

A Fuzzy Logic Approach towards Truck Dispatching Problem in Surface Mines

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ABSTRACT

This paper presents a mixed integer linear programming model to solve truck dispatching problem in surface mines. Although, all thus far developed models in the literature approach to the truck dispatching as a deterministic problem, we believe that most of the input parameters for truck dispatching are uncertain. To account for the parameters' inherent uncertainties, we implemented a fuzzy approach to solve the developed mathematical model. The developed model is implemented on a surface mining case study and results are compared against a benchmark model implementation on the same case. The results show that the model developed in this paper requires smaller fleet of trucks to meet the production requirement of the mine in comparison to the benchmark model.

1. INTRODUCTION

Decision making tools play important roles in surface mines. These tools are utilized in a varied range of planning horizons. The major mine plans are Long-term plans with a range of 5 to 20 years of mine life, medium-term plans with a range of 1 to 5 years, short-term plans with a range of 1 week to 1 year (Osanloo et al. 2008), and daily or shift by shift operational plans.

In the context of surface mining operational plan, truck dispatching problem was referred as a single-stage or a multi-stage decision making problem (Moradi Afrapoli & Askari-Nasab 2017; Alarie & Gamache 2002). In the single-stage approach, after finding the shortest paths between sources and destinations, optimization of each path flow rate and decision on active trucks dispatching are made by solving a single optimization model. While in the multi-stage approach, after finding the shortest paths in the road network, a decision making model provides the optimum flow rate for each specific path in the upper stage. Then, at the lower stage, another optimization model provides dynamic decisions on where to dispatch the truck in need of immediate assignment including other trucks that would seek assignment subsequently. Aside from the single-stage model developed by Hauck (1973), the rest of the published models are based on multi-stage approach. Major research in this area, as explained by Alarie and Gamache (2002) and Moradi Afrapoli and Askari-Nasab (2017), have been focused on the upper stage. Kappas and Yegulalp (1991), Xi and

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Yegualp (1993), and Ercelebi and Bascetin (2009) implemented queuing theory approach towards solving the upper stage sub problem. Soumis et. al. (1989) developing a non-linear model. The literature survey shows that other researchers have implemented different versions of linear programming (LP) to solve the upper stage. White and Olson (1986) and Li (1990) implemented general LP to deal with the upper stage problem. The solution of their models provide tonnage of material required to be transported from each loader to a specific destination. Temeng, Otuonye and Frendewey (1998), Gurgur, Dagdelen and Artittong (2011), and Upadhyay and Askari-Nasab (2017) developed upper stage models based on goal programming approach. Ta et al. (2005), Mena et al. (2013), Chang, Ren and Wang (2015), and Matamoros and Dimitrakopoulos (2016) have published different models to solve the upper stage problem. Readers are encouraged to read Moradi Afrapoli and Askari-Nasab (2017) and (Alarie and Gamache (2002) for a detailed overview of the researches conducted in the field.

Despite the fact that the problem of truck dispatching in surface mines contains an important lower stage, there are only a few published optimization models to make the lower stage decisions. White and Olson (1986), Li (1990), Olson, Vohnout and White (1993), Soumis, Ethier and Elbrond (1989), and Temeng, Otuonye and Frendewey (1997) are the only published decision making models to solve the lower stage of the truck dispatching problem. After the work by Temeng, Otuonye and Frendewey (1997) the problem have been abandoned by the researchers of the field for more than two decades. From amongst the published models, none account for the fuzzy behavior of the required input parameters. Most of the input parameters of the lower stage problem are imprecise or uncertain at the time of solving the decision making model. Although most of the uncertainties in these input parameters can be handled by implementing the probability theory, not all of these parameters are random phenomena and thus successful application of the probability theory is not possible (Brito et al. 2009). These types of problem can be solved using fuzzy linear programming (FLP) approach based on the researchers' view point of the definition of the input parameters. Importance of FLP implementation in the mining industry rises when in the decision making procedures it is possible to accept more than one solution (Pendharkar 1997). Giving an example from truck capacity, although the nominal capacity of a Cat 797B truck is 380 short ton, however, loading 390 short ton payload is acceptable as well. Thus, a typical LP constraint limiting the Cat 797B capacity to 380 short ton will ignore this possibility. This means that although there is a capacity limit for a truck payload, it can be violated to some extent.

