# A Multi Objective Multi Stage Mining Fleet Management System Linking Dynamic Operation to Short-Term Plan

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## ABSTRACT

*Fluctuation in market price of mineral products has enforced mining companies to cut down their operating costs. One useful way of reducing operating costs in mining operations is to make optimal operational decisions, incorporating efficient mining fleet management systems (FMS). Since 50 years ago several types of FMS have been developed and introduced in the mining systems around the world. However, there are two major shortcomings in existing systems. Firstly, none of the existing systems consider effects of the short-term plan on dynamic truck assignment. Secondly, most of the existing FMS make decisions in a way that optimize a specific objective while ignoring others. Herein, we propose a multi stage and multi objective FMS that deals with aforementioned shortcomings of the currently available systems. The developed FMS, in its upper stage, links semi-dynamic operational decision making process to the short-term production plan by simultaneously assigning shovels to mining faces and allocating trucks to the shovels by implementing its first multi objective decision making model. Then in its second stage, in a real time dynamic decision making process, it assigns trucks to shovels and corresponding destinations by optimizing its second multi objective decision making model. The developed fleet management system has been verified using an Iron ore case study and the results are presented in this paper.*

## 1. Introduction

Open pit mining method is the most common method to mine mineral from the earth. Based on (Wetherelt and van der Wielen, 2011) there exist 2500 open pit metal mines that are categorized as industrial scale mines. Several methods of material handling are used in to mine these open pit mines including dragline systems, bucket-wheel excavator systems, truck and shovel material handling systems, and etc. However, the amount of material handled using truck and shovel material handling system is more than the amount handled by all other systems together (Humphrey and Wagner, 2011). Because of that, studying truck and shovel mining operation is a matter of interest among the researchers working in the area of open pit mining. Fig. 1 shows a general scheme of an open pit mining operation with N digging points and M material dumping point connected to each other. It has been proven by several studies that more than 50 percent of operating cost in a truck and shovel based open pit mining operation is accounted for material handling (Alarie and Gamache, 2002; Ahangaran et al., 2012; Moradi Afrapoli and Askari-Nasab, 2017). Thus, introducing even 1 to 2 percent cut in its material handling cost saves huge amount of money for the stakeholders. To introduce that cut, two main ways have been used over the last 50 years. On one hand mining industries have been implementing equipment with higher production capacities, and on the other hand, researchers have been developing operation research techniques to make required decisions as close to optimal as possible to deduct operational costs in truck and shovel based mining operations.

Many decisions need to be make optimally in any open pit mine. These are included but not limited to Long-/Medium-/Short-term production planning (Bley et al., 2010; Shishvan and Sattarvand, 2015; Jélvez et al., 2016), ultimate pit determination (Rodovalho et al., 2016), fleet selection and size determination (Beaulieu and Gamache, 2006), finding the shortest paths (Ferone et al., 2016; Breugem et al., 2017), production optimization (White and Olson, 1986; Temeng et al., 1998; Ta et al., 2005; Gu et al., 2010; Topal and Ramazan, 2010; Upadhyay and Askari-Nasab, 2016; Chaowasakoo et al., 2017; Patterson et al., 2017), equipment maintenance and repair (Topal and Ramazan, 2012), fuel consumption (Soofastaei et al., 2016), and truck dispatching (White and Olson, 1986; Soumis et al., 1989; Temeng et al., 1997). Over the last decades several studies have been conducted in each of the above mentioned parts of decision making procedure in open pit mining operation optimization. However, one of the most important decision making tool in any open pit mining operation is fleet management system. After finding shortest paths, a fleet management system, as is presented in Fig. 2, makes required semi-dynamic and dynamic decisions in two steps. In the first step of its decision making procedure, it decides on optimum amount of material to be transported from a specific loading zone to a dumping location based on the objective function and the constraints defined for the model (Fig. 1). Then, each and every time a truck requires an assignment, the lower stage of the fleet management system finds a destination for the truck based on predetermined criteria.

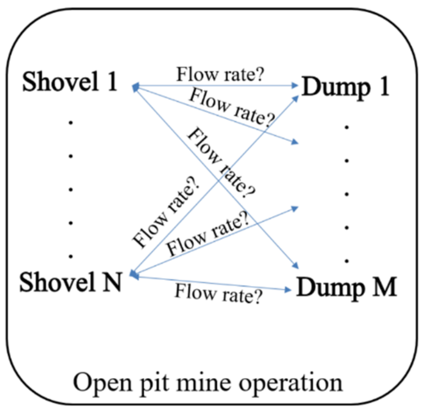



Fig. 1: Schematic of an open pit mining operation

Since late 1960s number of research have been done in both industries and academies to enhance productivity and reduce cost of mining operation by developing flexible allocation models and algorithms based on different strategies.

First, Bogert (1964) suggested the use of radio communication between equipment operators and the mine control centre. Then in the next decade, one of the first algorithms introduced to solve truck allocation and dispatching problem in open pit mines is a single stage algorithm presented by Hauck (1973). The main feature of presented algorithm is combination of operation plan and real-time scheduling in a single model. The model is based on solving a sequence of assignment problem by using of Dynamic Programming (DP). The model considers stripping ratio, blending objectives, capacity of the plant and stockpile. In the late 1970s, Mueller (1977) introduced implementation of the dispatching boards installed in the control centre using a simplified dispatching technique to manage the operation.

