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Mine Productivity Upper Bounds and Truck Dispatch Rules

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Mine Productivity Upper Bounds and Truck Dispatch Rules

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Abstract: This paper proposes an upper bound for mine productivity and also a simple truck dispatch rule that demonstrates how tight the upper bound can be using simulation. It also proposes a greedy search to approximate the productivity upper bound, which is faster and often exact. Uncertainty is added to the simulation in order to verify how the productivity responds to it. Typically, the productivity upper bound is less tight close to its saturation point as a function of the number of trucks, where adding more trucks only increases queues. Furthermore, more uncertainty in the model typically leads to a less tight upper bound. The results are conducted using real data from an open pit mine in Brazil.

Keywords: mine productivity; upper bound; truck dispatch rule

1. Introduction

Mining is a process of extracting valuable materials from underground and open pit mines. These materials, known as ores, are typically a combination of minerals, natural rocks or sediments, which have economic value when refined. Since the last few decades, mining has always played an important role in the economic development of several countries, especially in the emerging ones [1]. However, mining is a very complex industrial operation and its project must contain several planning stages, starting with prospecting for ore bodies and ending with the final reclamation of the land after mine is closed. In addition, a mining project must maximize net present value (NPV), extracting the ore at the lowest possible cost over the mine's life-cycle and, therefore, making the effort of such labor worthwhile.

In open pit mines, where operating costs are very high, it is even more essential to maximize productivity with minimum cost. Among the most expensive open pit mine operations, haulage and materials handling stand out, accounting for 50%-60% of the total operating costs [2]. In order to reduce this cost and thereby maximize NPV of the mining project, a fleet management system (FMS) is required, whose goal is to solve two problems: (i) find the shortest path to travel between each pair of locations (loading and dumping sites) in the mine (shortest path problem) and (ii) determine the number of truck trips required for each path and then dispatch the trucks to the locations in real-time, which is the focus of this paper.

Hence, an FMS can be a single-stage or a multi-stage. The single-stage approaches dispatch trucks without considering any production targets or constraints and typically consist of heuristics based on rules of thumb [3,4]. However, multistage approaches have a great advantage over single stage approaches by dividing problem (ii) into two sequential sub-problems [5,6]. This division into stages introduces a level of knowledge to the FMS that improves the quality of the solutions, as well as better adapting them to real scenario with uncertainties. The first sub-problem consists of efficiently allocating haulage resources for excavation activities based on truck loads and aiming to maximize truck productivity (truck and shovel allocation problem - upper stage), and the second sub-problem

consists of dispatching trucks to a loading or a dumping site (truck dispatching problem - lower stage) [7].

Although it has not been extensively investigated as the upper stage sub-problem, the truck dispatching problem is essential for the fleet management system. It is by solving the lower stage sub-problem that the planning come into operation to achieve the production targets defined in the previous stage. Formally, the truck dispatching problem, which can be treated as an assignment problem [5,8] or a transportation problem [9–11], is a real-time decision making on the destination of trucks to satisfy production requirements in a mining operation. To achieve these requirements, one or more objectives are usually defined, such as maximizing mine productivity or minimizing truck inactivity (whether through idle time, waiting time, loading/dumping time). Therefore, several formulations of this optimization problem have already been proposed, as well as different solutions for these formulations.

Since the truck dispatch problem also occurs in fuel and package deliveries, taxis and ride-hailing services and any other industry that has to manage a fleet of vehicles, some approaches used to solve the dispatch problem in other contexts were naturally adopted for the problem applied in the mining industry. However, the transition of approaches in different contexts can be inappropriate. In open pit mines, some important particularities must be considered in the optimization problem. For example, the travel distance between two locations is usually short, the time for the truck to load or dump is often longer than usual and the frequency of demand at each location is often higher [2].

Therefore, the efficiency of a solution to the truck dispatch problem aimed at maximizing the mine's productivity is strictly related to the fleet size and the haulage distances. A fleet with an insufficient number of trucks (under-truck) will result in substantially unproductive periods and a fleet with a high number of trucks (over-truck) may lead to queues for loading or dumping. Thus, several methods have been proposed to select the optimal size of the truck fleet in the truck dispatching problem, i.e. consider the number of trucks as a decision variable, which would avoid the aforementioned problems. Generally, these methods are based on match factor [12–15], artificial intelligence [16–18], operations research [19,20], life cycle cost analysis [21,22] or discrete event simulation [23–25]. However, the major drawback of these works is that they were developed to address only the equipment selection and sizing problem, in particular, the size of the haulage fleet handling the dump materials, and typically disregard the truck dispatch rules [15]. On the other hand, dispatching rules have been studied apart from fleet sizing, based on optimization models with dynamic truck allocation [26], heuristics with real-time data [27,28], simulation [29], or artificial intelligence [30].

