# Application of Simulation in Truck Fleet Selection and Sizing in Open-Pit Mining: With and Without Truck Failure Effect

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## ABSTRACT

*In this study, a novel simulation model is introduced to assess and determine the optimal configuration of truck fleet type and size for mining operations. The aim is to improve operational efficiency, productivity, and sustainability. The study investigates the performance of both homogeneous and heterogeneous fleets in various scenarios. The findings reveal that the heterogeneous fleet outperforms the homogeneous fleet in terms of meeting production targets and minimizing fuel consumption, thereby striking an effective balance between productivity and sustainability. Conversely, the homogeneous fleet exhibits higher total fuel consumption and fuel consumption per ton production. Additionally, smaller trucks in the fleet offer greater flexibility in transferring ore materials and prove advantageous in scenarios involving truck failures, with reduced average downtime. Therefore, homogenous fleet of smaller trucks outperforms the heterogenous fleet when truck failure is considered. The study emphasizes the importance of considering factors such as fleet type and sizing, truck failures, fuel consumption, and production rates in optimizing fleet performance and material flow in mining operations. These insights contribute to the development of strategies for improving overall mining efficiency and reducing costs.*

***Keywords:*** *Truck fleet selection and sizing, Open-pit mine, Sustainability, Truck failure, Simulation*

## 1. Introduction

Open-pit mining presents a variety of substantial challenges requiring solutions. These encompass mine design, road network analysis, infrastructure optimization, fleet management, truck quantity and type determination, and truck allocation. Achieving an efficient truck fleet size is crucial for a cost-effective hauling system in mining, ensuring production needs are met while minimizing expenses. Choosing the quantity and types of trucks for the fleet is a substantial financial commitment, given its non-reversible nature (Salhi and Rand, 1993). Within the mining system, an excess of trucks can lead to over-trucking, with trucks waiting for shovels, while too few trucks result in under-trucking, causing shovels to wait (Ataeepour and Baafi, 1999). Having the right fleet size is crucial for efficient transportation. Having too few or too many trucks can cause delays and underutilization. A shortage of trucks reduces production, while an excess raises GHG emissions. Achieving the optimum number of trucks maintains a balance between meeting production needs and minimizing GHG emissions.

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Simulation modeling proves potent for testing alternative actions, offering insights into optimal outcomes. In mining, these models predict the impact of new ideas and policies. Monte Carlo Simulation and specialized languages have simplified discrete event model creation, aiding analysis of production capacities, bottleneck identification, and resource utilization (Knights and Bonates, 1999). Manríquez et al. (2019) highlighted discrete event simulation's role in designing mining systems, including transportation routes and equipment types. For truck allocation, simulation has long been valued. Maran and Topuz (1988) stressed its importance, especially when traditional methods fall short. Discrete event simulation is widely used in optimizing truck and shovel systems due to its capacity to model randomness and complexity (Que et al., 2016).

This study employs Arena simulation software to develope a discrete event simulation model, evaluating fleet truck sizing and selection's influence on production rates and GHG emissions in open-pit mining. Truck allocation in the simulation model relies on a multi-objective optimization model aiming to minimize deviations from target production, shovel idle time, truck wait time, and fuel consumption. The study also examines the impact of truck failures in production and truck fleet selection.

In the upcoming sections, following a literature review, this research will introduce the simulation model and the integrated optimization model. Subsequently, a detailed explanation of the case study, including key performance indicators (KPIs), will be provided. Shifting to the results, the paper will analyze and compare the performance of different scenarios related to truck selection, sizing, and the impact of failures within a case study. Lastly, the paper will engage in a comprehensive discussion of the results, drawing conclusions, and outlining potential directions for future research.

## 2. Literature Review

The use of simulation techniques is crucial for effectively addressing fleet management and haulage systems within open-pit mining. Through the creation of a dynamic virtual environment, simulation empowers researchers and engineers to comprehensively analyze the impact of truck fleet selection and sizing in mining operations, production rate, and GHG emissions. As a result, decision-makers gain the insights needed to make informed choices. Simulation serves as a reliable tool for evaluating trade-offs and alternative scenarios, ultimately providing decision-makers with a clearer perspective, and enhancing efficiency, sustainability, and resource utilization. In what follows, a series of studies are presented that address the fleet selection and sizing challenge in open pit mining, followed by application of simulation in this context.

Bozorgebrahimi et al. (2003) reviewed critical parameters of fleet sizing in open pit mining. On the other hand, Burt and Caccetta (2018, 2014) explored fleet selection problem in mining, supported by case studies. They reviewed fleet selection problem challenges, applications, and solution approaches within the context of open-pit mining.

Over the years, various techniques have been used in fleet selecting and sizing in open-pit mining. Markeset and Kumar (2000) introduced the Lifecycle costing technique, followed by Samanta et al. (2002) who combined the Analytical Hierarchy Process and Life-cycle costing. Different approaches like the match factor concept (Burt and Caccetta, 2007; Douglas, 1964), queuing theory (Ercelebi and Bascetin, 2009), linear programming (Edwards et al., 2001; Ta et al., 2013), and machine repair modeling (A. Krause and Musingwini, 2007) have been used conventionally. In addition, innovative computer-based algorithms, including expert systems, fuzzy set theory, genetic algorithms, multiple criteria decision-making, and machine learning algorithms have also emerged (Bandopadhyay and Venkatasubramanian, 1987; Bazzazi et al., 2011; Li and Song, 2009; Marzouk and Moselhi, 2004; Nobahar et al., 2022). To address uncertainties in the selection of surface mining fleet, it is necessary to create a stochastic model. Discrete event simulation, pioneered by Rist (1961) for mine haulage, offers a solution by considering stochastic parameters. Noteworthy applications of this simulation method can be found in various mining studies (Ataeepour and Baafi, 1999; Baafi and Ataeepour, 1998; Chaowasakoo et al., 2017; Kolonja and Mutmansky, 1994; Que et al., 2016; Yuriy and Vayenas, 2008; Zeng et al., 2019; Zhang et al., 2022). However, these models often lack accuracy with respect to real-world fleet management systems and underestimate production capacity effects. To address these limitations, Moradi Afrapoli et al. (2019) presented an integrated simulation model encompassing mining, processing, and dispatching systems. Subsequently, several studies utilized the integration of simulation and dispatch optimization modeling to predict the optimal solution for the fleet selection and sizing problem in the presence of uncertainty (Mirzaei-Nasirabad et al., 2023; Mohtasham et al., 2021; Moradi-Afrapoli et al., 2021; Moradi-Afrapoli and Askari-Nasab, 2020; Moradi Afrapoli et al., 2022; Upadhyay et al., 2021; Yeganejou et al., 2022). Nevertheless, their model fails to account for energy efficiency, greenhouse gas (GHG) reduction, and truck failure. In this study, an integrated framework is established that integrates simulation and optimization, considering production capacity, energy efficiency, and GHG mitigation as well as truck failure.

## 3. Methodology

The integrated simulation and optimization model in this research relies on various input parameters and data, which encompass the short-term production schedule, the mine's road network, specifications for shovels and trucks detailing capacities and performance, information about dumping locations and their capacities, as well as the count of dumping points per dump location. Moreover, fitted probability distributions are necessary for numerous input variables, including loading and dumping times, hauling durations, empty travel times, backing times, spot times, shovel bucket capacities, and truck loading capacities. The majority of these inputs are stochastic, which makes them particularly challenging. Consequently, historical data for such random variables were employed to fit diverse probability density functions.

### 3.1. Multi-Objective Optimization Model

The truck dispatching optimization model utilized in this research is centered around four primary objectives: reducing deviations from target path flow rates, minimizing fuel consumption (and GHG emissions), minimizing shovel idle time, and minimizing truck wait time. Since these four objectives exist in varying dimensions, it is necessary to transform them into dimensionless forms. An efficient operation requires the satisfaction of several constraints. Furthermore, certain estimated parameters are utilized within the constraints, and their estimation methods (formulas) are presented in the equalization constraints of the mathematical model. Several indices, parameters, and decision variables are available within the optimization model. The indices are as follows:

| | |
|---|---|
| $t$ | Index for set of trucks: $t = \{1, \dots, T\}$ |
| $s$ | Index for set of shovels: $s = \{1, \dots, S\}$ |
| $d$ | Index for set of dumping points: $d = \{1, \dots, D\}$ |
| $d'$ | Index for set of locations where trucks are required to dump their load before traveling to the new shovel: $d' = \{1, \dots, D\}$ |
| $w$ | Index for set of weights assigned to individual goals: $w = \{1, 2, 3, 4\}$ |
| $g$ | index for the group of trucks that are currently waiting in a queue of the shovel: $g = \{1, \dots, NTWS\}$ |

