An Investigation into Dispatch Optimizers using Truck-Shovel Simulation and a New Multi Objective Truck Dispatching Technique

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

ABSTRACT

Over the past five decades several models have been developed to make the decision of assigning active trucks to the right shovels. Most of the algorithms try to make decisions that optimize a specific objective and ignore others. This paper introduces a new multi objective truck-dispatching model that assigns trucks based on optimizing multiple objectives at the same time, including the targets and production requirements from the upper stages. Moreover, we have developed a detailed simulation model to test the proposed model against the well-known White and Olson model. We have developed the simulation model in Rockwell Arena and incorporated CPLEX to solve the dispatching models while running the simulation model. However, incorporating complicated decision making tools in the simulation model causes a drastic increase in the simulation run time. Therefore, to deal with the high time consumption, we developed a heuristic dispatching subsystem mimicking the White and Olson model's decisions and compared the key performance indicators and run times for the three techniques.

1. Introduction

Mining projects, and more especially surface mines, are high cost operations that need millions of dollars or in the large mines billions of dollars of capital and operating costs. Material handling procedures, as a main contributor to the operating costs, play a critical role in the mining projects decision making procedure. A large portion of total mining costs in an open pit mine is related to excavating and transporting the material from the mining faces to different destinations outside or within the pit rim. Many researchers believe 50% of operating costs in open pit mines (Alarie and Gamache, 2002) and even in some cases in large open pit mines up to 60% of the operation costs is to be spent on material handling (Alarie and Gamache, 2002; Akbari et al., 2009; Ahangaran et al., 2012; Upadhyay and Askari-Nasab, 2015). Therefore, improving the transportation operation and subsequently decreasing expenses of this subset of the operation by a small percentage will result in significant savings. Two major approaches are usually taken towards decreasing the transportation costs. The first way is to use larger trucks in the truck fleet to transport more material in each cycle. The second way is to reduce the cost of material transportation by implementing operations research techniques to improve productivity of the operation.

In the literature of mining fleet management systems, different efforts have been done since (1964) suggested the use of radio communications between equipment operators and the mine control center. After that, one of the first algorithms to solve truck allocation and dispatching problem in open pit mines was introduced by (1973). In the late 1970s, (1977) introduced dispatching boards installed in the control center using a simplified dispatching technique to manage the operation. Although research continued over 1960s and 1970s, main efforts in the field started from the second half of the 1980s. Since late 1980s researchers focused on developing algorithms based on variety of approaches to optimize fleet management in mines. (Najor and Hagan, 2006; Ercelebi and Bascetin, 2009) developed algorithms based on queuing theory and (White and Olson, 1986; Bonates and Lizotte, 1988; Temeng et al., 1997) developed models based on linear programming.

Developing fleet management systems and evaluating their impacts on the mining operations requires running different operational scenarios in the mines. However, as mentioned above, mining operations and more specifically open pit mining operations are very high cost projects. Therefore, running a single scenario in the real operation for even a short period of time requires spending millions of dollars. Thus, (Sturgul, 1987; Bonates and Lizotte, 1988; Forsman et al., 1993; Kolonja and Mutmansky, 1993; Ataeepour and Baafi, 1999; 2008) implemented simulation modeling to evaluate various dispatching techniques and prove positive impacts of implementing dispatching techniques in mining operations. Most of the simulation studies, from 2010 to 2015, in the field of truck-shovel mining system including (Jaoua et al., 2012; Ta et al., 2013; Dindarloo et al., 2015; Upadhyay and Askari-Nasab, 2015; Chaowasakoo et al., 2017) implemented simulation as a tool to evaluate results of the developed optimization algorithms in their studies without incorporating a new component into their system.

In this paper, the interactions between trucks and shovels in an open pit mining operation is simulated. In the simulated mining operation the model developed in (White and Olson, 1986) has been used for the purpose of optimizing the operation fleet activities. It is worthnoting that the rationale behind using the model developed in (White and Olson, 1986) is its popularity among the mining companies as a proper fleet management system. The model developed in (White and Olson, 1986) is a separate optimizer system that needs to be run in an external optimmization software. Linking this external software to the simulation model increases the simulation model run time. To avoid this increase in simulation run time a simulation based algorithm had been developed to mimic the backbone algorithm of the model developed in (White and Olson, 1986). Then, a multiobjective alogrithm was developed for the so called lower stage (truck assignment) that tries to optimize task of truck dispatching considering three most important objectives of this stage. Afterwards , the simulation model was run for a case study using all three aformentioned optimization algorithms and the results of the simulation were compared.

