Journal of Cleaner Production 520 (2025) 146014

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

The impact of fleet electrification on productivity in heat-constrained underground mines

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ARTICLE INFO

Keywords:
Mixed–integer programming
Sustainable mining
Underground mine scheduling
Battery-powered equipment
Ventilation and refrigeration

ABSTRACT

Underground mine planning uses production schedules to determine a (near-)optimal sequence of activity execution to maximize net present value while considering resource limitations and spatial precedence. At the time of this writing, the mining industry relies heavily on the use of diesel-powered equipment, which accounts for heat accumulation and exhaust emissions that, if not managed, can create hazardous conditions in the work environment. Sustainable mining practices call for the transition from diesel- to battery-powered equipment. This study presents a large-scale production scheduling model that (i) prescribes activity start times in a medium-term schedule at daily fidelity, taking into account ventilation and refrigeration; and, (ii) determines a fleet composition, relative to a diesel-only fleet, that improves productivity. The authors implement an enumeration technique, embedded in the optimization model, whose special structure they exploit, to generate schedules within an operationally feasible amount of time. The findings show that the need for refrigeration, i.e., lowering the air temperature, is delayed by weeks to over a year, and exhaust emissions can be virtually eliminated as more battery-powered equipment is introduced, demonstrating the utility of battery-powered equipment to improve underground work environments while lowering infrastructure costs. Under the assumption that procurement and maintenance costs are sunk, this study shows a 1% to 26% improvement in net present value over an all-diesel fleet. Soot and NO_x emissions are reduced as battery-powered equipment is infused. The greatest average reduction in cumulative emissions is 31%, which occurs at the transition from a fleet composition of five battery-powered equipment pairs to six. These reductions range from 7% to 59% and are associated with five of the twelve scheduling cases presented. The results provide schedules and fleet compositions that enhance the integration of battery-powered equipment into an operation while assessing overall productivity and net present value to effect more environmentally friendly strategic decisions.

1. Introduction and literature review

Underground metal mining targets ore, i.e., rock with economic quantities of the desired commodity, and is often characterized by higher costs but a significantly smaller footprint relative to open-pit mining. A mine is constructed around an orebody, which is usually represented as a notional three-dimensional block model of the resource. Each spatial block is assigned an ore grade and tonnage. Any underground mine design requires construction of development to access the mine and corresponding ore. Fig. 1 depicts a layout from an underground hardrock mine employing sublevel stoping and sublevel caving mining methods. Ore handling systems, which extract and move the ore through the mine, ultimately transporting the ore to the surface, comprise primary infrastructure, as do ventilation systems; the latter provide fresh air to cool the airways and flush out contaminants, such as equipment exhaust and blasting fumes. Correspondingly, air is pushed into the mine via the intake-raises, circulates through the levels with active work, and leaves through either the exhaust or decline ramp. Refrigeration may also be employed for additional cooling when the underground environment is above acceptable temperatures for the workforce to tolerate.

A typical sequence of events at an underground metal mine includes drilling of the in situ rock to allow for the distribution of explosives,

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https://doi.org/10.1016/j.jclepro.2025.146014
Received 6 July 2024; Received in revised form 22 February 2025; Accepted 17 June 2025
Available online 11 July 2025

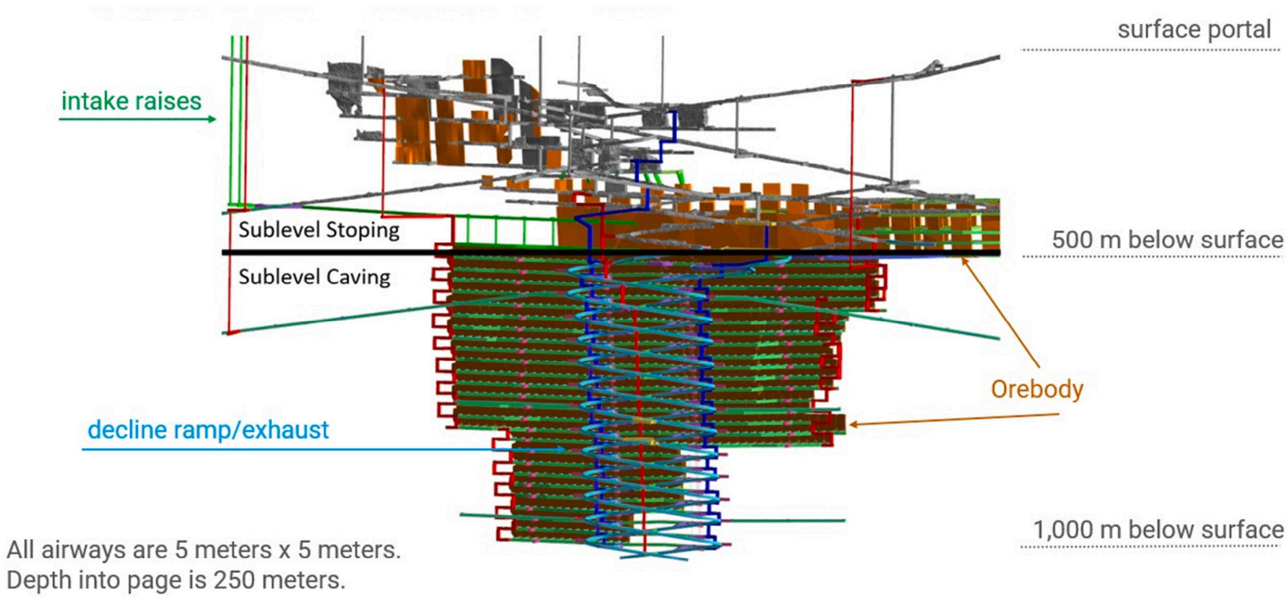

Fig. 1. The layout of a hardrock underground mine employing sublevel stoping and sublevel caving, which is partitioned into levels. This mine serves as the case study and extends as far as 1000 m below the surface.

blasting the rock into fragments, and extracting the broken ore or waste (via loaders) (Hustrulid and Bullock, 2001). The material is placed in trucks to be hauled to an ore pass and transported to the surface via a shaft. Some underground mines may utilize haulage trucks that transport the ore from the working areas to the surface via a decline ramp system. Heavy diesel-powered equipment contributes significantly to heat load (Hartman et al., 2012) and exhaust emissions related to the extraction and transportation of ore, and corresponding loading and hauling operations are among the most energy-intensive aspects of an underground mining operation (Norgate and Haque, 2010). A mining operation may alternatively employ rail, shaft, or conveyor systems to transport material depending on the production rate, depth of the orebody, and/or duration of operation (Costa et al., 2017). Typically, expensive ventilation systems are used to flush out heat and particulates from the underground environment to maintain safe working conditions (Hartman et al., 2012). Evolving health and environmental regulations exist to mitigate concerns associated with the use of diesel-powered equipment, to combat climate change, and to encourage corporate social responsibility.

The transition to battery-powered equipment helps support these regulations, and the mining industry is therefore interested in examining various ramifications of making this switch (Paraszczak et al., 2014). On the other hand, battery-powered equipment introduces hazards (e.g., thermal runaway leading to battery fires) and challenges (e.g., frequent interruptions for charging) that must be addressed. Nor should this equipment be thought of at the time of this writing as a panacea to minimize the carbon footprint associated with mining. Specifically, their manufacture requires many critical minerals and the technology does not yet benefit from the economies of scale afforded to mature alternatives (Nunes et al., 2022). The scope of this paper is therefore a study on the reduction of heat accumulation in underground mines through the use of battery-powered equipment; associated benefits include lower emissions. Fig. 2 provides illustrations of a diesel-powered loader and a truck and their battery-powered equivalents; the figure serves only illustrative purposes (Epiroc, 2024). In this paper, “battery-powered equipment” refers to mobile machinery such as battery-powered trucks and loaders; “diesel-powered equipment” denotes mobile machinery powered by diesel engines.

Optimization models can address the multi-faceted challenges, such as safety, efficiency and resource utilization, faced by underground mines. Formal optimization modeling consists of known input data (parameters), unknown data (variables), rules for determining acceptable combinations of variable values (constraints), and an objective function that represents a goal. Optimization yields the best solution, i.e., set of variable values associated with a minimum or maximum relative to an objective, that satisfies the constraints. A mixed integer program is one in which some of the variables assume only discrete integer or binary (0 or 1) values and is solved by allowing the discrete variables to assume continuous values (via a so-called *linear programming relaxation*) and then by strategically and systematically fixing them to discrete values for feasibility (Rardin, 2017). Throughout the course of the algorithm, this *linear programming relaxation objective function value* represents a *theoretical* optimum, i.e., “best possible”; an integer-feasible solution discovered by the algorithm represents a *bound*, i.e., “worst possible.” The difference between the two (referred to as the “gap”) is a measure of solution quality, which improves throughout the algorithm as the theoretical optimum becomes more realistic and as the best-found solution (i.e., *incumbent*) improves. Optimization models can be solved with exact mathematical techniques. “Hard” problems may be re-formulated and/or decomposed into subproblems to make them more tractable, perhaps at the expense of optimality.

Production scheduling optimization models determine when to extract notional blocks of ore within a mine, and can range in detail, i.e., the time fidelity used, and the time horizon under consideration. Models, such as the resource-constrained project scheduling problem, determine when to start activities in order to maximize revenue (King et al., 2017) or minimize deviations (Newman and Kuchta, 2007). Each activity is assigned a duration, precedence relationship(s), delay time between when a task can begin after its predecessor is complete, and fixed resource consumption – with each resource having a limit. The resource usage and capacities are modeled as knapsack constraints, i.e., restrictions that allow at most a certain subset of all activities to be chosen based on a prescribed limit.

Few studies examine the impact of the transition from diesel- to battery-powered trucks and loaders on production scheduling and on the mining work environment (GMG, 2022; Meshginqalam et al., 2024). Therefore, the contributions of this paper lie in: (i) building a large-scale optimization model that considers a strategy to infuse battery-powered trucks and loaders into the fleet. Because battery-powered equipment reduces heat load in a mine owing to lower heat output, and complements the refrigeration system, economic value

(a) Diesel-powered loader: Epiroc ST14
(b) Battery-powered loader: Epiroc ST14 SG
(c) Diesel-powered truck: Epiroc MT42
(d) Battery-powered truck: Epiroc MT42 SG

Fig. 2. Diesel-powered loaders and trucks versus their battery equivalent (Epiroc, 2024). These are for visual purposes only.

can be maximized while worker environment is improved; and, (ii) solving said optimization model with an algorithm that exploits the underlying resource-constrained project scheduling problem structure, and with an enumeration technique that reconciles the shortcomings of the solver by layering fleet transition plan decisions on top of the basic model, to examine the effect of fleet compositions on production schedules. Specifically, the study enumerates these compositions, which may consist of diesel and battery trucks and loaders, to determine the trade-off between fleet composition, refrigeration start time, and discounted net present value. In summary, this research contributes to the academic literature by formulating and solving an optimization model whose solutions can be used to understand the impact of equipment electrification on ventilation requirements, emissions, and production scheduling (as it relates to activity execution and the corresponding net present value).