From this perspective, we define a linear programming model that derives the upper bound for mine productivity by considering trucks of a heterogeneous fleet allocated in cycles (pairs of loading-dumping sites). In addition, we propose a simple truck dispatch rule that leads to a mine productivity, found in a discrete event simulation, close to this upper bound. Through a case study in an open pit mine in Brazil, we also show that the simulation takes into account fleet size problems and the results obtained are feasible to be implemented in the real world.

2. Mine model

The mine model used in this paper consider a productive cycle of individual trucks in a mine which are dispatched to a loading site, displaced to the chosen loading site where they are loaded, dispatched to a dumping site, displaced to the chosen dumping site where they are finally dumped and start the cycle all over again, as shown in Figure 1. The degree of freedom lies on where to dispatch the trucks to load or dump at each moment, which must maximize the mine productivity in long term. In the next section, an upper bound for mine productivity is proposed using linear programming, which is latter approximated by a greedy search. The mine productivity is physically realized by a discrete event simulation using a simple truck dispatch rule.
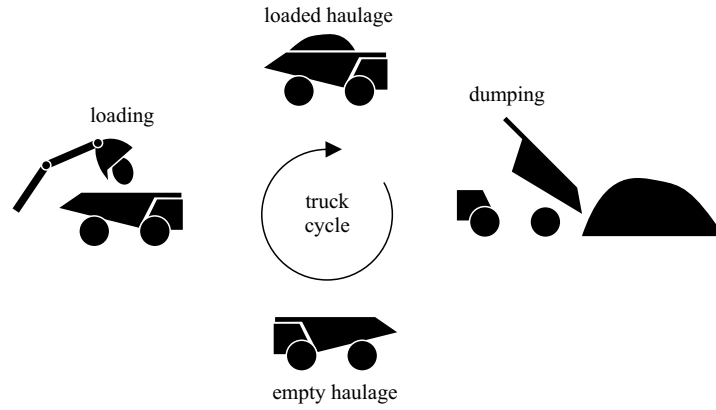
Figure 1. Truck cycle with its four states.

2.1. Optimization problem

In order to derive an upper bound for mine productivity, trucks are considered to be allocated in cycles defined by pairs of loading-dumping sites, where the cycle times are given by

$$t_{c,i_u,i_\ell,i_m} = 2\frac{d_{i_u,i_\ell}}{v_{i_m}} + t_{u,i_u,i_m} + t_{\ell,i_\ell,i_m}, \quad \forall i_u, i_\ell, i_m \tag{1}$$

where d_{i_u,i_ℓ} is the distance between dumping site i_u and loading site i_ℓ, v_{i_m} is the truck speed for model i_m, t_{u,i_u,i_m} is the dumping time at dumping site i_u for truck model i_m, t_{ℓ,i_ℓ,i_m} is the loading time at loading site i_ℓ for truck model i_m. The trucks are allowed to change loading and dumping sites after each load or dump operation. Hence, in order to derive an upper bound for productivity, the number of trucks of model i_m allocated in the cycle defined by loading site i_ℓ and dumping site i_u is a non negative real number N_{i_u,i_ℓ,i_m}, where fractions denote the truck relative time-slice in each cycle. The resulting productivity of this allocation is given by

$$\frac{N_{i_u,i_\ell,i_m} L_{i_m}}{t_{c,i_u,i_\ell,i_m}} \tag{2}$$

where L_{i_m} is the load of truck model i_m and t_{c,i_u,i_ℓ,i_m} is the respective cycle time.