2. Backbone of Dispatch Optimizer

The model developed in (White and Olson, 1986) takes two steps to dispatch available trucks in an open pit mine. In its first step it tries to optimize production of the operation using two weakly coupled linear programing (LP) models in a predefined time intervals. Afterwards, whenever a truck asks for a new assignment, implementing a dynamic programming (DP) approach, it tries to assign closest truck to the neediest shovel. Solving these three mathematical models, it optimizes mining operations. Vast usage of the the model developed in (White and Olson, 1986) across the world and more specifically over North America for more than 30 years convinced us to implement it in our simulation studies as a benchmark fleet management system. Therefore, we developed a fleet management system based on the backbone algorithm of the model developed in (White and Olson, 1986) in an external optimization software. The optimization model was linked to the simulation model and whenever the simulation reaches the point that requires an operational decision to be made, it calls the optimization model and implements the results of the optimization in the operation. The readers are referred to (White and Olson, 1986) for more information regarding the LP and DP algorithms of the model developed in (White and Olson, 1986) and the way it works to assign trucks to the right shovel.

3. Simulation Based Heuristic

We chose the model developed in (White and Olson, 1986) as a benchmark fleet management system to evaluate goodness of our model. However, calling external optimization software into a running simulation and asking for solutions to the LP models take a lot of time. Thus, runtime problem for the simulation model have forced us to develop a simulation based logic to mimic the model developed in (White and Olson, 1986). This simulation based logic will help the simulation model to not require any linkage to external optimization software. The algorithm follows n-truck-m-shovel approach addressed by (Alarie and Gamache, 2002). In this approach, the shovel's 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. The simulation based heuristic developed here in this research follows five general steps:

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.

4. Multi Objective Model for Truck Dispatching

To deal with the decision making process regarding truck assignment in fleet management system (FMS) a preliminary multi-objective model has been developed in this research which is being presented in this section. The model obtains its required inputs from the current status of the mining operation and using an MILGP approach tries to assign trucks to the shovels.

To introduce the model, the following subsections stand to define indexes, decision variables, parameters, and the calculation procedure to achieve the cost coefficients of the objective function, the MILGP formulation of the model, the governing constraints, and normalization of the goals, respectively.

Index for variables and parameters

i Index for set of Trucks: $i = \{1,...,N\}$;

j Index for set of Shovels: $j = \{1,...,M\}$;

k Index for set of Dumps: $k = \{1,...,D\}$;

t Index for set of weights for individual goals: $t = \{1, 2, 3\}$;

q Index for trucks waiting in queue at shovel: $q = \{1, ..., NTinQS\}$;

Decision variables

x_{ijk} Incoming flow to shovel *j* by assignment of truck *i* to the path of shovel *j* to dump *k*;

x'_{ijk} Outgoing flow from shovel *j* by assignment of truck *i* to the path of shovel *j* to dump *k*;

c_{jk}^{-} Negative deviation of the met path flow rate for path between shovel *j* and dump *k* compared to desired path flow rate;

c_{jk}^{+} Positive deviation of the met path flow rate for path between shovel *j* and dump *k* compared to desired path flow rate.

Parameters

S_{ijk} Idle time for shovel *j* if truck *i* is assigned to transport material from shovel *j* to dump *k*;

T_{ijk} Wait time for truck *i* if it is assigned to transport material from shovel *j* to dump *k*;

P_t Normalized weights of individual goals based on priority;

T_i Capacity of truck *i*;

MF Match factor of the current truck portion of truck fleet available for the assignment and required amount of haulage to meet the production requirements of the operation (it is not well-known match factor introduced by (Burt and Caccetta, 2007));

PC_k Capacity of the plant *k*: *k* = {1, ..., O};

SC_j Production capacity of shovel *j*;

MP_{jk} Path flow rate for the path from source *j* to the destination *k* that the production operation has met so far;

PT_{jk} Path flow rate for the path from source *j* to the destination *k*;

TR_{ij} Next time truck *i* reaches shovel *j*;

SA_{ij} Next time shovel *j* is available to serve truck *i*;

