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Fleet optimization considering overcapacity and load sharing restrictions using genetic algorithms and ant colony optimization

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Research Article

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Abstract

This paper presents a fleet model explained through a complex configuration of load sharing that considers overcapacity and is based on a life cycle cost (LCC) approach for cost-related decision-making. By analyzing the variables needed to optimize the fleet size, which must be evaluated in combination with the event space method (ESM), the solution to this problem would normally require high computing performance and long computing times. Considering this, the combined use of an integer genetic algorithm (GA) and the ant colony optimization (ACO) method was proposed in order to determine the optimal solution. In order to analyze and highlight the added value of this proposal, several empirical simulations were performed. The results showed the potential strengths of the proposal related to its flexibility and capacity in solving large problems with a near optimal solution for large fleet size and potential real-world applications. Even larger problems can be solved this way than by using the complete enumeration approach and a non-family fleet approach. Thus, this allows for a more real solution to fleet design that also considers overcapacity, availability, and an LCC approach. The simulations showed that the model can be solved in much less time compared with the base model and allows for the resolution of a fleet of at least 64 trucks using GA and 130 using ACO, respectively. Thus, the proposed framework can solve real-world problems, such as the fleet design of mining companies, by offering a more realistic approach.

Introduction

When a fleet of vehicles is designed, one of the most important goals is to establish its size (i.e., the number of elements it comprises) (Sha and Srinivasan, 2016) because the fleet size is related to key components of company operations. Mining companies and other mineral extraction operations work with a great number of vehicles in order to effectively handle their production plan. However, the cost related to those assets can be very high. Thus, optimizing the creation of an efficient and optimal fleet, in terms of how many vehicles are actually needed, could potentially reduce costs. This is a well-studied subject (Hoff *et al.*, 2010; Kumar and Panneerselvam, 2012; Gavalas *et al.*, 2016), and several models and techniques have been proposed to solve it. However, an important aspect to consider is the effect of overcapacity (higher capacity than required) in improving operational results in terms of the level of availability and the incorporation of operational and inefficiency costs. These costs are even more important when a fleet is already in operation and demand is reduced. In that case, the fleet size must be reduced and, then, decisions must be made about which vehicles to sell and which to maintain. The economical evaluation model for decision making is the same in both cases.

Overcapacity is a part of a greater design approach that considers different failure behaviors (Distefano and Puliafito, 2009), where reliability (availability) via a load sharing configuration and flexible work levels are also considered. This design approach is based on event space assessments (Ding *et al.*, 2017) with matrix-based dynamic evaluations over the multistate impact of each system element, obtaining an equivalent of the expected availability for the studied configuration (López-Campos *et al.*, 2014). This requires that the equipment be capable of operating at different load levels. Because of this, the impact of each element of the equipment will vary and the extent of variation will depend on the required load, reliability, ease of maintenance, and other characteristics of each piece.

In general, transport systems are characterized by their flexibility, their high amount of equipment, and their degree of dynamism (Chaowasakoo *et al.*, 2017). A particularity of a load sharing system is that the required capacity can be obtained based on the sum of available equipment that can operate at a lower load than required (Czerny *et al.*, 2016). Overcapacity is

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characterized by operating at a higher installed capacity than required. Thus, there exist a series of combinations that are capable of generating the same results.

Moreover, the classical approach consists of grouped asset families that are classified by make, year, capacity, and model, regardless of the reliability and behavior of each specific element under different requirements and operational characteristics, utilization and history. However, this is a common approach used to model availability (Oliveira *et al.*, 2017). This model considers all equipment to be a single unit in which the capability of this new entity is the sum of all of the capabilities of the collective if the new availability is the mean availability of all equipment. Although this solution could be useful in simplifying the problem, it is a simple generalization because it does not consider scenarios where some elements of the collective are available while others are not, instead of assuming the same state for all of the elements. In addition, when the fleet is in operation and statistics are available, vehicles of the same type have different availabilities and different failure rates as well as different operating costs, none of which are considered by this classical approach.

This study proposes solving this model without grouping equipment and instead considering acquisition/opportunity costs, operational costs, and inefficiency costs due to unavailability as main variables (Parra *et al.*, 2012) by using the life cycle cost (LCC) approach (Woodward, 1997; Durairaj *et al.*, 2002). A mathematical model is presented to integrate all of these aforementioned variables, creating a relatively complete model in terms of overcapacity and availability, relating them to a cost optimization problem.

Thus, the aim is to minimize the cost of equipment based on LCC analysis, with the restriction of capacity. This approach is based on the methodology presented by Woodward (1997), in which different costs were related to fleet size and investment. In this study, we utilized a cost-related objective function (Woodward, 1997), in which we presented investment costs as an opportunity cost that represents not selling equipment that is already possessed by the company and, therefore, represents an opportunity cost of equipment maintenance.

In addition, operation and inefficiency costs are key in selecting how many and what type of vehicles are the best for the company. The proposal for expected availability analysis included in the model is based on probabilistic variable modeling that allows for the inclusion of an overcapacity indicator as the main factor used to calculate fleet availability and, thus, estimate the benefits of the additional fleet elements (trucks). This concept is centered on the innovative analysis given that, traditionally, overcapacity analysis is underdeveloped, usually statistic-focused, and aimed at assessing fleet availability in comparison with the load transported. However, this analysis is not able to model the expected fleet availability because it depends on specific conditions of the period analyzed.