The maximum number of trucks that a resource (e.g. loading or dumping site) can support in a cycle without queues is given by

$$\frac{t_{c,i_u,i_\ell,i_m}}{t_{u,i_u,i_m}} \text{ or } \frac{t_{c,i_u,i_\ell,i_m}}{t_{\ell,i_\ell,i_m}} \tag{3}$$

so that each truck occupies a cycle time slice of length given by the service time and will be serviced in a continuous way without queue. Hence, the occupation due to an allocated number of trucks N_{i_u,i_ℓ,i_m} is given by

$$\frac{N_{i_u,i_\ell,i_m} t_{u,i_u,i_m}}{t_{c,i_u,i_\ell,i_m}} \text{ or } \frac{N_{i_u,i_\ell,i_m} t_{\ell,i_\ell,i_m}}{t_{c,i_u,i_\ell,i_m}} \tag{4}$$

which must be at most 1 to not generate queues.

The linear optimization problem for maximum productivity can be written as

$$\text{maximize} \quad \sum_{i_u=1}^{n_u} \sum_{i_\ell=1}^{n_\ell} \sum_{i_m=1}^{n_m} \frac{N_{i_u,i_\ell,i_m} L_{i_m}}{t_{c,i_u,i_\ell,i_m}} \tag{5}$$

$$\text{subject to} \quad \sum_{i_\ell=1}^{n_\ell} \sum_{i_m=1}^{n_m} \frac{N_{i_u,i_\ell,i_m} t_{u,i_u,i_m}}{t_{c,i_u,i_\ell,i_m}} \leq 1, \quad \forall i_u \tag{6}$$

$$\sum_{i_u=1}^{n_u} \sum_{i_m=1}^{n_m} \frac{N_{i_u,i_\ell,i_m} t_{\ell,i_\ell,i_m}}{t_{c,i_u,i_\ell,i_m}} \leq 1, \quad \forall i_\ell \tag{7}$$

$$\sum_{i_u=1}^{n_u} \sum_{i_\ell=1}^{n_\ell} N_{i_u,i_\ell,i_m} \leq n_{t,i_m}, \quad \forall i_m \tag{8}$$

$$0 \leq N_{i_u,i_\ell,i_m} \leq n_{t,i_m}, \quad \forall i_u, i_\ell, i_m \tag{9}$$

where N_{i_u,i_ℓ,i_m} (design variable) is the number of trucks of model i_m allocated in the cycle between dumping site i_u and loading site i_ℓ, n_{t,i_m} is the number of available trucks of model i_m, n_u is the number of dumping sites, n_ℓ is the number of loading sites, n_m is the number of truck models. The problem is basically a productivity maximization (5) subject to resources constraints (6)-(8).

2.1.1. Greedy search

A greedy search may be applied to find an approximate solution to the linear problem (5)-(9) by allocating trucks to the most productive cycles first.

Algorithm 1 depicts this greedy search. Lines 1 and 2 initialise the output parameters. Lines 3 and 4 initialise cycle time and cycle productivity. Lines 5-7 initialise resource (dumping sites, loading sites and trucks) allocation. Line 8 initialises remaining cycle indicator. Line 10 finds the most productive remaining cycle. Line 11 allocates truck according to resource availability. Lines 12-14 update resource availability. Lines 15 and 16 update output parameters. Lines 17-26 update remaining cycle indicator.

Algorithm 1 Greedy search for mine productivity.

Input

$\quad d \in \mathbb{R}^{n_u \times n_\ell}$ $\quad$ distance between dumping and loading sites

$\quad t_u \in \mathbb{R}^{n_u \times n_m}$ $\quad$ truck dumping time

$\quad t_\ell \in \mathbb{R}^{n_\ell \times n_m}$ $\quad$ truck loading time

$\quad n_t \in \mathbb{R}^{n_m}$ $\quad$ number of trucks

$\quad v \in \mathbb{R}^{n_m}$ $\quad$ truck speed

$\quad L \in \mathbb{R}^{n_m}$ $\quad$ truck load

Output

$\quad P \in \mathbb{R}$ $\quad$ mine productivity

$\quad N \in \mathbb{R}^{n_u \times n_\ell \times n_m}$ $\quad$ number of trucks in each loading-dumping cycle

1: $P \leftarrow 0$

2: $N_{i_u, i_\ell, i_m} \leftarrow 0, \ \forall i_u, i_\ell, i_m$

3: $t_{c,i_u,i_\ell,i_m} \leftarrow 2\frac{d_{i_u,i_\ell}}{v_{i_m}} + t_{u,i_u,i_m} + t_{\ell,i_\ell,i_m}, \ \forall i_u, i_\ell, i_m$ $\hspace{3cm} \triangleright$ cycle time

