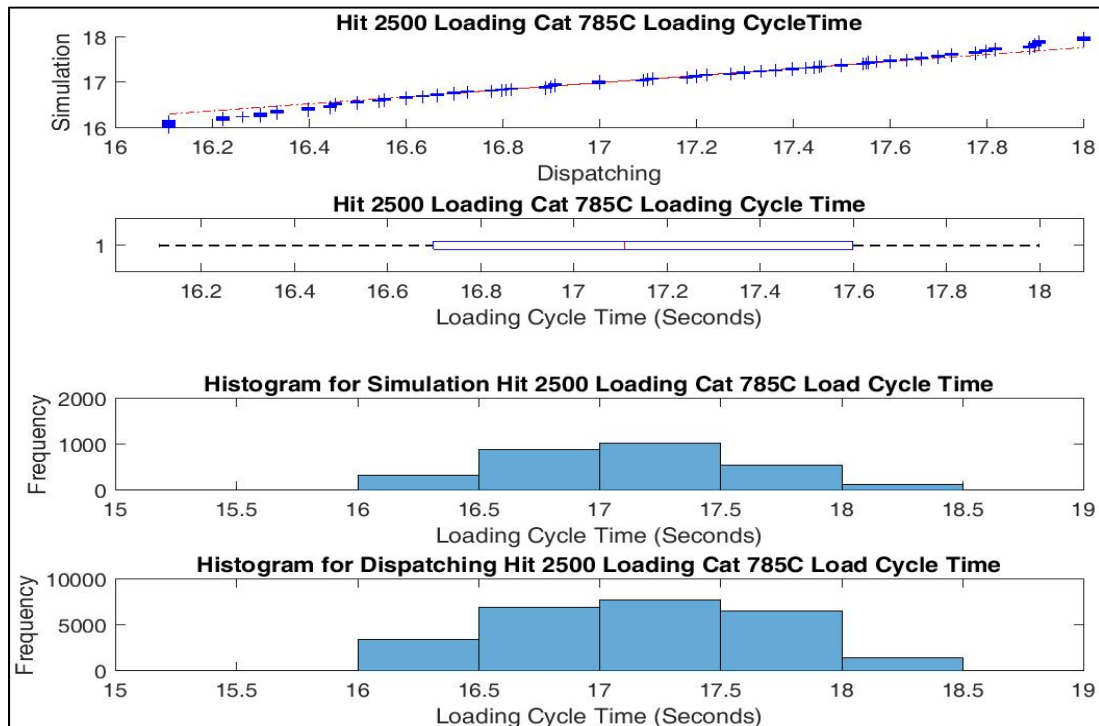


Figure 12: Hitachi EX2500 loading Cat 785C loading cycle time: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