The parameters are introduced below:

| | |
|---|---|
| $IT_{tsd}$ | Idle time for shovel $s$ if truck $t$ is assigned to transport material from shovel $s$ to the dumping point $d$ |
| $WT_{tsd}$ | Wait time for truck $t$ if it is assigned to transport material from shovel $s$ to the dumping point $d$ |
| $N_w$ | Normalized weights of individual goals based on priority |
| $AF$ | A factor balancing available trucks with the required capacity of plants |
| $PC_d$ | Capacity of the plant $d$: $d = \{1, \ldots, P\} \subset \{1, \ldots, \mathrm{D}\}$ |
| $SC_s$ | Production capacity of shovel $s$ |
| $MP_{sd}$ | Path flow rate for the path from shovel $s$ to the dumping point $d$ that the production operation has met so far |
| $TC_t$ | Actual capacity of truck $t$ (tonne) |
| $NTC_t$ | Nominal capacity of truck $t$ (tonne) |
| $P_{sd}$ | Path flow rate for the path from shovel $s$ to the dumping point $d$ |
| $TR_{tsd}$ | Next time truck $t$ reaches shovel $s$, if truck $t$ is assigned to transport material from shovel $s$ to the dumping point $d$ |
| $SA_{tsd}$ | Next time shovel $s$ is available to serve truck $t$, if truck $t$ is assigned to transport material from shovel $s$ to the dumping point $d$ |
| TNOW | Current time of the operation/simulation |
| $LD_{td'}$ | The distance truck $t$ must travel to reach the dumping point $d'$ to dump its load |
| $ED_{td's}$ | The distance truck $t$ must travel from the dumping point $d'$ to the next expected shovel $s$ |
| $ALT_t$ | Average loading time of truck $t$ |
| $APL_t$ | Average payload of truck $t$ |
| $LV_{td's}$ | Average loaded velocity of truck $t$ traveling to dumping point $d'$ and will travel to shovel $s$ after dumping its load |
| $EV_{td's}$ | Average empty velocity of truck $t$ traveling from dumping point $d'$ to the next expected shovel $s$ |
| $DQ_{td'}$ | Queue time for truck $t$ in the queue of the dumping point $d'$ |
| $DT_{td'}$ | Dump time for truck $t$ to dump its material in dumping point $d'$ |

| | |
|---|---|
| $NTWS_s$ | Number of trucks waiting in queue at shovel $s$ |
| $ST_g$ | Spotting time for the truck $g$ in the queue |
| $LT_g$ | Loading time for the truck $g$ in the queue |
| $\alpha_t$ | Intercept of truck $t$ for the fuel consumption |
| $\beta_t$ | Payload coefficient of truck $t$ for the fuel consumption |
| $\gamma_t$ | Loading time coefficient of truck $t$ for the fuel consumption |
| $\tau_t$ | Idle time coefficient of truck $t$ for the fuel consumption |
| $\omega_t$ | Empty traveling time coefficient of truck $t$ for the fuel consumption |
| $\varphi_t$ | Loaded traveling time coefficient of truck $t$ for the fuel consumption |
| $SIT_{tsd}$ | Shovel idle time coefficient, by assigning truck $t$ to the path of shovel $s$ to dumping point $d$ |
| $TWT_{tsd}$ | Truck wait time coefficient, by assigning truck $t$ to the path of shovel $s$ to dumping point $d$ |
| $F_{tsd}$ | Truck fuel consumption coefficient, by assigning truck $t$ to the path of shovel $s$ to dumping point $d$ |

Below are the decision variables:

| | |
|---|---|
| $x_{tsd}$ | Binary variable equals to 1 if truck t assigns to the path of shovel $s$ to dumping point $d$ , and 0 otherwise |
| $y_{sd}^{-}$ | Negative deviation of the met path flow rate and the desired path flow rate for the path between shovel $s$ and dumping point $d$ |
| $y_{sd}^{+}$ | Positive deviation of the met path flow rate and the desired path flow rate for the path between shovel $s$ and dumping point $d$ |

The model has the following objective functions:

$$f_1 = \sum_{s=1}^{S} \sum_{d=1}^{D} (y_{sd}^{-} + y_{sd}^{+}) \tag{1}$$

$$f_2 = \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{d=1}^{D} F_{tsd} x_{tsd} \tag{2}$$

$$f_3 = \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{d=1}^{D} SIT_{tsd} x_{tsd} \tag{3}$$

$$f_4 = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{d=1}^{D} TWT_{tsd}x_{tsd} \tag{4}$$

The following two formulas are used to normalize the objective functions and to present the normalized weighted sum objective function, respectively.

$$\bar{f_i} = \frac{f_i - U_i}{N_i - U_i} \qquad \forall i \in \{1,2,3,4\} \tag{5}$$

$$f = N_1\bar{f_1} + N_2\bar{f_2} + N_3\bar{f_3} + N_4\bar{f_4} \tag{6}$$

The constraints of the model are expressed below:

$$\sum_{s=1}^{S}\sum_{d=1}^{D} TC_t x_{tsd} \le NTC_t \qquad \forall t \in \{1,\dots,T\} \tag{7}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S} TC_t x_{tsd} \ge AF \times PC_d \qquad \forall d \in \{1,\dots,P\} \tag{8}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D} TC_t x_{tsd} \le SC_s \qquad \forall s \in \{1,\dots,S\} \tag{9}$$

$$\sum_{t=1}^{T} TC_t x_{tsd} + MP_{sd} + y_{sd}^{-} - y_{sd}^{+} = P_{sd} \qquad \forall s \in \{1,\dots,S\}\ \&\ \forall d \in \{1,\dots,D\} \tag{10}$$

$$AF = \frac{\sum capacity\ of\ available\ trucks}{\sum required\ flow\ rate\ at\ paths} \tag{11}$$

$$TR_{tsd} = TNOW + \frac{LD_{td'}}{LV_{td's}} + DQ_{td'} + DT_{td'} + \frac{ED_{td's}}{EV_{td's}} \tag{12}$$
$$\forall t \in \{1,\dots,T\}\ \&\ \forall s \in \{1,\dots,S\}\ \&\ \forall d \in \{1,\dots,D\}\ \&\ \forall d' \in \{1,\dots,D\}$$

$$SA_{tsd} = TNOW + \sum_{g=1}^{NTWS_s} \left(ST_g + LT_g\right) \tag{13}$$
$$\forall t \in \{1,\dots,T\}\ \&\ \forall s \in \{1,\dots,S\}\ \&\ \forall d \in \{1,\dots,D\}$$

$$SIT_{tsd} = \max\left(0, TR_{tsd} - SA_{tsd}\right) \tag{14}$$
$$\forall t \in \{1,\dots,T\}\ \&\ \forall s \in \{1,\dots,S\}\ \&\ \forall d \in \{1,\dots,D\}$$

$$TWT_{tsd} = \max\left(0, SA_{tsd} - TR_{tsd}\right) \tag{15}$$
$$\forall t \in \{1,\dots,T\}\ \&\ \forall s \in \{1,\dots,S\}\ \&\ \forall d \in \{1,\dots,D\}$$

$$F_{tsd} = \alpha_t + \beta_t \times APL_t + \gamma_t \times ALT_t + \tau_t \times TWT_{tsd} + \omega_t \frac{ED_{td's}}{EV_{td's}} + \varphi_t \frac{LD_{td'}}{LV_{td's}} \quad (16)$$

$$\forall t \in \{1, \dots, T\} \,\&\, \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \,\&\, \forall d' \in \{1, \dots, D\}$$

$$x_{tsd} \in \{0,1\} \qquad \forall t \in \{1, \dots, T\} \,\&\, \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \quad (17)$$

$$y_{sd}^{-} \geq 0 \qquad \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \quad (18)$$

$$y_{sd}^{+} \geq 0 \qquad \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \quad (19)$$

The first objective employs a goal programming approach to minimize deviations from path flow rates, which is computed using Eq. (1). The second objective function seeks to minimize the total fuel consumption of active trucks using Eq. (2). The third objective centers on minimizing the idle time of active shovels using Eq. (3). The fourth objective is to decrease truck wait time during operations, calculated using Eq. (4). To achieve the model's solution, the four objectives are made dimensionless using Nadir and Utopia points (Grodzevich and Romanko, 2006), defining lower and upper limits. This process scales objectives from 0 to 1 using Eq. (5). Priority weights for the weighted sum method are based on normalized versions of objectives from Eqs. (1) to (4) in Eq. (6). There are several constraints in the model. Constraint (7) restricts a truck's payload to its nominal capacity for tonnage transport in one cycle. In constraint (8), the material transported to processing plants via all trucks must fulfill processing targets set by each plant, adjusted by the AF factor (calculated in Eq. (11)). Only the AF portion of plant requirements can be fulfilled. Constraint (9) limits haulage capacity to a shovel's nominal digging rate, while constraint (10) calculates path flow rate deviations for paths linking a shovel as a source and a dumping location as a destination. Eq. (12) is employed to ascertain the arrival time of each truck for loading by a shovel. Shovel availability is determined using Eq. (13), predicting the next time the shovel will be available to load the truck. The coefficients for the three optimization objectives are computed through Eqs. (14), (15), and (16), corresponding to shovel idle time, truck wait time, and fuel consumption objective functions, respectively. Lastly, constraint (17) guarantees the binary nature of the first set of decision variables, while constraints (18) and (19) ensure non-negativity for the goal programming variables.

