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Heavy-duty truck simulator: a tool to plan charging and charger layouts

A Tool for Planning Charging Strategies and Charger Layouts in Electric Mining Fleets: Optimizing Efficiency with a Simulation Approach

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Gothenburg, Sweden 2024

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A Tool for Planning Charging Strategies and Charger Layouts in Electric Mining Fleets: Optimizing Efficiency with a Simulation Approach

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Abstract

Digital Twins (DTs) and simulation tools are virtual representations of physical objects or processes that can collect information from the real environment to represent, validate, and replicate the physical twin's present and future behaviour [1].

The aim of this thesis has been to gather the data requirements needed to prepare virtual tools capable of assessing mining sites, where traditional diesel-powered trucks are replaced by electric vehicles, with the organisation, analysis and incorporation of mining haul electric trucks in mines. This shift is driven by the need to reduce carbon emissions and improve sustainability in the mining sector. For the correct functioning of these virtual tools data requirements have to be recruited to make these tools work correctly.

An iterative research method has been chosen for this, reviewing the improvements in each step until the desired result is achieved. The research method used begins with a comprehensive literature review to know which is the status of the electrification in mines in the actuality and the existence of related virtual tools. The following step was to determine which were the research questions and elaborate the corresponding experiments modifying the backbone code, iterating all the needed times.

This thesis has explored the limitations in the existence of literature when referring to the simulation of mining heavy duty trucks in open pit mines, mostly due to the absence of real available data. Nevertheless, it has been demonstrated the potential of DTs and simulation models in optimizing the operation of electric mining fleets. The developed simulator provides a valuable tool for planning charging strategies, managing fleet sizes, and responding to dynamic environmental conditions. The study contributes to the goal of achieving efficient mining operations through the adoption of advanced digital technologies.

Keywords: Digital Twins, simulation tools, electric vehicles, mining haul electric trucks, fleet management, charging strategies, environmental conditions, advanced digital technologies.

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Óscar Galera Martínez, Gothenburg, June 2024

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AC	Alternating Current
BEV	Battery Electric Vehicle
BOT	Battery-only Truck
BT	Battery Trolley
BT-D	Battery Trolley Dynamic Charging
BT-S	Battery Trolley Stationary Charging
CAT	Caterpillar
DC	Direct Current
DET	Diesel-Electric Truck
DT	Digital Twin
ER-EV	Extended Range Electric Vehicle
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
FCS	Fixed Charging Station
HEV	Hybrid Electric Vehicle
HP	Horse Power
IEA	International Energy Agency
LDV	Light Duty Vehicle
LIB	Li-ion Battery
MCS	Mobile Charging Station
MHT	Mining Haulage Truck
MHET	Mining Haulage Electric Truck
PHEV	Plug-In Hybrid Electric Vehicles
RQ	Research Question
SSB	Solid State Battery
SOC	State Of Charge
TA	Trolley Assist
TAT	Trolley Assist Truck
TS	Truck-Shovel
V1G	Vehicle to Grid (unidirectional)
V2G	Vehicle to Grid (bidirectional)
V2H	Vehicle to Home
V2V	Vehicle to vehicle
V2X	Vehicle to Everything

Nomenclature

Below is the nomenclature of indices, sets, parameters, and variables that have been used throughout this thesis.

Variables

TAT	Total Amount of Time
TAT1L	Total Amount of Time doing 1 Lap
b	Time the truck is stopped charging battery
n°trucks	Number of trucks
Load	Quantity of Load transported by the truck

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1
Introduction

The existence of mines has been attached to the human since the beginning of the times. Silex, and other minerals and rocks were used to create tools and other utensils. However, over time, this need for the mining objects has progressively increased the demand of materials, and, after the industrialisation the increase has been even more pronounced. As a consequence, the mining sector has to evolve at the same time to provide the best possible service.

The benefits that mining materials provided for the civilisations led to the adoption of new technologies that allowed for the transportation of larger amounts of materials with less job. The first method of transport in mines appeared around the 1500s when the minecart started to be used. It was typically made out of wood and metal and running on fixed tracks.

The first dump truck appeared not until 1934. This heavy-duty vehicle was fitted with a 100HP gasoline engine and was 6.4m-long. It was the first step on the path to the monster dump trucks we see in the mining industry today. It was in 1998 when one of the most popular and well-known dump trucks emerged, the Caterpillar CAT 797. A 4,000 HP 20-cylinder engine and a 400-ton payload measuring 14.8m in length, 6.52m in height and 9.75m in width. The next step in the evolution of heavy duty trucks has been their automation. The automation of machines is being used as a general trend in the twenty-first century to try and eliminate the necessity for human control over machinery. Many mining truck manufacturers, including Komatsu, caterpillar, etc. Have been investing during this two lasts decades in automating their fleets.