The traditional LCC (Johannknecht *et al.*, 2016b*b*) is characterized by the assessment of direct maintenance costs in the operational expenditure (OPEX) estimate. This proposal also includes an analysis and evaluation of inefficiency costs, which is the measurement used to incrementally evaluate the expected fleet availability in an economic dimension and, from this perspective, justify capacity increases of the fleet (equipment quantity) in order to obtain an optimal size.

Literature review

There are four main topics that are covered in this paper's proposed model: (1) fleet design, (2) LCC analysis, (3) reliability, and (4) overcapacity. The main objective of this study is to identify which vehicles are actually needed for company operations in order to ensure good fleet design. In one sense, this topic is a well-studied subject and there is a great amount of literature regarding techniques, models, and solutions for different industries and particular problems within this field of the study.

In this study specifically, the work of Coelho *et al.* (2016) is of interest because the authors base their analysis on a heterogeneous fleet and propose a model for optimal routing in a vehicle routing problem (VRP) variant, all in order to minimize transportation cost. Because they worked with a heterogeneous fleet, they used a heuristic that they called GILS-VND. This heuristic combines iterated local search (ILS), the greedy randomized adaptive search procedure (GRASP), and the variable neighborhood descent (VND) procedure. Compared with other similar studies, this proposal achieved better economic and technical results. Another study from Coelho *et al.* (2012) also suggested that fleet design in a mining operation is a computationally demanding task, thereby supporting the use of heuristics to develop solutions to real-world applications. Finally, King *et al.* (2017) applied an appropriated branch-and-bound technique to solve the linear programming problem behind the transition between underground and above ground operations. Their technique included rounding heuristics and the authors applied their proposed methodology to a real metal extraction operation. It was a very large problem (50,000 variables and over 1.5 million constraints), but the framework managed to efficiently solve the linear programming problem.

In the case of LCC analysis, the study by Johannknecht *et al.* (2016*a*) combined fleet size, availability, and LCC for gas and oil services. This paper is interesting because it provides a model based on cost efficiency, where fleet size depends on availability. There is an important difference between this study and the proposed model in this study, which is the fact that this study does not uniformly characterize the fleet and also considers overcapacity. However, this study successfully integrated the LCC in order to create a follow-up cost analysis that considered the fleet size. Li and Epureanu (2018) optimized the use of a military fleet using the LCC approach. Their model was able to diminish costs related to operation with minor effects on fleet readiness. This was also demonstrated in a real-life military implementation and achieved excellent results.

Reliability is the third important component. In the study by Johannknecht *et al.* (2016b*b*), a thorough cost analysis considering availability and LCC for oil and gas operations was made. The authors proposed a framework that considered cost from the early concept phase all the way through to deployment. They acknowledged that this kind of consideration was needed to realistically model the expendables that a company must consider when acquiring a particular vehicle or tool, and then empirically demonstrate its efficiency. Finally, the work of Klosterhalfen *et al.* (2014) proposed a model that optimally determined the structure and fleet size for a chemical company while also considering availability constraints and a predefined number of vehicle types. Through this approach, a considerable reduction (120 vehicles) was made to fleet size without compromising company operations.

Finally, overcapacity is another key component to address in our proposed model for fleet design. However, to the best of our knowledge, there are no previously published studies that address this topic as it is presented here. There are, however, studies that have defined and explained the methodology (such as Vestergaard *et al.*, 2003; Kjærsgaard, 2010), but it has not yet been directly applied to fleet design. Thus, this study will

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contribute to the existing literature in this important field of study, which is particularly crucial for mining operations.

Fleet sizing with overcapacity

In order to model fleet size while also considering overcapacity, it is necessary to understand this objective and the justification behind it. Overcapacity is a long-term investment strategy aimed at ensuring better operational results through fleet availability and inefficiency cost reduction. For example, transportation costs in large mines are around 50% or 60% of total operational costs (Chaowasakoo *et al.*, 2017). Moreover, a system with overcapacity minimizes the failure effect and considers the possibility of replacing an unavailable element with a standby element or increasing the idle capacity of other elements. From a capital expenditure (CAPEX) point of view, fleet sizing with overcapacity increases the required investment but reduces OPEX due to higher fleet availability (Amado 2013).

Consider N as the total equipment to be evaluated. Let x_i be defined as follows:

$$x_i = \begin{cases} 1 & \text{if equipment } i \text{ is purchased/maintained} \\ 0 & \text{if equipment } i \text{ is not} \end{cases}$$
$$\forall\, i \in \{1, \ldots, N\}.$$

If the analysis is before the beginning of the project, $x_i = 1$ means that the vehicle would be bought. If an operating fleet is being evaluated, it would mean that the vehicle would be maintained and not sold.