The use of optimization tools in the mining industry dates back to the mid-twentieth century, and spans mine design, production scheduling, and resource usage maximization (Lerchs and Grossmann, 1965). Typically, a mine design is determined, and subsequently used, as an input to generate production schedules with the goal of maximizing value or minimizing cost associated with mining operations and/or activities (Little et al., 2013; Faria et al., 2022). Early applications focus on open-pit mining because of its inherent homogeneous nature which makes the resulting model easier to formulate and solve (Caccetta, 2007). The depletion of shallow mineral deposits, coupled with the environmental benefits of underground mining, indicates a growing reliance on these operations within the mining industry. While comprehensive metrics quantifying this shift are limited, Ghorbani et al. (2023) estimate that underground mining contributes approximately 12%–17% towards total metal ore production. There is correspondingly a rise in the use of optimization methods in underground mining; however, the heterogeneity in activity duration, precedence constraints, and resource consumption call for variations on open-pit modeling approaches (O'Sullivan et al., 2015; Musingwini, 2016).

Production scheduling determines the sequence of extraction for ore and waste materials. Different types of production scheduling models address varying aspects of the mine planning process and can adapt to changing market demand while efficiently meeting production goals. Long-, medium-, and short-term production schedules, more broadly, involve strategic planning over years, optimizing resource allocation over months, and determining daily operations, respectively. Long-term scheduling spans years to the end-of-mine life and determines the economic viability of the project. Godoy and Dimitrakopoulos (2004) develop an optimization model for long-term production scheduling that considers economic and technical factors such as orebody uncertainty and waste management. This risk-based optimization procedure enhances the quality of schedules produced by traditional optimization scheduling models. Medium-term production scheduling is associated with horizon lengths ranging from months to a few years and is used to optimize resource allocation and production targets. To maximize recovered copper over a five-year horizon, Smith and Wicks (2014) formulate a mixed-integer programming model that takes into account the production targets specified in a long-term plan. Short-term planning focuses on daily operations covering days to a few weeks with an overarching goal of meeting daily targets while adhering to broader strategic objectives (Amoako et al., 2023). This study focuses on medium-term production scheduling because it balances strategic decisions regarding the deployment of resources, e.g., vehicles, and operational decisions regarding when to extract ore.

Trout (1995) formulates a mixed-integer programming model to maximize before-tax net present value by scheduling extraction and backfill activities. Newman and Kuchta (2007) discuss a methodology for solving mixed-integer programs and apply it to the Kiruna iron ore mine in Sweden to yield solutions that minimize deviations from contractual production targets. O'Sullivan and Newman (2014) develop a heuristic that exploits precedence relations to produce schedules for an underground mine in Ireland. While the aforementioned authors develop models and solution methods for optimizing schedules, none incorporates risk and uncertainty inherent in underground mines. Geological variation necessitates the deployment of stochastic and simulation methods that not only quantify, but also mitigate, said risks. Huang et al. (2020) incorporate geological uncertainty into a mixed-integer programming model to produce schedules that maximize net present value.

Mine production scheduling results in large combinatorial problems, in the form of mixed-integer linear programs, that can be difficult to solve. This is because of the large number of binary decision variables, the precedence relationship(s) that exist between the activities, and the resource limits that must be accounted for. Reformulation techniques and heuristics mitigate long solution times. For example, Lagrangian relaxation, a classical reformulation approach, is widely used to move difficult constraints to the objective function where their violation is penalized (Dagdelen, 1986; Lambert and Newman, 2014). Sarin and West-Hansen (2005) formulate a mixed-integer program that generates schedules that maximize recovered coal by exploiting the problem's special structure via Bender's decomposition to yield good solutions. Similarly, Ramazan (2007) seeks to reduce the number of decision variables in their scheduling problem by reconstructing the set of mining blocks – using a "fundamental tree algorithm." Carefully incorporating inequalities, based on precedence and production constraints, can be a useful technique for tightening mixed-integer formulations– reducing the computational burden involved in obtaining a (near-)optimal integer solution (Haouari et al., 2014). Another technique assigns an early and late start to an activity to reduce the number of binary variables by eliminating instantiations of block-time period combinations prior to the early start and after the late start of said block (Topal, 2008; Lambert et al., 2014). Bienstock and Zuckerberg (2010) develop an algorithm for solving the linear programming relaxation of difficult, and large, precedence-constrained project scheduling problems by employing a Lagrangian relaxation to the difficult constraints and partitioning the variable sets; a rounding heuristic can produce good, integer-feasible solutions (Muñoz et al., 2018).

The use of battery-powered equipment in underground mines is associated with improved operational efficiency, reduced environmental impacts, and improved worker safety (Koniak et al., 2024). As such, Song et al. (2015a) propose a process control algorithm for estimating the work times of mobile equipment to improve the accuracy of scheduling and resource use. Mine operators can leverage this process

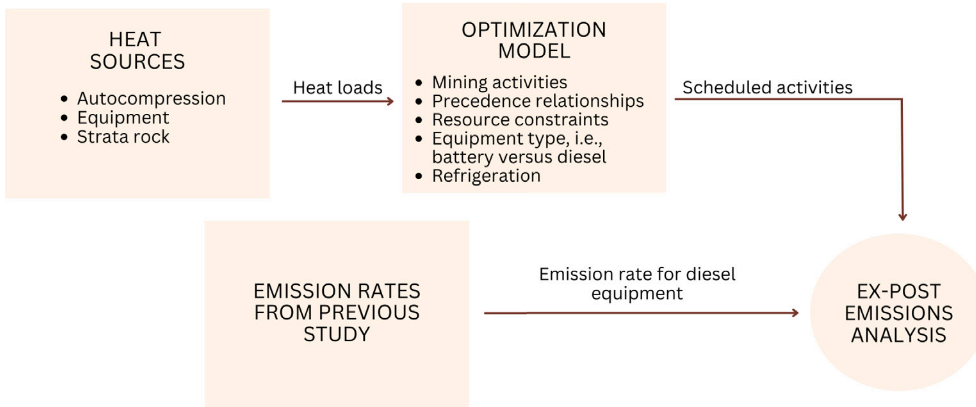

Fig. 3. A block diagram showing how the problem in this research is modeled. The study uses the Chilean Mine Planner– an algorithm for resource-constrained project scheduling problems – to solve the optimization model. The emission rates for the diesel-powered equipment are taken from a previous engine simulation study (Swift et al., 2023).

control tool to integrate battery-powered equipment in their operation. Subsequently, Song et al. (2015b) develop a fleet decision support model to improve operational efficiency, i.e., reduce downtime and adapt to unexpected events, by scheduling mobile equipment for an underground mine. The proliferation of battery-powered equipment can be linked to advances in battery technology, in which there are significant improvements in the form of charging efficiency, energy density, and safety (Sanguesa et al., 2021). Balboa-Espinoza et al. (2023) present a life-cycle comparison between diesel and battery trucks and determine that the significant upfront cost associated with their purchase is a barrier to adoption. While these studies discuss the various benefits of battery-powered equipment, none provides a mechanism for introducing this equipment into an operation.

Prior work on fleet management in mining focuses on truck assignment to transportation routes in a network (Samatemba et al., 2020). Because a mine fleet is capital intensive, Isnafitri et al. (2021) propose a mathematical model that determines truck allocation with the goal of minimizing overall capital and operational cost. In some cases, trucks are first allocated and then dispatched to shovels using queuing theory and linear programming, respectively (Ercelebi and Bascetin, 2009). The uncertainty in truck availability owing to operational changes and unforeseen circumstances warrants the development of optimization models that account for that fact (Ta et al., 2005; Mohtasham et al., 2021). Moradi Afrapoli and Askari-Nasab (2019) classify existing fleet management algorithms into either single- or multi-stage depending on whether the shortest path between shovels and destinations is determined via optimization a priori. While there is extensive literature on fleet management in open-pit mining, there is very little on underground mines. Beaulieu and Gamache (2006) seek to manage the fleet of underground mines by employing an enumeration algorithm that is based on dynamic programming. Similarly, Nehring et al. (2010) present a dynamic optimization model that combines short-term production scheduling and equipment allocation, accounting for uncertainties in an underground mine. In the wake of sustainable mining practices, there is little research regarding suitable transition plans from diesel- to battery-powered equipment in underground work environments.

The remainder of this article is organized as follows: Section 2 presents the methodology, including the optimization model. Section 3 describes the case study and scenarios. Section 4 provides the results and discussion, including *ex post* analysis. Section 5 concludes and highlights areas for future research.

2. Methodology

The procedure adopted in this study is a combination of thermodynamics and optimization frameworks, for which different software tools are used. Fig. 3 is a high-level depiction of this process. First, the study considers the heat sources within the mine to determine an allowable heat load on each level based on (i) the initial temperature due to autocompression and strata rock, (ii) the maximum allowable temperature, and (iii) the rate of airflow. Second, the study assigns a heat load to the various mining activities, which are then combined with precedence relations, resource limitations and equipment types to use as inputs to the optimization model. The optimization model is then solved with the Chilean Mine Planner (Muñoz et al., 2018; Rivera Letelier et al., 2020) to obtain a schedule. Third, the research utilizes the scheduled activities, equipment associated with those activities, average power output rates for each piece of equipment, and equipment emission rates estimated from a previous study (Swift et al., 2023), to conduct an ex-post analysis on the impact of the fleet electrification on emissions from the mining operation.