### 3.2. Integrated Simulation and Optimization Framework

The simulation section of the framework employs a step-by-step approach, as depicted in Figure 1. Initially, the model identifies trucks awaiting assignment to operational shovels and destinations. Subsequently, the multi-objective optimization model comes into action, efficiently allocating unassigned trucks. This ensures that all available trucks are effectively assigned their respective tasks. Throughout the simulation, the optimization model is recalibrated in response to specific events, such as truck initiation, dumping completion, or truck reactivation following a failure. These occurrences trigger a reassessment of the optimal assignment for each truck. The optimization process for assigning available trucks persists throughout the simulation runtime until the predefined time period for the simulation is reached. The input data for the framework encompasses the quantity and types of trucks present within the system. As a result of this input, the framework generates Key Performance Indicators (KPIs) statistical report, which will be elaborated upon in the subsequent section. Figure 2 depicts the hauling procedure executed by trucks in open-pit mining. The sequence commences at the terminal, where trucks are designated to ore or waste shovels, determined by considerations like production goals, travel durations, queue statuses, and processing periods. Following this, the trucks journey to either the waste dump or one of the crushers/plants, contingent on their cargo and the hopper capacities at each plant. Ultimately, the trucks are reassigned to a different shovel based on the timetable and objective functions, and this cycle persists. Finally, Figure 3 presents a flowchart of a truck status during the operation. Once a failed truck has been repaired, it becomes imperative to reassign it to a new loading or unloading point.

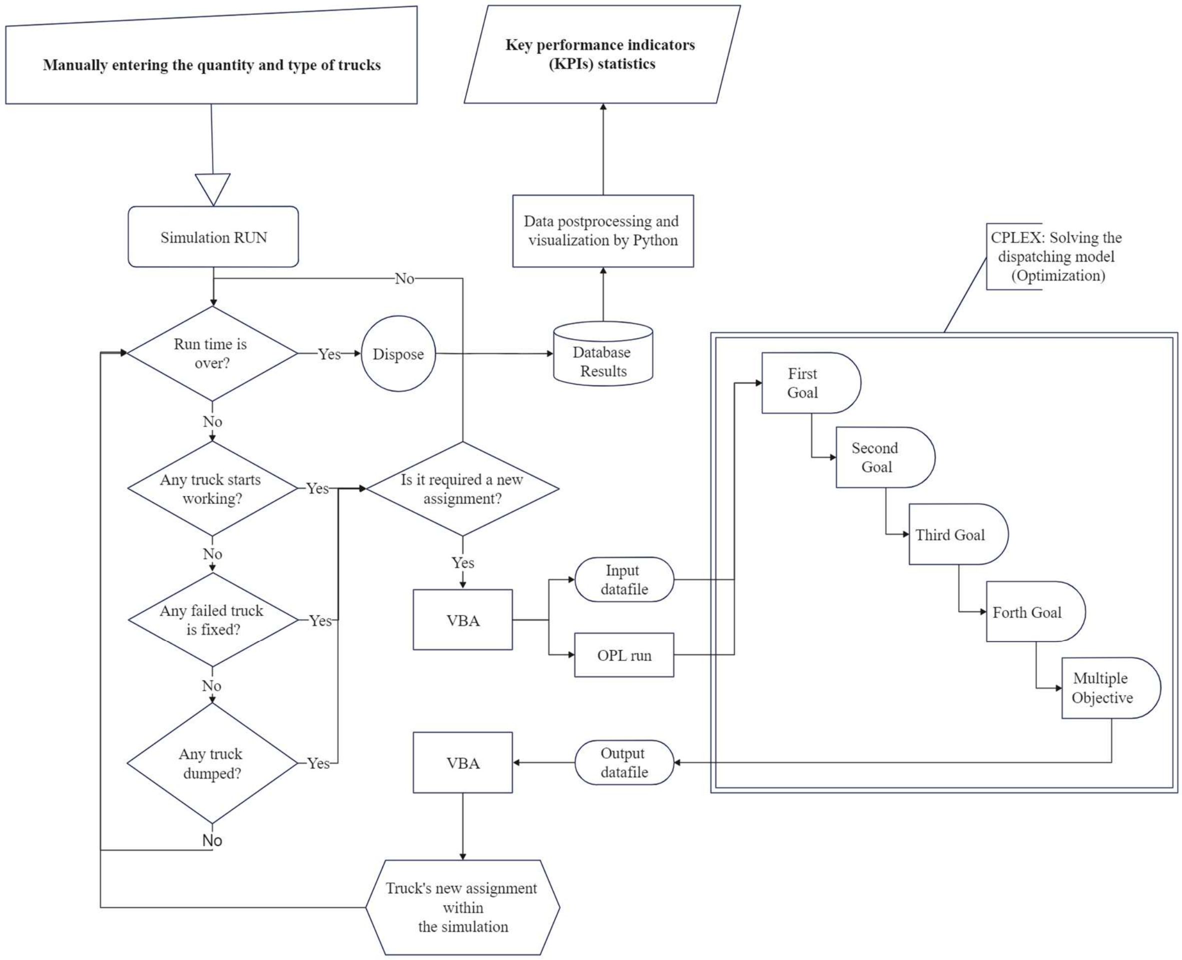

Figure 1. An overview of the simulation and optimization integration process.

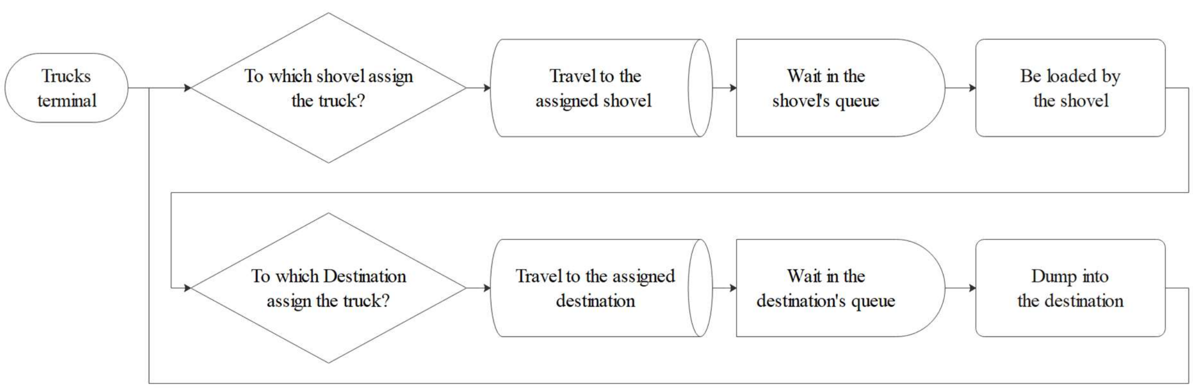

Figure 2. An active truck's operations.

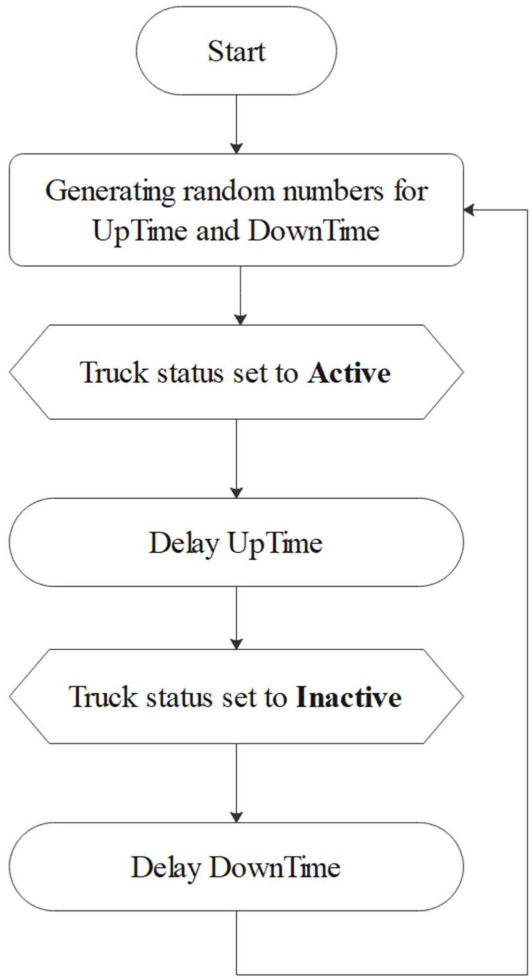


Figure 3. Truck status flowchart.

### 3.3. Key Performance Indicators (KPIs)

Variables below are introduced as KPIs in this study. Collectively, these variables wield a substantial influence in evaluating and optimizing truck dispatching within mining operations, facilitating improved decision-making, heightened operational efficiency, and enhanced profitability.