All equipment in the system have two possible operating states: available (with the value 1) and not available (with the value 0). Thus, the first step is to obtain all the possible combinations of operating states. Because operating states are binary, the total number of operating states in the system is J, defined as follows:

$$J = 2^{\sum_{i=1}^{N} x_i}. \tag{1}$$

Consider a combination of system operating states J and the corresponding binary variables used to visualize the operative status of each equipment item are defined as follows:

$$\delta_{ij} = \begin{cases} 1 & \text{if equipment } i \text{ is operative in state } j \\ 0 & \text{if equipment } i \text{ is inoperative in state } j \end{cases} \tag{2}$$
$$\forall\, i \in \{1, \ldots, N\},\ \forall\, j \in \{1, \ldots, J\}.$$

The available capacity of each combination of operative states can be obtained from the matrix δ:

$$C_j^A = \sum_{i=1}^{N} \delta_{ij} \cdot C_i^{\max} \quad \forall\, j \in \{1, \ldots, J\}. \tag{3}$$

Given the operative state j of the system, the ratio between the operational capacity of the corresponding equipment C_{ij}^O and its maximum capacity $\text{Cap}_i^{\max}$ will be the same for all equipment. To determine the final impact of each piece of equipment, it is necessary to identify the operative states j of these systems, so that the available capacity of the equipment is less than or equal to the required system capacity (otherwise, the impact will be defined as 0 because the system already meets the capacity requirement).

Therefore, the ω_j binary variable is defined as follows:

$$\omega_j = \begin{cases} 1 & C_j^A \geq C_S^R \\ 0 & \sim \end{cases} \quad \forall\, j \in \{1, \ldots, J\}. \tag{4}$$

The operative capacity C_{ij}^O of the equipment, therefore, will be given in the following expression:

$$C_{ij}^O = \frac{(\omega_j \cdot C_S^R + (1 - \omega_j) \cdot C_j^A) \cdot \delta_{ij} \cdot \text{Cap}_i^{\max}}{\text{Cap}_i^{\max} + \sum_{k=1 \wedge k \neq i}^{N} \delta_{kj} \cdot \text{Cap}_k^{\max}} \tag{5}$$
$$\forall\, i \in \{1, \ldots, N\}, \forall\, j \in \{1, \ldots, J\}.$$

When calculating impacts, that is, $C_S^R > C_j^A$, the operational state of the system is considered to be the state of reference for all equipment. The aim is to determine the loss of capacity that unavailable equipment exerts on the system, depending on the operational capacity that the system would have if such an equipment were operating. Hence, the formula used to determine the impact will be given in the following equation:

$$I_{ij} = \begin{cases} \dfrac{(C_S^R - C_j^A) \cdot (1 - \delta_{ij}) \cdot C_{i1}^O}{C_S^R \cdot \sum_{k=1}^{N} (1 - \delta_{kj}) \cdot C_{k1}^O} & C_S^R > C_j^A \\ 0 & \sim \end{cases} \tag{6}$$
$$\forall\, i \in \{2, \ldots, N\},\ \forall\, j \in \{2, \ldots, J\}.$$

Considering an operating state of the system, the required capacity will always be satisfied. Therefore, the probability based on the availability of each operating state of the system is defined as follows:

$$P_j^A = \prod_{i=1}^{N} A_i^{\delta_{ij}} \cdot (1 - A_j)^{(1-\delta_{ij})} \quad j \in \{1, \ldots, J\}. \tag{7}$$

The weighted impact of the equipment, considering all possible combinations for the operating state of the system, is given as follows:

$$I_i^{\omega} = \sum_{j=1}^{J} P_j^A \cdot I_{ij} \quad \forall\, i \in \{1, \ldots, N\}. \tag{8}$$

Finally, the availability of load sharing systems and overcapacity is calculated as follows:

$$A_{\text{sist}} = \sum_{i=1}^{N} A_i \cdot I_i^{\omega}. \tag{9}$$

Once the calculation of every component is ready, the related cost of having (or not having) a specific piece of equipment must be calculated. The first cost to calculate is the operational cost,

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which is defined in the following equation:

$$C_{\text{op}_{ij}} = \begin{cases} \dfrac{\delta_{ij} \cdot C_j^A}{\Delta} & C_S^A > C_j^R \\ \delta_{ij} \cdot C_j^A & \sim \end{cases} \quad \forall\, i \in \{2, \ldots, N\},\ \forall\, j \in \{2, \ldots, J\}. \tag{10}$$

where Δ is a scaling factor, introduced to diminish the impact of overcapacity.

With this, we can calculate the operational cost of all scenarios as defined in the following equation:

$$C_{\text{op}} = \sum_{i=2}^{N} \sum_{j=1}^{J} C_{\text{op}_{ij}} \cdot P_j^A \cdot \text{FA}. \tag{11}$$

Therefore, considering (9), we can calculate the inefficiency cost, as shown in the following equation:

$$C_{\text{in}} = (1 - A_{\text{sist}}) \cdot C_{\text{inef}} \cdot \text{FA} \cdot h. \tag{12}$$

where C_{inef} is the inefficiency cost of the fleet per hour due to unavailability, FA is the actualization factor, and h is the annual operational time.

Finally, we used the following cost-related objective function to minimize the global cost:

$$\min_x \sum_{i=1}^{N} x_i iv_i + C_{\text{in}} + C_{\text{op}}. \tag{13}$$

where x_i is the decision of purchasing/maintaining the equipment i (1 if it is purchased/maintained and 0 if not) and iv_i is the investment/opportunity cost related to equipment x_i.