2.1. Thermodynamic modeling

Heat emitted by equipment is a function of utilization and efficiency. The authors compute the heat for trucks, which perform work by hauling the ore up the ramp, using Eq. (1); the first expression corresponds to equipment operating across levels by transporting material through the mine or to the surface, while the second corresponds to equipment operating on a single level, which converts all input energy to heat.

$$\dot{q} = \begin{cases} \dot{W}\left(\frac{1}{\eta} - 1\right) & \text{for equipment operating across levels} \\ \frac{\dot{W}}{\eta} & \text{for equipment operating on a single level} \end{cases} \quad (1)$$

where $\eta = \dfrac{\text{mechanical power output}}{\text{input energy required}}$

and where $\dot{W}$ is the average mechanical power output in kilowatts and η, based on the drivetrain, is an assumed efficiency relating to the amount of energy a system consumes, in the form of electricity or the energy content of fuel, per unit of output; its value is always less than one because a portion of the input energy is dissipated as heat due to friction or other losses. This model considers diesel-powered equipment (trucks, loaders, explosives loading trucks, and service equipment), electric equipment (raise boring machine), and equipment that uses a diesel engine to transit but employs electric-powered equipment to perform its duty (jumbos). Each activity is executed by a subset of the equipment, and the heat load assigned to each activity is a weighted average of the heat load associated with each piece of relevant equipment. For example, a development activity requires the use of a jumbo (20%), charge truck (15%), loader (35%) and haul truck (30%) in the proportions noted over the duration of the activity. The heat load for each piece of equipment is a time-weighted average that accounts for work under full load, transit time, and idle time. Using this information, the study computes the activity heat load to be 160 kW and 46 kW for diesel and battery-powered fleets, respectively. The average mechanical work for trucks and loaders is estimated using HAULSIM, a discrete-event simulation tool for haulage systems in mining (RPMGlobal, 2023); a standard work shift prescribes this load for the other equipment types.

Characteristics of the underground environment, such as the ambient temperature, humidity, and virgin rock temperature, determine the maximum allowable heat load on each level, which is used in the constraints to keep temperatures within limits. The mass flow rate of air on each level, $\dot{m}_n$, is fixed to maintain linearity of the model and because of the medium-term horizon considered; Ayaburi et al. (2024) vary the flow rate by level for a short-term model. Finally, the study also assumes a fixed cooling capacity of the refrigeration plant.

2.2. Optimization model

This research extends an existing mathematical formulation (Ogunmodede et al., 2022) to consider decisions on the transition from diesel to battery trucks and loaders. The objective function of this new formulation, referred to as ($\mathcal{O}^F$), maximizes the discounted net present value associated with executing activities by determining the following: (i) when to start executing an activity, (ii) whether to activate refrigeration, and (iii) when to retire diesel-powered equipment and introduce battery-powered equipment. Operational decisions, such as activity execution, are combined with strategic decisions, namely equipment type employed for any given time interval, because lower-level mining operations inform higher-level fleet management. For example, if it proves profitable to extract blocks requiring high-intensity vehicle operations, then a synergistic decision would adopt more battery-powered equipment, and sooner. These types of “mixed-decision-level” optimization models also appear in other industries such as energy, e.g., in Ogunmodede et al. (2021) for distributed energy generation design and dispatch and in Cox et al. (2023) for concentrated solar power tower design and operation. We note that activities are modeled individually because they are associated with their own individual data such as heat output and profit (see the notation preceding the optimization model). Model ($\mathcal{O}^F$) is subject to precedence, resource consumption, heat, and fleet transition constraints. The collection of eligible activities consists of development, extraction, transportation, and backfilling, and each occurs on a single level in the mine. The research introduces a set of finite resources consumed by these activities, e.g., volume of backfill paste required to fill the voids created by extracting ore, extraction capacity, and ore tonnage. A duration is associated with the amount of time required to execute an activity, including any necessary lag(s) between activities, e.g., ore from an adjacent stope cannot start to be extracted until a given stope has backfilled and the backfill paste has cured. A fleet mode refers to the type of equipment, diesel or battery, used to execute an activity. Of all equipment types in the fleet, the model only considers transitioning to battery-powered trucks and loaders because they constitute the most energy-intensive aspect of the mine (Katta et al., 2020), and only activities that employ them are eligible to switch modes. The study accounts for the cost of constructing charging stations as well as the purchase, operation and maintenance cost of the equipment.

Data in model ($\mathcal{O}^F$) is composed of cost or revenue, activity heat load (varying based on fleet mode but constant over the duration of the activity), and precedence relationship(s) between activities. Other inputs are mass flow rate of air, fixed and operating cost of activating a single stage of refrigeration, and the salvage value of diesel trucks and loaders. The variables in ($\mathcal{O}^F$) are modeled at daily fidelity and represent when an activity is scheduled to start, when to activate refrigeration, and when to procure (and correspondingly infuse into the fleet) battery-powered trucks and loaders.

This study makes the following assumptions to simplify the model: (i) an activity can be executed via either diesel or battery fleet mode, i.e., the modes are substitutes; (ii) other than heat load, which differs based on fleet mode, an activity’s resource consumption (e.g., meters of face advancement, number of drills used) is the same regardless of diesel- or battery-powered equipment used; (iii) the haul capacities of diesel- and battery-powered equipment are the same; (iv) diesel- and battery-powered equipment must be swapped on a one-for-one basis, i.e., the model maintains a constant fleet size; (v) the mining rate is constant and each activity requires a minimum of one time period to execute; (vi) the heat load for each activity only affects the level on which it is executed; and, (vii) once activated, refrigeration must stay on. Furthermore, the study assumes that the operation’s initial fleet is composed entirely of diesel-powered equipment (e.g., trucks, loaders, light-duty vehicles, personnel carriers). This study considers only trucks and loaders to be eligible for swap from diesel- to battery-powered as they contribute most significantly to heat load among diesel-powered equipment and because their use is more cyclic and therefore easier to track. (By contrast, light-duty vehicles are used more sporadically and their driving patterns may not be as scrutinized through the use of dispatch software; lack of data, far lower overall emissions, and lower overall impact in any given work area reduce the significance of these vehicles in this study.) The authors assume that the existing diesel fleet is of sufficient age so as to be eligible for replacement in the near future; correspondingly, the optimization model determines the decision epochs during which to perform swaps between diesel and battery trucks and loaders. In this study, an epoch corresponds to a year and activity duration is given in days (i.e., time periods much shorter than those corresponding to the decision epochs). However, these respective time fidelities can be generalized to incorporate other durations, as long as the epochs are “much longer” than activity execution lengths. Replacing an existing diesel vehicle with one having better emissions controls can reduce exhaust emissions but does little to reduce heat loads, the latter of which is the focus of this study. Sets (Table 1), parameters (Table 2), variables (Table 3), objective function and constraints for model ($\mathcal{O}^F$) follow. Adhering to Teter et al. (2016), lower-case letters denote parameters, upper-case letters denote variables, upper-case script letters denote sets, and lower-case letters are used for indices. The modifications from and extensions to the model found in Ogunmodede et al. (2022) are colored in blue for ease of differentiation.

Table 1
Notation and description of sets and indexed sets.

Simple sets	Description
$\mathcal{A}$	Activities
$\mathcal{E}$	Decision epochs (years)
$\mathcal{M}$	Equipment modes (diesel or battery powered)
$\mathcal{N}$	Mine levels
$\mathcal{R}$	Production resources
$\mathcal{S}$	Stages of refrigeration
$\mathcal{T}$	Time periods
$\check{\mathcal{A}} \subset \mathcal{A}$	Activities eligible to switch modes
$\bar{\mathcal{A}}_a \subset \mathcal{A}$	Precedence activities for activity a
$\tilde{\mathcal{A}}_n \subset \mathcal{A}$	Activities that occur on mine level n
$\hat{\mathcal{A}}_r \subset \mathcal{A}$	Activities that consume production resource r
$\tilde{\mathcal{M}}_a \subset \mathcal{M}$	Modes available for activity a
$\mathcal{T}_e \subset \mathcal{T}$	Time periods in epoch e

Table 2
List of parameters used in the optimization model.

Parameters	Description	Units
c_p	Specific heat capacity of air	$\left[\frac{\text{kJ}}{\text{kg} \cdot {}^{\circ}\text{C}}\right]$
$\check{c}$	Infrastructure cost of invoking battery fleet	[$]
$\hat{c}$	Purchase cost of a piece of battery equipment	[$]
$\hat{d}_a$	Duration of activity a	[days]
$\bar{d}_{a'a}$	Delay between finishing activity a' and starting activity a	[days]
f_m	Initial number of equipment in mode m	[number]
$\bar{f}_m$	Maximum number of equipment in mode m	[number]
$\dot{m}_n$	Mass flow rate of air on mine level n	$[\frac{\text{kg}}{\text{s}}]$
$\dot{q}_{am}$	Heat load from activity a via mode m	[kW]
$\dot{q}^{v}_n$	Virgin rock heat load on mine level n	[kW]
r_{ar}	Amount of production resource r required for activity a	[tonnes, meters, –]
$\hat{r}_{rt}$	Amount of production resource r available in time period t	[tonnes, meters, –]
s	Salvage value of a piece of diesel equipment	[$]
$\bar{\tau}_n$	Maximum air temperature allowed on mine level n	[°C]
τ^{air}_n	Air temperature on mine level n based on auto-compression	[°C]
τ^{mix}_{sn}	Air temperature with refrigeration at stage s on level n	[°C]
δ	Daily discount rate	[–]
κ_1	Fixed cost of refrigerated air	[$]
κ_2	Operation and maintenance cost of refrigeration	[$]
ν_{am}	Profit derived from performing activity a via mode m	[$]

Table 3
Definition of decision variables.