- Total ore tonnage production: This metric reflects the overall volume of ore transported to processing plants, directly impacting the mining operation's profitability and productivity.
- Total ore and waste tonnages mined and delivered: Monitoring the total quantities of both ore and waste materials offers insights into mining process efficiency and facilitates resource utilization optimization.
- Utilization of ore and waste shovels: Evaluating the usage of shovels dedicated to ore and waste handling ensures optimal deployment and helps identify potential operational bottlenecks or underutilized equipment.
- Total and average queue times for trucks: Tracking queue times for trucks awaiting loading or unloading provides operational efficiency information and reveals areas where delays might occur.

- Trucks' fuel consumption: Effective fuel management is vital for cost control and environmental sustainability. Monitoring and optimizing fuel usage aids in minimizing operational expenses and carbon emissions.
- Fuel consumption of a truck per tonne of production: This measure offers insights into trucks' fuel efficiency relative to the amount of material transported. It identifies opportunities for enhancing fuel efficiency and reducing operational costs.
- Ore TPGOH (tonne per gross operating hour): This gauge quantifies mining productivity by calculating extracted ore per equipment operation hour. Higher TPGOH values signify better efficiency and productivity.
- Stripping ratio: This ratio compares waste material removal volume to ore extraction volume, shedding light on the balance between ore production and waste elimination.
- Trucks' availabilities and downtimes: Monitoring truck availability and tracking downtimes identifies potential equipment failures, planned maintenance activities, and minimizes mining operation disruptions. Additionally, it can significantly impact TPGOH.

## 4. Design of Experiments, and Results

This study includes a case study utilizing historical data from the Gol-E-Gohar iron ore open-pit mine in Iran to assess the developed framework. The evaluation aims to analyze the performance of different truck fleets in terms of their truck's types and quantities, and also to investigate the impact of truck failures on each fleet scenario. Figure 4 depicts the arrangement of loading and dumping points, as well as the operational road network. At the loading points, there are five active shovels, with two designated for ore extraction and three for waste. At the dumping points, there are three destinations including two processing plants and a waste dump.

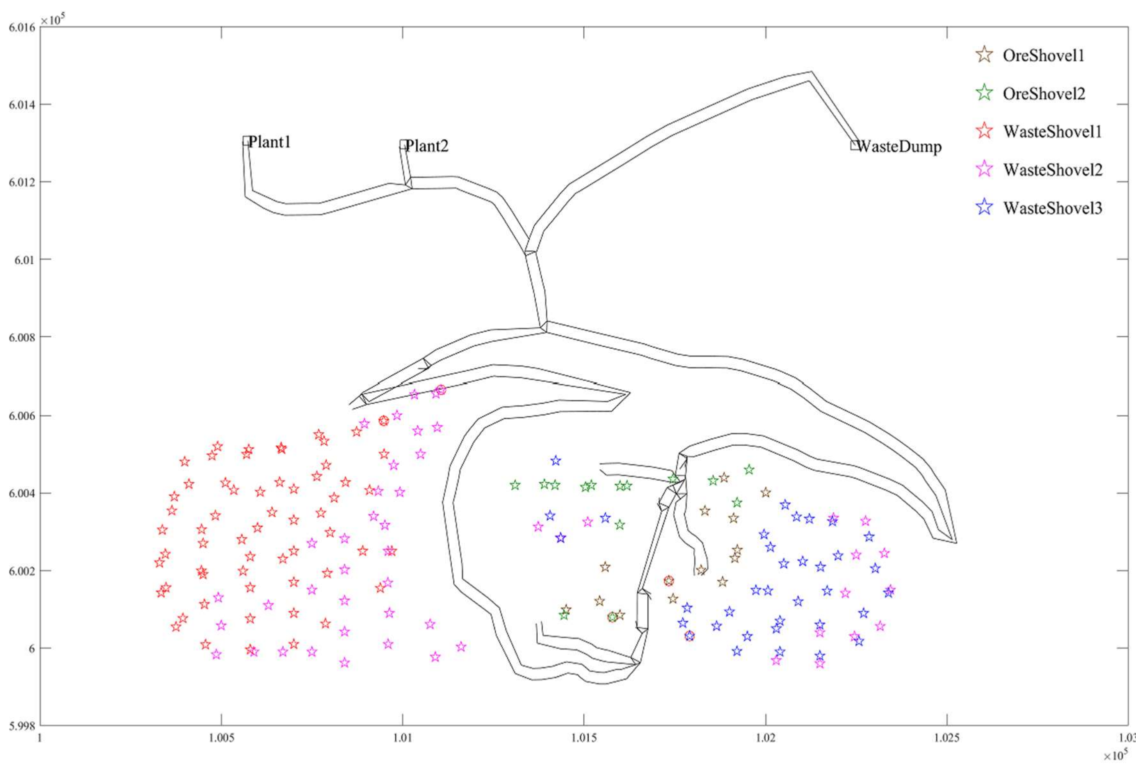


Figure 4. Gol-E-Gohar iron ore mine network.

The equipment present in the case study comprises Hitachi EX2500 and Hitachi EX5500 shovels, as well as Caterpillar 785C and Caterpillar 793C trucks for the transportation operations. The mining activities involve three distinct destinations: two processing plants equipped with two hoppers each, and a waste dump featuring multiple dumping points. The distribution of shovels and trucks to the excavation and dumping locations is outlined in Table 1.

Table 1. Equipment distributions.

| Origin | Destination | Shovel Type | Truck Type |
|---|---|---|---|
| Shovel 1 | Plant 1<br>Plant 2 | Hitachi EX2500 | Cat 785C<br>Cat 793C |
| Shovel 2 | Plant 1<br>Plant 2 | Hitachi EX2500 | Cat 785C<br>Cat 793C |
| Shovel 3 | Waste Dump | Hitachi EX5500 | Cat 785C<br>Cat 793C |
| Shovel 4 | Waste Dump | Hitachi EX5500 | Cat 785C<br>Cat 793C |
| Shovel 5 | Waste Dump | Hitachi EX2500 | Cat 785C<br>Cat 793C |

There is deterministic and stochastic information included in the case study's input data. The Arena Input Analyzer tool (Rockwell Automation, 2019) has been utilized in (Moradi Afrapoli, 2018) for the establishment of stochastic input distributions based on historical data. Each processing plant has a feeding rate target (capacity limit) of 2300 tonnes per hour.

The calculation of fuel consumption for individual CAT 785C trucks is performed using Eq. (20) obtained from (Dindarloo and Siami-Irdemoosa, 2016):

$$F(\frac{l}{cycle}) = 1.37071 + 0.00483 \times PL + 0.00398 \times LT + 0.00499 \times ES + 0.01471 \times ETR + 0.00278 \times LS + 0.0519 \times LTR \tag{20}$$

F: fuel consumption per cycle (liters)

PL: payload (tonnes)

LT: loading time (seconds)

ES: empty idle time (seconds)

ETR: empty travel time (seconds)

LS: loaded idle time (seconds)

LTR: loaded travel time (seconds)

The fuel consumption for the CAT 793C truck type is determined through Eq. (21), where a specific coefficient from the Caterpillar handbook (Caterpillar Performance Handbook Edition 29, 1999) is multiplied with it. This coefficient accounts for factors such as load and haul conditions, road conditions, grades, and rolling resistance. As a result, the CAT 793C's fuel consumption is approximately 1.59 times that of CAT 785C. Thus, Eq. (21) outlines the formula utilized to compute the fuel consumption for CAT 793C trucks in each operational cycle.

$$F(\frac{l}{cycle}) = 2.17943 + 0.00768 \times PL + 0.00633 \times LT + 0.00793 \times ES + 0.02339 \times ETR + 0.00442 \times LS + 0.0825 \times LTR \tag{21}$$

The simulation encompassed a duration of 10 days, involving 12 hours of operation per day, with the goal of achieving a satisfactory ore production of 550,000 tonnes for the planned mining operations over this period.

The operational efficiency, productivity, cost-effectiveness, and sustainability of a mining fleet are significantly impacted by the number and varieties of trucks within it. It is crucial to carefully consider the right quantity of trucks, select appropriate truck types, and efficiently manage their dispatch. This plays a vital role in developing a productive and financially viable fleet system. Through analysis of these factors and implementing fleet management approaches,, mining companies can streamline operations, boost productivity, and reduce expenses and environmental impacts. This research presents 40 scenarios based on different truck types and quantities. The first nine scenarios focus on a homogenous fleet of CAT 785C trucks.. Subsequently, the following eight scenarios involve a homogenous fleet of CAT 793C trucks, each with varying quantities. The remaining scenarios encompass a diverse fleet arrangement, incorporating both CAT 785C and CAT 793C trucks (heterogenous fleet) within the system. Within the Appendix, there is a comprehensive table (Table A. 1) that presents the key performance indicators (KPIs) for each distinctive scenario involving diverse combinations of truck types and quantities. Among the scenarios, scenario 6 with a homogenous fleet of 30 CAT 785C trucks, scenario 13 featuring 18 CAT 793C trucks in a homogenous fleet, and scenario 24 that combines 20 CAT 785C trucks with 5 CAT 793C trucks in a heterogenous fleet, demonstrate the best performance in terms of achieving production goals and reducing fuel usage as shown in Figure 5, Figure 6, and Figure 7.