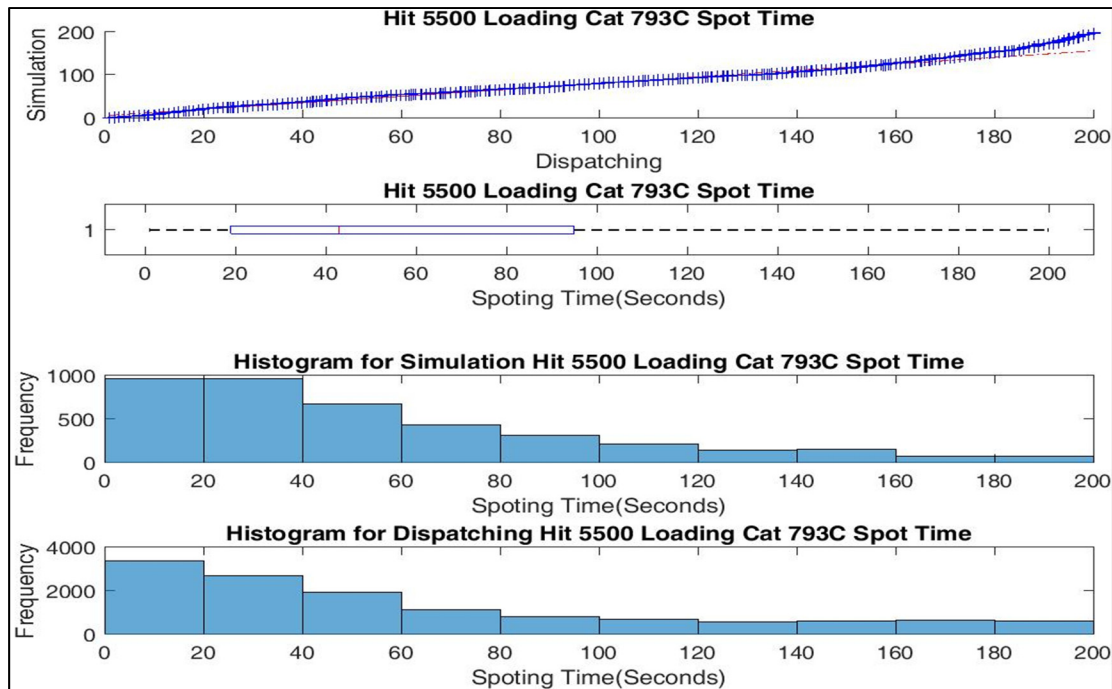


Figure 13: Hitachi EX5500 loading Cat 793C spotting time: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

## 8.2. Production

After proving that the distributions representing the uncertain input parameters match with the database, the simulation model was set up for 5 replications (decided based on required halfwidth shown in Figure 14 and Figure 15). Then, the model was run two times each time for 91 days of operation. At the first step, the model was run with the embedded DISPATCH. Afterwards, MOL dispatching heuristic was used to handle the truck assignments. Finally, the results of the two models were compared. The comparison considering weekly production of ore, removing the waste, and input material into each plant are represented in Figure 14 to Figure 21. Both models work using a short-term production schedule obtained from (Upadhyay & Askari-Nasab, 2016).

Results of the Gol-E-Gohar mining operation simulation model show that total weekly production of the mine with embedded DISPATCH starts with 1.08 million tonnes per week in the first week of the study. After having a smooth fluctuation between week five and week eight the production reaches a steady weekly rate of 92.5% of its initial production and 88.4% of the maximum achievable production of the system (Figure 14). On the other hand, the operation does not feed both of the plants with the same rate. Figure 14 shows that plant 2 is always being fed by 20 to 35% more than plant 1 since it is closer to pit.

The same simulation model for the case study was run with the embedded MOL heuristic to dispatch trucks. The result of the 91 days of the operation is presented in Figure 15. At the first week, the operation starts with removing 1.09 million tonnes of ore and waste meeting its highest production on week five with a 4% increase and its lowest production on week six with 3% short comparing with the first week of the operation. The operation reaches a steady state from week seven. Moreover, the processing plants are fed almost balanced with a gap of less than 5% difference between the amounts of material sent to each of the plants.

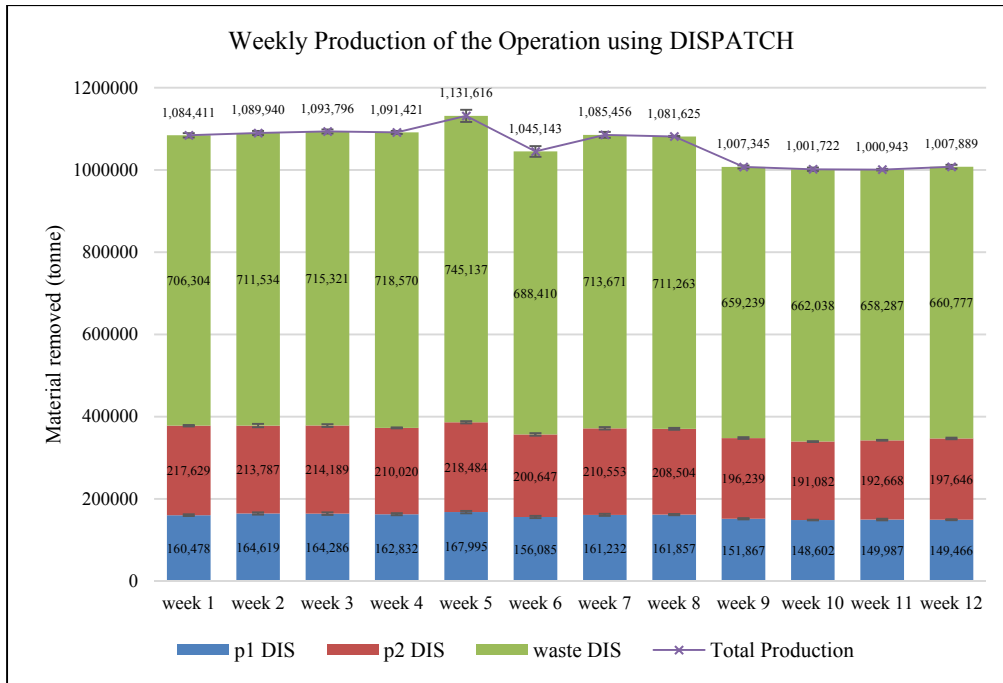


Figure 14: Weekly production of the operation using DISPATCH as the fleet management system over 12 weeks of the operation.