It should be noted that, in the case of fleets in operation, availability indicators, operating costs, and maintenance costs are much more distorted given their historical values. Therefore, the mathematical model can be summarized as follows:

Glossary

N	Number of possible equipment decisions
J	Total of possible scenarios given a set of equipment x_i
x_i	Decision of purchasing/maintaining equipment i, 1 if it is purchased/maintained and 0 if not.
δ_{ij}	Operational status of equipment i in state j
C_j^A	Available capacity for state j
ω_j	Relationship between the available capacity and the required system capacity for state j
C_{ij}^O	Operative capacity of equipment i in state j
I_{ij}	Impact of equipment i regarding the operative capacity of state j
P_j^A	Probability based on the availability of state j
I_i^{ω}	Weighted impact for equipment i considering all states
A_{sist}	System availability
$C_{\text{op}_{ij}}$	Operational cost of state j and equipment i
C_{op}	Operational cost of the system
C_{in}	Expected annual inefficiency cost
C_{inef}	Inefficiency cost of the system per hour
$\text{Cap}_i^{\max}$	Maximum capacity for equipment i
Q_{req}	System required capacity.
Q_{sys}	System total capacity
iv_i	Investment/opportunity cost related to equipment x_i
FA	Discount factor for an h payment
P_j^A	Probability of occurrence of state j
h	Operational planned time in a year

Mathematical model

$$\min_x \sum_{i=1}^{n} x_i iv_i + C_{\text{in}} + C_{\text{op}}$$

$$\text{s.t.} \quad Q_{\text{sist}} \leq Q_{\text{req}}$$

$$x \in \{0, 1\}$$

with

$J = 2^{\sum_{i=1}^{N} x_i}$	$\forall\, i \in \{1, \ldots, N\}$	(1)
$\delta_{ij} = \begin{cases} 1 & \text{if equipment } i \text{ is in operative status in scenario } j \\ 0 & \text{if equipment } i \text{ is inoperative in scenario } j \end{cases}$	$\forall\, i \in \{1, \ldots, N\},\ \forall\, j \in \{1, \ldots, J\}$	(2)
$C_j^A = \sum_{i=1}^{N} \delta_{ij} \cdot \text{Cap}_i^{\max}$	$\forall\, j \in \{1, \ldots, J\}$	(3)
$\omega_j = \begin{cases} 1 & C_j^A \geq C_S^R \\ 0 & \text{other} \end{cases}$	$\forall\, j \in \{1, \ldots, J\}$	(4)
$C_{ij}^O = \dfrac{(\omega_j \cdot C_S^R + (1 - \omega_j) \cdot C_j^A) \cdot \delta_{ij} \cdot C_i^{\max}}{C_i^{\max} + \sum_{k=1 \wedge k \neq i}^{N} \delta_{kj} \cdot C_k^{\max}}$	$\forall\, i \in \{1, \ldots, N\}, \forall\, j \in \{1, \ldots, J\}$	(5)
$I_{ij} = \begin{cases} \dfrac{(C_S^R - C_j^A) \cdot (1 - \delta_{ij}) \cdot C_{i1}^O}{C_S^R \cdot \sum_{k=1}^{N} (1 - \delta_{kj}) \cdot C_{k1}^O} & C_S^R > C_j^A \\ 0 & \text{other} \end{cases}$	$\forall\, i \in \{2, \ldots, N\},\ \forall\, j \in \{2, \ldots, J\}$	(6)
$P_j^A = \prod_{i=1}^{N} A_i^{\delta_{ij}} \cdot (1 - A_j)^{(1 - \delta_{ij})}$	$\forall\, j \in \{1, \ldots, J\}$	(7)

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$$I_i^{\omega} = \sum_{j=1}^{J} P_j^A \cdot I_{ij} \qquad \forall\, i \in \{1, \ldots, N\} \tag{8}$$

$$A_{\text{sist}} = \sum_{i=1}^{N} A_i \cdot I_i^{\omega} \tag{9}$$

$$C_{\text{op}_{ij}} = \begin{cases} \dfrac{\delta_{ij} \cdot C_j^A}{\Delta} & C_S^A > C_j^R \\ \delta_{ij} \cdot C_j^A & \text{other} \end{cases} \qquad \forall\, i \in \{2, \ldots, N\},\ \forall\, j \in \{2, \ldots, J\} \tag{10}$$

$$C_{\text{op}} = \sum_{i=2}^{N} \sum_{j=1}^{J} C_{\text{op}_{ij}} \cdot P_j^A \cdot \text{FA} \tag{11}$$

$$C_{\text{in}} = (1 - A_{\text{sist}}) \cdot C_{\text{inef}} \cdot \text{FA} \cdot h \tag{12}$$

Proposed solution algorithm

To solve the proposed model, two alternatives were explored. First, a deterministic approach was taken, solving the model (when possible) with a full calculation of every possible state. Second, a metaheuristic approach was taken, solving the model for all proposed cases in an approximated (but near-optimal) calculation.

Determinist model

This methodology analyzes and calculates the total cost of all possible scenarios for each combination. The number of calculations needs to achieve an optimal fleet is 2^J. The number of calculations and the way data is managed prevent a solution for fleets with a high number of vehicles.

As shown in Algorithm 1, each step is explained and justified.