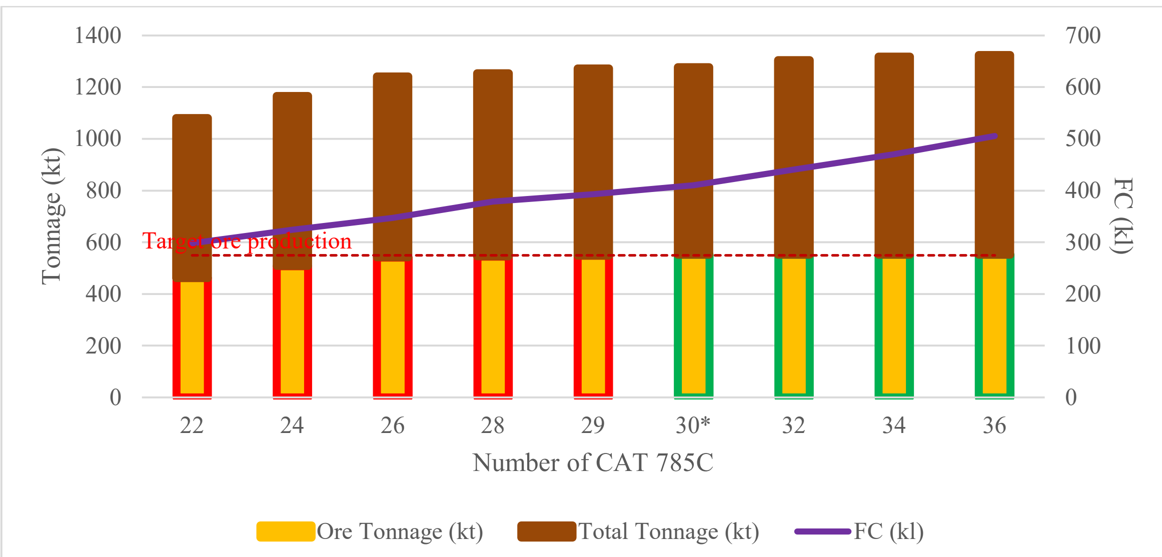


Figure 5. Production and fuel consumption in homogenous fleet of CAT 785C.

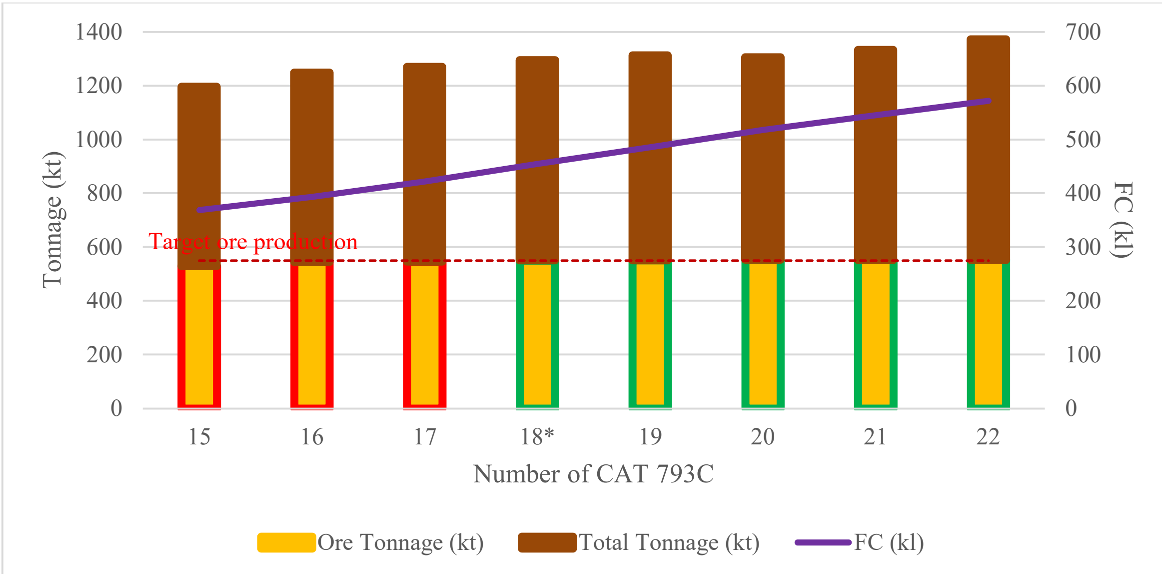


Figure 6. Production and fuel consumption in homogenous fleet of CAT 793C.

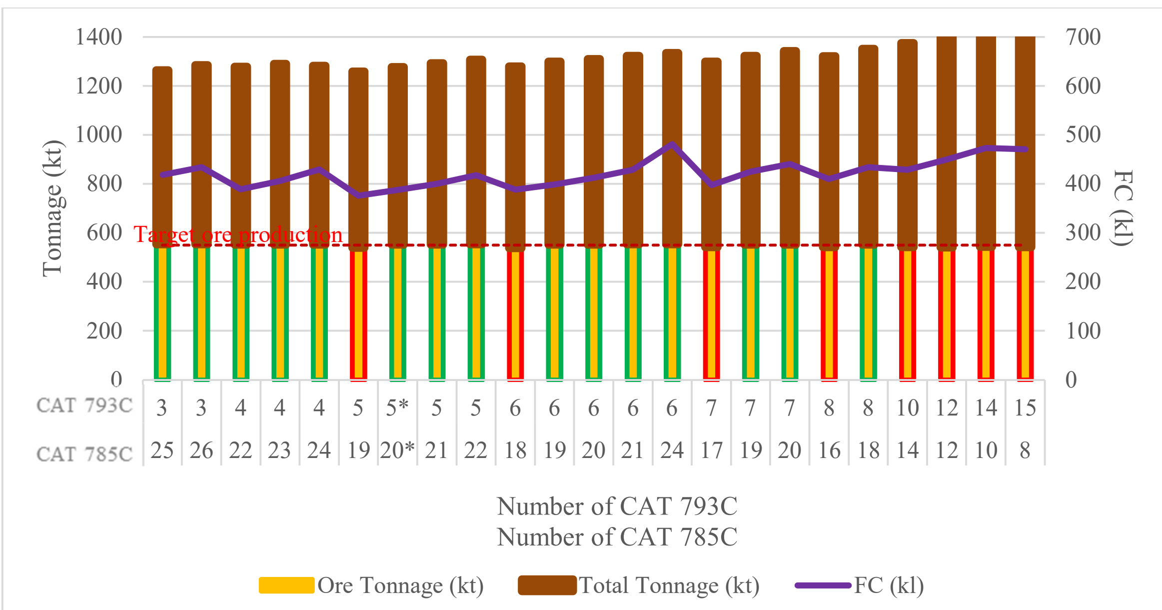


Figure 7. Production and fuel consumption in heterogenous fleet of CAT 785C and CAT 793C.

With the central aim being the maximization of production, scenario 24 emerges as the optimal selection by simultaneously achieving production targets, minimizing fuel usage, and reducing carbon emissions. This configuration involves a fleet composition comprising 20 smaller trucks (CAT 785C) and 5 larger trucks (CAT 793C). This choice effectively strikes a balance between the demand for high productivity and the imperative to curtail fuel consumption and environmental impact, aligning seamlessly with the sustainability objectives outlined in this study. Scenario 6 boasts the highest utilization of ore and waste shovels, closely followed by scenario 24. Among the three scenarios, scenario 13 demonstrates the lowest utilization of shovels. When considering average truck queue times, scenario 6 holds the record for the longest, followed by scenario 24. Scenario 13 displays the shortest average truck queue time among the three scenarios. All three scenarios achieve acceptable ore tonnage, with scenario 6 slightly surpassing in ore tonnage, and scenario 13 slightly lagging. Surprisingly, scenario 13 showcases the highest total tonnage, standing notably higher than the other scenarios, followed by scenario 6. In contrast, scenario 24 presents a slightly lower total tonnage when compared to scenario 6. In terms of fuel consumption, a comparison between scenario 6, scenario 13, and the lowest fuel consumption recorded in scenario 24 reveals a clear distinction. Scenario 6 shows a 5.83% higher fuel consumption ratio, while scenario 13 exhibits a significantly higher ratio difference of 17.35%.

Table 2 details the average cycle numbers for each shovel and destination for every truck in scenario 24. Moreover, it provides the OreCycles%, which is the percentage of times a truck transports ore material of the total cycles. Similarly, it presents the WasteCycles%, representing the percentage for waste material transport.