With the entrance of fuzzy set applications in the field of mining engineering in late 1980s (Nguyen 1985), (Bandopadhyay & Chattopadhyay 1986), (Bandopadhyay 1987), it has been extensively used in the decision making models for mine planning (Rahmanpour & Osanloo 2017) equipment selection and sizing (Bascetin et al. 2007; Aghajani Bazzazi et al. 2008) plant location selection (Yavuz 2008) as well as post-mining land use and reclamation (Bangian et al. 2012).

Lack of models that capture uncertainty and imprecision of the input parameters encouraged us to develop a fuzzy linear programming model to solve the truck dispatching problem. The aim of this paper is to introduce a new fuzzy linear programming (FLP) model that makes decision in the lower stage of truck dispatching problem in surface mines that incorporate imprecision of the input parameters in the solution procedure. The organization of the paper follows: model formulation, defuzzification, implementation, results, and conclusion.

2. MODEL FORMULATION

2.1. Simulation Model

The simulation model consists of eight different sub models. Table 1 lists the sub models developed to perform the simulation of the mining complex operation.

Each of the simulation sub models listed in Table 1 plays a crucial role in the simulation of the mining complex.

Table 1: List of sub models used to develop simulation model

No.	sub model	Task's description
1	Operation starting	Recalls available trucks from the bay and assigns them to the available shovels
2	Loading	Imitates the operation from the time a truck reaches to a shovel up until that truck leaves the shovel
3	Dumping	Imitates the process of dumping truck payloads into the dumping areas
4	Hopper and conveyor	Simulates the stockpile, hopper, and the conveyor that feed processing plants
5	Season change	This sub model simulates change of the season and thus corresponding changes in the parameter distributions affected by it.
6	Shift change	Simulates change of the operation shifts as well as days
7	Path flow rate	Prepares required input parameters to run the decision making model making decisions on the optimum path flow rate
8	Truck dispatching	Prepares required input data to run the truck dispatching decision making model

The procedure that developed simulation model to mimic the operation are listed below:

Step one: at the start of the simulation sub model 1 that handles the start of the operation process is responsible for the process of trucks travel from the bay to the available shovels.

Step two: at each shovel station, trucks are loaded by a shovel already assigned to the polygon in that specific position, all the required information are transferred from the polygon to the material loaded onto the truck, truck leave the shovel and polygon (coming from the short-term schedule) remains there until it is fully depleted.

Step three: the loaded truck travel on the road network taking the shortest path from the shovel to the dump destination.

Step four: if the destination is a waste dump, the truck backs up and dumps its material in the designated area, otherwise, a decision is made based on current line up in front of each hopper, then the truck is assigned to the hopper with the least number of trucks in its queue. Then, as soon as all the trucks in the line are done with the dumping process, the hopper capacity is tested, if it has enough room for the truck, truck can dump its material. Otherwise, the truck needs to wait for hopper to open enough room for its material.

Step five: if the truck is already assigned to a shovel, it leaves the dumping area to start travel to the designated shovel. Otherwise, the simulation model prepares required input data for the fuzzy truck dispatching decision making model. Then, implementing a VBA block, the required data are written into a file that can be read in CPLEX (IBM 2016). Once the decision is made by solving the fuzzy model, the truck is assigned to a shovel.

Step six: the truck travels to the shovel it is assigned.

Step seven: go to step two.

The procedure explained above consists of sub models 1, 2, 3, and 8. Sub model 4 controls stockpiles, hoppers, and conveyors. It accepts discrete truck loads in hopper and by simulating the conveyor that connects the hopper to the downstream processing operation, it continually feeds the plant based on the required hourly feed rate. Sub model 5 runs using a logical entity to change all the required input parameters when the simulation runs over two different seasons. In sub model 6, a logical entity works toward changing shifts of the operation when the simulation time reaches to the end of each shift. The process of production optimization decisions that must be made within a time interval are handled using sub model 7. This sub model collects required data from the status of the mining operation and sends them to an external decision maker tool to make required decisions regarding optimum path flow rate or allocation of trucks.

