A Transportation Problem Based Stochastic Integer Programming Model to Dispatch Surface Mining Trucks under Uncertainty

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ABSTRACT

Over the last 50 years several truck allocation and dispatching decision making models have been developed in the field of surface mining operation optimization. Despite the stochastic approaches towards truck allocation problem, the researchers have not considered effects of random parameters on truck dispatching problem. However, most of the factors affecting the truck dispatching decisions are random in behavior such as truck travel time to the next destination. This paper develops a truck dispatching decision making model based on the transportation problem approach. The developed model is a stochastic integer programming model that makes decisions on the trucks dispatching problem under condition of trucks' travel time uncertainty. Besides, a simulation model of an open pit mining operation has been developed to evaluate the developed stochastic truck dispatching model. Results of the implementation of the developed model proves impacts of the randomness in the operational parameters on the truck dispatching decisions.

1. Introduction

In surface mining operations, truck dispatching is the process of determining the best assignment of trucks to the right destinations. All thus far published research have introduced a two stage decision making model to solve truck dispatching problem with the exception of one proposed by Hauck (1973). The two stages are called upper stage or production optimization stage and lower stage or truck dispatching stage (Alarie & Gamache 2002). The set of decisions made in the lower stage is a set of dynamic operational outlines to meet the upper stage targets. Several decision-making models have been developed to address the two sets of decisions.

Researchers have applied different operational research approaches to solve the upper stage problem. White and Olson (1986) developed a two segment linear programming (LP) model that in its first segment it maximizes shovels' dig rate by minimizing total material handling costs (White & Olson 1986). Then, it determines optimum flow rate for each path in the mine. They developed the most popular currently available truck dispatching decision maker tool in the market (Modular Mining DISPATCH (2017)) based on their two segment LP model.

In 1989 a combination of mixed integer LP and none linear programming (NLP) operational research approach was introduced by Soumis et al. (1987) and (1989). The developed model

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schedules trucks' travel between any source and destination in the mine in two steps. One important advantage of the model developed by Soumis et al. (1987) and (1989) is that before implementing an NLP model to allocate trucks to shovels, it first runs an MILP to assign shovels to the right working faces.

Following that, Li (1990) published an LP model that was called transportation model for truck dispatching in mines. The model tries to minimize transportation work required for each path. Implementing the developed LP model, optimum number of trucks to meet the path production requirement is determined.

In late 1990s Temeng et al. (1998) developed a truck allocation model that works based on goal programming approach. With respect to ore grade, shovel dig rate, stripping ratio, and dumping points' capacities, the model maximizes shovel production.

A chance-constrained stochastic approach was applied to the upper stage (truck allocation or production optimization) problem by Ta et al. (2005). The developed model determines optimum number of trucks of a kind to be allocated to a path to meet its production requirement in presence of truck cycle time and its capacity uncertainties.

By adding shovel assignment to the mining faces, Gurgur et al. (2011) developed an LP truck allocation model that is capable of minimizing deviation from the strategic level production requirements. Ta et al. (2013) developed a mixed integer LP model that solves truck allocation problem based on the probability of shovel idle time. The objective of the developed model is to minimize total number of trucks required to meet the production target. In the same year, Mena et al. (2013) introduced an availability based mixed integer LP model that tries to solve upper stage problem using knapsack problem approach. The developed model maximizes cumulative truck fleet production within a fixed time horizon. Chang et al. (2015) developed a mixed integer LP model to solve truck allocation problem. The model maximizes transportation revenue with respect to priority of shovels. A heuristic algorithm was developed to solve the model for each operation shift. Readers are encouraged to read Alarie and Gamache (2002) and Moradi Afrapoli and Askari-Nasab (2017) for detailed information regarding the approaches and solution methodologies.

Despite all the aforementioned efforts in developing mathematical models to solve the upper stage problem, a limited number of models can be found in the literature that deal with the lower stage truck dispatching problem. White and Olson (1986) and Soumis et al. (1989) applied assignment problem approach towards making decisions on trucks next destination. Li (1990) developed a model that minimizes the relative difference between the actual time that next truck will arrive to a destination and the time that next truck must be in that destination based on upper stage results. Lizotte et al. (1989) developed a simulation based semi-automated model that assigns trucks to the destinations using three different heuristic models. Temeng et al. (1997) implemented a transportation-based approach towards dealing with the truck dispatching problem. However, there is a limitation in the above-mentioned models. Although most of the input parameters are uncertain and show stochastic behavior, the developed models use deterministic input parameter values. One of the input parameters that is used in many models is truck cycle time. The truck cycle time in a mining operation is subject to fluctuations from its deterministic value due to different factors including road conditions, traffic conditions, intersection blockages, trucks' bunching effects, etc.