Table 2. Heterogenous fleet cycles of scenario 24.

| Truck Type | Truck# | SH1 | SH2 | SH3 | SH4 | SH5 | P1 | P2 | WD | Ore Cycles (%) | Waste Cycles (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 785C | 1 | 84 | 82.2 | 50.4 | 56.6 | 51.6 | 82.8 | 83.4 | 158.6 | 51 | 49 |
| | 2 | 82.8 | 77.8 | 54.4 | 58.8 | 55.4 | 79.4 | 81.2 | 168.6 | 49 | 51 |
| | 3 | 75.4 | 78.4 | 60.4 | 59.8 | 58 | 74.8 | 79 | 178.2 | 46 | 54 |
| | 4 | 79.8 | 76.4 | 60.8 | 63.4 | 53 | 81.2 | 75 | 177.2 | 47 | 53 |
| | 5 | 80.6 | 74.6 | 61.6 | 67 | 52.6 | 75.6 | 79.6 | 181.2 | 46 | 54 |
| | 6 | 81.6 | 65.4 | 60.2 | 76 | 57.2 | 68.8 | 78.2 | 193.4 | 43 | 57 |
| | 7 | 84.2 | 67.6 | 65.8 | 71.8 | 51.2 | 69.6 | 82.2 | 188.8 | 45 | 55 |
| | 8 | 72.6 | 71.4 | 71.4 | 69.2 | 57.4 | 66.8 | 77.2 | 198 | 42 | 58 |
| | 9 | 81.6 | 65 | 66.6 | 83 | 51 | 69.4 | 77.2 | 200.6 | 42 | 58 |
| | 10 | 71.8 | 68.4 | 67.2 | 85.6 | 56.4 | 65.2 | 75 | 209.2 | 40 | 60 |
| | 11 | 72.2 | 70.8 | 77.4 | 82.4 | 47.6 | 69.8 | 73.2 | 207.4 | 41 | 59 |
| | 12 | 73.6 | 63.4 | 72 | 85.4 | 54 | 66.4 | 70.6 | 211.4 | 39 | 61 |
| | 13 | 73.4 | 65.8 | 76.6 | 88 | 48.2 | 67 | 72.2 | 212.8 | 40 | 60 |
| | 14 | 68.4 | 68 | 78.2 | 88.6 | 53 | 67.2 | 69.2 | 219.8 | 38 | 62 |
| | 15 | 71.4 | 64.6 | 79.4 | 82.8 | 55.2 | 63.8 | 72.2 | 217.4 | 38 | 62 |
| | 16 | 77 | 64.8 | 84.2 | 83.2 | 45.8 | 65.2 | 76.6 | 213.2 | 40 | 60 |
| | 17 | 78.4 | 64 | 73.2 | 80.2 | 50.2 | 67.6 | 74.8 | 203.6 | 41 | 59 |
| | 18 | 76.2 | 76 | 78.6 | 75 | 43.4 | 74 | 78.2 | 197 | 44 | 56 |
| | 19 | 70.6 | 77.6 | 78 | 84.4 | 41.4 | 67.6 | 80.6 | 203.8 | 42 | 58 |
| | 20 | 76 | 78.2 | 79 | 75.6 | 41 | 74 | 80.2 | 195.6 | 44 | 56 |
| 793C | 21 | 47.8 | 67.8 | 48.4 | 44.8 | 95.8 | 67.4 | 48.2 | 189 | 38 | 62 |
| | 22 | 45.4 | 60.4 | 58.4 | 39 | 104.2 | 61.8 | 44 | 201.6 | 34 | 66 |
| | 23 | 48.2 | 61 | 53.8 | 42.6 | 98 | 61.4 | 47.8 | 194.4 | 36 | 64 |
| | 24 | 52.2 | 57 | 54.4 | 44.4 | 101.4 | 58.2 | 51 | 200.2 | 35 | 65 |
| | 25 | 51.4 | 61.6 | 46.8 | 39.4 | 103.2 | 61.8 | 51.2 | 189.4 | 37 | 63 |

The findings highlight that CAT 793C trucks transport larger quantities of waste in comparison to CAT 785C trucks. While waste dumping isn't constrained by hourly capacity, plants have specific hourly hopper limits. Trucks with lower capacities offer greater flexibility for transferring ore materials within the system, making them a more suitable choice for assignment to ore shovels. Furthermore, a significant distinction is observed in the assignment of large trucks to waste shovel

5. This difference primarily arises from the fact that shovel 5 boasts a higher digging rate and capacity than the other waste shovels.

In Table 3, the KPIs for the most promising scenarios, accounting for truck failures, are shown. These scenarios, previously discussed without factoring in truck failures. Considering truck failures, scenario 6, featuring a homogeneous CAT 785C truck fleet with 30 number of trucks, stands out for its remarkable tonnage transportation, production rate, and shovels' utilization. Although its fuel consumption isn't the lowest, its rate per tonne of production is acceptable.. Examining the impact of truck failures, it becomes evident that a fleet with a higher number of smaller trucks holds advantages in achieving the hourly ore production rate. Despite their smaller capacities, the flexibility of smaller trucks enhances their effectiveness Moreover, these smaller trucks (CAT 785C) experience reduced downtime when compared to the larger trucks (CAT 793C), further enhancing their performance in the context of truck failures.

Table 3. KPIs of the Best Scenarios with the Trucks failure, and differences' percentages in KPIs.

| **Scenario** | **Util. Ore (%)** | **Util. Waste (%)** | **Average Q time (Mins)** | **Total Q time (Hrs)** | **FC (KL)** | **Ore Tonnage (KT)** | **Total Tonnage (KT)** | **Ore TPGOH (T)** | **SR** |
|---|---|---|---|---|---|---|---|---|---|
| 6(F) | 78.1 | 53.5 | 3.4 | 527 | 361 | 531 | 1222 | 4421 | 1.30 |
| 13(F) | 66.6 | 43.3 | 2.3 | 190 | 389 | 512 | 1180 | 4264 | 1.31 |
| 24(F) | 71.8 | 50.1 | 2.9 | 378 | 343 | 502 | 1171 | 4181 | 1.33 |
| (%) Diff. 6(F) and 6 | -3.8 | -4.8 | -11.4 | -15.3 | -12.0 | -4.0 | -4.4 | -4.0 | -0.8 |
| (%) Diff. 13(F) and 13 | -7.0 | -10.2 | -11.0 | -17.4 | -14.4 | -7.0 | -8.9 | -7.0 | -3.0 |
| (%) Diff. 24(F) and 24 | -8.8 | -7.1 | -15.7 | -21.8 | -11.4 | -9.0 | -8.3 | -9.0 | 1.5 |

Scenario 6 stands out with the least variation in KPIs compared to other scenarios. This suggests that incorporating a larger number of smaller trucks in the fleet can minimize production losses in the event of unplanned failures. However, when considering the presence of a stockpile or several stockpiles in the system and a slightly higher number of trucks in both types, a heterogenous fleet still outperforms homogenous fleets.

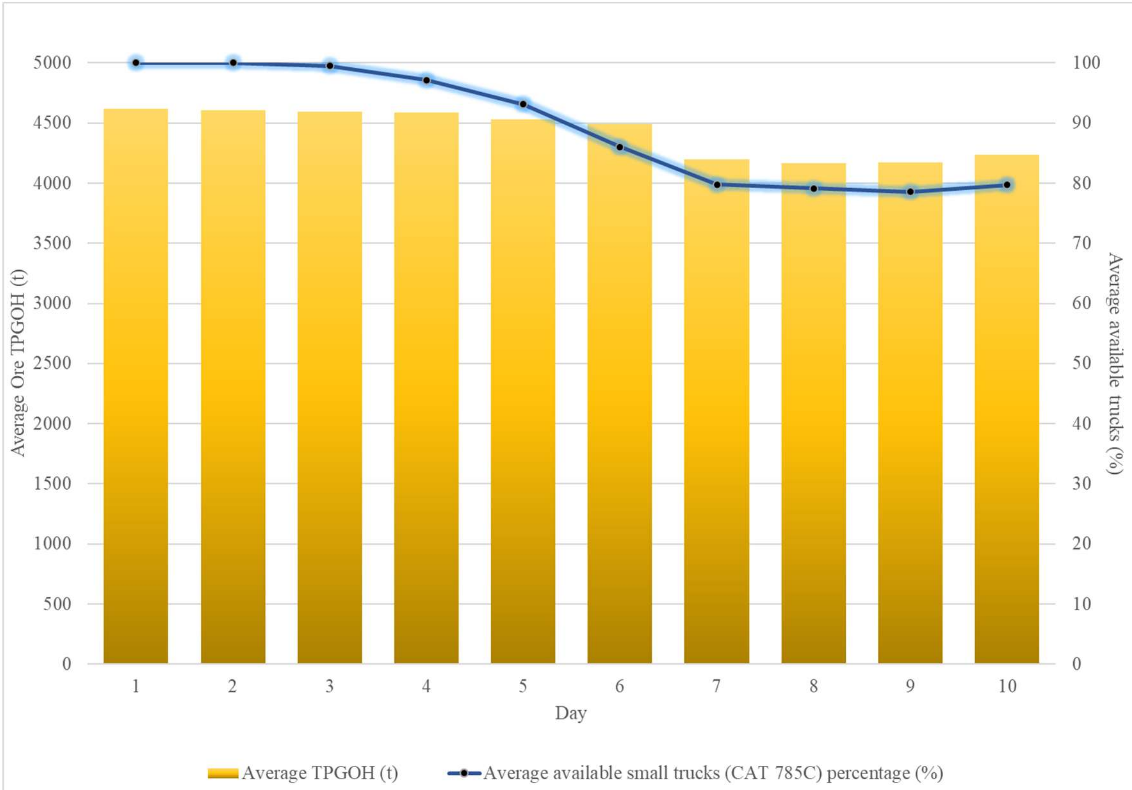


Figure 8, and Figure 9 illustrate that the daily average TPGOH for scenario 6 and scenario 24, respectively, is significantly impacted by the daily average number of active trucks available in the system. This underscores that a decrease in the active truck count can result in a corresponding reduction in the TPGOH and consequently, total ore production.