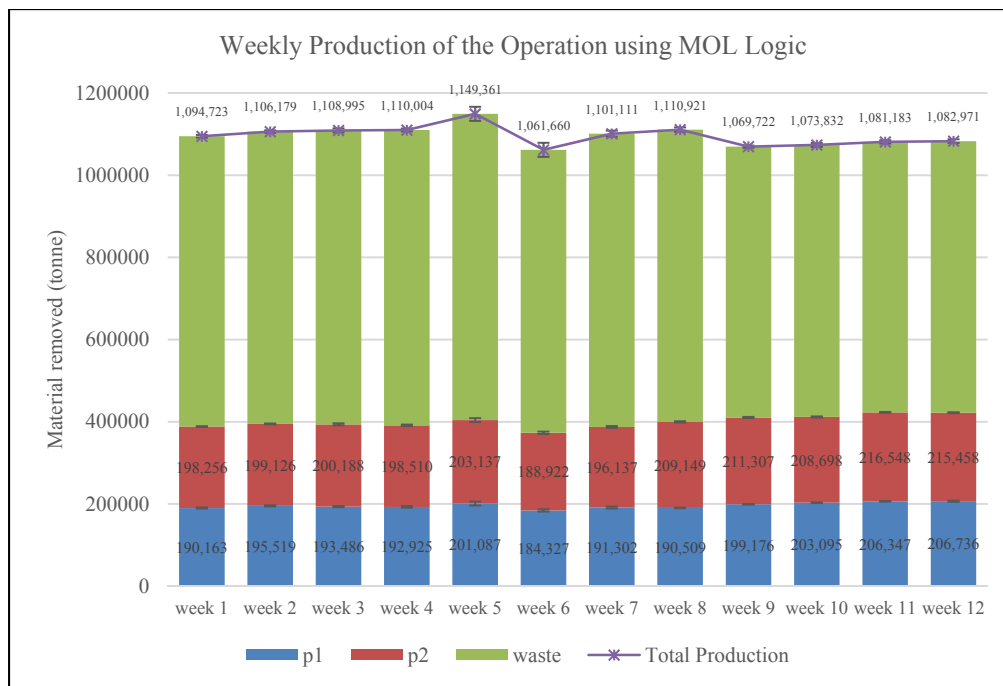


Figure 15: Weekly production of the operation using MOL fleet management system over 12 weeks of the operation.

### 8.3. Queue at shovels

Number of trucks in queue at each loader is one of the important KPIs to evaluate the performance of a dispatching technique. To have a more representative graph, box plots of queue length at shovels are presented in Figure 16 for over the first 20 shifts of the operations. The upper graph

illustrates how trucks line up in queue of shovels in the simulation model with embedded MOL heuristic. The second graph in Figure 16 shows the number of trucks in queue at shovels in each shift when the simulation model uses DISPATCH as its fleet management system.

Although the first graph in Figure 16 represents that 35% of the time there are less than or equal to two trucks in line of the shovels when MOL heuristic is being used, investigation over the period of 20 days as shown on the same figure prove that both dispatching systems have almost the same line up in queue of shovels over the shifts.