Last but not least, the electrification of mines is conquering the mines all around the world as a global tendency in order to reduce emissions. The global warming and all the negative related effects come as a consequence of the excess of pollution emissions that the human has released during time. As a result of this, the world is collectively shifting to non fuel based appliances, this includes the mining sector [3]. According to the International Energy Agency's (IEA) industry carbon budget outlined in the last decade, mining companies, like those in any sector, are expected to decrease their emissions by 58% by 2050 compared to 2010 levels. In fact, in 2019 there were approximately 28,000 large mine hauling trucks worldwide, predominantly powered by diesel. Each of these trucks consumed an average of 900,000 liters of diesel per year and contributed to 30%–50% of their respective mines' total energy consumption. Collectively, these mining trucks emitted 68 million tons of

CO_2 annually, which is equivalent to the total greenhouse gas emissions of countries like Finland or New Zealand [4]. Apart from the pollution restrictions that the mining sector is slowly acquiring, this sector also faces several other challenges due to increasing demand for minerals and the depletion of high-quality resources. Among these difficulties are lower grades and deeper depths in open pit mining, which raises operating expenses and energy usage. With deeper mines comes a greater need for waste material extraction and an expanding fleet of haulage trucks. More energy-intensive processing techniques are also required due to decreasing copper ore grades. The fluctuation in the price of fossil fuels, also takes a part on the game, which has a big influence on mining operations but is out of the miners' control for the most part [5]. These restrictions are motivating the mining industry to go electric.

Electric vehicles that can be charged are the future of mining. However, the electrification of big haul trucks, the "elephants", need from new technologies in development related to batteries. Instead, managing an electric site with different vehicles that are smaller like "ants", is a solution that can be approached right now, as this vehicles are already electrified. This is why mining is also betting on autonomous driving to manage these swarms of smaller electric vehicles [6].

Although a lot of study has been done on charging systems and electrification of heavy-duty vehicles operations in different sectors, there is still a lack of information in the literature about how these technologies are used in open-pit mines. Previous research has mostly concentrated on road traffic and urban environments, ignoring the unique difficulties and factors related to mining operations. Furthermore, there is not much empirical data accessible, making the choice of charging systems for heavy-duty vehicles in open-pit mines a largely unexplored field. This absence of research impedes mining businesses' capacity to make well-informed decisions about the adoption of technology and investment in sustainable mobility solutions. To tackle these obstacles, a thorough comprehension of truck dynamics and the implementation of suitable charging methods customised to the distinct demands of open-pit mining settings will be necessary.

The contribution of this work could therefore help plan mining sites, study their viability, and optimize the utilization of electric vehicles in replacing traditional, highly polluting diesel vehicles. Working on these simulation tools also gave us a chance to study the input requirements, the input data requirement needed for a DT to operate in a real mining site. So this proof of concept is a tool to establish which data requirements are needed to implement a DT to optimize electric mining sites. The research questions that have been formulated in order to tackle the aim of this project are the following:

- RQ1. Which are the data requirements when using a simulation tool to plan charger positions?
- RQ2. How to use simulation tools to evaluate how many trucks should a mine operate concurrently?
- RQ3. How real-time data and DTs can help solving problems during operation

(e.g., heavy rain, wind, snow, etc.)?

In order to establish a conceptual foundation for mining electrification, the procedure started with a survey of the literature, during which an open-source code was found and examined. After that, three research questions were developed.
Every research question was investigated through an experiment that was carried out in iterative phases and allowed for method and code modifications. Each question involved changing the code, doing the experiment, and analyzing the findings while continuously iterating and evaluating under the supervisor's guidance.

Section 2 talks about the theoretical concepts and tools that have been used, as well as presents a review of the literature on the electrification of vehicles and mines. Then, Section 3 presents the methodology, introducing each of the experiments that were performed. Afterwards, in Chapter 4, the results of the explained experiments in the previous section will be exposed, in Chapter 5 these results will be examined, discussed and the future work will be added. Finally, in Chapter 6 the main learnings and insights will be stated.