2.2. Optimization Model

Under the multi-stage truck dispatching approach (Moradi Afrapoli & Askari-Nasab 2017; Alarie & Gamache 2002), we developed a deterministic ILP mathematical model to make decisions on the trucks' next destination. After that, we identified fuzzy parameters and based on those fuzzy parameters we improved the crisp model to a fuzzy model. The sets, parameters, and variables used in the model development are as follows:

Parameters:

$l_{t_{td}}$	loaded travel time from current truck t position to dump d
$q_{t_{td}}$	time truck t must spend in queue at dump d to get the permission to dump its material
$d_{t_{td}}$	time truck t spends at dump d to back up and dump its load into the dumping area
$e_{t_{ts}}$	time it takes truck t to travel empty from where its empty travel starts to shovel s
$t_{inq_{ts}}$	time a truck of type tt that is already in queue must spend in shovel s queue
$t_{enr_{ts}}$	time a truck of type tt must travel from its current position to reach shovel s before truck t
$s_{t_{ts}}$	spot time for a truck of type tt at shovel s
$l_{t_{ts}}$	loading time for a truck of type tt at shovel s
t_{c_t}	capacity of truck t (ton)
TC_t	nominal truck capacity for truck t (ton)
s_{c_s}	capacity of shovel s
p_{c_d}	capacity of dump d (ton per hour)
m_f	factor that shows with the available trucks what portion of the current demands can be met by the fleet
$p_{f_{sd}}$	optimal path flow rate for path from shovel s to dump d based on upper stage decisions
$p_{msf_{sd}}$	portion of the required path flow rate for current time span that have been met so far

Variables:

x_{tds}	binary integer variable to assign truck t to the path connecting shovel s to dump d
AF	variable factor that adjusts trucks available to be assigned with the demands of dumping locations

In this study we first developed a new deterministic model that makes truck dispatching decisions in a way that minimizes cumulative lost time for the entire active material handling fleet including both the loader fleet and the transporter fleet, accounting for the operational limitations such as truck capacity, shovel digging rate, and processing plants feed rate requirement. The objective function coefficient for each of the variables is calculated using Eq. (1):

$$C_{tds} = \left| \begin{array}{l} l_{t_{td}} + q_{t_{td}} + d_{t_{td}} + e_{t_{ts}} \\ - \sum_{t=1}^{TT} (t_{inq_{ts}} + t_{enr_{ts}}) \times (s_{t_{ts}} + l_{t_{ts}}) \end{array} \right| \quad (1)$$

The developed model is a deterministic model with all its input parameters taking deterministic values. It also can be categorized as mixed integer transportation problem based decision making model. The objective function of the model is presented in Eq. (2). The objective function of the model tries to minimize the cumulative time difference between the times truck t will reach to

shovel s after dumping its load at dump d and the time shovel s will be available next time with its first part of objective. The second part of objective function tries to maximize the adjustment factor (AF), where VBN stands for very big number. This will help to attain higher precision in dispatching decisions.

$$\min Z = \sum_{t=1}^T \sum_{d=1}^D \sum_{s=1}^S C_{tds} x_{tds} + VBN(1-AF) \quad (2)$$

Subject to:

$$\sum_{d=1}^D \sum_{s=1}^S t c_t x_{tds} \leq TC_t \quad \forall t \in \{1, \dots, T\} \quad (3)$$

$$\sum_{t=1}^T \sum_{d=1}^D t c_t x_{tds} \leq sc_s \quad \forall s \in \{1, \dots, S\} \quad (4)$$

$$\sum_{t=1}^T \sum_{s=1}^S t c_t x_{tds} \geq AF \times pc_d \quad \forall d \in \{1, \dots, D\} \quad (5)$$

$$AF \begin{cases} \leq mf & \text{if } mf > 1 \\ \leq 1 & \text{otherwise} \end{cases} \quad (6)$$

$$x_{tds} \in \{0, 1\} \quad (7)$$

$$mf = \frac{\sum_{t=1}^T t c_t x_{tds}}{\sum_{s=1}^S \sum_{d=1}^D (pf_{sd} - pmsf_{sd})} \quad (8)$$

The decisions are made by optimizing the objective function under the operational constraints given by Eq. (3) to Eq. (7). Constraint (3) makes sure that the truck t cannot accept loads more than its nominal capacity. Constraint (4) ensures that summation of nominal capacity of all the trucks assigned to shovels 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 constrained by mf (Eq. (6)) which is calculated by the formula presented in Eq. (8). The model is also constrained to meet as much targeted plants' capacity as possible by Eq. (5). Eq. (7) guarantees that both sets of the decision variables are binary integer.