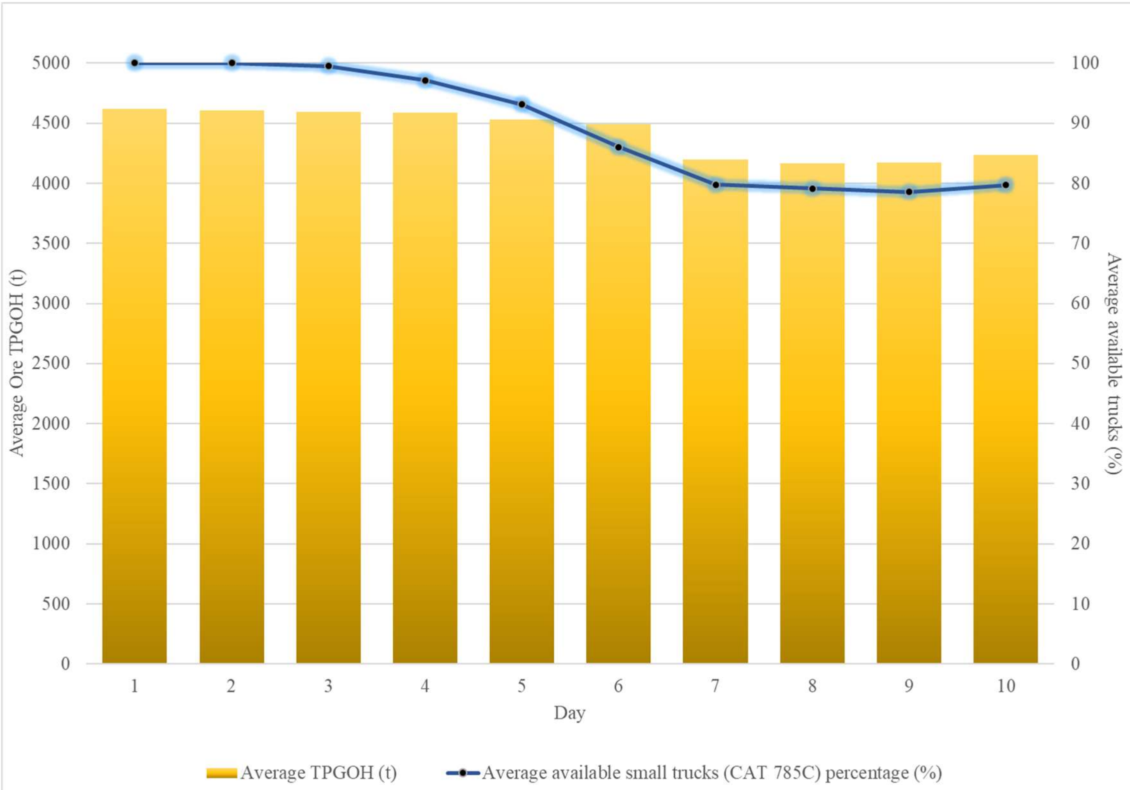


Figure 8. Scenario 6 (Homogeneous fleet - 30 small trucks) - impact of truck failures on average TPGOH.

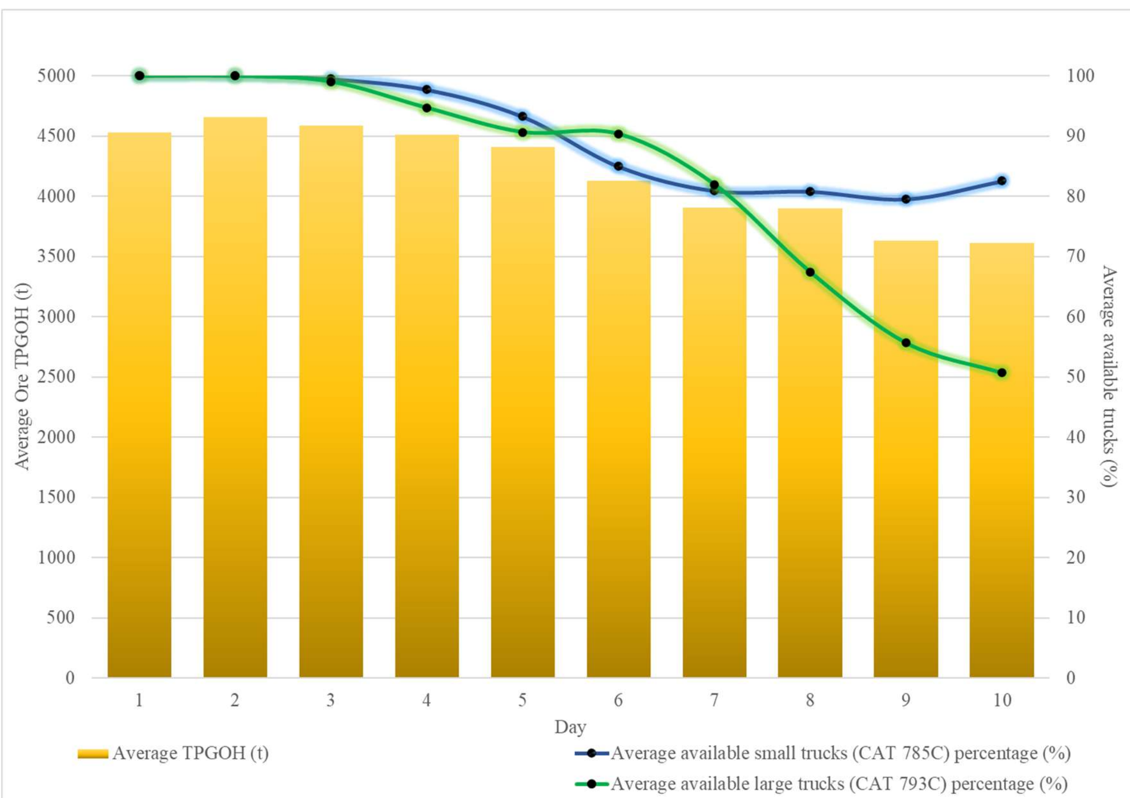


Figure 9. Scenario 24 (Heterogenous fleet - 25 Small and 5 large trucks) - impact of truck failures on average TPGOH.

## 5. Conclusions

The study primarily focused on determining the optimal quantity and types of trucks required within the system, utilizing a developed truck dispatching optimization model. model's primary objective was to minimize deviations in path flow rates, shovel idle time, truck wait time, and truck fuel consumption. An important contribution of this research was the incorporation of fuel consumption and GHG emissions as criteria for truck fleet selection and sizing. Furthermore, the study enhanced the model's practicality and reliability by considering truck uptime and downtime.

The number and types of trucks within a mining fleet exerted a substantial impact on operational efficiency, productivity, and cost-effectiveness. Apart from an efficient dispatching system, optimizing the selection and quantity of available trucks played a pivotal role in establishing a sustainable and productive haulage system for open-pit mines. Among the various scenarios explored, scenario 24, a mix of 20 CAT 785C and 5 CAT 793C trucks in a heterogeneous fleet, displayed optimal performance in meeting production targets and minimizing fuel consumption. This configuration effectively balanced high productivity with the imperative to reduce fuel consumption and environmental impact, aligning well with the study's sustainability goals. Scenario 6, consisting of 30 CAT 785C trucks, exhibited a 5.83% higher fuel consumption ratio and 5.45% higher fuel consumption per tonne of production. The CAT 793C trucks transported more waste material per truck due to their higher capacity. Notably, while dumping in the waste disposal area had no hourly capacity restriction, the processing plants had specific hourly hopper capacities. Trucks with lower capacities offered enhanced flexibility in transferring ore materials and were better suited for assignment to ore shovels.