2

Related Work

2.1 Simulation vs Digital Twins

The development of simulations has greatly benefited humans and industry. Industries can innovate, improve safety, and optimise operations thanks to simulations, which eliminate the hazards and limitations associated with actual testing. For instance, simulations are revolutionising vehicle design and testing in the automobile industry by enabling engineers to find improvements and anticipate results prior to producing real prototypes, therefore lowering costs and speeding up development. In addition to the automotive industry, simulations have an influence on the aerospace, healthcare, and urban planning domains. They aid in the testing of novel technologies, professional training, and the prediction of forthcoming issues [7].

Digital twins expand on the idea of simulations by acting as practice runs in a virtual environment. A DT is a virtual version of a real-world system or item that serves as a real-time mirror of the real one [8]. Consider a vehicle in the automotive sector that has a DT of its engine as a permanent companion. This DT communicates in real time with the actual automobile and is constantly updating critical data, such as fuel economy and engine condition. Through sharing information and learning from the actual automobile, this reciprocal connection guarantees peak performance and timely maintenance.

In the case of this thesis, there is not a real heavy duty truck working in a mine that can be mirrored and analysed. Instead, a model of the vehicle has been reproduced to predict different features about heavy duty trucks operating in a determined mining circuit. Those predictions are related with chargers position, number of trucks in a fleet and change of the performance due to sudden changing in the climate.

Simulations are based in models. Those models serve as an essential tool in the conceptualisation of physical systems by providing a mathematical representation of these systems [9]. This process, known as modelling, involves creating an abstraction of a system that recreates it. By formalising these abstractions, models enable researchers and engineers to understand, analyse, and predict the performance of complex systems under various conditions. These models can range from simple equations representing basic relationships to complex representations involving numerous variables and interactions. In fields such as engineering, physics, and environmental science, models provide the foundation for developing simulations that can be executed on computers. To ensure that the results of the simulation are applicable to the real world, the user must understand the assumptions, conceptualisations, and constraints specified on its models.

2.2 V-model and Data Requirements

Software has been and will continue to be a crucial component of the current computer environment. Likewise the software development models, which aim to provide systematic guidance for the coordination and management of the actions required to accomplish the project's goals and produce the final result. Software engineering is built on top of the software development paradigms. Only a small number of the many software development models that have been established throughout the years have persisted and are still in use today. The activities that must be completed, the input and output from each task, the preconditions and postconditions for each task, and the order and flow of these tasks are all defined by a process model for the software development process [10].

The V-model, a widely recognized software development process, is particularly relevant in the automotive sector. Similar to the iterative engineering research model, it is a sequential development process where each phase must be completed before the next begins. It includes four key phases: requirement analysis, specification, design, and implementation, each paired with corresponding verification and validation phases. Testing progresses through levels from unit testing to acceptance testing, ensuring thorough assessment throughout development [2]. For the correct

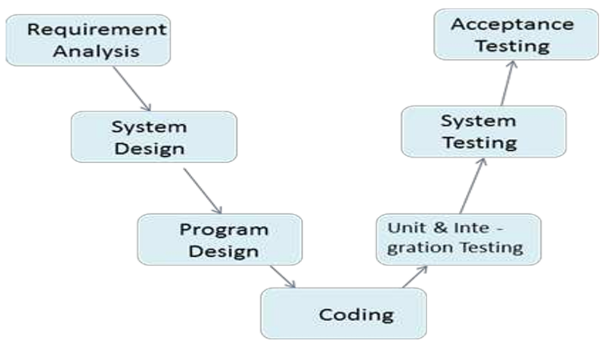

Figure 2.1: V-model as represented by Stephen et al. [2].

establishment of requirements, the first step involves gathering system data to determine what is necessary for building the model. This should be dictated primarily by the scope and level of detail required to achieve the model objectives, moving from general to specific. Initially, focus on defining the overall process flow to provide a framework for attaching more detailed information. As the development process progresses, engineers may need to request additional data or clarifications from the client. This ongoing exchange is essential; without the client's cooperation in providing detailed information, the engineer cannot accurately develop the application to meet the client's needs and expectations. This collaboration ensures that the final product aligns with the original requirements and functions as intended [11].

2.3 Matlab as a Simulation Tool

The high-level programming language and interactive environment known as Matlab, created by MathWorks, is extensively utilized for numerical calculation, data analysis, algorithm creation, and visualization.

Its simulation feature is one of its best qualities. Because of its high-level language, anyone without extensive programming experience may construct and comprehend non-trivial simulations.

The numerical solvers and libraries that this program has facilitates the accuracy and computation of simulations, from simple linear models to non-linear systems. Additionally, the software's integration capabilities allow interfacing with other programming languages and real-time data acquisition hardware, improving its simulation potential [12].