TN Current time of the operation;

LD_{ik} The distance truck *i* must pass to reach the destination *k* to dump its load;

$ED_{ikj'}$ The distance truck *i* must pass from the destination *k* to the next expected shovel *j'*;

$v_{ijk-loaded}$ Average loaded velocity of truck *i* traveling from shovel *j* to destination *k*;

$v_{ij'k-empty}$ Average empty velocity of truck *i* traveling from dump *k* to the next expected shovel *j'*;

$Q@D_{ik}$ Queue time for truck *i* in the queue of the dump *k*;

D_{ik} Dump time for truck *i* to dump its material in dump *k*;

$NTinQS_j$ Number of trucks in queue at shovel *j*;

$TSpotT_q$ Spotting time for the truck *q* in the queue;

$TLoadT_q$ Loading time for the truck *q* in the queue;

Calculations

$$S_{ijk} = TR_{ij} - SA_{ij} \tag{1}$$

$$T_{ijk} = SA_{ij} - TR_{ij} \tag{2}$$

$$TR_{ij} = TNOW + \frac{LD_{ik}}{v_{ijk-loaded}} + Q@D_{ik} + D_{ik} + \frac{ED_{ikj'}}{v_{ij'k-empty}} \tag{3}$$

$$SA_{ij} = TNOW + \sum_{q=1}^{NTinQS_j}\left(TSpotT_q + TLoadT_q\right) \tag{4}$$

Model formulation

The model is formulated considering three operational goals of the operation: 1) minimize the summation of shovel idle times; 2) minimize the summation of truck wait times; and 3) minimize the deviation in the path flow rate compared to the desired flow rate.

The MILGP objectives formulated to optimize the goals are presented in Eq. (5), (6), and (7):

$$G_1 = \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{D} S_{ijk}x_{ijk} \tag{5}$$

$$G_2 = \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{D} T_{ijk}x_{ijk} \tag{6}$$

$$G_3 = \sum_{j=1}^{M}\sum_{k=1}^{D}\left(c_{jk}^{-} + c_{jk}^{+}\right) \tag{7}$$

Eq. (5) represents total idle time for all the shovels working in the operation. Eq. (6) represents total truck waiting times for all the trucks available for assignment. Eq. (7) represents the difference between flow rate of the paths and the desired flow rates. Applying a non-preemptive goal programming approach the objective function is given by Eq. (8). 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. (8).

$$\min Z = P_1 G_1 + P_2 G_2 + P_3 G_3 \quad (8)$$

Constraints

$$\sum_{i=1}^{N} \sum_{k=1}^{D} x'_{ijk} = \sum_{i=1}^{N} \sum_{k=1}^{D} x_{ijk} \qquad \forall\, j \in \{1 \ldots N\} \quad (9)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{M} x_{ijk} = \sum_{i=1}^{N} \sum_{j=1}^{M} x'_{ijk} \qquad \forall\, k \in \{1 \ldots D\} \quad (10)$$

$$\sum_{i=1}^{N} \sum_{k=1}^{D} x_{ijk} \leq T_i \qquad \forall\, i \in \{1 \ldots N\} \quad (11)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{M} x_{ijk} \geq MF \times PC_k \qquad \forall\, k \in \{1 \ldots O\} \quad (12)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{D} x_{ijk} \leq SC_j \qquad \forall\, j \in \{1 \ldots M\} \quad (13)$$

$$\sum_{i=1}^{N} x_{ijk} + MP_{jk} + c_{jk}^{-} - c_{jk}^{+} = PT_{jk} \qquad \forall\, j \in \{1 \ldots M\} \;\&\; \forall\, k \in \{1 \ldots D\} \quad (14)$$

Constraint (9) assures that incoming trucks to the shovels are equal to the outgoing trucks from the same shovel meaning that whatever truck capacity arrived into a shovel queue will leave that shovel. Constraint (10) makes sure that total incoming haulage capacity into a dump area is equal to the empty trucks' capacity for the trucks leaving that specific dump location. Constraint (11) limits the maximum capability of a truck to incorporate in a transportation task to its capacity. Constraint (12) ensures that material hauled to the processing plants using all the trucks meet the required processing target of each plant. Constraint (13) limits the total haulage capacity sent to a shovel to the shovel's digging rate. Constraint (14) ensures that the path flow rate for each path connecting a source to a destination point is of the desired path flow rate. Moreover, all the variables have a non-negativity constraint.