Although some research had been undergoing in 1960s and 1970s, main efforts in the field started from the second half of the 1980s.The literature of the optimization part is mainly categorized based on their solution approaches. White and Olson (White and Olson, 1986) use Linear Programming (LP) approach to optimize production target of the time horizon by dividing it into two separated but weakly coupled models from which the first one optimizes total operation including mine sector, plant sector and stockpile, and the second part maximizes the fleet production by minimizing total required volume to be handled. The model developed by Soumis et al. (1989) performs the upper stage in two steps. As the first step, it fixes shovels' location by implementing combinatory Mixed Integer Linear Programming (MILP) model with respect to available trucks and the objective of maximizing the production and subject to quality constraints. By solving the MILP model it suggests some location for shovels to be seated on the computer screen, and it needs a human to make a decision on the shovels sitting locations. Then after, as the second step of the algorithm Soumis et al. (1989) represents truck travel plan between shovels and dumping points by solving a Non-Linear Programming (NLP).

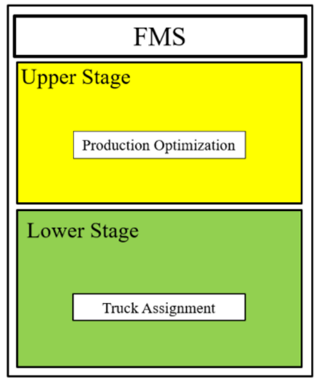



Fig. 2: A fleet management system

(Kappas and Yegulalp, 1991) offered a queuing theory model by considering truck – shovel system as a production network with regard to trucks as customer and shovels, crushers, waste dump, roads and maintenance service areas as servers. In their model, it is assumed that a mining system is a stochastic system with Markovian nature. Although it is stochastic, because of some parameters like service time distribution in different service areas, it is not Markovian (Newman et al., 2010).
Najor and Hagan (2006) applied queuing theory to analyze equipment (trucks and shovels) utilizations in the stochastic environment. Application of the model in an Australian case study shows that ignoring queue of trucks at hoppers (or plant capacity) causes overestimation of the production.

Later, Ercelebi and Bacetin (2009) represent a queuing theory model to allocate trucks in an open pit mine based on (Carmichael, 1987) which can estimate some of mining systems performance parameters including number of trucks, throughput of the processing plant and the waiting time.

After 2010, researchers mainly focused on implementing linear programming to solve the upper stage decision making problem in fleet management systems. Gurgur et al (2011) proposed an LP model of operation optimization that helps to minimize deviation of the operation from the strategically set targets in short- and long-term schedules. To link operational plan to the strategic ones the model provides shovel assignment. Ta et al. (2013) developed a mixed integer linear programming (MILP) model to allocate trucks of a fleet to different shovels based on probability of shovels' idle time. Mena et al. (2013) defined a knapsack problem which tries to maximize cumulative truck fleet production by a fixed time horizon. Chang et al. (2015) introduced an MILP model that schedules trucks over a shift by implementing MILP with the objective of maximizing transportation revenue. However, the models developed so far have some drawbacks as well. Main limitations of the existing fleet management systems can be highlighted as: Linkage to the strategic level short-term schedule, the impacts of drilling and blasting operations on the fleet operation, the effects of uncertainty and correlation of parameters governing the operation, Not accounting for the lost tons caused by mobility and equipment access problems particularly for shovels, The effects of the downstream active processes on the transportation operation, The impacts of the weather and traffic conditions on the shortest path between loaders and destinations, Optimum assignment of the shovels into the faces, Dynamic truck control, Incorporating mixed fleet systems (in most of the models). These limitations push models to result further from the real optimal decisions.

In this paper we develop a multi objective multi stage mining fleet management system that covers some of the aforementioned drawbacks of currently available systems. The developed fleet management system at its upper stage links operational plan of the mining operation to the mines short term plan or its production schedule by assigning the available shovels to the right polygons. At the same time it determines optimum path flow rate for each path connecting a loading point to a dumping location. Results of this step are being used in its lower stage to assign trucks to the right shovel by minimizing lost tons caused by equipment idle and wait times.

## 2. Models and Methods

### 2.1. Simulation Model

#### 2.1.1. System

The system includes one open-pit mine, its haul network, its 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 fleet management system (FMS) 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. Another major optimization component of the system is the step three of the FMS that runs in a specific time intervals and whenever the system experiences a major change.

#### 2.1.2. Key Performance Indicators

We have to define major Key Performance Indicators (KPIs) in order to evaluate systems' performance and asses the reliability of the models. Herein, 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.

#### 2.1.3. Model inputs

The simulation model input can be illustrated within two categories of short-term schedule and the technical inputs. The required inputs from the first category are including: coordinates and node IDs for the digging locations, total tonnage of the blocks, material average grade for each block, ID of the destinations the materials are supposed to be sent to, Shovel number, sequence number for each shovel, precedence, and distances from the digging location to the dumping locations. The required technical inputs are: shovels' ID, bucket capacities, loading cycle time, availability, trucks' ID, number of trucks of each type, capacities, dump time, spot time, availability, average speed of trucks when empty and when loaded, backing time, desired grade of each material type at processing plants, maximum rate of processing at processing plants, geographical information regarding dumping locations, all information regarding coordinates of the nodes connecting different parts of the road network, information regarding activity of any paths within sources and destinations, bucket count for each combination of shovel type-truck type, and seasonal loading cycle times for each and every shovel type-truck type combination.

### 2.2. Optimization Models

#### 2.2.1. Upper Stage Model Description

The upper stage of the model is formulated to provide shovel assignments and required path flow rates of trucks to the lower stage of FMS to comply with the short term plans and attain desired production and grades during mining operations. This stage uses a goal programming approach to optimize three objectives: 1) minimize the deviation in production, 2) minimize the deviation in tonnage of ore delivered to crushers, and 3) minimize the deviation in average grade delivered to crushers, as compared to maximum production, desired tonnage and desired grade at the crushers respectively. The problem is formulated as multi-period optimization model, where although the optimal decisions of the first period are passed on to the lower stage, the model solves the problem for multiple periods in the future and thus incorporates future requirements and state of the mine as well. The major set of constraints used in the model include: shovel assignment and movement constraints, material availability at faces, production capacity of shovels, production and grade constraints of the destinations, face precedence constraints and truck allocation constraints. Apart from these major constraints shovel failure constraints are also included to account for the dynamic mining system state. The model also incorporates shovel-material locking constraint to lock specific shovels to material if desired.