Variables	Description	Units
Continuous non-negative variables:		
F_{nt}	Final air temperature on mine level n at time period t	[°C]
Integer variables:		
I_{me}	Inventory of equipment in mode m at the beginning of epoch e	[number]
V_{me}	Number of equipment of mode m retired or purchased at epoch e	[number]
W_e	1 if battery fleet is invoked by epoch e, 0 otherwise	[binary]
Y_{amt}	1 if activity a starts via mode m at time t, 0 otherwise	[binary]
Z_{st}	1 if refrigerated air of stage s is activated by time period t, 0 otherwise	[binary]

Objective function

$$(\mathcal{O}^F) : \max \sum_{e\in\mathcal{E}} \sum_{t\in\mathcal{T}_e} \left(\frac{1}{1+\delta}\right)^t \cdot \Bigg(\underbrace{\sum_{a\in\mathcal{A}} \sum_{m\in\tilde{\mathcal{M}}_a} \nu_{am} \cdot Y_{amt}}_{\text{Activity revenue}} - \underbrace{\sum_{s\in\mathcal{S}} (\kappa_1 \cdot (Z_{st} - Z_{s,t-1}) + \kappa_2 \cdot Z_{st})}_{\text{Refrigeration cost}} - \underbrace{\check{c} \cdot (W_e - W_{e-1})}_{\text{Electrification infrastructure cost}} - \underbrace{\hat{c} \cdot V_{\text{battery},e}}_{\text{Battery-powered equipment purchase cost}} + \underbrace{s \cdot V_{\text{diesel},e}}_{\text{Diesel-powered equipment salvage value}} \Bigg) \tag{2}$$

subject to:
Precedence and activity occurrence (see Section 2.2.2)

$$\sum_{m\in\tilde{\mathcal{M}}_a} \sum_{t'\le t} Y_{amt'} \le \sum_{m\in\tilde{\mathcal{M}}_{a'}} \sum_{t'\le t-\bar{d}_{a'a}-\hat{d}_{a'}} Y_{a'mt'} \quad \forall\, a \in \mathcal{A}, a' \in \bar{\mathcal{A}}_a, t \in \mathcal{T} \quad \text{[precedence between activities]} \tag{3a}$$

$$\sum_{m\in\tilde{\mathcal{M}}_a} \sum_{t\in\mathcal{T}} Y_{amt} \le 1 \quad \forall\, a \in \mathcal{A} \quad \text{[packing for each activity]} \tag{3b}$$

Resource consumption (see Section 2.2.2)

$$\sum_{a\in\hat{\mathcal{A}}_r} \sum_{m\in\tilde{\mathcal{M}}_a} \sum_{t'\le t} \frac{r_{ar}}{\hat{d}_a} \cdot Y_{amt'} \le \hat{r}_{rt} \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T} \quad \text{[knapsack for each resource]} \tag{4}$$

Heat and ventilation (see Section 2.2.2)

$$\dot{q}^{v}_n + \sum_{a\in\tilde{\mathcal{A}}_n} \sum_{m\in\tilde{\mathcal{M}}_a} \sum_{t'\le t} \dot{q}_{am} \cdot Y_{amt'} = c_p \cdot \dot{m}_n \cdot (F_{nt} - \tau^{air}_n \cdot (1 - Z_{st}) - \tau^{mix}_{|\mathcal{S}|n} \cdot Z_{st}) \quad \forall\, n \in \mathcal{N},\ t \in \mathcal{T} \text{ [heat flow balance]} \tag{5a}$$

$$Z_{st} \le Z_{s-1,t} \quad \forall\, s \in \mathcal{S} : s > 1, t \in \mathcal{T} \quad \text{[precedence by refrigeration stage]} \tag{5b}$$

$$Z_{s,t-1} \le Z_{st} \quad \forall\, s \in \mathcal{S}, t \in \mathcal{T} : t > 1 \quad \text{[precedence by time]} \tag{5c}$$

Equipment mode availability (see Section 2.2.2)

$$W_e \le W_{e+1} \quad \forall\, e \in \mathcal{E} \quad \text{[precedence by decision epoch]} \tag{6a}$$

$$\sum_{e'\le e} V_{me'} \le \bar{f}_m W_e \quad \forall\, e \in \mathcal{E},\ m \in \mathcal{M} \quad \text{[limit on equipment purchase and retirement]} \tag{6b}$$

$$V_{\text{battery},e} = V_{\text{diesel},e} \quad \forall\, e \in \mathcal{E} \quad \text{[balance between fleet modes]} \tag{6c}$$

$$I_{me} = I_{m,e-1} + V_{me} \quad \forall\, m \in \mathcal{M} : m = \text{battery},\ e \in \mathcal{E} : e \ge 1 \quad \text{[inventory on battery-powered equipment]} \tag{6d}$$

$$I_{me} = I_{m,e-1} - V_{me} \quad \forall\, m \in \mathcal{M} : m = \text{diesel},\ e \in \mathcal{E} : e \ge 1 \quad \text{[inventory on diesel-powered equipment]} \tag{6e}$$

$$I_{m,0} = f_m \quad \forall\, m \in \mathcal{M} \quad \text{[initial conditions]} \tag{6f}$$

$$I_{m,|\mathcal{E}|+1} \le \bar{f}_m \quad \forall\, m \in \mathcal{M} : m = \text{battery} \quad \text{[inventory limit on battery-powered equipment]} \tag{6g}$$

$$\sum_{a\in\check{\mathcal{A}}} \sum_{t'=t-d_a+1}^{t} Y_{amt'} \le I_{me} \quad \forall\, e \in \mathcal{E},\ t \in \mathcal{T}_e,\ m \in \mathcal{M} \quad \text{[activity limit by equipment]} \tag{6h}$$

Non-negativity and integrality (see Section 2.2.2)

$$0 \le F_{nt} \le \bar{\tau}_n \quad \forall\, n \in \mathcal{N}, t \in \mathcal{T} \tag{7a}$$

$$I_{me}, V_{me} \ge 0,\ \text{integer} \quad \forall\, m \in \mathcal{M},\ e \in \mathcal{E} \tag{7b}$$

$$W_e \text{ binary} \quad \forall\, e \in \mathcal{E} \tag{7c}$$

$$Y_{amt} \text{ binary} \quad \forall\, a \in \mathcal{A},\ m \in \mathcal{M},\ t \in \mathcal{T} \tag{7d}$$

$$Z_{st} \text{ binary} \quad \forall\, s \in \mathcal{S},\ t \in \mathcal{T} \tag{7e}$$

2.2.1. Objective function

The objective function maximizes the discounted net present value of executing activities. That is, it considers the discounted benefits for each activity and the salvage value from the sale of diesel-powered equipment, less the following discounted costs: (i) mine refrigeration, (ii) battery-powered equipment infrastructure, and (iii) equipment procurement.

2.2.2. Constraints

Description(s) for each of the constraints in the model follow:

Mining constraints

Constraint (3a) enforces the precedence relationships between activities. For example, activity $a' \in \bar{\mathcal{A}}_a$ must be completed before execution of activity a can start. Constraint (3b) is a packing constraint on activity occurrence, i.e., an activity can occur at most once in the schedule horizon. The resource knapsack, which ensures that resource consumption of scheduled activities does not exceed the daily available capacity, is enforced through constraint (4).

Heat, ventilation, and refrigeration constraints

Constraint (5a) balances heat load, ventilation and refrigeration. While $\dot{q}_n^v$ captures heat from the strata rock for any given mine level n, $\dot{q}_{am}$ accounts for the heat load associated with executing activity a via fleet mode m. This heat load on each level n is balanced by the cooling effect of the ventilation air, which is a function of the temperature difference before absorbing the heat load, τ_n^{air}, and after, F_{nt}. Refrigeration (Z_{st}) may be activated to reduce the starting air temperature to τ_n^{mix} on each level. Because refrigeration must stay on once activated, it is modeled using the preposition *by* in the variable definition; the requirement is enforced via constraints (5b) and (5c).

Equipment mode availability

Constraint (6a) includes the *by* variable W_e, which ensures battery mode remains on, once activated. Constraints (6b) state that once in battery mode, the amount of battery-powered equipment purchased and diesel-powered equipment salvaged cannot exceed their respective capacities. The one-for-one swap between diesel- and battery-powered equipment is implemented in constraint (6c). Constraints (6d) and (6e) enforce the inventory levels of battery- and diesel-powered equipment at the beginning of epoch e, respectively; in other words, these constraints dictate the fleet composition. Constraints (6f) and (6g) impose the required starting and ending inventory levels, in which the model starts and ends with an all-diesel and an all-battery (or hybrid) fleet, respectively. Lastly, constraints (6h) ensure that the number of ongoing activities via mode m at time t does not exceed the inventory of mode m at the beginning of epoch e.

Non-negativity and integrality

Constraint (7a) limits the maximum air temperature in the mine for all levels and time periods. The upper bound, $\bar{\tau}_n$, can be adjusted based on local mine regulations. Constraints (7b) ensure integer non-negativity on the equipment inventory levels at the beginning of time t, on the amount of battery-powered equipment that can be procured, and on the diesel-powered equipment that can be salvaged at any time in the schedule horizon. The ability to switch to battery fleet mode, to determine when an activity is scheduled to start, and when refrigeration is activated are modeled as binary variables in constraints (7c), (7d), and (7e), respectively.

2.3. Solution procedure

The study implements the optimization model ($\mathcal{O}^F$) in the Chilean Mine Planner version 1.15 (Rivera Letelier et al., 2020) to understand the trade-offs between equipment electrification, refrigeration start time, and productivity for various medium-term schedules. The algorithm resides in a proprietary software tool that uses the Bienstock–Zuckerberg algorithm to solve the linear programming relaxation of the monolith after which it restores integer feasibility by employing rounding and fix-and-relax heuristics based on the linear programming relaxation solutions (Chicoisne et al., 2012; Muñoz et al., 2018; Pochet and Wolsey, 2006). The solver is invoked (without modification to the classical algorithms) on a Dell PowerEdge R610 computer with two 6-core Intel Xeon X5670 CPUs at 2.93 GHz, 128 GB RAM, and 1 TB HDD. The total number of binary decision variables ranges between 327,040 and 6,716,028 depending on the case, and the authors implement an (exact) *early start* procedure, which eliminates about 50% of the binary decision variables, i.e., binary variables that correspond to start times before the earliest possible start time are eliminated (Topal, 2008; Lambert and Newman, 2014).

Because of the problem structure required of the solver, the study determines a (near-)optimal solution by fixing and enumerating across the fleet composition, I_e^d and I_e^b, and refrigeration start time, Z_{st}, variables. The study generates fleet compositions of existing diesel truck–loader pairs that are nearing the end of their useful life and must be replaced by their battery equivalent, i.e., the study solves the optimization model for scenarios with different equipment replacement timings. For those medium-term cases with schedule horizons that are less than five years, the authors generate fixed fleet compositions consisting of 7 total truck–loader pairs, with some combination being battery-powered and the remaining being diesel; this combination remains static throughout the horizon, which, in these cases, is too short for a realistic fleet transition plan. However, for cases with horizon lengths of at least 1,825 days (5 years), the study generates fleet compositions that can vary from one year (decision epoch) and the next. The study assumes that the mine is currently operating with an aging all-diesel fleet and that battery-powered equipment is gradually introduced until the fleet is fully electrified by the end of the horizon.