Normalization of goals

As mentioned before, the goals in the objective function of this study do not match with each other in term of the dimension. Besides, a non-preemptive goal programming approach has been chosen for the optimization of the model. Thus, normalization of the goals before the optimization process is required. In this study, normalizing will be done by the difference of the optimal function values for two so called Utopia and Nadir points. Utopia point sets a lower bound on individual goals in a minimization problem. Nadir point on the other hand, sets an upper bound on the goals in the same types of problems. The results will provide us with the lower and upper bounds of the interval that the objective functions will vary in the Pareto optimal set. Optimizing the system (minimizing) considering only one goal will result in the Utopia point which provides the lower bound of values for individual goals. The upper bounds are derived using the components of a Nadir point presented in (Grodzevich and Romanko, 2006). After normalizing the goals we can solve our multi objective model using an optimization tool.

5. Case study

An iron ore mine located in Iran was chosen as a case study to be used for evaluating the models developed in this research. Mining operation in the case study is being handled by a truck and shovel system. There are three main dumping points for the loaded trucks including two processing plants and one waste dump.

We built a simulation model of the case study. 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 on the historical data. Using Kolmogorov-Smirnov and Chi Square tests, the best function was selected for each parameter.

6. Results and Discussions

In order to compare the performance of the dispatching algorithms, we developed a simulation model that incorporates one of the following as the FMS: the model developed in (White and Olson, 1986), the multiobjetive model proposed in this paper, and the heuristic dispatcing technique. The model uses a short-term production schedule obtained from (Upadhyay and Askari-Nasab, 2016) other distribuitions, road network and parameters from the Iron ore mine. Our goal is to compare our model against (White and Olson, 1986) but we developed a simple heuristic mimicing decisions made by (White and Olson, 1986) to avoid run time increases caused by calling the optimization engine in every step of the simulation. The heuristic mimics the model developed in (White and Olson, 1986) to a very good extend with a difference in production of less than 0.9%. At the same time, it runs approximately 650% and 850% faster than a simulation model of the same operation with implementing externally linked FMS in a simple and a complex case, respectively. However, in this paper we only compare our multi-objective model against the original model from (White and Olson, 1986). The simulation model was built in Rockwell Arena and connected to an external optimization software (CPLEX) to solve the models.

After proving that the distributions representing the uncertain input parameters match with the database, the simulation models were set up for 5 replications (decided based on required halfwidths). Then, the model was run for 91 days of operation. Finally, the results of both the simulation models are being presented in Fig. 1 to Fig. 3. Fig. 1 is showing the weekly production of the operation implementing the model developed in (White and Olson, 1986) as the operation FMS. Fig. 2 provides weekly production requirement of the operation implementing the multi-objective model developed here in this reserch. Fig. 3 depicts the histograms of how the queue time at shovels vary implementing each optimization models as the operation's FMS.

Acording to Fig. 1, the operation moved an average of 950 thousand tonnes of material from the pit per week with a minimum of 903 thousand tonnes and a maximum of 999 thousand tonnes. Beside that, although the total amount of ore produced is following an average of around 250 thousand tonnes, the amount of material sent to each processing plant is varying wildly. In the first four weeks of the operation the FMS tries to send more material to the processing plant 1. This pattern changes by starting the week 5 of the operation by sending more material to the processing plant 2 than processing plant 1 which ends by the end of the week 10 of the operation. This fluctuation is due to the rationle behind the optimization model developed in (White and Olson, 1986).

Fig. 2 represents weekly production of the operation over 12 weeks of the simulation run time implementing the multi-objective model developed here in this research as the FMS. The figure shows that the simulation-optimization model of the operation is removing an average of 1.11 million tonnes of material from the pit on a weekly basis.

It also shows that the amount of ore produced per each week of the operation time is consistent over the run time period. Another major depiction of the graph is that both of the processing plants are fed with the same amount of material with an average difference of only 2.2%.