### 2.2.2. Lower Stage Model Description

The step four of the decision making procedure for FMSs to be implemented in any open pit mining operations working on the truck-shovel material handling bases is formulated considering three operational goals of the mining companies:

1. Maximize shovel utilization;
2. Minimize truck waiting time;
3. Minimize the deviation in the path flow rate compared to the desired flow rate.

A linear goal programming model has been formulated to optimize the goals.

First goal of the multi objective model represents total idle time for all the shovels working in the operation. The second goal of the model represents total truck waiting times for all the trucks available for assignment. And the last goal represents the difference between flow rate of the paths and the desired flow rates.
The multi objective truck assignment model is constrained by seven sets of limitations. The first set of constraints tries to balance truck rate at each shovel. It says that whatever truck goes to a shovel must leave the shovel as well. There exists another set of truck input balance constraint that governs the dumping location area. These constraints indicate that if any truck goes to a dumping location to dump its material, it must leave that location as well. Third set of constraints limit the system to make decision in a way that the operation is not allowed to use a truck more than its capacity that is called supply constraint. Besides, there is a set of demand constraints imposing the processing plants requirement to be met. Then, there are constraints governing deviations from the required path flow rate for each path. A set of non-negativity constraints limit variables to only accept non-negative values. Fig. 3 illustrate how any mining operation can talk to our developed multi objective multi stage fleet management system in a mining operation.

## 2.3. Optimization Model Solution Method

The Goal Programming (GP) was first introduced by Charnes and Cooper (1955) and (1961). In the simplest version of GP, the designer prepares some goals he or she wishes to achieve for each objective function. Then, the solving procedure will minimize deviations from the goals. This means that it does not maximize or minimize an specific objective, it tries to find an specific goal value of those objectives, though (Caramia and Dell'Olmo, 2008).

In the mining operation optimization there exist variety of goals to be achieved such as production maximization and maintenance of ore quality between the desired limits (Temeng et al., 1998), optimization of the processing plant utilization and minimization of trucks and shovels movement costs (Upadhyay and Askari-Nasab, 2015). In the former algorithm, the model maximizes shovel production and ensure ore grade requirement achieved as much as possible. The main advantage of GP model developed by (Temeng et al., 1998) is that it optimizes two major goals of the open pit operation simultaneously without neglecting any of them. Besides covering the objective function drawbacks of previous models it covers another disadvantage of LP models which is defining upper and lower limits for the target grade of material are being sent to the plant. As it was introduced before, in LP models it is usual to control the grade by imposing it between upper and lower limit. Let us assume that objective is to maximize the production. Then truck assignment to the shovel closer to the crusher which results shorter truck cycle time will be higher. If the average grade at these closer faces are pretty close to one of the allowed grade boundaries, then whatever the dispatching algorithm is controlling the feed grade within the interval is difficult. As a result, existing of stockpile and subsequently re-handling cost associated with it is undeniable. However, the model has some disadvantages. It does not consider all the goals are supposed to be met in an open pit mine operation such as equipment movement costs, of which some of them are covered by Upadhyay and Askari-Nasab (2015). The model the mining operation as a multi-period operation which needs to meet strategic goals of the project. It does not consider stochastic nature of the grade of material are feeding to the plant as well. The most recent open pit operation optimization model based on GP can be found in (Upadhyay and Askari-Nasab, 2015) where the authors enhanced aforementioned model's objective with adding two new goals. The newly added goals are minimizing the deviation of calculated plant feed to desire feed and minimizing cost of both trucks and shovels operation, respectively.