The aim of this paper is to minimize the idle time of shovels and trucks through improved dispatch logic that quantifies the impact of empty haulage travel time uncertainty on the haulage cycle time calculations and truck assignments. To achieve the objective of the paper, we present a stochastic integer programming model that makes truck dispatching decisions while considering the uncertainties in truck travel time. The travel time has been selected due to its higher contribution in the material handling cycle time than any other components of a cycle time such as spot time, load time and dump time. To assess the developed model, we implemented it in an open pit mine operation simulation and results are presented here.

2. Model Formulation

The model development consists of two main steps. At the first step of the model development, a deterministic model was developed. Then, implementing the recourse approach (Birge & Louveaux 2011) we developed a stochastic model based on the model developed in the first step to capture uncertainty in truck travel time.

The model presented in this section is a deterministic model with all its input parameters taking deterministic values. It can also be categorized as a mixed integer linear programming model based on transportation problem. The objective function of the model, presented in Eq. (1), minimizes the cumulative absolute time difference between the times truck t will reach shovel s after dumping its at dump d (tts) and the time shovel s will be available to load the next truck (nas). The second part of the objective function tries to maximize the adjustment factor (AF) encouraging the model to maximize a balanced material delivery to all destinations. AF will be explained later on. Finally, VBN stands for very big number.

$$\begin{gathered} \min Z = \sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{s=1}^{S} C_{tds} x_{tds} + VBN(mf - AF) \\ \forall t \in \{1,...,T\}, \forall d \in \{1,...,D\}, and \ \forall s \in \{1,...,S\} \end{gathered} \tag{1}$$

The objective function coefficient for each of the variables is calculated using Eq.(2):

$$\begin{gathered} C_{tds} = \left| t_{ts} - na_s \right| \\ = \left| T(t, 3+s) - S(4,s) \right| \\ = \left| ltt_{td} + qt_{td} + dt_{td} + ett_{tds} - \sum_{t'=1}^{TT} \left(tinq_{t's} + tenr_{t's} \right) \times \left(st_{t's} + lt_{t's} \right) \right| \\ \forall t \in \{1,...,T\} \ \& \ \forall s \in \{1,...,S\} \ \& \ \forall d \in \{1,...,D\} \end{gathered} \tag{2}$$

Where:

ltt_{td}	loaded travel time from current truck t position to dump d
qt_{td}	time truck t must spend in queue at dump d to dump its material
dt_{td}	time truck t spends at dump d to back up and dump its material
ett_{ts}	time truck t spends to travel empty from the dump location d to shovel s
$tinq_{t's}$	time a truck of type t' that is already in queue must spend in shovel s queue
$tenr_{t's}$	time a truck of type t' must travel from its current position to reach shovel s
$st_{t's}$	spot time for a truck of type t' at shovel s
$lt_{t's}$	loading time for a truck of type t' at shovel s

Moreover, the decisions need to meet operational constraints such as trucks’ and shovels’ supply (Eq. (3) and Eq.(4)), destination demand constraint (Eq. (5)), balancing truck distribution over the paths (Eq. (6)), and binary constraints (Eq. (7)).

$$\sum_{d=1}^{D}\sum_{s=1}^{S} x_{tds} \le 1 \ \forall t \in \{1,...,T\} \tag{3}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D} tc_t x_{tds} \le sc_s \ \forall s \in \{1,...,S\} \tag{4}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S} tc_t x_{tds} \geq AF \times pc_d \;\forall\, d \in \{1,...,D\} \tag{5}$$

$$0 \leq AF \leq mf \tag{6}$$

$$x_{tds} \in \{0,1\}\; \forall t \in \{1,...,T\},\; \forall d \in \{1,...,D\}, and\; \forall\, s \in \{1,...,S\} \tag{7}$$