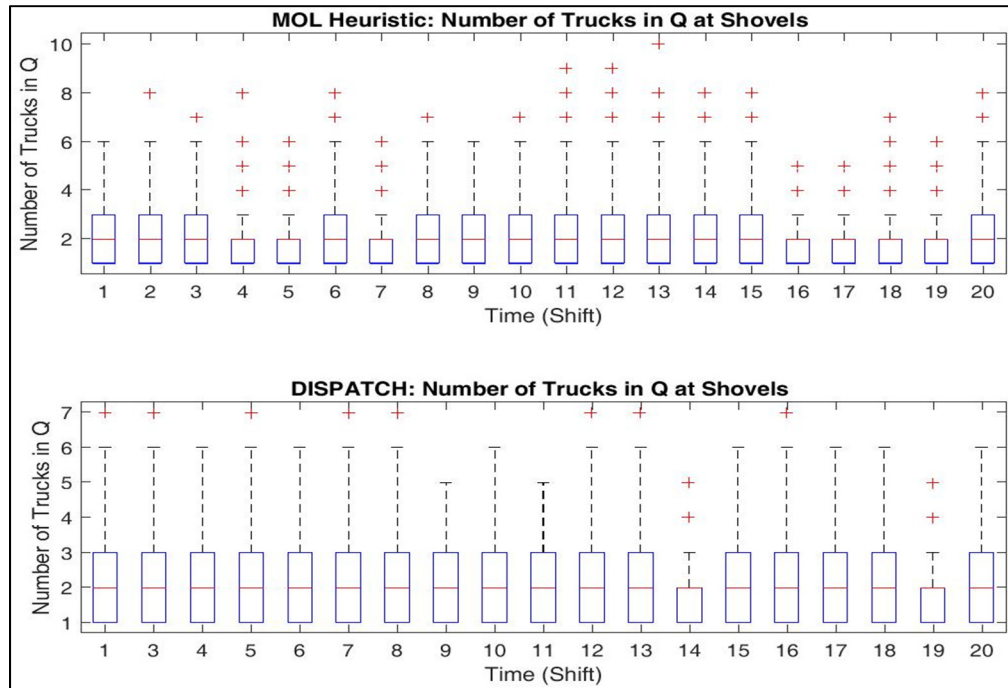


Figure 16: Queue length at shovel 1 per shift: upper plot stands for MOL logic and lower plot presents simulation with embedded DISPATCH

#### 8.4. Shovel utilizations

As one of the most expensive mining equipment in open pit mining operation, utilization of the shovels is one of the important KPIs to measure in the open pit mining simulation modeling. As it was mentioned in the case study section of the paper, there are five active shovels working in Gol-E-Gohar open pit mining operation: three Hitachi EX2500 and two Hitachi EX5500. Utilizations of these five active shovels were tracked over the simulation time of 91 days of the operation. Figure 17 provides overall instantaneous utilization for the shovels. Orange bars stand for shovels' utilization in the operation with embedded DISPATCH and the blue bars represent utilization of the shovels in the operation using MOL heuristic to dispatch trucks to the shovels.

Figure 17 shows that in the operation with embedded DISPATCH send more trucks to shovel 5 than shovel 1. The reason is that DISPATCH is considering minimum distance to send truck to the shovels. Here in this case shovel 5 is working in a closer distance to the dumping points than shovel 1 which is working in the bottom of the pit. As a result, DISPATCH sends more trucks to the shovel 5 than shovel 1. However, in the mining operation with the same priority shovels preference is to produce as much ore material as possible. As shown in Figure 17 the rule is followed by MOL logic. It is sending more trucks to the ore shovel (shovel 1) than the waste shovel (shovel 5) increasing the ore production.

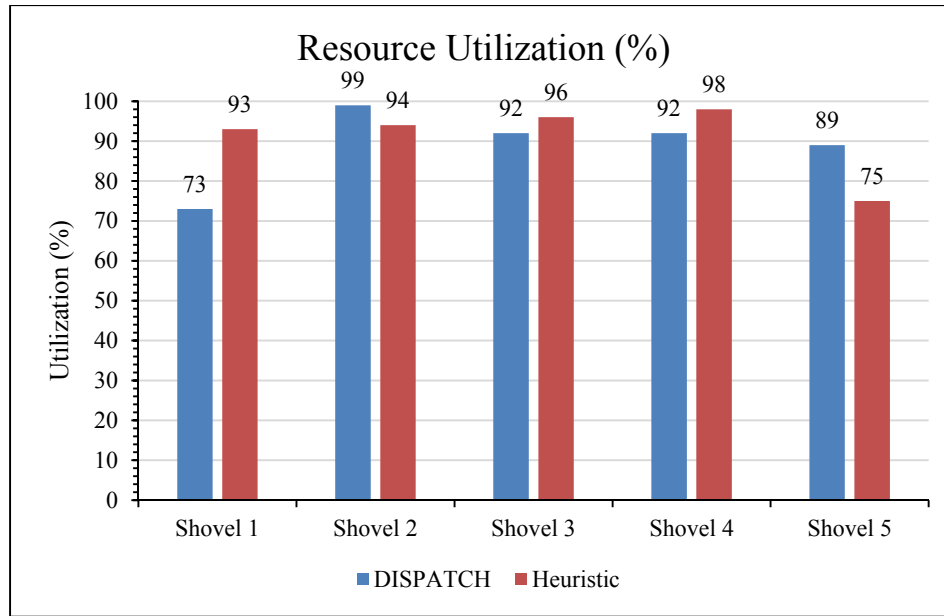


Figure 17: comparing shovels' utilization (MOL logic vs. DISPATCH)