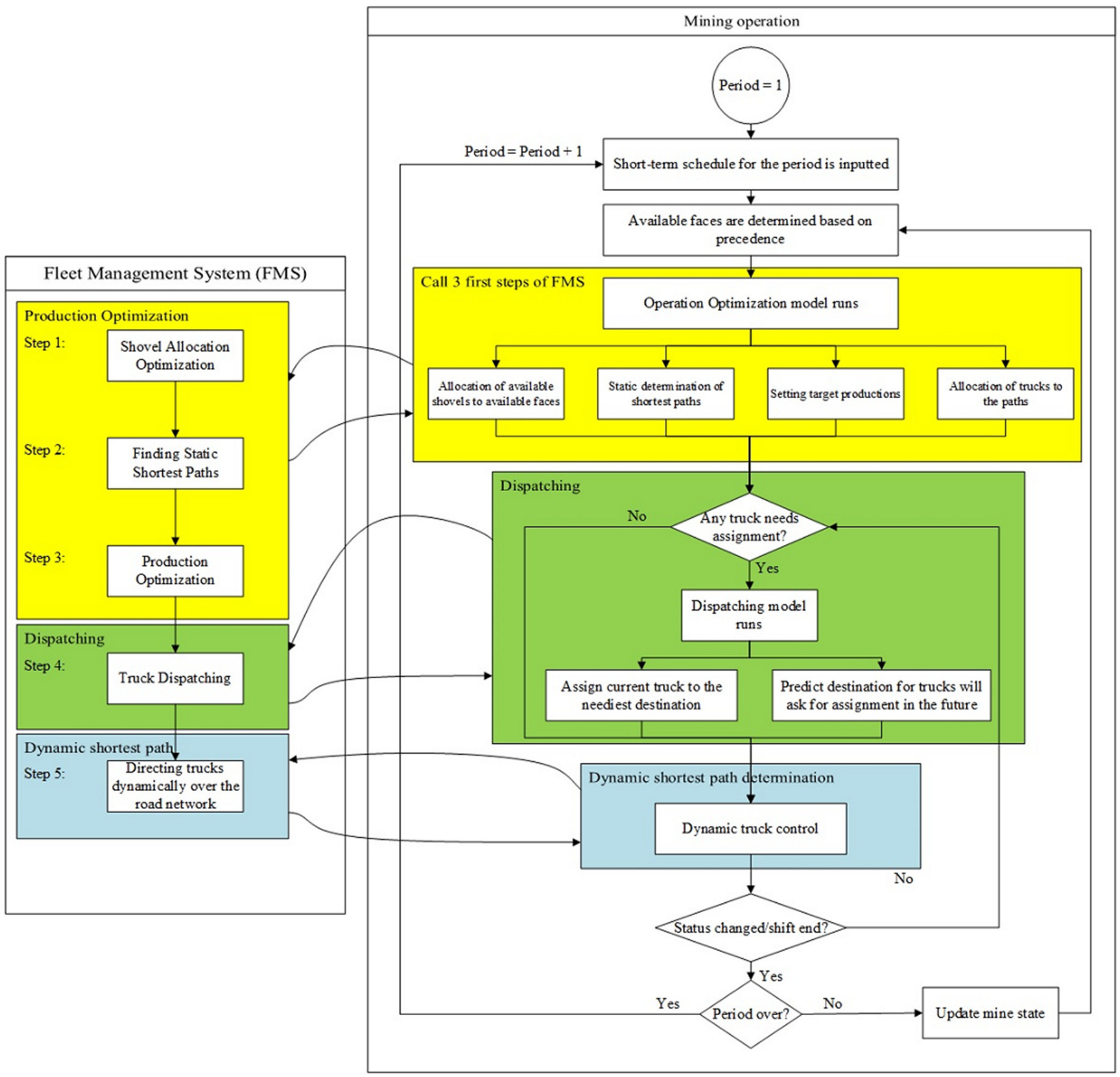



Fig. 3: Schematic representation of how the simulation model of a mining operation talks to the multi objective multi stage fleet management system we developed here.

Applying a non-preemptive goal programming approach the objective function of the truck assignment stage of the decision making process in the FMS is given by Eq.(1). A challenge here is that the goals are in different dimensions. To have a dimensionless objective function combining all the above mentioned goals it is necessary to normalize the goals. The normalization is done by determining Utopia and Nadir values for each and every goal. The normalized goals are multiplied by the weights to achieve desired priority and the final objective function obtained as Eq.(2).

$$\min Z = P_1\overline{G}_1 + P_2\overline{G}_2 + P_3\overline{G}_3 \tag{1}$$

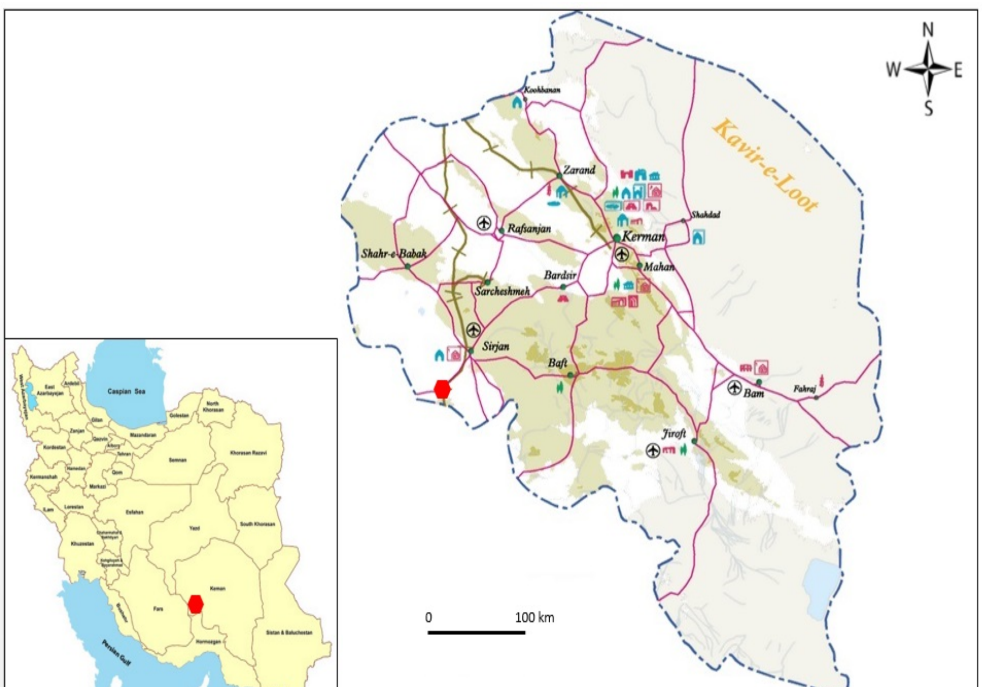
Where:

$$\overline{G}_i = \frac{\left(G_i - z_i^U\right)}{\left(z_i^N - z_i^U\right)} \qquad i \in \{1,2,3\} \tag{2}$$

## 3. Case study– Gol-E-Gohar Iron Ore Mine

### 3.1. 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 (Fig. 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). Furthermore, Table 1 presents general specifications of the operating system. It is also worth noting that the mine operates for two 8 hours shift a day for 340 days a year.




Gol-E-Gohar Location, Kerman, Iran

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

Table 1: 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 |

### 3.2. Input parameters into the simulation model

Input parameters are required to run the simulation model. However, the values of these required input parameters are uncertain due to their nature. To account for the uncertainty of the parameters different distributions were fitted on the historical data from the database. Using Kolmogorov-Smirnov and Chi Square tests, the best function with the least square error from the empirical data was selected for each parameter. Fig. 5 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 for what distribution fitting are required 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 2 introduces the best fitted models on some of the aforementioned parameters to be used in the simulation.