4: $P_c \leftarrow \frac{L_{i_m}}{t_{c,i_u,i_\ell,i_m}}, \ \forall i_u, i_\ell, i_m$ $\hspace{4cm} \triangleright$ cycle productivity

5: $n_{r,i_m} \leftarrow n_{t,i_m}, \ \forall i_m$ $\hspace{5cm} \triangleright$ remaining trucks

6: $a_{u,i_u} \leftarrow 0, \ \forall i_u$ $\hspace{4.5cm} \triangleright$ dumping site occupation

7: $a_{\ell,i_u} \leftarrow 0, \ \forall i_\ell$ $\hspace{4.5cm} \triangleright$ loading site occupation

8: $b_{i_u,i_\ell,i_m} \leftarrow 1, \ \forall i_u, i_\ell, i_m$ $\hspace{4cm} \triangleright$ remaining cycles

9: **while** any $n_{r,i_m} > 0$ and any $b_{i_u,i_\ell,i_m} = 1$ **do**

10: $\quad (i_u^\star, i_\ell^\star, i_m^\star) \leftarrow \arg\max_{(i_u,i_\ell,i_m) : b_{i_u,i_\ell,i_m}=1} \frac{(1-a_{u,i_u})t_{c,i_u,i_\ell,i_m} P_{c,i_u,i_\ell,i_m} (1-a_{\ell,i_\ell})}{}$ $\hspace{1cm} \triangleright$ best cycle

11: $\quad n_{\min} \leftarrow \min \left\{ n_{r,i_m^\star}, \ \frac{(1-a_{u,i_u^\star})t_{c,i_u^\star,i_\ell^\star,i_m^\star}}{t_{u,i_u^\star,i_m^\star}}, \ \frac{(1-a_{\ell,i_\ell^\star})t_{c,i_u^\star,i_\ell^\star,i_m^\star}}{t_{\ell,i_\ell^\star,i_m^\star}} \right\}$ $\hspace{0.5cm} \triangleright$ allocation

12: $\quad a_{u,i_u^\star} \leftarrow a_{u,i_u^\star} + \frac{n_{\min} t_{u,i_u^\star,i_m^\star}}{t_{c,i_u^\star,i_\ell^\star,i_m^\star}}$

13: $\quad a_{\ell,i_\ell^\star} \leftarrow a_{\ell,i_\ell^\star} + \frac{n_{\min} t_{\ell,i_\ell^\star,i_m^\star}}{t_{c,i_u^\star,i_\ell^\star,i_m^\star}}$

14: $\quad n_{r,i_m^\star} \leftarrow n_{r,i_m^\star} - n_{\min}$

15: $\quad P \leftarrow P + \frac{n_{\min} L_{i_m^\star}}{t_{c,i_u^\star,i_\ell^\star,i_m^\star}}$