Zimmermann (1976) and (1978) for the first time implemented fuzzy set theory in conventional LP models (Madadi & Wong 2014). Then after, several FLP models have been developed to deal with different real-world problems and more specifically in mining industries. The most recent FLP model developed in a mining operation context can be credited to (Rahmanpour & Osanloo 2017) where the authors developed a FLP model to solve surface mines short term planning problem. Even though all the input parameters to solve the optimization models in the truck dispatching problem might behave in a fuzzy behavior, none of the developed models have considered that fuzzy behavior so far. Thus, in this paper, we developed the fuzzy version of our deterministic model as follows:

$$\min \tilde{Z} = \sum_{t=1}^T \sum_{d=1}^D \sum_{s=1}^S \tilde{C}_{tds} x_{tds} + VBN(1-AF) \quad (9)$$

Subject to:

$$\sum_{d=1}^D \sum_{s=1}^S \tilde{t} c_t x_{tds} \leq \tilde{TC}_t \quad (10)$$

$$\sum_{t=1}^T \sum_{d=1}^D \tilde{t}c_{t,ids} \leq \tilde{s}c_s \quad (11)$$

$$\sum_{t=1}^T \sum_{s=1}^S \tilde{t}c_{t,ids} \geq AF \times \tilde{p}c_d \quad (12)$$

And Eq. (6) to Eq. (8) where:

$$\tilde{C}_{ids} = \left[\begin{array}{c} \tilde{l}t_{td} + \tilde{q}t_{td} + \tilde{d}t_{td} + \tilde{e}t_{ts} \\ -\sum_{it=1}^{IT} (\tilde{t}i nq_{its} + \tilde{t}e n r_{its}) \times (\tilde{s}t_{its} + \tilde{l}t_{its}) \end{array} \right] \quad (13)$$

It is worth noting that \tilde{x} represents fuzzy parameter for x in the deterministic ILP model. In this research we implement defuzzification method developed by Jiménez *et al.*(2007) to rank fuzzy constraints and objectives and solved the problem based on their developed approach.

3. RESULTS AND DISCUSSION

3.1. Case Study

The case study is derived from an iron ore surface mine located in central Iran. The mine has two processing plants that must be fed by a truck and shovel based material handling system. Based on the short-term production schedule of the mine, the fleet must be capable of meeting an hourly feed rate requirement of 2300 tons for each of the active processing plants and meets a stripping ratio of 1.3. The material handling fleet to be implemented in the study consists of two types of shovels (Hitachi Hit 2500 and Hit 5500), and one type of truck (Cat 785C). The study consists of five active faces where two small shovels work on the ore mining faces and serve the processing plants, and two large shovels and one small shovel remove the waste material. To determine minimum truck fleet size to handle the material, we implemented match factor (MF) approach (Burt & Caccetta 2007; Chaowasakoo et al. 2017). The match factor calculation showed that the operation needs a fleet of 37 trucks to have a balanced operation. However, the approach does not account for the effects of the truck dispatching tools on the optimum number of trucks to meet the production requirement. Thus, we developed different operational scenarios by varying the number of trucks in the simulation to determine optimum fleet size which can meet the production requirement. The simulation study of different operational scenarios showed that the production requirement will be met using a fleet of 28 Cat 785C trucks when the trucks are dispatched using the FLP model. For the optimum scenario, the truck dispatching model was replaced with the model developed by (White & Olson 1986; Olson et al. 1993) as a benchmark model. Then, the results of implementing FLP model and the benchmark model were compared against each other.

3.2. Implementation on Case Study

As mentioned in the previous section, result of the deterministic calculation shows that the production requirement will be met by using a fleet of 37 trucks. Adding a fleet management system results in efficient truck allocations and consequently less number of required trucks. Thus, we designed experiments with less number of trucks to perform material handling operation in the case study. The designed experiments are listed in Table 2.

Table 2: Operation Scenarios of the case study ran for evaluation of the developed truck dispatching model

Scenario	S01	S02	S03	S04	S05	S06	S07
Fleet Size	25	26	27	28	29	30	31
Scenario	S08	S09	S10	S11	S12	S13	
Fleet Size	32	33	34	35	36	37	

For the designed experiments, we ran the simulation and optimization model of the case study for a designated operation time of 10 consecutive 12-hour shifts for two times. We named the first time as Case A and the second time as Case B. In Case A, the simulation and optimization model uses the benchmark fleet management system to make required upper and lower stage truck dispatching decisions. However, in Case B, the lower stage decision making model of the benchmark fleet management system is replaced by the fuzzy based decision making model. After running the developed simulation and optimization models for the case study, we plotted the production for different scenarios in Fig.1 to compare results.