## 9. Discussions

First of all, as presented in the first section of the results, Figure 7 to Figure 13 illustrate accuracy of the distributions used in the simulation modeling for the six main uncertain input parameters consisting of trucks' speed when they travel empty (Figure 7), loaded velocity of the trucks (Figure 8), time it takes a truck to back up at a dump location (Figure 9), shovels bucket tonnage when loading an specific truck type (Figure 10), dumping time of trucks at dumping points (Figure 11), loading cycle time (Figure 12), and spotting time of the trucks (Figure 13). The quantile-quantile plots of the samples obtained from the simulation results versus the data collected from the database for fitting the random distributions and the histograms of the simulation results and collected data verify that all of the random distributions are fitted properly on the collected data.

After running the simulation for 3 months of the mining operation as the case study, production KPIs of the models were extracted. Figure 18 shows the total amount of material removed from the mine on a weekly base. According to Figure 18 operation implementing MOL heuristic produces higher tonnage of material over the research period except for week one and week five. Results show that in the first week simulation model with embedded DISPATCH produces 0.8% in the first week and 0.2% in the fifth week more than the second model. However, the MOL heuristic helps the operation to remove almost 4% more material over 3 months of the operation. Figure 19 and Figure 20 represent comparison between total ore production as well as weekly feed to each of the active plants, respectively. Considering the average total ore produced over each week of the operation, the model implementing MOL heuristic sends about 9.8% more material to the plants than the benchmark model with embedded DISPATCH (bars in Figure 19 and blue line graphs in Figure 20). Comparison between material sent to each plant (green graphs showing ore sent by MOL heuristic and red graphs showing ore sent by DISPATCH in Figure 20) an average of 30% difference between feeds of plant 1 and plant 2 in DISPATCH is corrected to a gap of less than 5%. The reason behind 30% difference in total plant feeds in DISPATCH is that plant 2 is closer to the pit rim than plant 1. However, this closeness does not have any effect on the material sent to the plant in the model using MOL heuristic. Another aspect of the result of the study to be discussed is that the operation has higher stripping ratio when implementing MOL logic in comparison with the operation using DISPATCH by 5% (Figure 21).

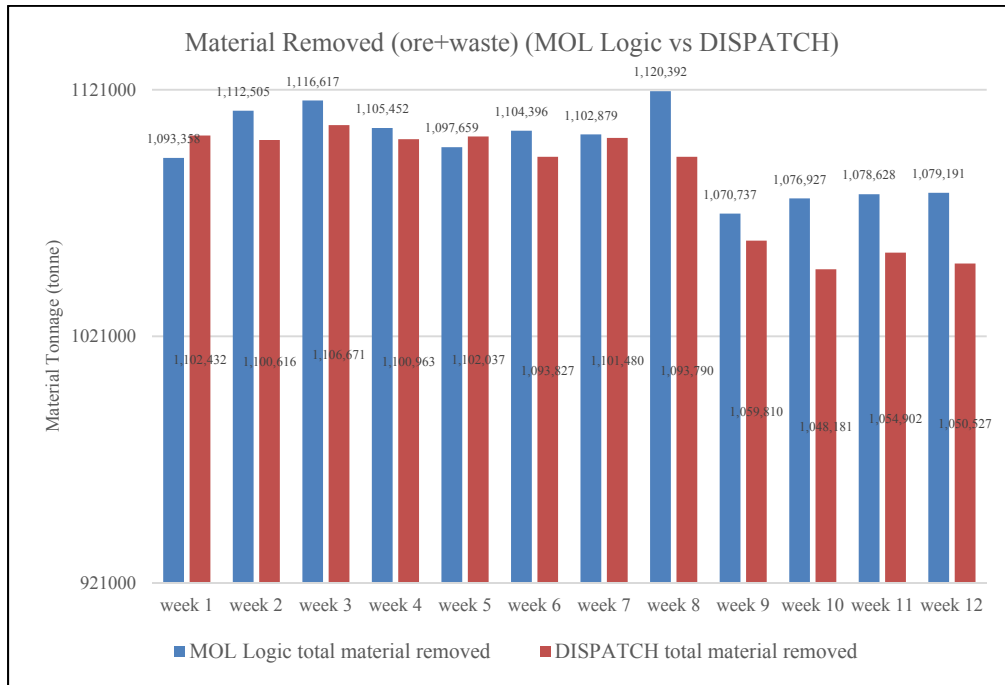


Figure 18: Total material mined including ore and waste over 12 weeks of the operation (a comparison of MOL with DISPATCH)