Where:

x_{tds}	binary integer variable to assign truck t to the path connecting shovel s to dump d
tc_t	capacity of truck t
sc_s	capacity of shovel s
pc_d	capacity of dump d (ton)
AF	adjustment factor that forces model to evenly distribute extra available trucks among all the possible destinations
mf	proportion of the cumulative available trucks' capacity to the cumulative required path flow rate that can be met using the available trucks
pf_{sd}	required path flow rate for path from shovel s to dump d based on upper stage decisions
$pmsf_{sd}$	met so far path flow rate for path from shovel s to dump d

Constraint (3) makes sure that truck t cannot be assigned to more than one shovel. Constraint (4) ensures that summation of nominal capacity of all the trucks assigned to shovel s does not exceed the shovel's nominal digging rate (capacity). AF in constraint (5) is defined as adjustment factor. The adjustment factor is a variable that is forcing the model to evenly distribute the truck fleet capacity between all the destinations and is constrained by mf as in Eq. (6). mf is a matching factor that is calculated based on cumulative available truck capacity and cumulative path material handling requirement. This factor is equal to 1 when the total truck fleet capacity is less than the required path flow rate and is equal to the proportion of the available truck capacity to the total path requirements when there is extra fleet capacity available. The adjustment factor is constrained by mf in order to uniformly distribute the extra truck fleet capacity among all the needy paths to balance ore and waste production.

The presented model uses expected (deterministic) values for the input parameters. However, most of the parameters affecting the truck dispatching decisions are random variables. In this paper, we formulated our model as a stochastic integer programming model with recourse (Birge & Louveaux 2011) to capture uncertainty of one of the major parameters affecting the operation (trucks' empty travel time). Reason to capture uncertainty in trucks' empty travel time is that more than 90% of trucks' cycle time in each cycle is spent in traveling. From that time, about 50% is spent in travel empty. As most of the time a truck needs to be dispatched has already passed some portion of its loaded travel or even completed its loaded travel, the most important parameter where the uncertainty associated with it needs to be captured is empty travel. Thus, the objective function of the stochastic model that captures empty travel time uncertainty is (Eq. (8)):

$$\begin{aligned} Minimize\; Z = & \overbrace{\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{s=1}^{S} C_{tds} x_{tds}}^{1st} \\ & + \overbrace{VBN(1-AF)}^{2nd} \\ & + \overbrace{\frac{1}{nR}\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{s=1}^{S}\sum_{r=1}^{nR} \left| ltt_{td} + qt_{td} + dt_{td} + ett_{tds}^{r} - \sum_{t'=1}^{TT}\left(tinq_{t's} + tenr_{t's}\right)\times\left(st_{t's} + lt_{t's}\right)\right| x_{tds}}^{3rd} \end{aligned} \tag{8}$$

Where:

ett_{tds}^{r}	time truck t spends to travel empty from the dump location d to shovel s in rth realization
r	is an index referring to a scenario in the stochastic integer model
nR	number of realizations implemented to generate random variables for empty travel time from its distribution.

In the developed model, the first two components of the objective function are the same as the deterministic model. The third component is the minimization of the truck or shovel idle time in material handling given the uncertainty in trucks empty travel time. The model is constrained with Eq. (3) to Eq. (7). For each of the realizations r in the stochastic model with nR number of realizations, a random value is being sampled from the fitted distribution of the historical data of the empty truck velocity. The sample is then imported into the model after preprocessing procedure that calculates required travel time and is used during the decision making procedure.

The developed model was implemented in a simulation study of an iron ore mine and the results of Key Performance Indicators (KPI) were compared against model developed by White & Olson (1986) which is used as the backbone of the operation optimization in Modular Mining DISPATCH (2017) fleet management system. There are two small size shovels in the operation serving two active processing plants with an input feed rate requirement of 2,300 ton per hour of the operation. Another small shovel alongside with two large ones are digging waste material to meet the stripping ratio requirement.

3. Results

Some key performance indicators (KPI) were chosen to compare results of implementation of the developed stochastic truck dispatching model against the benchmark truck dispatching model as listed in Table 1.

Results of the simulation of the case study show that the required plant feed rates are met when using the developed model as the dispatching logic while plant feed rates will be short by 5 to 10 percent when using the benchmark dispatching logic (Fig. 1).