Algorithm 1

Step 1: Determine all possible combinations for the fleet.
Step 2: For each combination (Step 1), determine all possible scenarios for the operating states of the system as $J = 2^{\sum_{i=1}^{N} x_i}$ [Eq. (1)].
Step 3: Determine the available capacity for each operative state as $C_j^A = \sum_{i=1}^{N} \delta_{ij} \cdot \text{Cap}_i^{\max}$, given the binary variable δ_{ij} [Eq. (3)].
Step 4: Calculate the operative capacity as $C_{ij}^O = \dfrac{(\omega_j \cdot C_S^R + (1 - \omega_j) \cdot C_j^A) \cdot \delta_{ij} \cdot \text{Cap}_i^{\max}}{\text{Cap}_i^{\max} + \sum_{k=1 \wedge k \neq i}^{N} \delta_{kj} \cdot \text{Cap}_k^{\max}}$, given the binary variable ω_j [Eq. (5)].
Step 5: Determine the probability based on the availability as $P_j^A = \prod_{i=1}^{N} A_i^{\delta_{ij}} \cdot (1 - A_j)^{(1-\delta_{ij})}$ [Eq. (7)].
Step 6: Obtain the weighted impact of the equipment as $I_i^{\omega} = \sum_{j=1}^{j} P_j^A \cdot I_{ij}$ [Eq. (8)].
Step 7: Calculate availability of the load sharing system and overcapacity as $A_{\text{sist}} = \sum_{i=1}^{N} A_i \cdot I_i^{\omega}$ [Eq. (9)].
Step 8: Calculate operational costs from all scenarios as $C_{\text{op}} = \sum_{i=2}^{N} \sum_{j=1}^{J} C_{\text{op}_{ij}} \cdot P_j^A \cdot \text{FA}$ [Eq. (11)], given the individual operational cost C_{op_j}.
Step 9: Calculate the inefficiency cost as $C_{\text{in}} = (1 - A_{\text{sist}}) \cdot C_{\text{inef}} \cdot \text{FA} \cdot h$ [Eq. (12)].
Step 10: Determine the objective function as $\min_x \sum_{i=1}^{N} x_i iv_i + C_{\text{in}} + C_{\text{op}}$ for all possible combinations of the fleet.
Step 11: Select the minimum objective function of all possible combinations of the fleet.

Metaheuristic approaches

There are 2^J possible scenarios that need to be checked in order to find the optimal solution with the entire model being used in each case. Due to this a high number of possibilities, two metaheuristics were tested to find the optimal solution, namely genetic algorithm (GA) and ant colony optimization (ACO). The reason why we chose this type of algorithm is because model complexity scales quickly in relation to the number of trucks that are currently owned by a company. This means that, in real-life applications, a deterministic approach will be very inefficient, costing the company time and money. International mining companies can have fleets as large as 400 trucks that they then seek to optimize (see the Results section for links regarding this fleet size). This makes computation time, even if there is an ample time in which to run the model, an important factor to consider.

GA is an evolutionary algorithm (EA) that was first presented by Holland and Reitman (1977). It is based on a Darwinian approach of the survival of the fittest, an evolutionary process that identifies the best candidate to solve the problem. Through the evolution, genetic operators, such as crossover and mutation, are applied in addition to a selective process that preserves the best individuals over generations. The application to the current problem is presented and described below. ACO, introduced by Dorigo and Gambardella (1997), is a population-based algorithm that mimics the behavior of ants and how they communicate with each other in order to find an optimal path to a specific goal. Specifically, each ant follows a path that leads to a solution of the problem, and ants leave pheromones along the best path (the shortest) that are stored. This allows the next generation to know what paths are better. After enough generations have passed, the ants should, in theory, obtain the optimal solution or a near optimal solution.

The GA algorithm pseudocode is shown in Algorithm 2.

The ACO pseudocode is shown in Algorithm 3.

Specifically, we follow the proposed algorithm by Xiong *et al.* (2006) for the GA approach and Hristakeva and Shrestha (2004) for the ACO approach. The specifications for both algorithms can be seen in Table 1.

Simulation experiment

The proposed model was tested in a simulation using different fleet sizes and applied these two metaheuristic approaches to solve it. Table 2 presents a technical description of the trucks used for this simulation, including capacity, availability, and opportunity cost.

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Algorithm 2 (GA)

Step 1: Initialize the first population as an alternative fleet option.
Step 2: While (generation < maximum generations) or (stall < maximum stall) perform:
Step 2.1: Evaluate each chromosome in Algorithm 1, where Eq. (13) is the fitness function.
Step 2.2: If the stopping criteria are not reached, apply genetic operators to form the next generation.
Step 2.3: Sum 1 to generation, and return to Step 2.
Step 3: When at least one of the stopping criteria is reached, end the sequence and present the best chromosome identified so far.

Algorithm 3 (ACO)

Step 1: Initialize the first population of ants.
Step 2: For 1 to maximum iterations, do.
Step 2.1: For each ant, do.
Step 2.1.1: Randomly select the path of the ant.
Step 2.1.2: Calculate the cost and solution for that particular ant, using Eq. (13) as the objective function and restricting the computation by Algorithm 1.
Step 2.2: Update pheromones and evaporate.