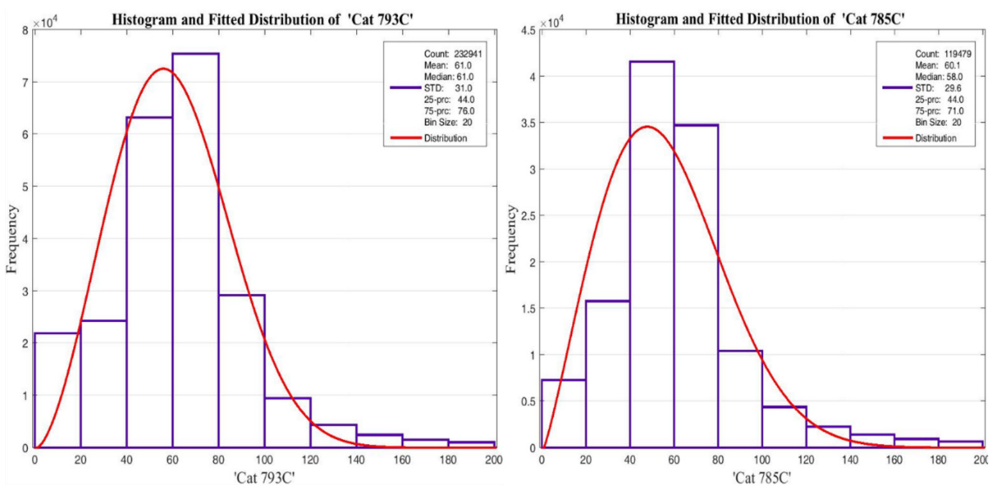



Fig. 5: Best fitted distributions on dump time to be used as input parameter in simulation: a) time (seconds) it takes Cat 785C to dump its loaded material; b) Cat 793C dump time (seconds)

## 4. Results and Discussions

In this section, we measure previously defined key performance indicators in the simulation model of the case study to illustrate performance of our developed system. To do so, we developed a linkage between the developed fleet management system and simulation model of the case study.

Table 2: 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) |

### 4.1. Linking the fleet management system to the simulation model

A fleet management system is a tool that is used to make required decisions over the operation. The decisions to be made must be as close to optimality as possible. Thus, the system needs to solve an optimization model for each decision to be made. To solve these optimization models fleet management system needs an external optimization solver that is linked to the simulation model. Each time a decision is to be made, required input data from the simulation model are written into an external file. And then, using a linker, the simulation model recalls the fleet management system to make decision based on the provided data. At this time, fleet management system solves the decision making problem using an external optimization software and report the results to the simulation model.

In this study, fleet management system is linked to the simulation model using two linkers. Fig. 6 illustrates how the simulation model is linked to the fleet management system.

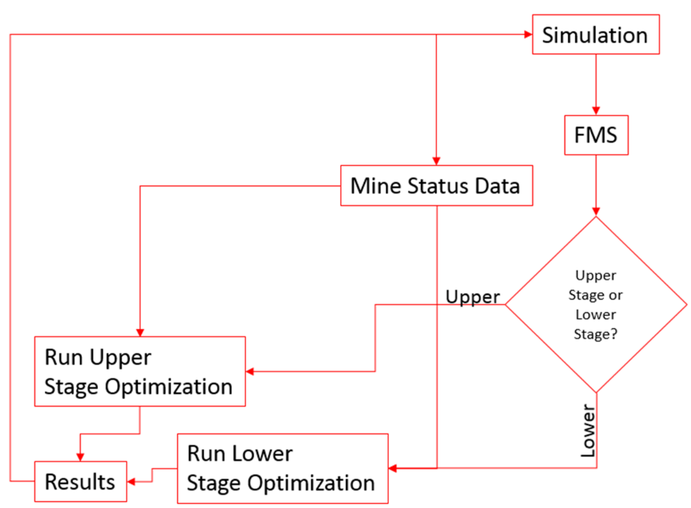



Fig. 6: Linkage between simulation of the mining operation and the fleet management system

### 4.2. Simulation Run Setup

We ran the simulation and optimization model of the case study for five replications in Rockwell Arena (Rockwell Automation, 2016) software linked to MATLAB R2016a (Mathworks, 2017), and CPLEX (IBM, 2016) for 37 Cat 785C truck type over 10 days of operation with 2 shifts per day. The operation is running for 8 hours per shift. Uncertainties associated with all the input parameters are being accounted for using statistical distributions.

After running the model for the replication length of 160 hours, the results of the study exported to a database and post processing of the data has been done. The results are presented in following subsections.

### 4.3. Production Schedule

Simulation study shows that managing the mining operation fleet for the case study using developed fleet management system will help the operation to meet the short term schedule requirement as shown in Fig. 7.