16: $\quad N_{i_u^\star,i_\ell^\star,i_m^\star} \leftarrow n_{\min}$

17: $\quad b_{i_u^\star,i_\ell^\star,i_m^\star} \leftarrow 0$

18: $\quad$ **if** $a_{u,i_u^\star} \geq 0.999$ **then**

19: $\quad\quad b_{i_u^\star,i_\ell,i_m} \leftarrow 0, \ \forall i_\ell, i_m$

20: $\quad$ **end if**

21: $\quad$ **if** $a_{\ell,i_\ell^\star} \geq 0.999$ **then**

22: $\quad\quad b_{i_u,i_\ell^\star,i_m} \leftarrow 0, \ \forall i_u, i_m$

23: $\quad$ **end if**

24: $\quad$ **if** $n_{r,i_m^\star} \leq 0.001$ **then**

25: $\quad\quad b_{i_u,i_\ell,i_m^\star} \leftarrow 0, \ \forall i_u, i_\ell$

26: $\quad$ **end if**

27: **end while**

28: **return** P, N

2.2. Simulation

The truck cycles can be simulated using discrete event system simulation considering a dispatch rule, as depicted in Figure 2. Initially, one event is scheduled in the event calendar for each truck. In order to improve the simulation warming up, the trucks are distributed on dumping sites according to their respective cycle capacity obtained from the optimization model (5)-(9). The simulator then basically fires the next event in the calendar at each time, until the time horizon is reached. Each fired event schedules a new event in the calendar and changes the respective truck state. The scheduled times may follow a particular probability distribution, leading to a stochastic simulation. Despite simple, this computational model may be extended to consider further model details as needed.
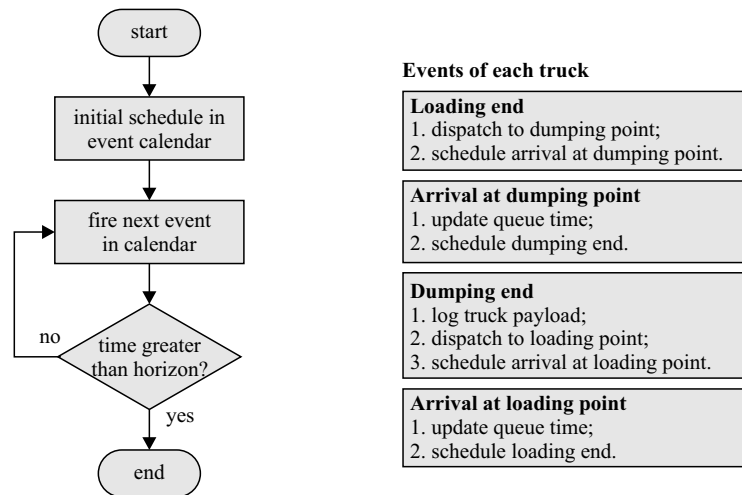
Figure 2. Discrete event simulator for mining truck cycles in a time horizon.

The proposed dispatch rule is to route trucks to services (i.e. loading or dumping) which will finish first in a prediction at dispatch moment, as depicted in Algorithm 2 to dispatch to a loading site. The algorithm to dispatch to a dumping site is analogous. This dispatch rule is easy to implement and, as shown in the result section of this paper, it leads to an almost optimal solution when compared to the productivity upper bounds provided by the optimization model (5)-(9),

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Algorithm 2 Dispatch rule to a loading site.

Input

$t \in \mathbb{R}$	current time
$d \in \mathbb{R}^{n_u \times n_\ell}$	distance between dumping and loading sites
$t_\ell \in \mathbb{R}^{n_u \times n_m}$	truck loading time
$v \in \mathbb{R}^{n_m}$	truck speed
$i_u \in \mathbb{N}$	current dumping site
$i_m \in \mathbb{N}$	truck model
$\tilde{t}_q \in \mathbb{R}^{n_\ell}$	loading queue time

Output

$i_\ell \in \mathbb{N}$	next loading site
$\tilde{t}_q \in \mathbb{R}^{n_\ell}$	loading queue time

1: $t_{h,j_\ell} \leftarrow d_{i_u,j_\ell}/v_{i_m},\ \forall j_\ell$ ▷ transit time
2: $\tilde{t}_{j_\ell} \leftarrow \max\{\tilde{t}_{q,j_\ell}, t + t_{h,j_\ell}\}.\ \forall j_\ell$ ▷ loading starting time prediction
3: $i_\ell \leftarrow \arg\min_{j_\ell} \tilde{t}_{j_\ell} + t_{\ell,j_\ell}$ ▷ select earliest loading finishing time prediction
4: $\tilde{t}_{q,i_\ell} \leftarrow \tilde{t}_{i_\ell} + t_{\ell,i_\ell}$ ▷ update queue time
5: **return** $i_\ell, \tilde{t}_q$

Following Algorithm 2, the predicted service (i.e. dumping and loading) finish time is tracked in a variable $\tilde{t}_q$. During the dispatch, the predicted service finish time $\tilde{t}_{j_s} + \tilde{t}_{s,j_s}, s \in \{u, \ell\}$, is calculated for each destination server j_s, considering the service time t_{s,j_s} and the predicted service starting time $\tilde{t}_{j_s}$, which in turn depends on the transit time t_{h,j_s}, the current time t, and the predicted last finish time of the respective server $\tilde{t}_{q,j_s}$. The truck is then dispatched to the server i_s with the earliest predicted service finish time, which is set to the respective service finish time in $\tilde{t}_{q,is}$. For stochastic simulations, the mean value of respective probability distributions are considered in the prediction.

3. Results

The main objective of the tests in the next subsections is to show how tight the proposed upper bound for productivity can be, verified by a physical realization obtained from simulation using the simple proposed truck dispatch rule.