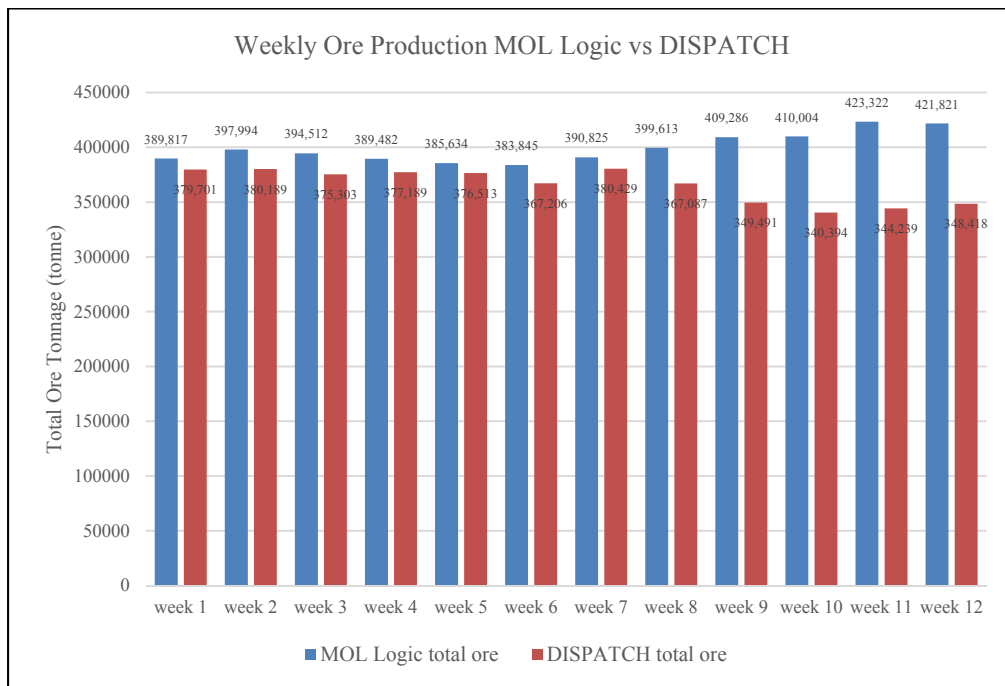


Figure 19: Total ore tonnage sent to the plants over 12 weeks of the operation (a comparison of MOL with DISPATCH)