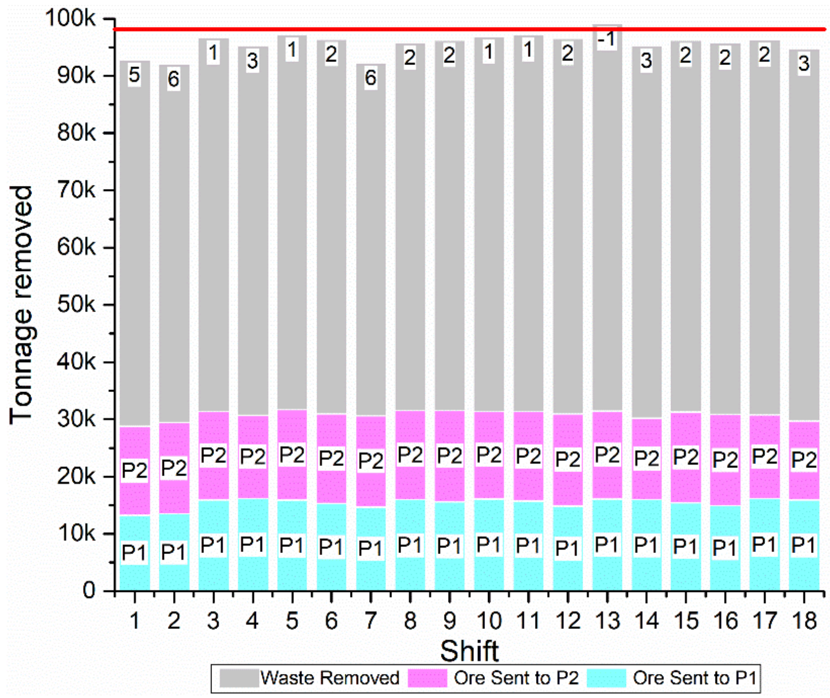



Fig. 7: Shift by shift production schedule met by the operation using developed fleet management system (numbers on the top of each bar shows shift production deviation from the desired production and the red line is the required production per shift).

Fig. 7 shows that by implementing the developed multi objective multi step mining fleet management system, the short term schedule of the operation is met with an average of 2% deviation. To be able to analyze the material sent to each processing plant more precisely, Fig. 8 and Fig. 9 illustrate how desired feed rate for each processing unit is met by implementing the multi objective multi stage fleet management system.

It is depicted in Fig. 8 that despite two first shifts of the operation that need to be reconsidered in the future works, in the simulation model of the case's operation the multi objective multi stage fleet management system meets plant 1 desired feed rate with an average deviation of 2%. However, this deviation from plant required feed rate for each shift is a bit higher in the case of processing plant 2.

Fig. 9 shows that implementing the developed fleet management system in the case study operation results in an average of 4% deviation from plant 2 desired feed rate.

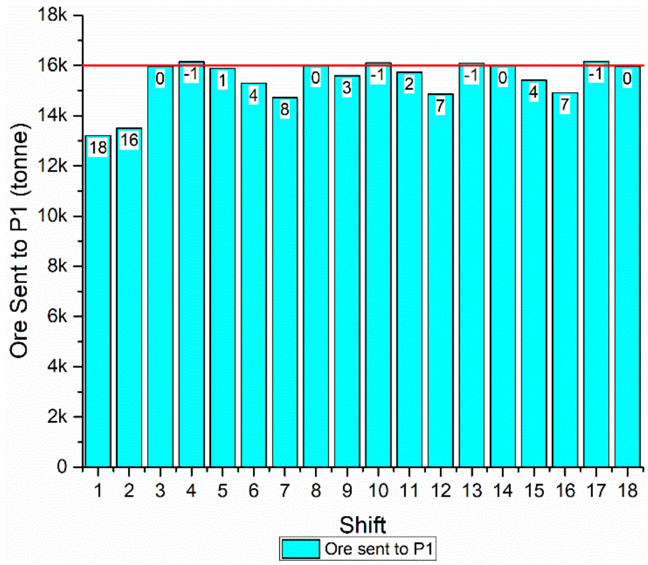



Fig. 8: Ore sent to processing plant 1 in each shift (number on the top of each bar shows percentage deviation from the desired feed per shift (red line))

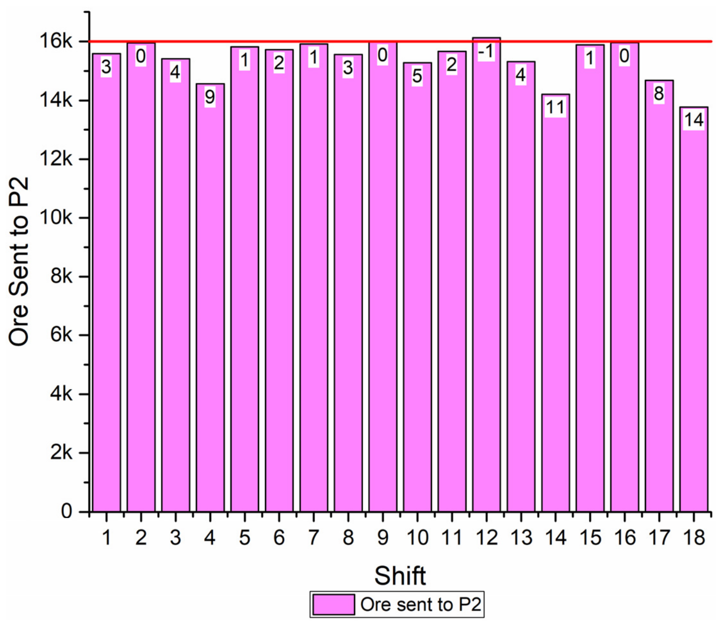



Fig. 9: Ore sent to processing plant 2 in each shift (number on the top of each bar shows percentage deviation from the desired feed per shift (red line)).

### 4.4. KPIs measurement

#### 4.4.1. Plant Head Grade

As it was mentioned above, the mining operation has two active processing plants. Each of these plants has its own average, lower limit, and upper limit for head grade of material sent to them in hourly bases. Table 3 lists the acceptable range for the grade of material to be sent to each of the plants.

Results exported from the simulation output database show that hourly head grade requirement for both of the active processing plants have been met by the FMS developed hear in this research. Fig. 10 represents hourly head grade for the material fed to each of the plants over simulation running time. It is shown that for both of the plants feed grades are fallen into the acceptable range around desired average head grade.