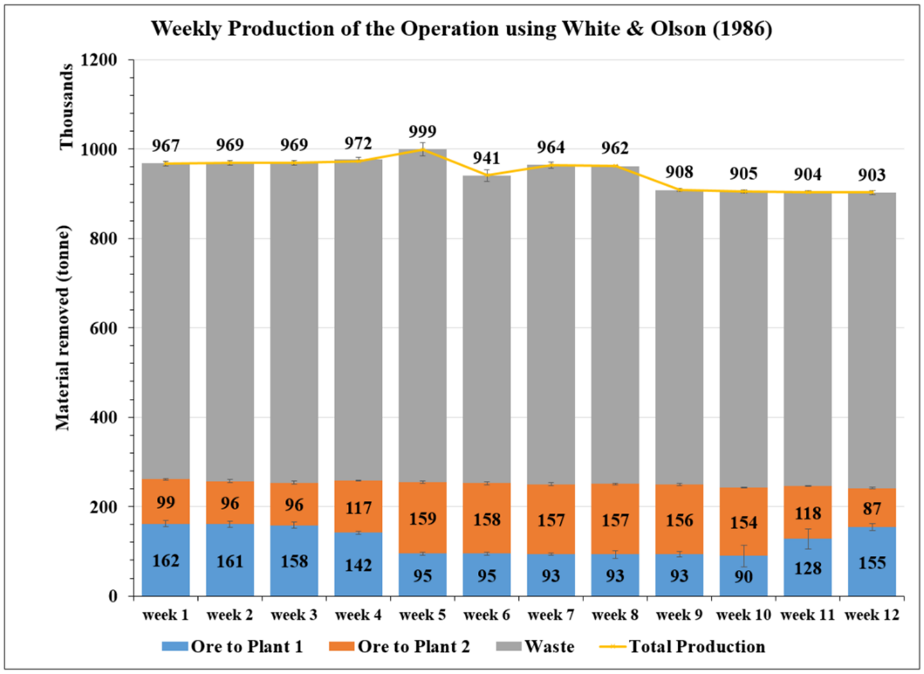

Fig. 1: Total material mined including ore and waste over 12 weeks of the operation implementing the model developed in (White and Olson, 1986).

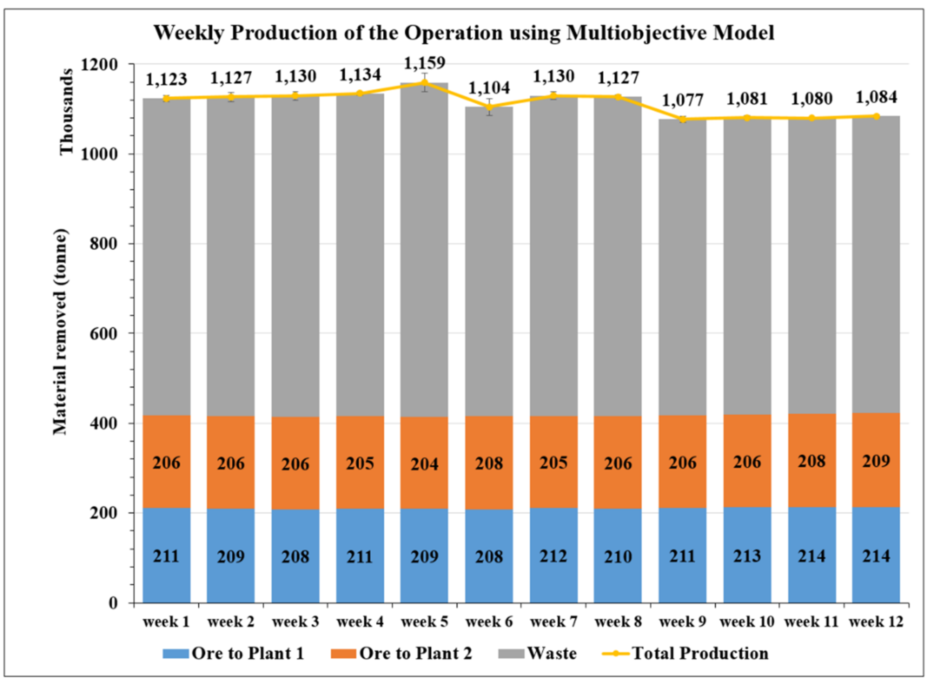

Fig. 2: Total material mined including ore and waste over 12 weeks of the operation implementing the multi objective model developed in this study.