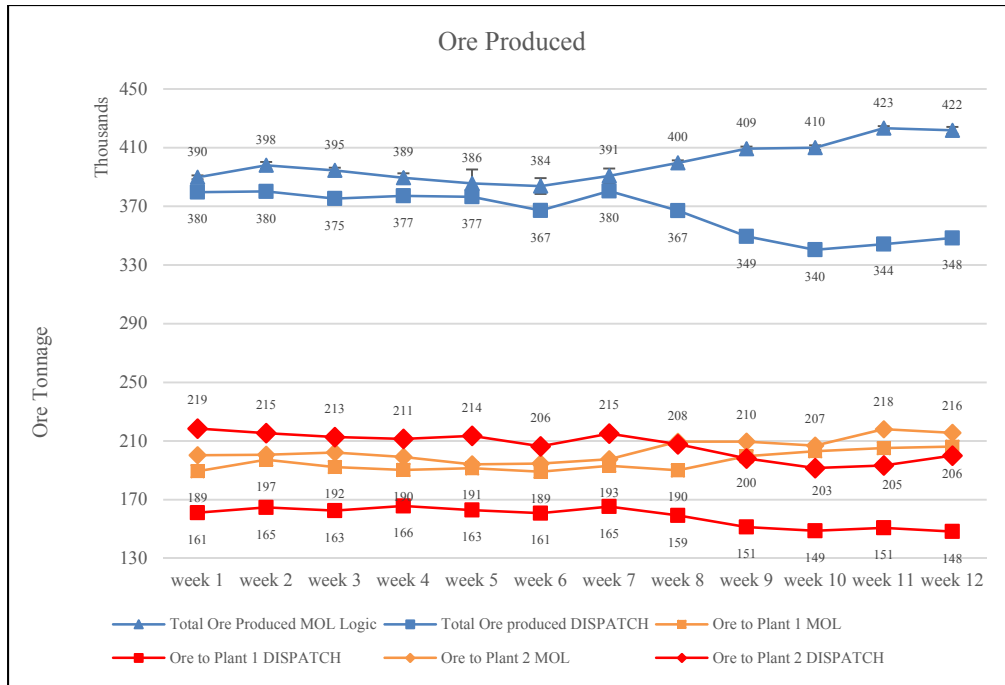


Figure 20: Ore sent to each processing plant and total ore produced over 12 weeks of the operation (MOL logic vs. DISPATCH)

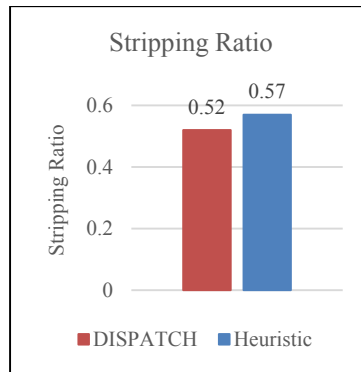


Figure 21: Stripping Ratio for the material removed in the period of 91 days.

To sum up, results of the study show three major improvements in the production of the case study (Gol-E-Gohar Iron Mine) where DISPATCH was substituted with the heuristic developed by MOL to handle truck dispatching. First of all, the study shows about 10% improvement in total tonnage extracted from the mine over the operation period of three months. Previous studies in the literature proved that implementing DISPATCH in a mining operation improves the production by somewhere between 10 to 15 % in different case studies (Kolonja & Mutmansky, 1993; White & Olson, 1986) in comparison with the fixed truck allocation. As a result, having 10% improvement in production of an operation using DISPATCH means having total improvement of 20 to 25% comparing with the operation with trucks locked to each shovel that has been used as a benchmark model for almost all of the studies addressed in the literature of truck dispatching (Ataepour & Baafi, 1999; Bonates & Lizotte, 1988; Hashemi & Sattarvand, 2015; Kolonja & Mutmansky, 1993; Y. Lizotte, et al., 1987; Olson, et al., 1993; Soumis, et al., 1989; Temeng, Otuonye, & Frendewey, 1997; White & Olson, 1986). Second advantage of the MOL heuristic over DISPATCH shown in the results of this study is more reliable feed balance in a multi plant mining operation. Using MOL heuristic instead of DISPATCH in a multiple ore destination operation dramatically improve

balance in feeds delivered to each of the processing plants. As it was shown in this paper, in an operation with two processing plants with a distance of around 350 meters between plants, 30% difference in plant feed rates reduced to less than 5% by replacing DISPATCH with MOL heuristic. This improvement happens due to DISPATCH logical drawback of being a single plant algorithm. The third major result from this study is 5% improvement in the operation stripping ratio by substituting DISPATCH with MOL heuristic. The reason behind this improvement is preference of ore to waste to be produced when all the shovels are in demand with the same priority.

## 10. Conclusions and future work

A heuristic dispatching algorithm was developed in MOL to be used in open pit mining as a part of the operation fleet management system to handle truck dispatching. To verify the goodness of the algorithm, first a case study of an Iron ore mining operation was selected. Then, well-known and widely used Modular mining fleet management system (DISPATCH) was embedded into the system to be used as the benchmark model. Afterwards, simulation model was run with both of the truck dispatching systems for a time horizon of three months. Comparing the results show improvement in the key performance indicators of the system when DISPATCH is substituted by MOL heuristic. Higher tonnage of material removed, less variation in plant feed rates, higher stripping ratio, balance in plant feed rates in a multi plant mining operation were obtained by replacing DISPATCH with MOL heuristic. Moreover, the developed algorithm feeds the plants with a difference in feed rate of less than 5% between two plants which shows an improvement of 25 to 30%. Stripping ratio of the operation was also improved by 5%. However, there is a limitation to deal with: although capacity of the plants is not the bottle neck of this model, they need to be taken into account in future works.

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