3.1. Simulated productivity convergence and its upper bound

Figure 3 shows the productivity convergence for a discrete event system simulation for

$$d = \begin{bmatrix} 4095 & 3427 & 2700 & 5200 & 5394 & 5189 & 4617 & 4615 & 2293 & 2617 & 2816 & 3135 & 3242 & 3587 & 3862 \\ 4198 & 3029 & 2770 & 5300 & 5400 & 6626 & 4800 & 4800 & 3325 & 3516 & 3374 & 3436 & 3210 & 2638 & 4000 \\ 3554 & 2907 & 2704 & 5509 & 5736 & 5534 & 4985 & 4995 & 1607 & 1932 & 2212 & 2475 & 2529 & 2926 & 4248 \end{bmatrix} m,$$

$n_u = 3$ dumping sites, $n_\ell = 15$ loading sites, $n_m = 2$ truck models, dumping time t_u given in Table 1, loading time t_ℓ in Table 2, truck speed v given in Table 3, truck load L given in Table 4 and truck number $n_t = (12, 9)$. These data were obtained from 7 months of real operation in mine Pico in Brazil, whose truck models are respectively CAT-785C and CAT-789D. Notice that one day of simulation is enough for a long term productivity estimation, and also that the simulated productivity never gets larger than the upper bound. The gap between the simulated steady state productivity and its upper bound is majorly explained by the heterogeneous fleet. A queue priority for more productive models would make the gap smaller, but it is beyond the scope of this paper and it could be a research theme for further investigation.
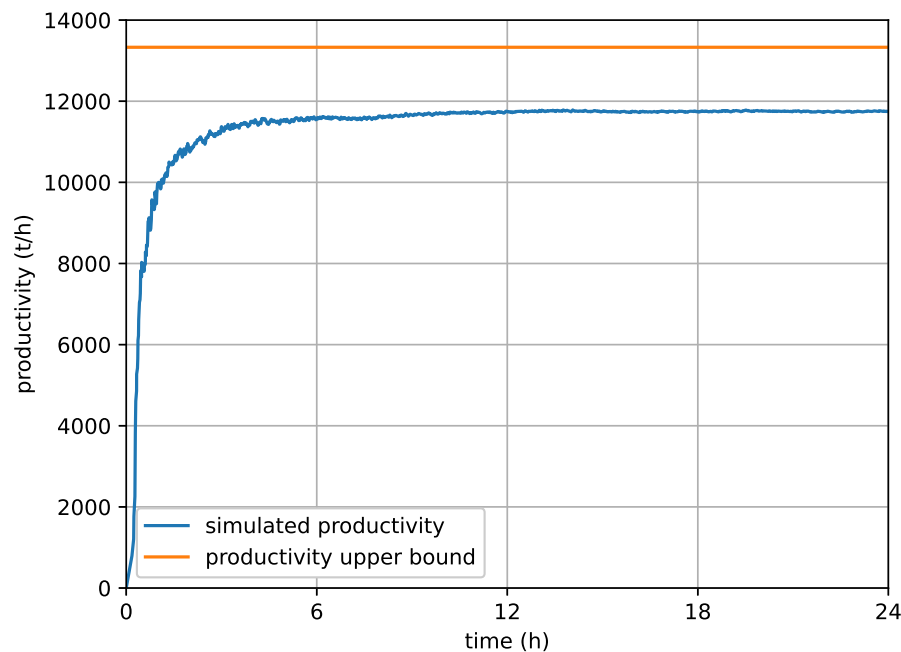

Figure 3. Productive convergence using a discrete event system simulation for the mine, which must be bellow the upper bound given by the linear optimization problem (5)-(9)
.

Table 1. Dumping time t_u for each truck model (i.e. they are the same for every dumping site) following a triangular distribution in interval $[a, b]$ with mode at c.

Truck model i_m	Minimum a (s)	Maximum b (s)	Mode c (s)
1	23	47	35
2	30	54	42

Table 2. Loading time t_ℓ for each truck model (i.e. they are the same for every loading site) following a triangular distribution in interval $[a, b]$ with mode at c.

Truck model i_m	Minimum a (s)	Maximum b (s)	Mode c (s)
1	146	298	222
2	185	349	267

Table 3. Truck speed v for each truck model following a triangular distribution in interval $[a, b]$ with mode at c.

Truck model i_m	Minimum a (km/h)	Maximum b (km/h)	Mode c (km/h)
1	15	31	23
2	17	33	25

Table 4. Truck load L for each truck model following a triangular distribution in interval $[a, b]$ with mode at c.