Table 1. Hyperparameter settings for ACO and GA

GA settings		ACO settings	
Generations	200	Maximum iterations	200
Stall	50	Number of ants	80
Population size	20	Alpha	0.1
Crossover rate	0.7	Beta	0.002
Mutation rate	0.1	Rho	0.1

The first column shows the main hyperparameters of the GA. Generations refer to the maximum number of iterations that the algorithm can perform to find the solution. Stall refers to the maximum number of generations have to pass consecutively and, if an error does not improve, the algorithm stops. Population size refers to the number of genes that are candidates to solve the problem. Crossover rate and mutation rate are the percentages at which these two operators are applied. The second column contains the main hyperparameters of the ACO. Maximum iterations refer to the maximum times that the algorithm can be run to solve the problem. The number of ants are the population of ants that search for the optimal solution. Alpha and beta refer to the relative importance of track and visibility, respectively, and rho is the durability of the track.

The computational environment used was Matlab 2018a, Xubuntu 16.04, two Intel Xeon E5-2630 processors, and 12 GB of ram.

The simulation experiment was developed in an incremental fashion. Five scenarios were tested considering fleets of size 10, 12, 15, 18, and 20, in which the GA, ACO and complete enumeration approaches were selected to solve the problem. The results for each approach were then compared. In all simulations, the required capacity was set at 70% of total capacity, inefficiency cost at $110 (USD/h), 10% annual interest rate, and 10 years for an evaluation period. As expected, the complete enumeration (deterministic) found the global optimal solution, so the two metaheuristics were tested against this approach. Additional experiments consisting of 22, 25, and 30 trucks, for which the deterministic approach take over a day to compute, were also performed. The results of all experiments can be seen in Tables 3–5 for the deterministic, ACO, and GA approaches, respectively.

The simulations that used small fleet sizes were developed in order to determine the relationship between the actual global minimum and the minimums found by the metaheuristic approaches. We can see that, in general, both metaheuristics managed to find the global minimum but under different conditions. ACO found the exact global minimum for small fleet sizes, that is, 10, 12, and 15 trucks, but only found a near optimal solution for 18 (0.34% difference) and 20 trucks (1.75% difference). On the other hand, GA did not behave well for small fleet sizes, resulting in considerable differences with the optimal case (2.43% for 10 trucks and 0.34% for 12 trucks). However, GA interestingly find the exact global minimum for 15 and 18. Yet, it also failed to determine the actual global minimum for 20 trucks, having a difference of 1.07%. This is a very important result because it shows that this kind of algorithm can actually find the optimal solution for particular problems, opening up the possibility of applying this method to a real-world application with excellent results.

Considering the above, the time consumption analysis was also worth performing, especially given the fact that the actual global minimum can be reached through metaheuristic methods. For very small cases, as expected, the deterministic approach was faster than the metaheuristic methods. This is not a surprising result because, for small problems, the algorithm takes more time in preparing their configurations than actually finding the solution. Specifically, for the first two simulations, there was a big difference in time (×5 for ACO and ×3 approximately for GA). Yet, in the simulation of 15 trucks, ACO managed to reduce time consumption by around 38%, and GA was slightly higher (3.63% higher). When the 18 trucks simulation was performed, time was reduced in both approaches by a seventh of the time that it took the deterministic approach to complete the same problem. Significantly, GA managed to actually find the global minimum, which is a promising result for larger applications. In the case of 20 trucks, these findings made this even more evident, given that the deterministic approach took almost 2 days to find the solution, while the metaheuristic methods took just seconds.

It is important to notice the actual trucks that were selected in each case. For the fleet size of 10 trucks, only ACO found the actual global minimum, which was to select all the trucks. In contrast, GA dropped the 8th truck, finding a higher cost function. For the 12 trucks, both ACO and GA kept 11 of the 12 trucks, but again only ACO actually dropped the correct one (the third one) and GA dropped the 10th, again finding a higher cost function.

An interesting result happened in the 15 fleet size simulations. In that case, both ACO and GA found the global minimum and, therefore, dropped the correct truck, the third one. Until this simulation, we had noticed that ACO behaved better than GA in solving the problem, both in terms of cost function as well as identification of the actual solution and time consumption.

However, for higher fleet sizes, GA achieved better results, finding the global minimum (and therefore, selecting the correct trucks to drop) for 18. Both algorithms failed to find the optimal minimum for 20 trucks, but ACO selected the same amount of trucks in the fleet (17 trucks), but made different choices than GA, which selected 18 of the 20 trucks. Yet, GA actually reached a solution close to the actual minimum, regardless of selecting one more truck. When taking time into consideration, we believe that this result could be due to the configurations regarding the number of ants, maximum iterations, and alpha setting of the ACO algorithm. This could be a topic for further research as finding the best hyperparameters for this algorithm will not be considered

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Table 2. Fleet technical description

ID	Availability (%)	Capacity (ton)	Opportunity cost (MUSD)	ID	Availability (%)	Capacity (ton)	Opportunity cost (MUSD)
1	74.20	400	23.20	16	73.50	300	16.26
2	71.20	300	15.60	17	75.40	350	15.58
3	71.50	400	23.92	18	83.10	350	14.00
4	87.00	250	11.75	19	79.70	250	11.20
5	75.90	350	16.94	20	81.20	350	15.16
6	85.60	350	16.59	21	87.10	300	12.72
7	83.30	400	17.56	22	87.30	200	8.32
8	69.80	250	10.43	23	83.90	350	14.98
9	78.90	250	12.80	24	83.10	300	17.16
10	65.50	350	18.31	25	77.50	300	14.70
11	85.60	300	14.94	26	65.60	400	18.36
12	86.90	300	14.82	27	69.10	300	14.64
13	79.20	300	14.58	28	71.40	350	20.51
14	66.80	400	17.24	29	82.30	250	13.85
15	65.50	200	10.72	30	76.60	250	10.83

The information in this table is organized as follows: Availability and capacity are unique parameters measuring confidence that are specific to each truck. Opportunity cost refers to how much the truck cost, meaning that, in the optimal solution, the truck not selected is actually a source of positive revenue for the organization.