Table 3: Acceptable range for grade of material to be sent to the plants per hour

| Plant | Lower Bound of Head Grade | Average Head Grade | Upper Bound of Head Grade |
|---|---|---|---|
| Plant 1 | 60% | 65% | 70% |
| Plant 2 | 70% | 75% | 80% |

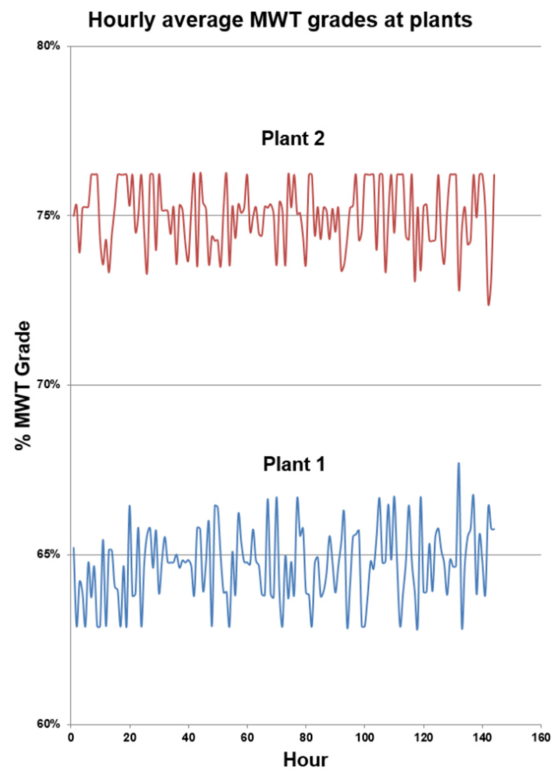



Fig. 10: Hourly plant head grade met by the FMS over 160 hours of the mining operation.

### 4.4.2. Plant Feed Rate

Another important KPI to be tracked in each mining operation is the tonnage of input to each processing plant. Hear in the described case study each of the processing plants need to be fed of around 2000 tonnes per hour. Fig. 11 and Fig. 12 show histogram of hourly input to plant 1 and plant 2 of the operation, respectively.

According to Fig. 11 the fleet management system allocates equipment semi-dynamically and assign them dynamically in a way that the plant 1 feed rate is met with a deviation of the mean of less than 2%. The model is delivering an average of 1935 tonnes per hour to plant 1 with a standard deviation of 190 tonnes. The same conclusion can be extracted from Fig. 12 regarding plant 2 feed rate. Fig. 12 indicates that plant 2 desired hourly feed rate is met with a deviation of the mean of less than 3% by implementation of the multi objective multi step fleet management system. As shown in Fig. 12 the fleet management system is able to make decisions resulting in delivering an average of 1930 tonnes per hour to plant 2 with a standard deviation of 190 tonnes. This proves that the operation will meet the goals of strategic plans and it will be able to satisfy the predicted market to a very good extent.