There is a large fixed cost associated with refrigeration, so the study fixes and enumerates across the potential refrigeration start days, Z_{st}; this enumeration procedure in which a restricted version of ($\mathcal{O}^F$) is solved, is tantamount to allowing the variable to be determined as part of the monolith solve of ($\mathcal{O}^F$) and essentially illustrates the computational trade-off between solving more, smaller problems and one large problem. In this case, we obtain tighter bounds (or a smaller gap) using the former method. Similarly, fixing the fleet composition also helps improve the bounds of the optimization model. Using enumeration, after obtaining an optimal solution (or one within a reasonable gap given solve time considerations), the net present value is post-processed, accounting for both fixed and operating cost of refrigeration and equipment procurement, infrastructure, operation and maintenance costs. Appendix B captures all fleet-related costs using a levelized-cost-of-tonnes-hauled formula, with a 5% productivity difference assumption between diesel- and battery-powered equipment owing to the latter having a longer recharge time than their diesel equivalents require for refueling, which affects their availability.

2.4. Ex post analysis of equipment emissions

Model ($\mathcal{O}^F$) omits constraints on emissions because the assumed air flow rate on each level, $\dot{m}_n$, is above the ventilation requirements for all equipment. Therefore, constraints requiring adherence to safe levels would be superfluous. However, an ex-post analysis provides useful managerial insights on the quantity of tailpipe emissions (NO_x and soot) associated with any given fleet composition. The schedule obtained from model ($\mathcal{O}^F$) is analyzed to estimate the average daily concentration of NO_x and soot in the mine from exhaust emissions. The rate of equipment emissions associated with each ongoing activity (in g/h) is computed for each day by multiplying the average power output in kW (as given in Section 2.1) by an emissions rate in g/kW·h taken from Swift et al. (2023) for trucks and loaders, or the Environmental Protection Agency Tier 2 maximum for all other equipment. (Tier 2 equipment is used at the case study mine.) These values are divided by the air mass flow rate in m^3/h, to determine a concentration.

3. Case study mine and scenario descriptions

This section presents the case study mine, scenario descriptions, and data for both thermodynamic and optimization models. Model ($\mathcal{O}^F$) is solved with and without the equipment purchase and operation and maintenance cost to examine the impact of cost on fleet electrification in capital-intensive underground operations.

3.1. Case study mine

This study utilizes data from a large-scale hardrock underground mine (see Fig. 1) with an average wet-bulb surface temperature of 23°C; local regulations specify a wet-bulb temperature limit of 28°C in underground working areas, above which work must be curtailed for safety. The mine operates on a 24-h schedule and utilizes two different top-down methods, i.e., sublevel caving or stoping, depending on the level. Drifts at various elevations emanate from the shaft to allow for access to different areas of the orebody, i.e., stopes. The ventilation system provides fresh air to the mining zones and consists of a 28 m^2

Table 4
Daily maximum resource capacities for the case study underground mine. Ore extraction is the quantity of the mineral extracted from executing activities. Lateral development entails constructing horizontal passages to access the ore. Production meters is a measure of the length of drilling or extraction in a production phase. Haulage is the combination of the weight and distance of ore material transported. Slot raises are vertical openings used for either ventilation or as a pathway for moving materials. Production drill, explosive charger, and raise borer are pieces of equipment used for drilling holes, placing explosives in drilled holes for blasting, and boring vertical holes between levels, respectively.

Resource-constrained activity	Maximum capacity (daily)	Units
Ore extraction	6,900	Tonnes
Lateral development	33	Meters
Production meters	550	Meters
Haulage	42,000	Tonnes-kilometers
Slot raising	4	–
Production drilling	3	–
Explosives charging	5	–
Raise boring	1	–

Table 5
Model ($\mathcal{O}^F$) cases and their corresponding number of eligible activities and schedule horizon (days). These activities consist of development, extraction (stoping), transportation, and backfilling.

Case	Model ($\mathcal{O}^F$)	
	Number of activities	Horizon (days)
1	896	365
2	1,522	365
3	2,271	365
4	2,271	548
5	2,953	365
6	2,953	548
7	6,883	730
8	6,883	913
9	7,356	730
10	7,356	913
11	6,883	1,825
12	7,356	1,825

airway and a 3 m/s airspeed which is greater than the Mine Safety and Health Administration (MSHA) ventilation rate requirements for all equipment; an industry partner provided mine-specific information. Table 4 presents the daily maximum available resource, which is assumed to be the same, regardless of the fleet mode. This heat-constrained case study underground mine has a total of 14 diesel loaders and trucks, i.e., seven truck–loader pairs, which the optimization model seeks to transition to their battery-powered equivalent.

3.2. Scenario descriptions

Table 5 highlights the medium-term cases, including the number of potential activities to schedule and the schedule horizon in days. These cases are taken from different portions of the mine and do not constitute the entire complex. For an activity that requires a truck–loader pair, the model chooses between the diesel- or battery-powered equivalents (but not both) subject to availability. The study determines a reasonable set of fleet compositions, which are termed *instances*, that takes into account the truck–loader cycle; a cycle starts with loading blasted ore (using a loader) into a truck, which then transports the material to the dump site via haul roads. Although the decision to assign trucks to specific loaders depends on the mine's strategy, it is common practice to have dedicated assignments to improve cycle times which subscribes to the assumption that diesel- and battery-powered equipment must be swapped on a one-for-one basis (Song et al., 2015b; Burt and Caccetta, 2018). Given that the case study mine has a fleet size of 14 trucks and loaders, the authors define the fleet compositions as follows: (i) no battery-powered equipment, (ii) two battery-powered pieces of equipment, (iii) subsequently adding two pieces of battery-powered equipment (a loader and a truck) at a time, until all vehicles are battery powered. Table 6 provides a comprehensive summary of the cost parameters and includes fixed and operating cost of refrigeration, battery-powered truck and loader procurement and operation and maintenance cost, and cost of constructing charging stations. The authors solve the optimization model with and without equipment procurement and operation and maintenance costs to understand how cost impacts fleet electrification.

Table 6
Comprehensive summary of cost parameters for the case study underground mine. An industry partner and Rafi et al. (2020) provide refrigeration data and the fast-charging station costs, respectively.

Parameter	Value	Units
Charging stations	1	$ million/station
Fixed cost of refrigeration	13.2	$ million
Operating cost of refrigeration	15,378	$/day

4. Results and discussion

Table 7 presents the time-weighted average heat load for each piece of equipment used in the model, based on Eqs. (1). The higher efficiency of battery-powered equipment results in lower heat dissipation. For a truck with similar power rating, the battery-powered equipment produces approximately 80% less heat compared to its diesel equivalent.

4.1. Trade-offs between fleet electrification, refrigeration, and net present value without equipment cost

To focus on the performance and benefits of transitioning to a battery fleet, this analysis does not consider the cost of equipment, which is assumed to be sunk, but does include fixed and operational costs for refrigeration. Table 8 portrays results for the net-present-value-maximizing instance of (fleet composition, refrigeration activation day) which happens to be the maximum number of seven battery-powered equipment pairs for each case. Information regarding the refrigeration start day (in contrast to the length of the scheduling horizon), number of activities scheduled, net present value relative to that of the diesel-only fleet, and the optimality gap are also given. Table 10 (see Appendix A) presents comprehensive results for each fleet composition for the first ten cases, i.e., those for which we enumerate eight fleet combinations fixed in all decision epochs; for the remaining two (not shown in detail), we enumerate an all-battery, an all-diesel, and a hybrid instance consisting of infusing two truck–loader pairs each year.

Using the Chilean Mine Planning solver, solution times range from 145 s to 173,000 s (48 h), which is reasonable for medium-term planning, especially considering the size of the models and the computation required: solving between 304 and 744 models (in parallel) for each case, corresponding to enumerating the eight fleet compositions over the number of 10-day increments (refrigeration start times) during the schedule horizon (plus one with no refrigeration). (We actually perform additional enumeration in that the first set is at 10-day increments to determine an approximate day corresponding to the highest net present value, and then the next set is in one-day increments around that day to provide the detailed optimum, assuming unimodal behavior.) Preliminary testing with a standard, state-of-the-art general purpose solver such as Gurobi (Gurobi Optimization, LLC, 2024) resulted in exceptionally long solve times and large gaps. For example, Case 3 in Table 5 required four days to reach a 30% optimality gap, and the solver failed to obtain a feasible solution on the larger instances before running out of memory.

Battery-powered equipment has reduced heat outputs that leads to lower thermal load which either reduces the demand or delays the need for refrigeration in underground work environments. This study finds that refrigeration is not activated when the mine utilizes either a hybrid or all-battery fleet and operates closer to the surface. For instance,

Table 7
Time-weighted average heat loads for the types of equipment in the optimization model, including down time for breaks, shift change and lunch. The assumed efficiency of the equipment, η, is from GMG (2022), with battery-powered equipment being more efficient than its diesel-powered counterpart. Estimated power output for trucks and loaders is taken from discrete-event simulations.

Equipment	Motor	Actual power output estimation	Heat load (kW)
Truck	400 kW diesel	140 kW average power, η = 35%	260
	400 kW electric	140 kW average power, η = 73%	52
Loader	200 kW diesel	98 kW average power, η = 35%	182
	200 kW electric	98 kW average power, η = 73%	36
Jumbo	158 kW electric	158 kW, 30% duty cycle	47
Drill	158 kW electric	158 kW, 30% duty cycle	47
Raise bore	290 kW electric	290 kW, 30% duty cycle	87
Charge truck	98 kW diesel	30 kW average power, η = 35%	55
Service equipment	120 kW diesel	36 kW average power, η = 35%	66

Table 8
Best results, with respect to net present value, obtained from solving each model ($\mathcal{O}^F$) case. The base instance refers to an all-diesel fleet. For each scheduling case, the table shows the refrigeration start time, number of activities scheduled, and net present value over its base instance value. The table excludes fleet composition details; the optimal fleet in each case is fully battery-powered. Not all models solve to optimality though most are within 3%. These results do not account for equipment procurement and operation and maintenance costs.⁻Denotes no refrigeration NPV: net present value.