Moreover, Matlab's visualization tools enable the creation of graphs and plots, allowing users to analyze and interpret simulation results. This capability is useful for verifying and validating models, ensuring that the simulations represent real-world scenarios.

2.4 Euler Method

The Euler method, also known as the forward Euler method, is a first-order numerical process used in mathematics and computing science to solve ordinary differential equations starting from a specified beginning value. For the numerical integration of ordinary differential equations, it is the simplest explicit method available.

$$\frac{d(SOC)}{dt} = f(y, SOC) \tag{2.1}$$

This method approximates the solution by taking small, discrete steps from an initial value (h). In the used simulation the step is an increase in the y_n altitude and the corresponding energy associated to it when moving in the X horizontal distance.

$$y_{n+1} = y_n + h \tag{2.2}$$

For each step, it uses the current value of the function and its derivative to estimate the next value. This process iteratively builds the approximate solution over time, demonstrating how the system evolves from its initial state towards its steady state. In our used simulation calculates the energy spent or recovered and computes the SOC in every step done by the vehicle.

$$SOC_{n+1} = SOC_n + hf(SOC_n, y_n) \tag{2.3}$$

The analysis relies on energy conservation. This method is preferred because it tends to offer numerical stability, especially when using simple forward Euler integration. By focusing on distance-based steps, the energy conservation principles are more effectively maintained, reducing numerical errors and improving the accuracy of the simulation outcomes.

2.5 On-road Electric Vehicles

The appearance of electric vehicles (EVs) has meant a change in the paradigm of transport, not only in the light duty vehicle (LDV) sector, which is the foremost developed sector, the electrification of vehicles is reaching all types and sizes of vehicles. Sanguesa et al. [13] in their article report that light duty EVs can be classified into five groups: Battery electric vehicles (BEVs), Plug-In Hybrid Electric Vehicles (PHEVs), Hybrid electric vehicles (HEVs), Fuel Cell Electric Vehicles (FCEVs), and Extended-range EVs (ER-EVs).

BEVs run exclusively on battery power, offering an autonomy of 160 to 250 km [14] and in the same way as PHEVs they can both be connected to the grid to recharge their batteries, The later one combines conventional fuel and electric engines, having an electric range of around 50 km with the electric engine. Instead, HEVs feature both conventional and electric engines, with its battery being recharged by the kinetic energy or the combustion engine-generated power. FCEVs are provided with an electric engine that utilizes compressed hydrogen and emits only water as waste. Finally, ER-EVs combine electric propulsion with a supplementary combustion engine for extended-range driving, having 260 km of autonomy and 130km of extended range driving. A common factor in all these cars is the presence of a battery. The most used battery in EVs industry are Li-ion batteries (LIB), but alternatives like solid-state batteries (SSB) offer improved safety with non-flammable electrolytes, despite higher production costs [14].

EVs require charging when their battery's state of charge (SOC) is low, taking longer charging times compared to refuelling internal combustion engine vehicles. Moreover, the increasing demand for EVs could strain local grids if an effective coordination was not taken into account. There are different types of charging methods registered in literature for actual on-road EVs.

Conductive charging is characterized by the use of cables in the charge of batteries and can occur at home or at public charging stations, the power/voltage discharge rate is classified into Level 1, 2 (low and mid AC voltage) and 3 (DC fast charging), with extreme fast charging being explored but raising safety and battery lifespan due to thermal concerns which may generally be detrimental to the EV battery. Moreover, it is believed that repeatedly heating the battery from DC fast charging might accelerate the aging process of the battery [15].

Controlled charging is another way how EVs plan their charging, including seasonal variations, time of day, location, and day type. It covers charging demand influenced by electricity prices, driving patterns, and SOC. To be able to cope with all this conditions different charging concepts appear. V1G or V2G (Vehicle-to-grid) makes reference to the unidirectionality or bidirectionality of the charge of the electric vehicle to the grid. The next concept, V2X (vehicle-to-everything), is an extension of the last group of charging techniques, but considering not only the grid as a receiver but any external system. Finally, other concepts such as V2H (vehicle-to-home) which is a subsection inside vehicle-to-grid category, and V2V (vehicle-to-vehicle) which allows the transmission of energy between vehicles and could help in emergency situations would complete this controlled charging section [13].

Wireless and dynamic charging for electric vehicles (EVs) is an alternative to cable charging, including both dynamic (charging while driving) and static (charging while stationary) methods [16]. Inductive wireless charging eliminates the need for a physical connection between the EV and the grid. However, attention must be paid in the data communication between the vehicle and ground assembly, ensuring proper charging conditions, also to foreign object detection, and payment processing.