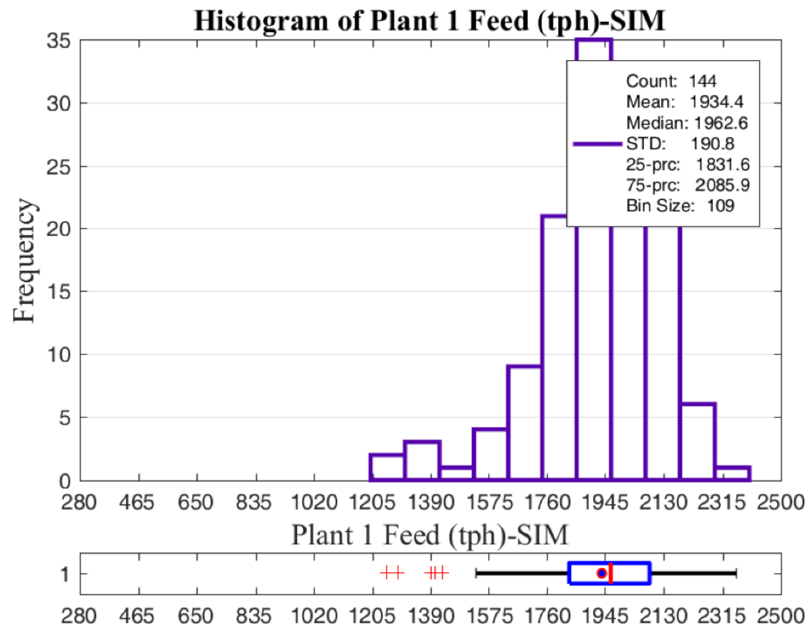



Fig. 11: Histogram of plant 1 hourly feed rate

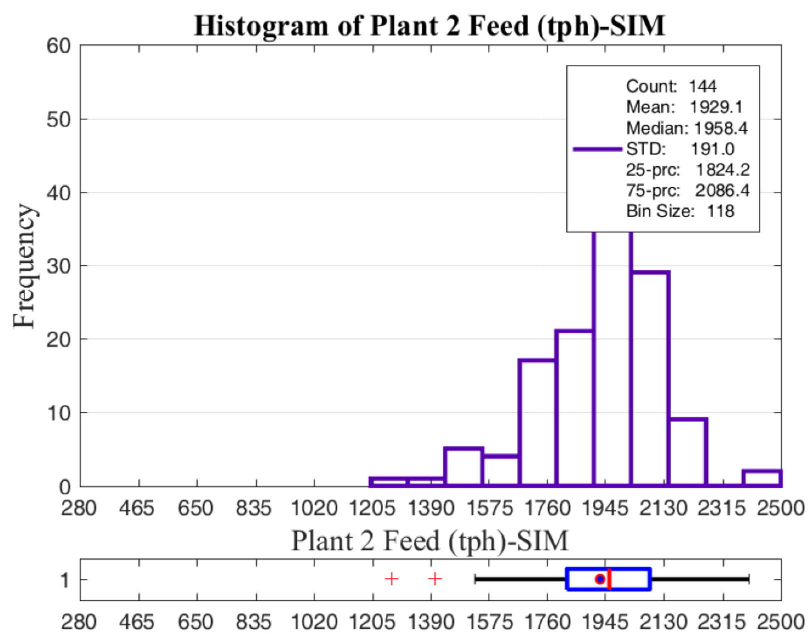



Fig. 12: Histogram of Plant 2 hourly feed rate

### 4.4.3. Queue at Origin and Destination Points

Queue of the trucks at loading or dumping points suggests inefficient use of the truck fleet, which may even result in production loss. So the fleet size for a mining operation is determined to be the smallest possible fleet size that is capable to meet the production requirements. However, losing some times in queues either at shovels or at dumps cause production losses. As a result, to overcome these production losses the operation will require a fleet size larger than its optimum fleet size. Thus, having a shorter queue length at both origin and destination points will help the operation to have less production losses and as a result to need smaller fleet size. One of the major advantages of the multi objective multi stage fleet management system developed hear is that it tries to minimize queue length. Fig. 13 and Fig. 14 illustrate statistical summary and histogram of the queue length at dumping points and loading areas when implementing the developed multi objective multi stage fleet management system to make decision in the case study's operation, respectively. It is worth noting that the histograms are plotting over the times there was a queue at the point. It means that all the queue lengths equal to zero were excluded from the histograms and the statistical results. Statistical analysis of the queue at dumping locations show that if any happens, an average of 1.7 trucks line up at dump locations with a median of 1 truck. Regarding queue length at shovel, the statistical data analysis and the histogram presented in Fig. 14 show that decisions made by the developed fleet management system causes an average of 1.8 trucks line up in queue at shovels with a standard deviation of 1 (if any queue happens at any shovel).

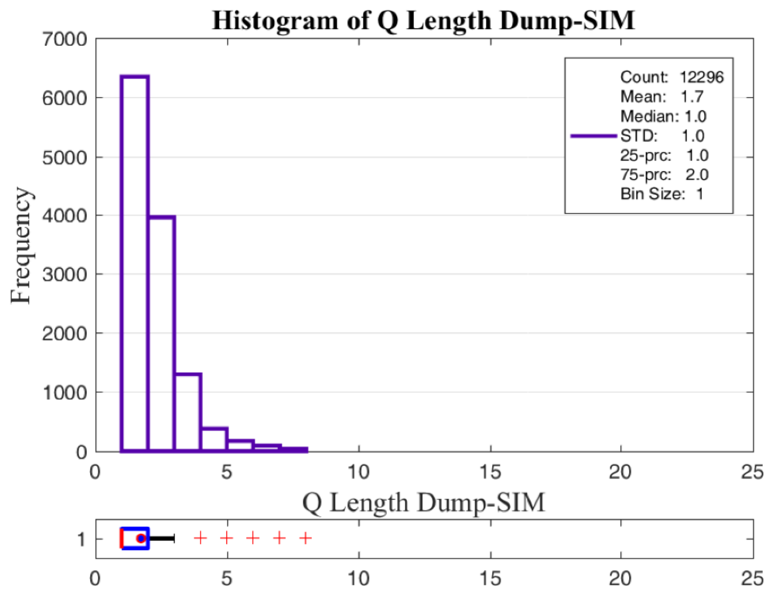



Fig. 13: Histogram of queue length at dumping locations (queue lengths of zero are excluded).

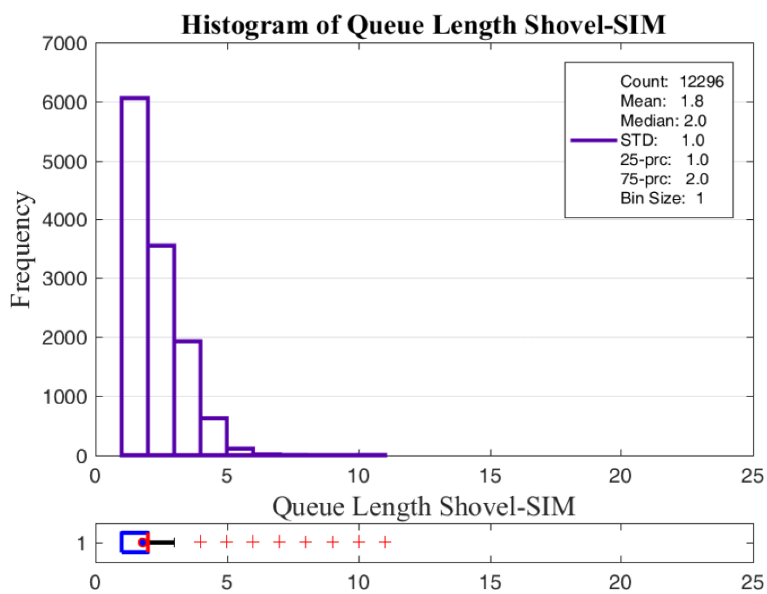



Fig. 14: histogram of queue length at loading points (queue lengths of zero are excluded).

## 5. Conclusions

A multi objective multi stage mining fleet management system that has capability of making operational decisions in open pit or any surface mining operation was developed and introduced in this paper. The developed fleet management system has number of advantages over the currently available systems. The main advantage of the developed system is that it minimizes the human intervention in both production optimization and truck dispatching steps. By making optimal decision on the shovel assignment to the available faces it links mining operation to the strategic plans of the mine. Besides, after running a multi objective decision making model for production optimization step by the time any kind of big change happens, it decides on trucks next destinations whenever any truck asks for new assignment. The truck assignment optimization model is coupled to and follow the production goals imposed by upper stages and minimizes deviation from them. It is also capable of maximizing productivity of both the transportation equipment and loading units. Another advantage of the developed fleet management system over currently available systems is that no matter how many trucks require assignment at the moment, the system dispatches them in an optimum way. To verify the developed fleet management system it was linked to a simulation model of a mining operation and the result of the simulation study are presented in this paper. The results show that the scheduled production of the mine's strategic plan is followed by the decisions made using the multi objective multi stage mining fleet management system developed in this study with less than 4% deviation.

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