Table 3. Results from the deterministic approach

	Deterministic			
Fleet size	Best cost	Time (s)	# Trucks In	Trucks Left
10	1,927,057	0.16	10	–
12	2,096,203	1.33	11	3
15	2,490,907	28.15	14	3
18	2,841,593	704.41	16	3, 10
20	3,021,71	7053.01	17	3, 10, 15

This table shows the results of solving the problem by using the complete enumeration approach. Best cost refers to the total cost of the trucks selected. Time refers to how much time it takes for the algorithm/approach to find the solution. # Trucks In refer to how many trucks must be considered in the optimal solution of the problem. Trucks Left refer to which trucks, specifically, are left out of the solution.

Table 4. Results from the ACO approach

	ACO			
Fleet size	Best cost	Time (s)	# Trucks In	Trucks Left
10	1,927,057	4.35	10	–
12	2,096,203	6.79	11	3
15	2,490,907	17.45	14	3
18	2,851,261	49.58	15	3, 10, 15
20	3,074,692	109.19	17	2, 15, 16

This table shows the results of solving the problem by using the ACO approach. Best cost refers to the total cost of the trucks selected. Time refers to how much time it takes for the algorithm/approach to find the solution. # Trucks In refer to how many trucks must be considered in the optimal solution of the problem. Trucks Left refer to which trucks, specifically, are left out of the solution.

in this work. Thus, it was relatively expected that ACO would take less time but fail to find the optimal solution.

This allows us to conclude that, considering the time required for the deterministic approach to complete simulations, the experiment with larger fleet's sizes would be pointless to solve using this approach because of the clear exponential growth that occurs with increases in fleet size. Thus, three more simulations were made that only considered the results of the metaheuristic methods. Their results are shown in Tables 6 and 7.

In this extended simulation, we saw that GA managed to obtain better cost functions than ACO in two of the three experiments. However, ACO found the better solution for the smallest of these simulations (of 22 trucks). The time consumption observation that was previously described was also seen here. Indeed, GA took more time but was able to find better solutions to the problem. A very interesting result was in relation to the actual truck composition that each approach found. GA tended to

Table 5. Results from the GA approach

	GA			
Fleet size	Best cost	Time (s)	# Trucks In	Trucks Left
10	1,973,939	2.82	9	8
12	2,104,238	4.58	11	10
15	2,490,907	29.17	14	3
18	2,841,593	118.17	16	3, 10
20	3,053,994	596.47	18	3, 16

This table shows the results of solving the problem by using the GA approach. Best cost refers to the total cost of the trucks selected. Time refers to how much time it takes for the algorithm/approach to find the solution. # Trucks In refer to how many trucks must be considered in the optimal solution of the problem. Trucks Left refer to which trucks, specifically, are left out of the solution.

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Table 6. Extra ACO simulations

Fleet size	ACO			
	Best cost	Time (s)	# Trucks In	Trucks Left
22	3,208,036	220.12	19	3, 9, 14
25	3,580,795	770.50	20	2, 8, 10, 15, 17
30	4,253,014	6,190.40	24	1, 15, 17, 25, 27, 28

This table shows additional results obtained by using the ACO approach, specifically for greater fleet sizes, which are not possible to solve by using the complete enumeration approach. Best cost refers to the total cost of the trucks selected. Time refers to how much time it takes for the algorithm/approach to find the solution. # Trucks In refer to how many trucks must be considered in the optimal solution of the problem. Trucks Left refer to which trucks, specifically, are left out of the solution.

Table 7. Extra GA simulations

Fleet size	GA			
	Best cost	Time (s)	# Trucks In	Trucks Left
22	3,210,289.29	1092.50	19	1, 8, 15
25	3,469,942.15	4717.10	21	1, 3, 10, 15
30	4,209,019.51	68,526.00	25	1, 2, 3, 8, 15

This table shows additional results obtained by using the GA approach, specifically for greater fleet sizes, which are not possible to solve by using the complete enumeration approach. Best cost refers to the total cost of the trucks selected. Time refers to how much time it takes for the algorithm/approach to find the solution. # Trucks In refer to how many trucks must be considered in the optimal solution of the problem. Trucks Left refer to which trucks, specifically, are left out of the solution.

drop slightly less trucks compared with ACO. Although the difference was just one truck in these simulations, this difference could result in a bigger difference for bigger fleet sizes. An important point to consider is that, in general, better solutions were found when more trucks were selected rather than when more trucks were dropped, an important fact for larger fleets.