Battery swapping is an approach to a charging method which involves quickly replacing a depleted battery with a fully charged one at designated stations, making it particularly useful for fleets, such as electrified taxi cabs. This method can significantly reduce downtime compared to traditional charging methods [17].

Finally, mobile charging is the last option for alternatives to cable charging. This way of charging overcomes the high cost and space limitations of fixed charging stations (FCS) in urban areas by using portable charging units, like vans equipped with batteries, which can be booked via an app to charge EVs on demand. This flexibility helps manage peak demand times and provides convenient charging options for EV drivers [18].

2.6 Mine Structuring

The electrification of LDV is in actual process, instead in large vehicles, such as heavy-duty trucks, it has a progressive and slow development. Electric trucks have drawn interest from mining industries in particular as a potential way to lower emissions, improve operational effectiveness, and lessen the environmental impact of their operations. The feasibility of electrification in heavy-duty applications has been demonstrated by companies such as Komatsu or Caterpillar, which have created electric truck prototypes specifically designed for open-pit mine conditions.

The use of battery-powered vehicles in mining operations is fueled by a number of factors. Firstly, electric trucks perform better than their conventional diesel-powered counterparts thanks to features like regenerative braking and fast torque delivery. Second, electric drivetrains may be customized and scaled to fit the unique needs of mining fleets due to their modular design. Further encouraging the switch to electric propulsion systems is the possibility of financial savings from lower fuel and maintenance costs as well as adherence to ever stricter environmental standards.

Nonetheless, there are still issues with the broad use of electric trucks in mining operations. Adoption is restricted by worries about upfront investment prices, battery technological constraints, the availability of charging infrastructure. Incorporating electric haul trucks into current mining fleets also needs meticulous planning and operational and logistical considerations due to the physical limitations of a mine, and its continuous change.

2.6.1 Diesel Powered Systems

Historically, mining operations have relied on diesel machinery for material transport and handling, what are called the conventional Truck-Shovel (TS) systems [19]. These systems are composed of trucks which transport the load from the downhill part to the uphill part of the mine, and shovels which are operative in the bottom part of the mine to load the trucks and also in the top to rearrange the material unloaded by the trucks. TS systems continue to dominate open-pit mines due to the flexibility of e-powered trucks in handling different kind of materials, their good scalability, and easy manoeuvrability. They remain the most viable, flexible, and widely used mining systems, with autonomous trucks further enhancing their safety and effectiveness.
But mining has adopted different electrification trends when referring to their fleets and installations. However, these configurations are still dependent on important constraints, for instance the availability electric high power.

2.6.2 Hybrid Powered Systems

An alternative to the TS systems are the In Pit Crushing and Conveying systems (IPCC). In these systems the transport of the ore and materials is done by a conveyor belt. The materials are previously crushed in the pit by crushers which breakdown the transported material that will be placed in the conveyor belt by trucks. Depending on the mobility of the crusher in the system the IPCC model varies being Fixed, Semi-Fixed, Semi-Mobile [20], and Fully Mobile (in which trucks are not used and the shovel can directly carry the material into the conveyor belt) [21]. Differently from TS systems, IPCC allows for a continuous flow of material.

Another solution that is a practical first step on the path to low-emission mine sites is Trolley Assist (TA) [22]. It is a proven technology capable of providing external electrical power to diesel-electric equipment. The TA system is the most cost-effective on the ramps. After operators manoeuvre diesel-electric trucks leaving the workface to arrive at the trolley ramp (being fuelled by diesel) , the most appropriate time and approach speed is determined to enter trolley mode and raise the pantograph. The truck switches to trolley electricity when the pantograph is activated and connected to the overhead power lines. This is how the alternance of electric and diesel fuel would power the trucks.

2.6.3 Electric Powered Systems

Using the same overhead power line configuration, there is Battery Trolley Systems. Those are only available for battery-electric trucks and are distinguished between dynamic charging, stationary charging and dual Battery Trolley charging. Dynamic BT [23] charging accounts for a continuous charging and propulsion from the overhead powerlines and use of the battery when no powerlines are available. Stationary BT charging refers to the system in which trucks are able to run with electric propulsion coming from overhead powerlines, but have no possibility for recharging their batteries. Instead, specific battery stations will be designed for the recharge of the batteries, and regenerative braking will be used for recharging their batteries in downhill ramps. Finally, dual trolley battery systems stand for those stationary BT charging systems in which regenerative braking produced in the downhill ramps can be captured back to the grid (via overhead powerlines).