($\mathcal{O}^F$) case	Schedule horizon (days)	Refrigeration start (day)	Number of activities scheduled	NPV over diesel-only fleet (%)	Optimality gap (%)
1	365	–	366	25.89	0.51
2	365	–	398	4.94	18.50
3	365	80	1,145	4.00	2.22
4	548	230	1,458	3.18	1.59
5	365	30	1,249	12.37	12.81
6[a]	548	310	1,299	2.52	2.90
7[a]	730	110	4,126	2.93	1.23
8[a]	913	180	4,726	1.14	0.68
9[a]	730	200	3,517	1.98	2.65
10[a]	913	200	5,113	0.83	0.82
11[a]	1,825	150	4,726	1.21	1.32
12[a]	1,825	450	5,113	1.26	1.30

[a] Denotes cases solved using the sliding time window heuristic feature of the Chilean Mine Planning solver.

refrigeration is not activated in ($\mathcal{O}^F$) scheduling Cases 1 and 2 when the mine utilizes battery-powered trucks and loaders (see Table 8). This is because the installed ventilation system provides sufficient air to lower ambient temperatures. However, as the mine progresses deeper into the earth, surpassing the critical depth (the depth at which autocompression increases the temperature of incoming air above ambient), the need for refrigeration is delayed with the infusion of battery-powered trucks and loaders, i.e., there is a noticeable separation in time in refrigeration start day between an all-battery and all-diesel fleet.

Cases 11 and 12 consider five-year time horizons as the counterparts to Cases 8 and 10, respectively, but with the composition of equipment changing over the horizon as opposed to being static. In these longer-horizon cases, the number of scheduled activities is the same as in Cases 8 and 10, with the same net present value as the all-diesel instances but lower than the all-battery instances. The fleet composition with the highest net present value activates refrigeration at the beginning of time for both the hybrid and all-diesel fleets because they have the same composition for the first year (not shown in the table); Table 8 demonstrates that refrigeration is delayed for the all-battery fleet (best instance) for Case 12 but not for Case 11. Maximizing net present value pulls forward revenue-generating activities which might, in turn, cause refrigeration to be activated earlier; hence, providing a longer time horizon does not necessarily delay refrigeration nor lead to more completed activities because executed activities must, in aggregate, contribute to the *accumulated, discounted* value. In short, the model ($\mathcal{O}^F$) has the flexibility of choosing the potential activities that maximize discounted profit by prioritizing higher-revenue-generating activities subject to all constraints. Table 8 shows approximately a 1% to 26% improvement in net present value over an all-diesel fleet across the scheduling cases based on the fact that the net-present-revenue maximizing solutions all consist of a 100% battery vehicle fleet.

The selected three-dimensional plots demonstrate trends which the remaining cases follow. Specifically, Fig. 4 illustrates the trade-offs in mine production (net present value) as combinations of refrigeration and equipment electrification are used to manage heat loads without violating temperature limits. The lower heat load of battery-powered equipment induces more activities to be executed concurrently in the same area without needing refrigeration. When refrigeration is activated at the beginning of the horizon, there is little difference in net present value as sufficient cooling capacity exists to complete all activities; when the refrigeration start is delayed, net present value decreases as activities are postponed due to the lack of adequate cooling capacity. The decrease is more pronounced with diesel-powered equipment because their heat load is higher while the equivalent all-battery instance has a smaller decrease in net present value when refrigeration is activated later, indicating that the later instances are less sensitive to refrigeration. The ridge at day 366 in panel (a) or day 714 in panel (b) represents no refrigeration. Fig. 4(a) and (b) both show a decrease in net present value for all fleet compositions as the refrigeration activation is delayed. While (b) always requires refrigeration to maximize net present value, omitting refrigeration may be an acceptable alternative in (a). For instances in Case 3 that considers between two and seven battery truck–loader pairs, net present value decreases between 4 and 11 percent with no refrigeration relative to a solution in which refrigeration is deployed for the entire schedule. In both figures, refrigeration is required earlier in the schedule when there are more diesel-powered equipment pieces in the fleet. The refrigeration plant tends to be activated during the most heat-constrained portion of the schedule, i.e., when the accumulated heat on a mine level is at its allowable limit. The lower heat loads of battery-powered equipment delay the need for refrigeration and provide more flexibility in optimizing net present value whose improvement is not necessarily uniform with the infusion of battery-powered trucks and loaders because of the fluctuation in refrigeration start day and the type of activities scheduled. For example, Fig. 4(b) shows a delay in refrigeration start day, i.e., from day 10 to 110, which results

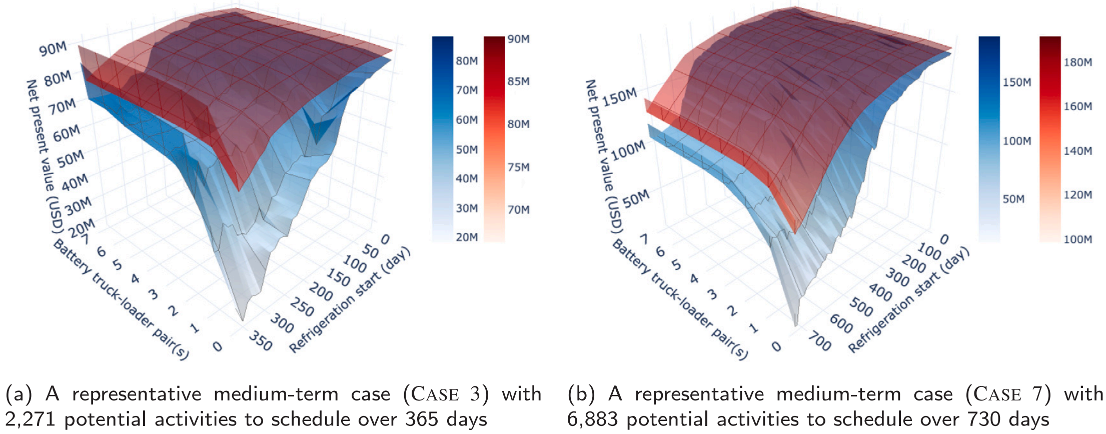

Fig. 4. Output from solving the optimization model for selected medium-term cases. The upper (red) and lower (blue) layers represent the theoretical maximum, i.e., upper bound, and best feasible solution, i.e., lower bound, for each fleet composition-refrigeration start day combination, respectively. The ridge at refrigeration start day 366 in (a) and refrigeration start day 714 in (b) represent cases in which no refrigeration is used.

in potential cost savings because the refrigeration plant will not be activated until day 110. The underground mine benefits from reduced operation and maintenance cost of running the plant, compared to when an all-diesel fleet is used, due to the delay in refrigeration start time. The combination of operating an all-diesel fleet and delaying refrigeration is associated with lower productivity because of increased temperatures which violates the safety constraints enforced in model ($\mathcal{O}^F$), resulting in a decrease in the number of scheduled activities in areas with high temperatures.

4.2. Accounting for equipment purchase and operation and maintenance cost

Accounting for equipment cost is important for understanding the economic and investment implications of transitioning from diesel- to battery-powered trucks and loaders in heat-constrained underground mines. Because different accounting methods have varying cost implications, the authors develop a conservative cost procedure termed *levelized cost of tonnes hauled* (see Appendix B), which measures the average net present cost of procuring and operating equipment over its lifespan. It is applied to individual pieces of equipment because the fleet composition may change throughout the time horizon and each piece of equipment only affects execution of the activities to which it is assigned. By contrast, activating the refrigeration system incurs a one-time cost because it affects production on all levels of the mine from the time it is activated until the end of the horizon. This study uses an annual interest rate of 9% over 10 years to compute the recovery factor, which is then applied to the equipment procurement cost. The operation and maintenance costs include overhaul, maintenance, fuel, electric power, parts and labor. CostMine Intelligence (CostMine, 2024) provides data on underground equipment cost, i.e., fixed, operation and maintenance costs, and reveals that diesel trucks cost less than their battery counterparts. Similarly, battery loaders cost more than diesel loaders. Computations yield a levelized cost of tonnes hauled of \$6.83 per tonne per diesel loader versus \$11.24 per tonne per battery loader, i.e., battery loaders cost 65% more than their diesel counterparts. Diesel trucks cost \$7.74 per tonne per vehicle versus \$11.46 per tonne per battery truck, i.e., battery trucks cost 48% more than their diesel counterparts. Battery replacement cost is not included; Harlow et al. (2019) present aging data for lithium-ion batteries in which the estimated capacity is greater than 80% after four years (the time horizon of this study), even at temperatures above 20°C. Fig. 5 depicts the impact of accounting for equipment-related cost in the optimization model on the trade-offs between fleet composition, refrigeration start day and net present value for representative scheduling cases. The results favor the use of an all-diesel fleet and activating refrigeration earlier, relative to either a hybrid- or an all-battery fleet. This can be attributed to the cost variations between diesel- and battery-powered equipment. For example, Fig. 5(b) shows an all-diesel fleet as the most cost-effective, and this trend spans the remaining ($\mathcal{O}^F$) cases, except for CASE 1, which selects a hybrid fleet. In effect, cost matters; to witness an increased infusion of battery-powered trucks and loaders into underground mine operations, stakeholders and policymakers, i.e., mining companies, investors, government and environmental groups, and battery-electric equipment manufacturers and suppliers, need to provide incentives commensurate with the realized difference in net present value between an all-diesel and an all-battery fleet.

Diffusion of Innovation Theory can be used to explain the high cost of battery-powered equipment in underground mines and also factors affecting the widespread adoption of such technology. New technologies are characterized by high research and development cost which are mainly recouped via higher prices which early adopters must be willing to pay (Sánchez and Hartlieb, 2020; Yuen et al., 2020). While the high cost of battery-powered equipment may serve as a barrier to adoption, it is a characteristic in the evolution of technology. Fig. 6 provides a conservative sensitivity analysis on the purchase cost of battery-powered trucks and loaders, demonstrating that a 25% reduction in levelized cost of tonnes hauled is required to attain parity between battery- and diesel-powered truck and loader costs. After applying the 25% reduction, the levelized cost of tonnes hauled drops to \$8.43 and \$8.59 for battery-powered loaders and trucks, respectively. As manufacturers achieve economies of scale, the technology matures, cost diminishes, and the prices of vehicles will decrease, making battery-powered trucks and loaders competitive with their diesel-powered counterparts. If maintenance costs, i.e., parts and labor, decrease to commensurate diesel-equivalent levels, costs for both vehicle types will be approximately on par. Furthermore, battery pack costs are forecast to reach \$80/kW·h by 2030 (König et al., 2021), a 30% reduction from 2024 prices. Battery costs in heavy equipment constitute a greater portion of the equipment cost than in light-weight passenger electric vehicles. Accounting for this cost renders battery-powered equipment more expensive than an equivalent diesel vehicle; neglecting the cost, battery-powered equipment can be two-and-a-half times more expensive than an equivalent diesel-powered piece of equipment (Gleeson, 2020). In the meantime, if the aforementioned stakeholders desire to increase adoption of battery-powered equipment in underground mines, they should provide incentives, e.g., tax rebates or discounts commensurate with a 25% equipment cost reduction.