The important reduction in time consumption presented an opportunity to apply the proposed model to real mining industry situations, where the companies have to optimize very large fleets. To name a few, two of the biggest Chilean mining operations work with 172 haul trucks (Escondida[1]) and 120 trucks (Chuquicamata[2]). Rio Tinto[3] (Australia) works with 400 haul trucks and Grasberg[4] (Indonesia) works with 170 trucks. Although the simulation made in the study was relatively small compared with the real fleet sizes used today in the mining industry, they allow for a fair comparison between the two models. Now, given what happened with the deterministic approach, the exponential time that was needed to make all the necessary calculations makes it impossible to apply this method to such large fleets. The fairly small amount of time that ACO and GA needed to find near-optimal solutions make them good possibilities that could be effective in real-world applications. In order to better visualize this, Figure 1 showed a log-time graph with the three approaches.

This figure is a log–log graph of fleet size and shows how long it takes the algorithm/approach to find the optimal solution for that particular configuration. The deterministic approach can solve a problem only to a certain point, after which it can no longer solve problems. Also, metaheuristic approaches are better suited for larger problems as they (1) can solve them within a reasonable time and (2) for smaller problems, the complete enumeration is faster and is guaranteed to find the optimal solution.

This figure clearly shows the rapid growth of the deterministic approach, even in log transformation. Both ACO and GA had a slower tendency, expressed in the slope of the log-time function. The higher slope for the deterministic approach means that it consumes much more time when there are more trucks in the fleet. This allows us to estimate the time required for every approach in a real-world application. Considering that most companies perform fleet optimization once a year, ACO could solve this problem in less than a year (in 338 days) for a fleet composed of 130 trucks, whereas GA could solve the problem in less than a year (333 days) for a fleet composed of 64 trucks. Considering the companies that were cited early, both approaches could actually solve problems for even larger fleets, depending on the computational environment and algorithm enhancement that could be performed on the approaches presented here. This is open to future research. However, this work has already shown that large fleets can be optimized – while also considering overcapacity, availability, and inefficient cost – in less than a year.

Discussion and conclusions

In this study, we proposed a complete framework that considers overcapacity, availability, and LCC for fleet design problems. To the best of our knowledge, there is no currently published study that includes all of these topics at once in relation to mining operations. Thus, this paper contributes to the literature and the current practical resolution for the model can be easily applied to real-world situations. Specifically, we presented a theoretical optimization model and tested it in different simulation scenarios, solving the problem via complete enumeration (deterministic) approach (when possible) as well as ACO and GA.

We obtained some interesting results in the simulation experiment, where the metaheuristics successfully found the global minimum. For the smaller-sized problems (10 and 12 trucks), ACO behaved more robustly than GA, both in terms of cost function finding and time consumption. However, GA managed to obtain better global minimum solutions for larger fleets, whereas ACO, although faster, only obtained near optimal solutions.

Given the time consumption associated with each approach, the deterministic approach grew exponentially with the fleet size, and we could only solve problems for fleets of a maximum size of 20 trucks. However, metaheuristic methods allowed us to solve problems for much larger fleets, with a theoretical maximum of 64 trucks for GA and 130 trucks for ACO, with the restriction being the computational environment used.

Considering the fleet size of actual companies that are in the mining business today, this framework could be used to optimally

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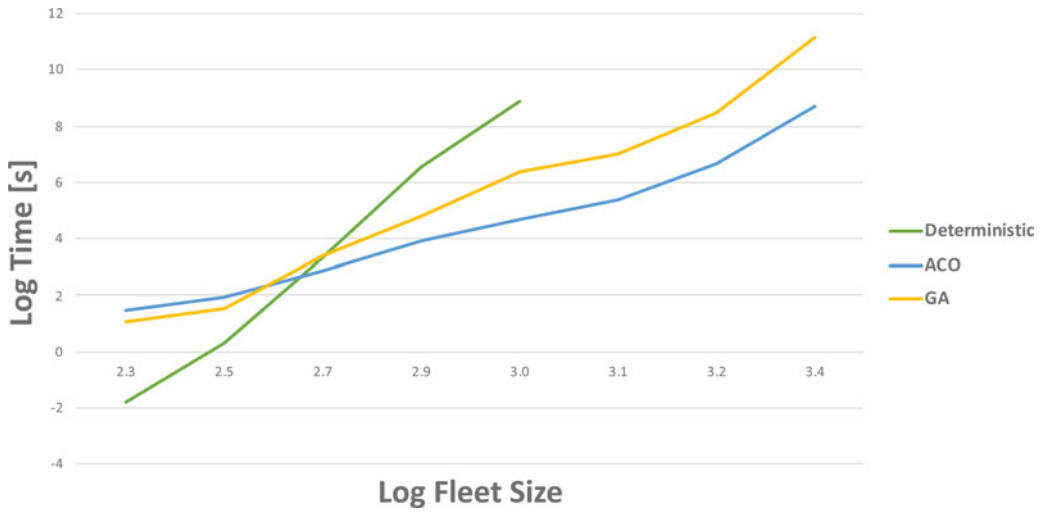


Fig. 1. Time consumption based on fleet size.

determine the fleet size in real-world applications that would only require a few changes to be made to the computational environment and a few adjustments to the metaheuristic algorithms. However, we have demonstrated here that a model that includes overcapacity, availability, and LCC for fleet design is not only possible but also provides more realistic results where each truck is treated separately based on its own specifications.

In terms of future research, we believe that newer metaheuristic algorithms (such as NGA-II or a robust version of ACO) could enable better solutions for large fleets.

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