As already stated previously in the introduction, the electrification of mines is an event that is taking place right now. One example of big haul trucks which are shifting to electric power are Liebherr Mining T 264 trucks, they will convert the fleet from diesel-electric to battery deployed haul trucks. Those trucks will carry a 15 tones 1.4MWh battery. The electrification process has already started but they are not planning to be net zero emissions until 2030 [24].

2.7 Simulation as a Planning Tool

In many industries, including mining, simulation is a vital tool for arranging and optimizing processes. Simulations aid in decision-making by simulating complex systems and offering insights. Several studies work as examples of how simulation can be used to plan heavy-duty truck charging and operational behavior in mines, in our case two scenarios will be analysed.

Bao et al. [25], from the University of Queensland, present a comprehensive review of recent technological advancements in powertrains for Mining Haulage Truck (MHT). The evaluated configurations compare their performance in terms of time spent and energy consumed in a determined hypothetical but typical mining trajectroy. The evaluated configurations include Diesel-Electric Truck (DET), Trolley Assist Truck (TAT), Battery-only Truck (BOT), Battery Trolley with Dynamic charging truck (BT-D), and Battery Trolley with Stationary charging truck (BT-S). According to the analysis, the less energy demand option is BT-D covering the circuit with a consumption of 466 kWh.

In another study done by Lindgren et al. [26], a team from the Chalmers University of Technology, investigated the viability and economics of using battery-electric power, charged via an electric road system utilizing overhead trolley lines (Battery Trolley with Dynamic charging truck (BT-D)). The simulation model used in this investigation has been validated against actual performance data from diesel-electric haul trucks under normal operating conditions. This model was tested using five drive cycles that represent typical operations at the Aitik copper mine in northern Sweden. The findings of this simulation demonstrate that operating haul trucks with battery-electric power and an electric road system is a practical option.

These studies demonstrate how simulation may be used as a planning tool to increase the effectiveness and reduce the negative environmental effects of heavy-duty vehicle operations in the mining industry. Mining businesses can improve the overall performance by anticipating problems more accurately, optimizing their processes, and making data-driven decisions.

3
Methodology

One of the most well-known tools for assessing automotive plan decisions is to simulate their behaviour. Literature about the topic presented different examples of which [26] and [25] interestingly used simulations to replicate how heavy duty trucks transported load in a mine. Those simulations used similar strategies implementing the functioning of Heavy Duty Trucks with overhead powerlines.

The used simulation tool in this work is Matlab, and the scripts used were provided by an open-source project previously commented in this section [26]. This was very convenient because it allowed us to replicate different driving cycles and study how to determine where electric vehicle chargers should be positioned. We consider this simulation tool to be a proof of concept showing that simulation tools and DT that receive real-time information about the vehicles and the chargers can be used to optimize a mining site.

3.1 Iterative Engineering Research

To be able to complete this thesis successfully and the consequent investigation around it, the followed methodology has been an iterative engineering research in the topic with associated experiments. This method combines the sequential structure with iterations and periodic reviews allowing for a more flexible and adaptable development.

The first step was the reviewing of the literature, were many analysis and academic articles on the topic were found. This review allowed to establish a theoretical basement for the understanding of the mining electrification status and how to tackle the rest of the thesis. During this literature review the open source code that has been used as a backbone in the thesis was found and subsequently analyzed.
Once the literature review was completed and the analysis of the code done, the three different research questions that would guide this study were established.

Afterwards, each of the research questions was approached. In each of the research questions an experiment was designed to help answering it. Those experiments were executed in iterative phases allowing for the reevaluation and adjustment of the method and codes between each of the existing phases. In each of the research questions after establishing the experiment the modification of the code, the execution of the experiment and finally the interpretation of the different results took place.

As it has been previously said in this process continue iteration and evaluation has been hold by the supervisor.