As another important key performance indicator (KPI), queue time at shovel for both FMSs had been investigated and the results are presented in Fig. 3. As it is represented by the graph, using the model developed in (White and Olson, 1986) trucks wait in queue of shovels with a mean of 1.7 minutes which is deviated for about 1 minute. The results are showing slight difference when we implement the multi objective model. Average truck waiting time at shovels while implementing multi objective model is 2.2 minutes with an standard deviation of 1.4 minute.

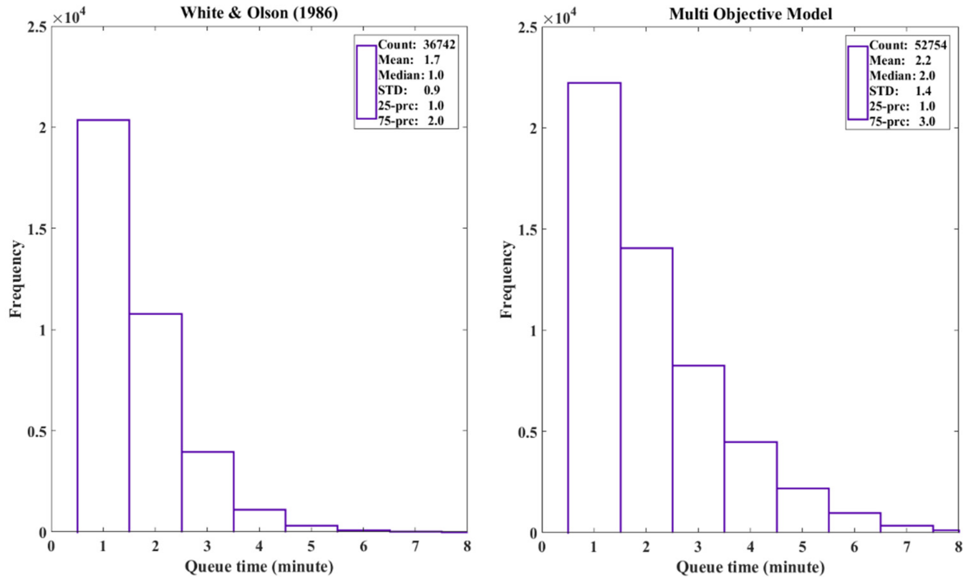

Fig. 3: Histogram of the truck queue time over 12 weeks of the operation (graph in right side represents queue time while implementing optimization model developed in (White and Olson, 1986) while graph in the left side is showing queue time implementing multi objective model developed in this research).

7. Conclusions

In this paper, authors developed two truck dispatching algorithms. The first one is a simulation based heuristic algorithm. This algorithm tries to follow the backbone algorithm of the model developed in (White and Olson, 1986). The second one is a multi-objective mathematical model. This model tries to make decisions of truck assignments in open pit mines based on three major objective of minimizing shovels' idle time, minimizing trucks' wait time, and minimizing deviation from the paths' flow rates. The three aforementioned models were attached to a simulation model of an open pit mining operation. The simulation model was run with the models and some of the results have been presented in this paper.

Comparing the two optimization based FMS, total material removed increases for an average of 8.4% when implementing the multi objective model. The second worth noting conclusion is that, although total weekly ore production of the operation using both fleet management systems are consistent, the plant feed rate for each plant in an operation with multiple processing plants is fluctuating over the production period when implementing the model developed in (White and Olson, 1986). However, this study shows that the multi objective model developed here does not have the feed rate fluctuation problem in a multiple processing operation. The last but not the least conclusion is that truck waiting time at shovels are falling within almost the same range for both of the models with a 30 seconds difference in the average waiting time.

8. References

[1] Ahangaran, D. K., Yasrebi, A. B., Wetherelt, A., and Foster, P. (2012). Real –time dispatching modelling for trucks with different capacities in open pit mines. *ARCH MIN SCI*, *57* (1), 39-52.

[2] Akbari, A. D., Osanloo, M., and Shirazi, M. A. (2009). Minable reserve estimation while determining ultimate pit limits (UPL) under price uncertainty by real option approach (ROA). *ARCH MIN SCI*, *54* (2), 321-339.

[3] Alarie, S. and Gamache, M. (2002). Overview of Solution Strategies Used in Truck Dispatching Systems for Open Pit Mines. *INT J MIN RECLAM ENV*, *16* (1), 59-76.

[4] Ataeepour, N. and Baafi, E. Y. (1999). ARENA simulation model for truck-shovel operation in despatching and non-despatching modes. *International Journal of Surface Mining, Reclamation and Environment*, *13* (3), 125-129.