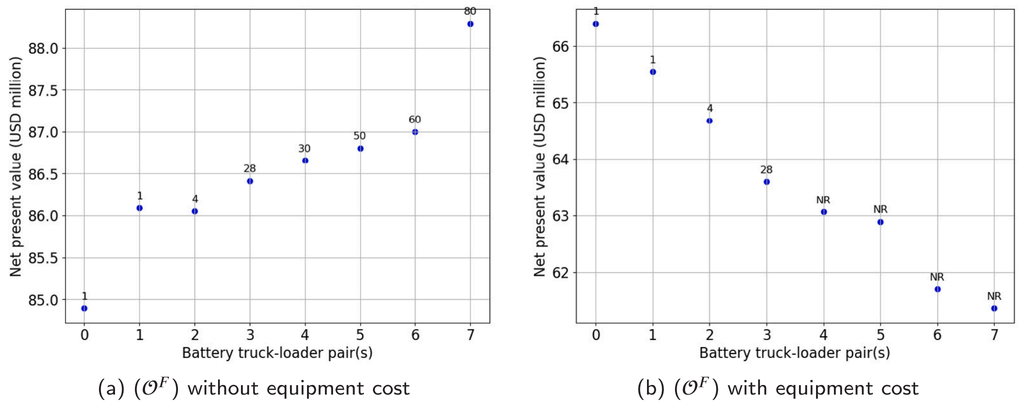

Fig. 5. Trade-offs between fleet composition, refrigeration and net present value for Case 3 with 2,271 eligible activities scheduled over 365 days. The blue dots represent the best feasible (i.e., integer) solution and the label next to each blue dot is the refrigeration start day for the corresponding fleet composition. Panel (b) includes the levelized cost of tonnes hauled for both diesel- and battery-powered trucks and loaders. NR represents no refrigeration.

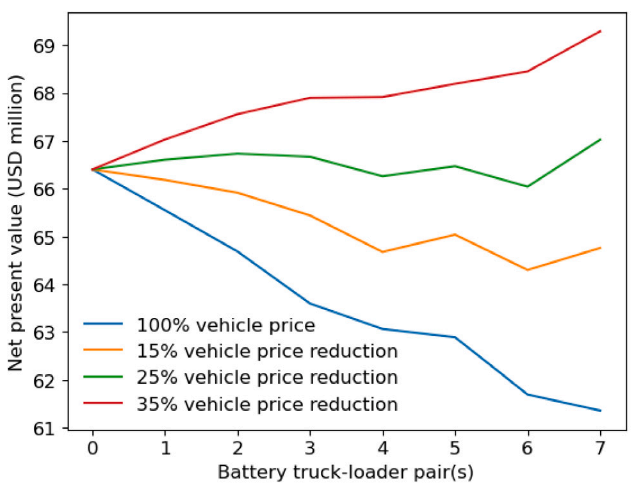

Fig. 6. Sensitivity analysis on the cost of battery trucks and loaders; each reduction is applied to the levelized cost of tonnes hauled.

The use of battery-powered equipment promotes cleaner production and improves the safety, via reduced heat loads, of heat-constrained underground work environments.

4.3. The impact of fleet electrification on equipment emissions

This section presents results from an *ex post* analysis on the impact of each fleet composition on contaminants such as NO_x (a weighted average of NO and NO_2) and soot computed based on the results of the scheduling model. The proposed fleet compositions have varying impacts on emissions; therefore, understanding these impacts has potential environmental, health and economic benefits to both underground workers and stakeholders. For each ($\mathcal{O}^F$) case and fleet composition, the optimization model determines a (near-)optimal activity schedule and, correspondingly, the fleet mode utilized. The authors use this information, together with the average equipment power rating and emissions rate from the manufacturer's specification sheet, the duration of each scheduled activity, and the schedule horizon to compute the cumulative total NO_x and soot levels. The emission rates (taken from Swift et al. (2023) and in units of g/kW·h) for trucks are 8.55 and 0.35 for NO_x and soot, respectively; for loaders, they are 0.62 and 0.38, respectively, to reflect the Tier 2 equipment in use at the case study mine. The number of operating hours per day for these pieces of equipment is 16. Total emissions are obtained by multiplying the emissions rate by an average power output, the number of operating hours per day, and the duration (in days) of the activity, for all activities in the schedule that use diesel-powered equipment.

Emissions from trucks and loaders represent a majority of the emissions because (*i*) the trucks and loaders are among the most powerful pieces of equipment in the mine, (*ii*) they operate at a high power output to transport the ore, and (*iii*) they operate for long periods of time because they are directly involved with the extraction of ore from the mine. Light-duty vehicles also produce emissions, although individual vehicle contribution is significantly less than that from a truck or loader (see e.g., Bugarski and Hummer, 2020). Fig. 7 depicts how the various truck-and-loader fleet compositions contribute to emissions for a representative case. The all-diesel fleet produces the highest emissions, while transitioning to an all-battery fleet reduces cumulative emissions to near zero; diesel-powered equipment that are not eligible for swapping, such as jumbos, charge trucks, and personnel carriers, continue to contribute minimally, precluding absolute-zero emissions. Our analysis across all scheduling cases shows that the highest average reduction in cumulative emissions, 31%, occurs when transitioning from a fleet composition of five battery-powered equipment pairs to six. These reductions range from 7% to 59% and are associated with Cases 3, 4, 5, 8, and 9. The second-highest average reduction, 26%, is linked to transitioning from a fleet composition of four to five battery-powered equipment pairs, with reductions ranging from 12% to 51%, and is associated with Cases 2, 6, and 7. The smallest average reductions are 15% (ranging from 5% to 59%) and 13% (ranging from 9% to 21%), associated with Cases 1 and 10, respectively. In the absence of equipment cost considerations, the optimization model has an incentive to assign battery-powered equipment, when available, because more activities may be performed concurrently due to a less-constrained thermal envelope, and it delays the need for refrigeration with its large upfront and ongoing operational costs. This highlights the utility of battery-powered equipment in promoting cleaner production in an underground work environment because an increase in the number of battery-powered equipment pairs corresponds to a reduction in cumulative soot and NO_x emissions while maintaining or increasing productivity.

Table 9 provides an estimation of the average and maximum daily emissions concentrations for the level of the mine with the greatest number of scheduled activities, each corresponding to the best instance for Case 3 with respect to net present value. The table contains results both for Tier 2 diesel-powered equipment, which is used in the case study mine, and for Tier 4 diesel-powered equipment, which subscribes to the most recent Environmental Protection Agency emissions standard and represents equipment available for purchase. For each day in the schedule, the average contaminant concentration is determined

Table 9
Estimated average and maximum daily NO_x and soot concentrations for Tier 2 and Tier 4 equipment emission standards on the most active mine level for Case 3, with 2,271 eligible activities scheduled over 365 days. An *instance* refers to a specific number of battery truck–loader pairs. While this study focuses on transitioning from Tier 2 to battery-powered equipment, Tier 4 data is included for comparison to illustrate the emissions reductions achievable with newer diesel engines.

Instance	Tier 2				Tier 4			
	NO_x (mg/m^3)		Soot (mg/m^3)		NO_x (mg/m^3)		Soot (mg/m^3)	
	Average	Maximum	Average	Maximum	Average	Maximum	Average	Maximum
0	6.3	15.0	0.36	0.93	3.76	9.47	0.04	0.11
1	3.6	11.0	0.18	0.64	1.98	6.67	0.02	0.08
2	2.6	7.0	0.10	0.35	1.26	3.87	0.01	0.04
3	2.6	9.8	0.10	0.41	1.27	4.93	0.01	0.06
4	2.3	6.1	0.08	0.33	1.06	3.51	0.01	0.04
5	1.6	4.7	0.03	0.10	0.59	1.77	0.01	0.02
6	1.6	4.7	0.03	0.10	0.59	1.77	0.01	0.02
7	1.6	5.6	0.03	0.12	0.60	2.12	0.01	0.02

by dividing the total emissions rate of working diesel-powered equipment by the airflow rate. These values are then aggregated across the schedule to determine the maximum realized value and the daily average. Since the optimization model seeks to maximize NPV, there is an incentive to schedule activities as soon as possible. As more battery-powered haulage trucks and loaders are introduced, their lower heat output creates slack in the heat constraint, allowing for more activities to be executed in parallel using smaller diesel-powered equipment (those not eligible for swapping) which can increase contaminant levels. This is seen in the maximum values between the two-pair and three-pair instance, in which the increase is attributable to more concurrent scheduling of activities requiring the use of a charge truck. Nonetheless, average values for NO_x (the combination NO and NO_2) and soot decrease with more battery-powered equipment. Soot averages for the zero- and one-battery pairs are above the MSHA action level of 160 μg/m^3 (0.160 mg/m^3). The permissible exposure level for soot is determined by the time-weighted average exposure over an eight-hour period. Although this model schedules activities, not personnel, the ambient concentration levels can help to inform worker exposure.

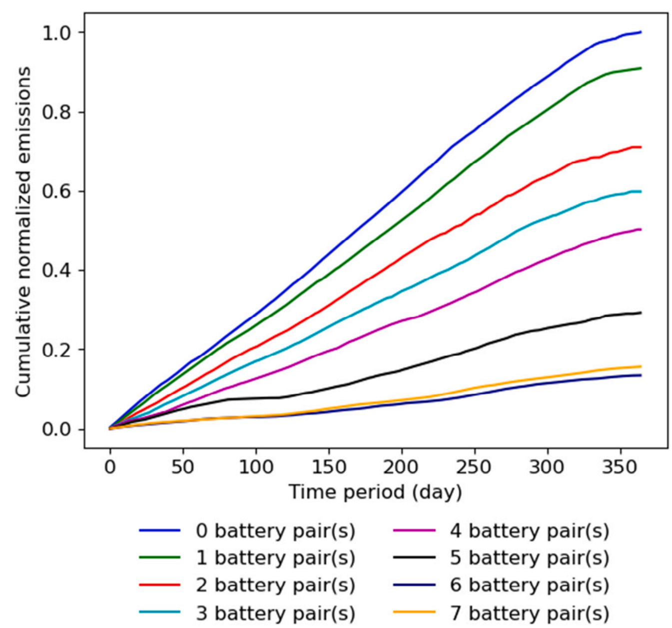

Fig. 7. Cumulative normalized emissions for Case 3 with 2,271 eligible activities scheduled over 365 days excluding emissions from the electricity grid. All the scheduling cases follow a similar trend; results show that an all-diesel fleet has the most emissions while transitioning to an all-battery truck-and-loader fleet reduces cumulative emissions by more than 75%. Emissions do not reach zero due to the presence of other diesel-powered equipment in the mine that is not eligible to be replaced with a battery-powered equivalent. The seven-pair result in this instance does not yield the lowest emissions levels because slack created in the heat constraint due to electrification of trucks and loaders allows more activities to be scheduled; these require smaller diesel-powered equipment to execute.