Table 1. Key performance indicators to assess the developed stochastic model

No.	KPI	Description
1	Plant Feed Rate (t/hr)	Amount of material delivered to each processing plant in an hour of operation
2	Shovels’ Utilization (%)	Percentage of shovels’ available time being used in the operation
3	Queue Length	Number of trucks lining up in front of a resource when a truck reaches there

Using benchmark truck dispatching model, none of the plants are fed with their required hourly feed rate. Plant 1 is on average 12% short on its hourly feed target rate , whereas plant 2 is on average of 8% short. However, by replacing the benchmark truck dispatching model with the stochastic truck dispatching model, both plants’ target rate is met. Fig. 1 also shows that implementing benchmark truck dispatching, plant 2 is fed 4% more than plant 1. It is due to a critical drawback of the benchmark model. The benchmark model dispatches trucks based on minimum distance between trucks and destinations. However, it does not account for the queue that might happen after a truck reaches to the assigned destination. Thus, if we have multiple destinations similar to what we have in this case study, the benchmark model dispatches trucks to the destinations with the shorter distance. Here in this case study, plant two is located about 400 meters closer to the ore shovels than plant one. As a result, plant one is served more by the benchmark model comparing to plant two.

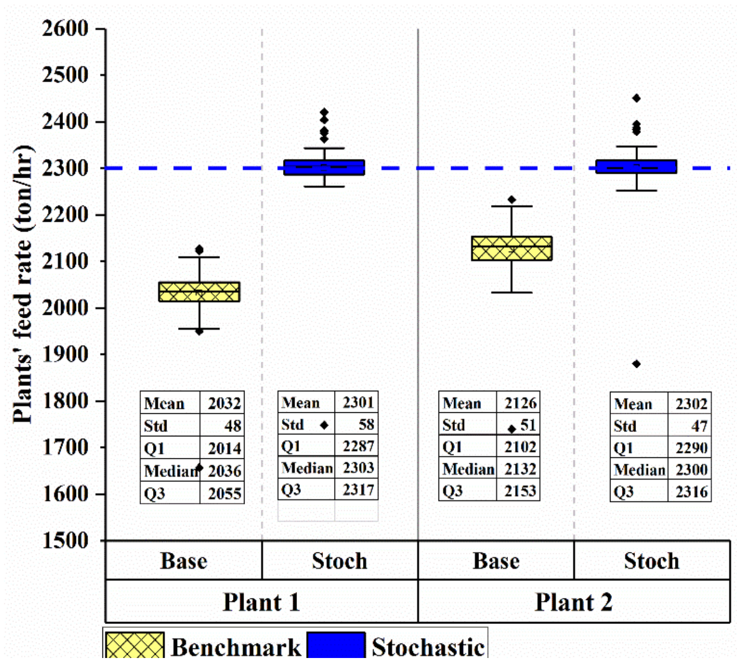

Fig. 1. Ore delivered to processing plants; the horizontal dashed line on 2300 (t/hr) stands for the required plant feed rate for each of the active processing plants in the operation. For each processing plant, the left hand side box plot (hatched yellow) shows plant feed rate using benchmark model and the right hand side box plot (blue) shows the plant feed rate using the proposed model.

This difference in feeding rate is not happening when the benchmark truck dispatching model is replaced by the stochastic truck dispatching model. As one of the advantages of the stochastic model, it does account for all of the possible queueing that will happen when the truck is assigned. Thus, it is capable of feeding the plants equally in a multi plant mining operation.

Another important KPI is the utilization of the shovels as the second most expensive equipment after the processing plant in mining operation. A comparison of shovels' utilization when using the developed and the benchmark dispatching logic is presented in Table 2. Shovel 1 and Shovel 2 feed the processing plants by extracting ore material and Shovel 3, Shovel 4, and Shovel 5 remove waste materials. Shovels working on the waste mining faces are approximately 10% more utilized than the ore shovels when using the benchmark truck dispatching decision making model.

Table 2. Comparison of utilization of active shovels in the operation

	Utilization (%) (benchmark)		**Utilization (%) (stochastic model)**		**Difference (%)**
Shovel	Mean	Standard deviation	Mean	Standard deviation	
1	88.9	1.1	96.4	2.9	8
2	84.7	1.2	95.5	3	11
3	97.5	1.7	75.8	2.8	-22
4	96.4	1.4	76.7	2.9	-20
5	99.9	5.1	90.5	2.6	-9

However, the trend is reversed when using the stochastic model: the ore shovels are utilized more than 90% of their available time whereas the waste shovels are utilized about 80% of their available time. The difference is mainly due to the fact that the benchmark truck dispatching model makes decisions based on the distance between trucks and the shovels and it does not include the time trucks have to spend in queue at each specific shovel when they reach to that shovel. Though, the stochastic model involves the expected queue time in the decision making procedure.