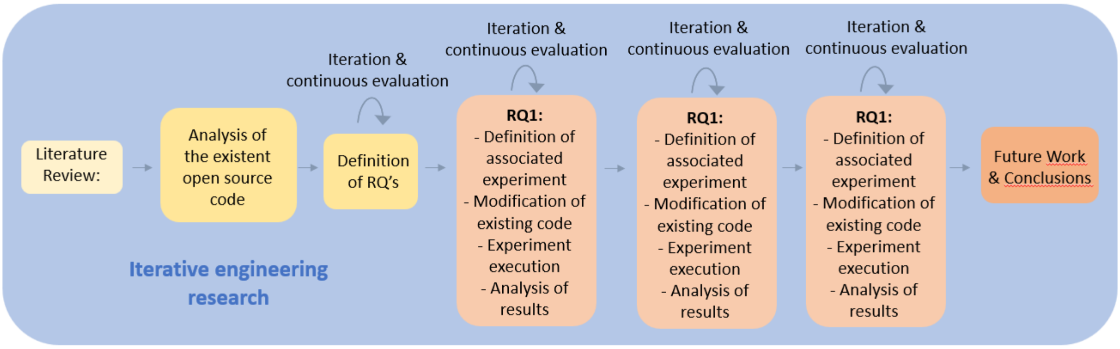

Figure 3.1: Iterative engineering research

3.2 Proof-of-concept Simulator

The simulator that it has been used it is divided in different parts, Figure 3.2 shows the Matlab used files used to execute simulation and visualise results. Working on these simulation tools also gave us a chance to study the input data requirements needed for a DT to operate in a real mining site. Therefore, this proof of concept is a tool to establish which data requirements are needed to implement a DT to optimize some features of electric mining sites.

In our case, to simulate heavy duty trucks operation the used simulation has been elaborated from the open base code used in Lars Lingren et al. work [26]. This simulation tool has been calibrated with real data from 13 drive-cycles. To check if the simulation tool was working correctly the energy consumption at the DC-bus of the actual vehicle was compared with the energy consumption calculated using the simulation model. When the rolling resistance was set to 1.4% (A rolling resistance of 1.4% appears reasonable, as the industry commonly uses a rough estimate of 2%, incorporating a safety margin), the simulation's average calculated DC-bus energy consumption was 358 kWh per cycle, while the measured DC-bus energy consumption was 361 kWh per cycle. This minor difference of only 1% indicated a high level of accuracy [26]. Furthermore, an expert familiarized with the mining industry and electric vehicles was contacted. This person was able to verify the data requirements proposed by the thesis and showed which are the limitations of the mine and our system (specified more in detail in section 3.4).

The code used for the simulation of this project is hosted in the following repository `https://github.com/oscargalera/HeavyTruckSimulator` .

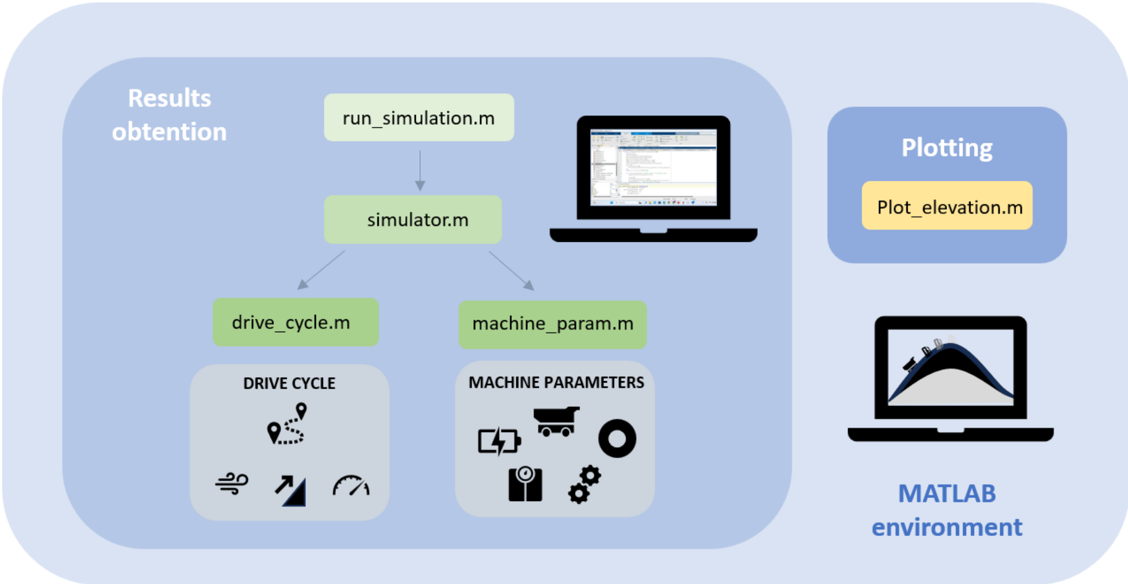

Figure 3.2: Map of the Matlab used files

3.2.1 Trajectory setup

The main objective of this file is to define the trajectory where the truck will be circulating in. The route and the small variations in the relief of the path due to a repetitive passing by of the trucks over the circuit are defined in this section. The unloading spot of the truck will be also fixed in this part of the code. Finally, the chargers set up is defined also in the **drive_cycle.m** file. The chosen trajectory is one similar to the ones appearing in the base code
The considered drive cycle have the following characteristics:

- Circular drive cycle (end = beginning)
- 15% slope uphill and downhill
- Small random variation in the ground, imitating real data from the 13 drive cycles from [26]

In our setup, we modify the simulation to adapt to drive cycles that are not too different from the described above. The code of the simulator has been restructured and complemented to simulate electric trucks using static charging stations to refuel their batteries, which is a non-contemplated study in the actual literature.