5. Conclusion

This study extends an existing optimization model (Ogunmodede et al., 2022) for strategic decision support in underground mines. The contributions of this paper include: reformulating and developing a solution technique for an optimization model that considers how to switch from diesel- to battery-powered trucks and loaders while maximizing net present value of the mining operation; providing an in-depth sensitivity analysis on the trade-offs between fleet composition, refrigeration, and net present value; and, understanding the impact of fleet composition on equipment heat output and exhaust emissions in underground areas. This paper does not examine the impact on respirable dust or other aerosols (to include silica), but studies show potential reductions in these pollutants from the use of battery-powered equipment (Halim et al., 2022; Ireland, 2023). The analysis also neglects emissions from the operation of light-duty vehicles. The resulting mixed-integer program is computationally intractable, owing to the large number of decision variables. Therefore, the authors develop an enumeration procedure embedded in the algorithm for a more standard resource-constrained production scheduling optimization model to obtain solutions to within 3% proof-of-optimality for most cases; horizon lengths range from 365 to 1,825 days. Post processing examines the impact of the transition from a diesel to a battery fleet on exhaust emissions, i.e., NO_x and soot. With sunk procurement and maintenance costs, this study shows a 1% to 26% improvement in net present value over an all-diesel fleet; a 100% battery-powered fleet is most economically advantageous. Soot and NO_x emissions decrease as the fleet composition of battery trucks and loaders increases; the most significant reduction in average cumulative emissions occurs at 31% as the fleet transitions from five to six battery-pairs.

This study does not account for reduced productivity and frequent interruptions due to battery charging. Inclusion of downtime results in varying durations for an activity depending on whether diesel or battery equipment is used, but the optimization algorithm best able to handle long-term production scheduling models requires an activity to have uniform duration irrespective of the equipment. Therefore, accounting for the downtime is beyond computational capabilities at the time of this writing and is therefore outside of the scope of this study. This omission is likely to have only a minor effect on results: charging downtime decreases the production rate by approximately 5 percent based on Akinnuoye (2018); and, simulations by the authors corroborate this. Battery swapping requires between 10 and 20 minutes, and fast charging can be completed in as few as 30 minutes with commercially available equipment.

Due to the call for sustainable mining (Onifade et al., 2024), mine operators should either replace their equipment fleet or revamp their ventilation setup to lower energy use, the latter of which cannot be changed quickly due to high upfront cost and/or regulatory requirements. The reduction in exhaust emissions and heat afforded by a battery fleet promotes the safety of workers and allows operators to mine deeper into the earth to extract high-grade ore. The findings indicate a positive relationship between the infusion of battery trucks and loaders in the case study mine and the realized net present value when equipment purchase and operation and maintenance cost is not considered (see Table 8). However, the results favor an all-diesel fleet when equipment cost is accounted for. Nevertheless, as equipment manufacturers attain economies of scale and technology matures, the price of battery-powered equipment is expected to drop. In the meantime, government and stakeholders could offer incentives, e.g., rebates and discounts of 25% equipment cost reduction, to increase the adoption of battery-powered trucks and loaders in the mining sector. With parity in pricing, the use of battery-powered equipment, with lower heat loads than their diesel counterparts, allows for more concurrent activities to be executed while adhering to the temperature limits. Additional benefits include ventilation cost savings, reduced noise levels, and increased safety of heat-constrained underground work environments via reduced levels of particulate and gaseous vehicle exhaust. This work, broadly, provides a tool which mine planners can use to make more environmentally friendly strategic decisions. The optimization model also may be extended to incorporate considerations for refrigeration plant sizing or ventilation quantities, for long-term and short-term mining plans, respectively, or to account for downtime associated with charging battery equipment. Solution techniques would need to be correspondingly developed.

CRediT authorship contribution statement

John Ayaburi: Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Aaron Swift:** Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Jason M. Porter:** Writing – review & editing, Validation, Supervision. **Andrea Brickey:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Alexandra M. Newman:** Writing – review & editing, Supervision, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research is funded in part by the National Institute for Occupational Safety and Health, United States as part of the Mine Ventilation and Safety Research Capacity Building program, contract number: 0000HCCS-2019-36404. We would like to thank our industry sponsors for providing data and funding this project. We extend our gratitude to Patricio Lamas and Orlando Letelier from Alicanto Labs for providing valuable insights about the Chilean Mine Planner solver, and Alex Zolan from the National Renewable Energy Lab in deriving the levelized cost of tonnes hauled.

Appendix A. Detailed results from model ($\mathcal{O}^F$) without equipment cost

Table 10 provides a general summary of the optimization results obtained from solving each of the scheduling cases using model ($\mathcal{O}^F$). It contains information about the fleet composition, refrigeration start day, and the optimality gap. The model outputs the integer program (LB) and linear programming relaxation (UB) solutions, which are used to determine the quality of the solution, i.e., $(\frac{UB-LB}{UB}) \cdot 100$.

Table 10
Optimization results for the first ten scheduling cases with their corresponding fleet composition-refrigeration start day combination without equipment cost consideration. For each fleet composition, the authors solve the model for the integer program (LB) and linear programming relaxation (UB) solutions as well as the refrigeration start day, if activated. – Denotes when refrigeration is not activated.

($\mathcal{O}^F$) case	Fleet composition				Optimality gap (%)	Refrigeration start (day)
	Number of trucks		Number of loaders			
	Diesel	Electric	Diesel	Electric		
1	7	0	7	0	3.65	143
	6	1	6	1	5.59	150
	5	2	5	2	5.74	159
	4	3	4	3	10.31	–
	3	4	3	4	4.65	–
	2	5	2	5	1.30	–
	1	6	1	6	1.27	–
	0	7	0	7	0.51	–
2	7	0	7	0	12.5	7
	6	1	6	1	20.50	6
	5	2	5	2	23.60	14
	4	3	4	3	24.69	1
	3	4	3	4	20.50	1
	2	5	2	5	23.40	5
	1	6	1	6	23.02	30
	0	7	0	7	18.50	–
3	7	0	7	0	3.72	1
	6	1	6	1	3.83	1
	5	2	5	2	4.46	4
	4	3	4	3	4.21	28
	3	4	3	4	4.01	30
	2	5	2	5	3.87	50
	1	6	1	6	3.65	60
	0	7	0	7	2.22	80

(continued on next page)

Table 10 (*continued*).

4	7	0	7	0	2.16	10
	6	1	6	1	3.95	120
	5	2	5	2	3.54	120
	4	3	4	3	3.37	140
	3	4	3	4	3.00	160
	2	5	2	5	2.47	180
	1	6	1	6	2.32	190
	0	7	0	7	1.59	230
5	7	0	7	0	21.27	1
	6	1	6	1	35.09	10
	5	2	5	2	39.15	1
	4	3	4	3	43.54	1
	3	4	3	4	32.38	50
	2	5	2	5	33.28	20
	1	6	1	6	36.08	–
	0	7	0	7	12.81	30
6	7	0	7	0	2.99	10
	6	1	6	1	13.57	10
	5	2	5	2	14.28	70
	4	3	4	3	15.45	90
	3	4	3	4	13.39	130
	2	5	2	5	13.38	130
	1	6	1	6	9.68	120
	0	7	0	7	2.90	310
7	7	0	7	0	2.39	1
	6	1	6	1	2.78	1
	5	2	5	2	2.36	30
	4	3	4	3	2.23	80
	3	4	3	4	2.11	100
	2	5	2	5	1.85	110
	1	6	1	6	1.60	130
	0	7	0	7	1.23	110
8	7	0	7	0	0.64	1
	6	1	6	1	1.42	1
	5	2	5	2	1.65	1
	4	3	4	3	1.82	100
	3	4	3	4	1.40	160
	2	5	2	5	1.26	200
	1	6	1	6	1.06	210
	0	7	0	7	0.68	180
9	7	0	7	0	3.55	1
	6	1	6	1	7.62	1
	5	2	5	2	10.70	1
	4	3	4	3	9.37	30
	3	4	3	4	9.52	80
	2	5	2	5	8.93	80
	1	6	1	6	8.17	130
	0	7	0	7	2.65	200
10	7	0	7	0	0.61	1
	6	1	6	1	3.82	30
	5	2	5	2	4.57	1
	4	3	4	3	4.81	20
	3	4	3	4	4.69	100
	2	5	2	5	4.59	130
	1	6	1	6	4.32	40
	0	7	0	7	0.82	200

Appendix B. Derivation of levelized cost of tonnes hauled

Levelized Cost of Tonnes Hauled (LC) measures the average cost to transport a ton of ore, e.g., using either diesel or battery equipment, per distance. It incorporates equipment procurement cost and operational cost such as fuel, labor, maintenance, and other costs directly related to hauling ore (see Table 11).

Table 11
Parameters, including their descriptions and units, used to compute the Levelized Cost of Tonnes Hauled.

Parameters	Description	Units
c	Equipment operating cost	\$ per year
κ	One-time equipment procurement cost	\$ per equipment
r	Discount rate	–
h	Annual tonnes hauled	tonnes
f	Fixed cost ratio	–
s	Total value	\$
δ	Discount factor	–
A	Annuity factor	–
T	Schedule horizon	year
LC	Levelized cost of tonnes hauled	\$ per tonne

$$\delta = \frac{1}{1+r}$$
$$s = 1 + \delta + \delta^2 + \ldots\ldots$$
$$\delta \cdot s = \delta + \delta^2 + \delta^3 + \ldots.$$
$$s - \delta s = 1 \Longrightarrow s = \frac{1}{1-\delta}.$$
$$A = s - \delta^T s \Longrightarrow \frac{1}{1-\delta} - \delta^T \frac{1}{1-\delta} \Longrightarrow \frac{1-\delta^T}{1-\delta}$$
$$f = \frac{1}{A} \Longrightarrow \frac{1-\delta}{(1-\delta^T)}$$
$$\therefore\ LC = \frac{f \cdot \kappa + c}{h}.$$

Data availability

The data that has been used is confidential.

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