In scenarios accounting for truck failures, a fleet with a higher number of smaller trucks proved advantageous in maintaining the hourly ore production rate due to increased flexibility, despite the smaller average capacity per truck. Additionally, smaller trucks had lower average downtimes compared to larger counterparts, contributing to their superior performance in the context of truck failures. When prioritizing fuel consumption per tonne of production, scenario 6 with a homogeneous fleet of 30 small trucks, along with scenarios 20 (comprising 22 small and 4 large trucks) and 24 (comprising 20 small and 5 large trucks) with heterogeneous fleets, emerged as the most reliable and efficient choices. However, scenario 6 stood out due to its higher production rate and dispatching flexibility, making it the optimal selection when accounting for unforeseen failures in the model. In conclusion, considering truck failures, fuel consumption, and production rates, scenario 6 with a homogeneous fleet of 30 CAT 785C trucks demonstrated favorable performance. Nonetheless, introducing one or more stockpiles into the system and having a slightly higher number of trucks of both types could potentially lead to a heterogeneous fleet outperforming homogeneous ones. It is important to note that stockpiling wasn't a part of this study's framework. These considerations ensured steady material flow, mitigated truck failure effects, and optimized overall production efficiency in mining operations.

Future research should consider aspects such as truck age, shovel failure impact, and stockpile integration to improve the modeling approach's reliability, realism, and comprehensiveness. Incorporating these factors could lead to more accurate predictions, refined optimization strategies, and ultimately, greater efficiency and sustainability in mining operations.

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## 7. Appendix

List of abbreviations:

| | |
|---|---|
| CAT | Caterpillar |
| HIT | Hitachi |
| TPGOH | Tonne Per Gross Operating Hours |
| OTPGOH | Ore Tonne Per Gross Operating Hours |
| SR | Stripping Ratio |
| Q | Queue |
| SIT | Shovel Idle Time |
| TWT | Truck Wait Time |
| PD | Production Deviation |
| FC | Fuel Consumption |
| min | Minutes |
| hrs | Hours |
| t / kt | Tonnes / Kilo Tonnes |
| l / kl | Liters / Kilo Liters |
| tph | Tonne Per Hour |

Table A. 1. KPIs for Various Types of Trucks and Number of Trucks.

| Scenario | Number of trucks 785C | Number of trucks 793C | Utilization Ore (%) | Utilization Waste (%) | Average Q time (mins) | Total Q time (hrs) | FC (kl) | Ore Tonnage (kt) | Total Tonnage (kt) | Ore TPGOH (t) | SR |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 22 | 0 | 67.84 | 47.55 | 2.72 | 373.29 | 298.31 | 461.50 | 1080.23 | 3845.87 | 1.34 |
| 2 | 24 | 0 | 74.92 | 50.84 | 2.82 | 416.18 | 324.12 | 508.44 | 1166.06 | 4237.02 | 1.29 |
| 3 | 26 | 0 | 79.40 | 54.31 | 3.12 | 488.36 | 346.97 | 541.50 | 1241.02 | 4512.54 | 1.29 |
| 4 | 28 | 0 | 80.20 | 54.98 | 3.51 | 555.85 | 378.91 | 545.41 | 1253.44 | 4545.11 | 1.30 |
| 5 | 29 | 0 | 80.60 | 56.15 | 3.67 | 591.81 | 392.78 | 548.64 | 1272.59 | 4572.02 | 1.32 |
| 6* | 30 | 0 | 81.16 | 56.22 | 3.85 | 622.29 | 410.04 | 552.39 | 1277.51 | 4603.23 | 1.31 |
| 7 | 32 | 0 | 81.29 | 58.40 | 4.16 | 686.96 | 440.67 | 552.36 | 1304.78 | 4603.02 | 1.36 |
| 8 | 34 | 0 | 81.18 | 59.44 | 4.61 | 770.65 | 470.49 | 552.26 | 1317.77 | 4602.15 | 1.39 |
| 9* | 36 | 0 | 81.19 | 60.14 | 4.92 | 825.31 | 506.12 | 552.32 | 1324.50 | 4602.65 | 1.40 |
| 10 | 0 | 15 | 68.85 | 43.14 | 2.13 | 175.38 | 369.04 | 529.10 | 1196.37 | 4409.20 | 1.26 |
| 11 | 0 | 16 | 70.85 | 45.66 | 2.28 | 195.68 | 393.42 | 544.77 | 1248.65 | 4539.73 | 1.29 |
| 12 | 0 | 17 | 70.96 | 46.96 | 2.40 | 213.87 | 421.65 | 545.57 | 1270.10 | 4546.44 | 1.33 |
| 13* | 0 | 18 | 71.60 | 48.20 | 2.63 | 229.66 | 454.54 | 550.06 | 1295.28 | 4583.85 | 1.35 |
| 14 | 0 | 19 | 71.73 | 49.06 | 2.66 | 239.92 | 485.36 | 551.08 | 1312.29 | 4592.29 | 1.38 |
| 15* | 0 | 20 | 71.95 | 48.64 | 2.84 | 254.45 | 517.51 | 552.31 | 1305.70 | 4602.59 | 1.36 |
| 16 | 0 | 21 | 71.94 | 50.61 | 3.00 | 274.56 | 545.11 | 552.14 | 1333.44 | 4601.17 | 1.42 |
| 17 | 0 | 22 | 72.07 | 52.89 | 3.18 | 299.42 | 572.12 | 552.27 | 1372.42 | 4602.28 | 1.49 |
| 18 | 25 | 3 | 80.05 | 53.94 | 3.75 | 552.06 | 418.24 | 552.21 | 1263.46 | 4601.73 | 1.29 |
| 19 | 26 | 3 | 80.15 | 55.59 | 3.83 | 577.76 | 433.62 | 552.23 | 1285.20 | 4601.89 | 1.33 |
| 20* | 22 | 4 | 79.39 | 54.70 | 3.59 | 521.00 | 388.72 | 551.17 | 1277.53 | 4593.06 | 1.32 |
| 21 | 23 | 4 | 79.70 | 55.45 | 3.70 | 543.67 | 405.79 | 551.96 | 1289.60 | 4599.71 | 1.34 |
| 22 | 24 | 4 | 79.55 | 54.89 | 3.77 | 549.45 | 429.54 | 551.29 | 1281.59 | 4594.05 | 1.32 |
| 23 | 19 | 5 | 76.77 | 53.48 | 3.14 | 432.65 | 376.35 | 538.51 | 1258.84 | 4487.59 | 1.34 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 24* | 20 | 5 | 78.71 | 53.89 | 3.45 | 483.93 | 387.44 | 551.52 | 1276.65 | 4596.02 | 1.31 |
| 25 | 21 | 5 | 79.12 | 55.32 | 3.67 | 522.96 | 400.03 | 551.37 | 1292.61 | 4594.76 | 1.34 |
| 26 | 22 | 5 | 79.12 | 56.31 | 3.75 | 543.72 | 417.23 | 552.27 | 1306.81 | 4602.26 | 1.37 |
| 27 | 18 | 6 | 76.15 | 54.49 | 3.17 | 431.62 | 388.18 | 536.69 | 1279.36 | 4472.42 | 1.38 |
| 28 | 19 | 6 | 78.55 | 54.92 | 3.46 | 481.03 | 398.40 | 551.41 | 1298.85 | 4595.12 | 1.36 |
| 29 | 20 | 6 | 78.62 | 55.95 | 3.68 | 518.31 | 412.42 | 552.12 | 1309.17 | 4601.03 | 1.37 |
| 30 | 21 | 6 | 78.71 | 56.96 | 3.82 | 545.51 | 428.61 | 552.37 | 1322.11 | 4603.12 | 1.39 |
| 31 | 24 | 6 | 79.14 | 57.73 | 4.29 | 623.72 | 481.38 | 552.35 | 1334.03 | 4602.92 | 1.42 |
| 32 | 17 | 7 | 76.28 | 54.88 | 3.32 | 445.52 | 397.33 | 540.61 | 1298.82 | 4505.10 | 1.40 |
| 33 | 19 | 7 | 78.32 | 56.42 | 3.70 | 512.38 | 424.99 | 552.04 | 1322.56 | 4600.33 | 1.40 |
| 34 | 20 | 7 | 78.52 | 57.61 | 3.85 | 543.51 | 440.50 | 552.04 | 1341.86 | 4600.34 | 1.43 |
| 35 | 16 | 8 | 76.08 | 55.82 | 3.35 | 442.32 | 409.77 | 540.87 | 1321.28 | 4507.23 | 1.44 |
| 36 | 18 | 8 | 77.87 | 57.77 | 3.80 | 522.46 | 433.74 | 551.64 | 1351.33 | 4597.04 | 1.45 |
| 37 | 14 | 10 | 75.36 | 58.24 | 3.51 | 455.19 | 428.78 | 541.39 | 1375.32 | 4511.56 | 1.54 |
| 38 | 12 | 12 | 74.47 | 59.72 | 3.67 | 462.28 | 449.87 | 540.02 | 1413.49 | 4500.14 | 1.62 |
| 39 | 10 | 14 | 74.22 | 60.61 | 3.78 | 461.28 | 472.90 | 542.37 | 1449.22 | 4519.73 | 1.67 |
| 40 | 8 | 15 | 73.56 | 58.48 | 3.80 | 437.64 | 470.42 | 541.60 | 1423.36 | 4513.37 | 1.63 |