There are two possibilities when a truck reaches a loader. Either it encounters a shovel standing idle and waiting for the next truck to load or it meets a shovel that is currently loading a truck and has to enter a queue. In either case, the mine is not working efficiently. In the former, shovel is utilized less than its available time and in the latter the truck is losing its available time in queue. Fig. 2 represents a graphical and statistical comparison of the histograms of the number of trucks in queue at shovels when a truck arrives to that shovel between the time the base decision making model makes decisions on the truck dispatching problem and the time the base decision making model is substituted by the stochastic model developed in this study.

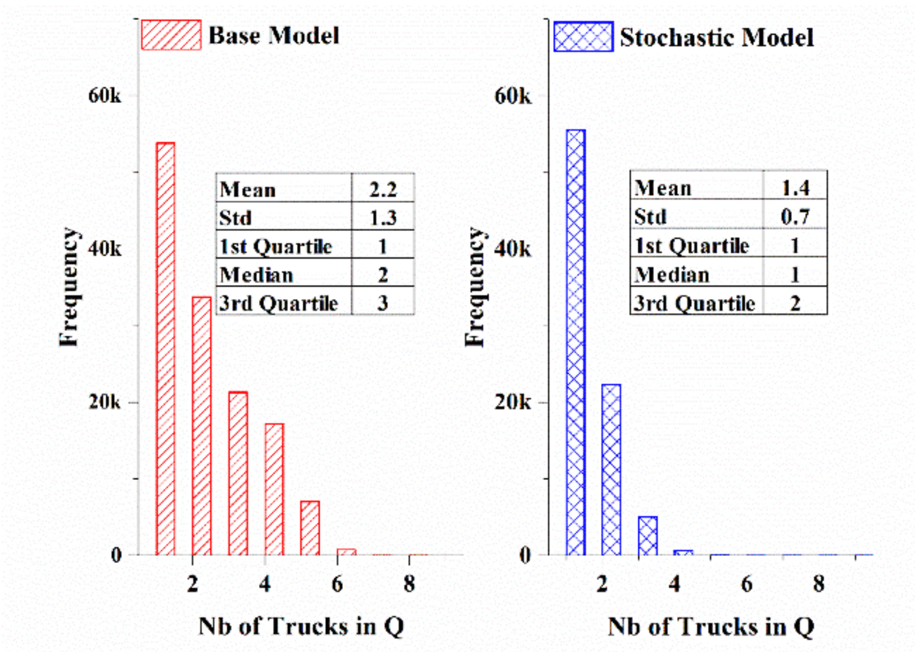

Fig. 2. Histogram of number of trucks waiting in queue when a truck arrives to a loading point when the truck dispatching decisions are made by the base model (red bars) and the time the truck dispatching decisions are made by the stochastic model (blue bars)

Simulation results show that the average number of trucks in queue at shovel when a truck arrives at that shovel decreases by 36% by replacing the benchmark model with the stochastic model. The developed stochastic model also shows a 50% reduction in the median. It means by replacing the base model with the developed model most of the time when a truck reaches to a shovel it encounters with only one truck waiting in queue instead of 2 which happens in the base model. This consequently results in shorter queue time.

4. Conclusion

Truck dispatching problem in the surface mining operations has been addressed in this paper. Despite uncertainties associated with the governing operational parameters, most of the conducted research in the field thus far have ignored random nature of input parameters. However, in this paper, a stochastic integer programming model was introduced that accounts for the uncertainties associated with truck travel times into the truck dispatching problem solving procedure. This helps to make more realistic decisions for trucks optimal destinations. The model was developed based on the transportation problem approach. The model was implemented in a simulated case study and results of its implementation were compared against results of implementation of the model developed by White & Olson (1986) which is backbone of Modular Mining DISPATCH (2017) as benchmark truck dispatching model from the literature. Results of the comparisons show a promising improvement in all of the measured KPI.

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