Truck model i_m	Minimum a (t)	Maximum b (t)	Mode c (t)
1	138	148	143
2	189	201	195

3.2. Fleet sizing

Figure 4 shows the mine productivity increasing with the number of available trucks of model CAT-789D until a saturation point where more trucks will only generate queues. Notice that the greedy search solution matches the optimal solution, which is typical but does not happen always (sometimes the greedy search productivity is a little smaller just before the saturation point). This quantifies the optimality of the greedy search. Notice also that the simulated productivity, which is a feasible realization of trucks in the mine, starts close to the optimal productivity upper bound given by the solution of (5)-(9), gradually gets smaller because of queues as the number of trucks increases, and ends close to the upper bound again as the number of trucks is large enough to occupy all loading and dumping services without gaps. This quantifies the optimality of the dispatch rule and also quantifies how tight the upper bound can be. Finally, notice also that a greater uncertainty in simulation leads to less productivity due to unforeseen queues, whose gap becomes smaller as the number of trucks gets farther from saturation point. For 50% of uncertainty (i.e. triangular distribution with mean $c = \mu$, minimum $a = 0.5\mu$ and maximum $b = 1.5\mu$), the gap between the simulated productivity and its upper bound can get as large as 25%.
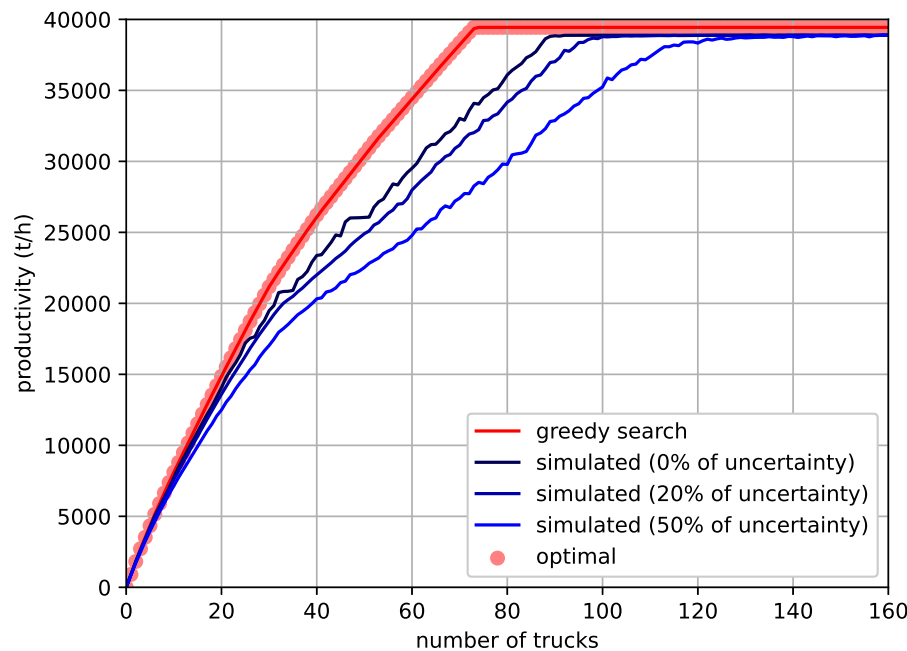
Figure 4. Mine productivity as a function of number of trucks available in the mine. Models with uncertainty $p \in \{20\%, 50\%\}$ consider the average productivity of 30 runs using symmetric triangular distributions with mean at μ, whose minimum and maximum are at $(1 - p)\mu$ and $(1 + p)\mu$ respectively.

4. Conclusions

The mine productivity upper bound proposed in this paper is considerably tight when the number of trucks get large and it can be quickly obtained. This makes it suitable for long term planning of a mine (e.g. truck and shovel allocation problem). On the other hand, the simulation is slower, but it provides a physical realization of the mine operation. Furthermore, more details can be added to the simulation, making it suitable for short term planning (e.g. truck dispatch problem).

The simple dispatch rule proposed in this paper leads to a productivity close the its upper bound for homogeneous fleets, which indicates how good it is. When queues in the mine are small or when there are too many trucks in the mine, the proposed dispatch rule tends to provide a productivity close to its upper bound. Considering that the dispatch rule is greedy, the good agreement between the greedy search and the linear programming productivity upper bound supports the good performance of the dispatch rule.

Conflicts of Interest: The authors declare no conflict of interest.

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