[5] Bogert, J. R. (1964). Electronic eyes and ears monitor pit operations. *Met. Min. Process*, 42-45.

[6] Bonates, E. and Lizotte, Y. (1988). A computer simulation model to evaluate the effect of dispatching. *International Journal of Surface Mining, Reclamation and Environment*, *2* (2), 99-104.

[7] Burt, C. N. and Caccetta, L. (2007). Match factor for heterogeneous truck and loader fleets. *International Journal of Mining, Reclamation and Environment*, *21* (4), 262-270.

[8] Chaowasakoo, P., Seppälä, H., Koivo, H., and Zhou, Q. (2017). Digitalization of mine operations: Scenarios to benefit in real-time truck dispatching. *International Journal of Mining Science and Technology*, *27* (2), 229-236.

[9] Dindarloo, S. R., Osanloo, M., and Frimpong, S. (2015). A stochastic simulation framework for truck and shovel selection and sizing in open pit mines. *115* (March), 209-219.

[10] Ercelebi, S. G. and Bascetin, a. (2009). Optimization of shovel-truck system for surface mining. *J. South. Afr. Inst. Min. Metall.*, *109* (7), 433-439.

[11] Forsman, B., Rönnkvist, E., and Vagenas, N. (1993). Truck dispatch computer simulation in Aitik open pit mine. *International Journal of Surface Mining, Reclamation and Environment*, *7* (3), 117-120.

[12] Grodzevich, O. and Romanko, O. (2006). *Normalization and Other Topics in Multi-Objective Optimization*. in Proceedings of Fields–MITACS Industrial Problems Workshop, MITACS, Toronto, ON, Canada, pp. 89-101.

[13] Hauck, R. F. (1973). *A Real-Time Dispatching Algorithm for Maximizing Open-Pit Mine Production under Processing and Blending Requirements*. in Proceedings of Seminar on Scheduling in Mining, Smelting and Metallurgy, Montreal, pp. 1-10.

[14] Jaoua, A., Riopel, D., and Gamache, M. (2012). A simulation framework for real-time fleet management in internal transport systems. *Simulation Modelling Practice and Theory*, *21* (1), 78-90.

[15] Kolonja, B. and Mutmansky, J. M. (1993). Analysis of Truck Dispatching Strategies For Surface Mining Operations Using SIMAN. in *SME Annual Meeting*, vol. 296, SME, Ed. Reno, NV: SME Preprint, pp. 1845-1851.

[16] Mueller, E. R. (1977). Simplified dispatching board boosts truck productivity at Cyprus Pima. *MIN ENG-LITTLETON*, *29* (8), 40-43.

[17] Najor, J. and Hagan, P. (2006). *Capacity constrained production scheduling*. in Proceedings of 15th Sympos. Mine Planning Equipment Selection (MPES), FIORDO S.r.l., Torino, Italy, pp. 1173–1178.

[18] Sturgul, J. (1987). *Simulating mining engineering problems using the GPSS computer language*. in Proceedings of Aus IMM, Melbourne,

[19] Ta, C. H., Ingolfsson, A., and Doucette, J. (2013). A linear model for surface mining haul truck allocation incorporating shovel idle probabilities. *EUR J OPER RES*, *231* (3), 770-778.

[20] Temeng, V. a., Otuonye, F. O., and Frendewey, J. O. (1997). Real-time truck dispatching using a transportation algorithm. *INT J MIN RECLAM ENV*, *11* (4), 203-207.

[21] Upadhyay, S. P. and Askari-Nasab, H. (2015). Truck-shovel allocation optimisation: a goal programming approach. *Mining Technology*,

[22] Upadhyay, S. P. and Askari-Nasab, H. (2016). Truck-shovel allocation optimisation: a goal programming approach. *Min Tech*, 1-11.

[23] White, J. W. and Olson, J. P. (1986). Computer-based dispatching in mines with concurrent operating objectives. *MIN ENG-LITTLETON*, *38* (11), 1045-1054.

[24] Yuriy, G. and Vayenas, N. (2008). Discrete-event simulation of mine equipment systems combined with a reliability assessment model based on genetic algorithms. *International Journal of Mining, Reclamation and Environment*, *22* (1), 70-83.