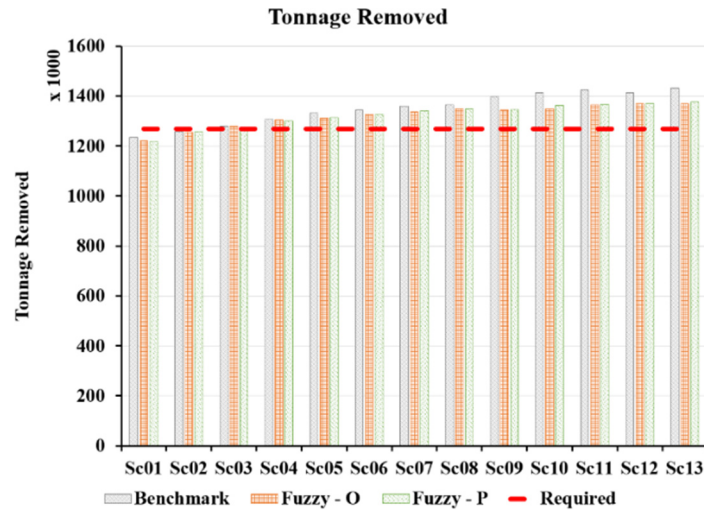


Fig.1. Total material removed from the pit over the simulation run time using different fleet where Fuzzy – O stands for optimistic fuzzy decisions (with degree of optimism equal to 75%) and Fuzzy – P stands for pessimistic fuzzy decisions (with degree of optimism equal to 25%)

Fig.1 shows that from scenario Sc03 with 27 trucks on, both approaches to solve the truck dispatching problem result in meeting the total production (ore + waste) requirement. However, producing as much material as possible is not the only goal of a mining operation. Meeting plants' requirements (tonnage of ore sent to the plants) is another critical objective of the mining operation. Thus, the best fleet is a fleet with the minimum number of truck in it that can meet both total production requirement and ore sent to plants' requirement. Fig.2 represents how various scenarios with the two truck dispatching models can meet the required ore delivery.

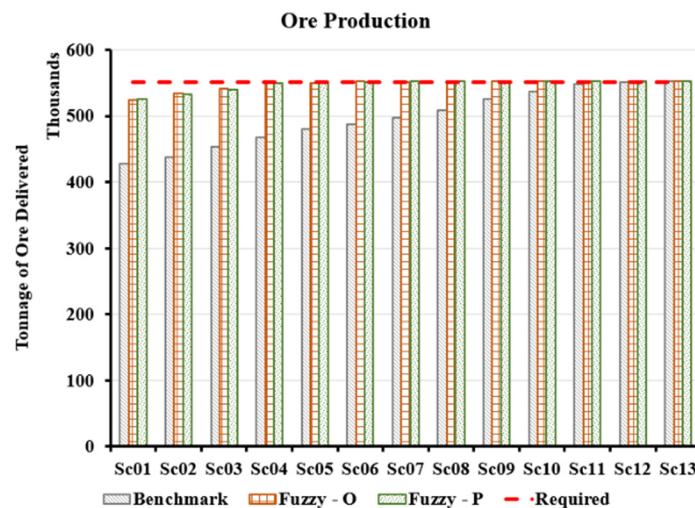


Fig.2. Cumulative tonnage of ore delivered to the processing plants during the simulation run time using each scenario

Although using both benchmark model and the FLP model the production requirement is met in scenario Sc03 with 28 trucks, the plants are fed in their full capacity in scenario Sc04 with 29 trucks when implementing FLP model and in scenario Sc12 with 36 trucks when using benchmark truck dispatching model. Thus, the optimum fleet required to meet the schedule is a fleet of 36 trucks when using benchmark truck dispatching model and a fleet of 29 trucks when using FLP truck dispatching model.

4. CONCLUSIONS

Several mathematical models have been developed to solve the truck dispatching problem in surface mines. The existing and publicly available models are all deterministic mathematical models. However, most of the required input parameters to solve such a problem are stochastic in nature. This paper introduces a new mathematical model to solve the truck dispatching problem in surface mines considering stochastic behavior of the required input parameters. The paper takes a FLP approach to deal with the developed model. To evaluate the performance of the developed model, the paper uses backbone of a currently in the market truck dispatching model as the benchmark. Results of implementation of benchmark truck dispatching model and the developed FLP model in a surface mining case study show that the developed model requires a smaller fleet of trucks to meet the production requirement given by the short-term mine schedule. This consequently results in lower costs and higher profits. The results also show that using the developed model, trucks spend less time in the queue at different destination.

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