3.2.2 Simulation engine

In the **machine_param.m** file, all the different parameters referring to the truck, weight, power, rolling resistance, acceleration/deceleration power, etc. are specified. In this simulation the same truck as in the initial simulation is used, CAT795F AC Haul truck. Other trucks could have been implemented but there was not enough information about all the characteristics necessary for the proper functioning of the simulation. The main simulation is then run in the **simulator.m**. The Euler method is implemented to calculate the energy consumed by the truck in every x-distance step. The SOC is also refreshed in every horizontal step that the truck goes forward.

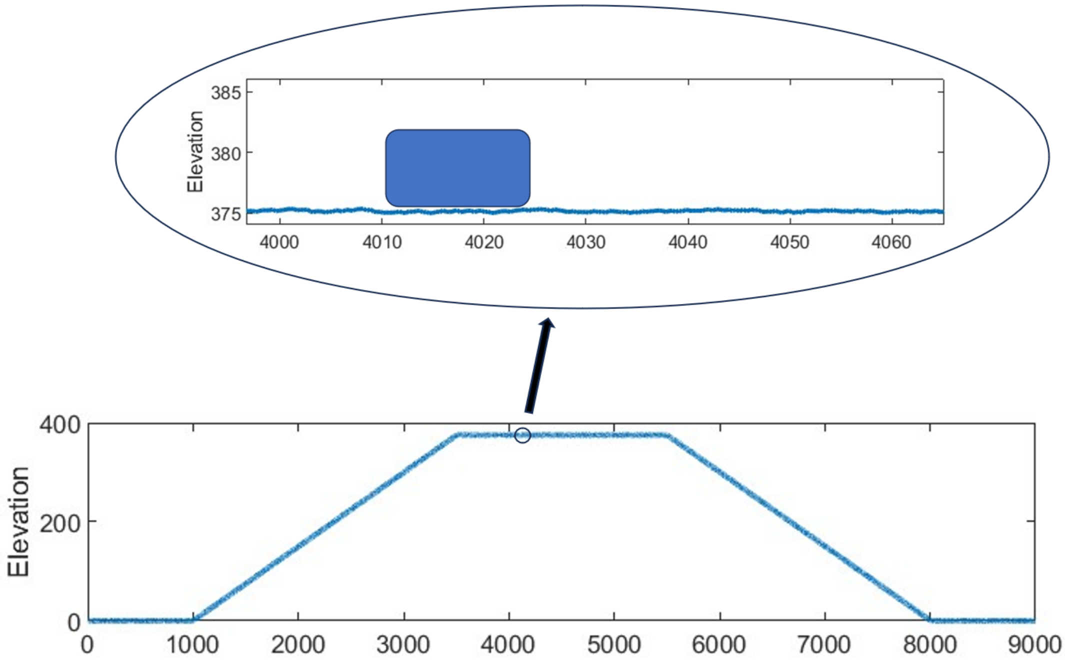

Figure 3.3: Recreation of CAT795 dimensions and the drive cycle profile

Finally, the **run_simulation.m** file is the one responsible for the execution of the whole simulation, it is also printing the most relevant results in each of the simulations.

3.3 Experiments

A brief explanation to each of the experiments will be written in the following subsections.

3.3.1 Experiment 1.1

The first experiment conducted is the simulation of a single truck and study when the SOC goes under a battery threshold in order to determine when chargers would be needed. However, it is known, by discussing with industrial partners, that chargers cannot be positioned anywhere along a drive cycle in a mining site because of power supply restraint restrictions. The aim of this experiment is to be able to find which is the best configuration to use when moving the load from a place to another by a heavy duty truck, and identify which are the data requirements that must be ensured for the correct performance of the simulation.

A heavy duty truck is capable of driving at different speeds and being loaded at different capacities, these two variables, **load** and **maximum speed**, are the **independent variables** of the experiment. Those variables will vary, having loads from 0.8 to 1 (fully loaded) increasing the load in 0.05 each time. When referring to the maximum velocities those will change from 15km/h to 35km/h with 5km/h increase gaps.

The **dependent variable** of the experiment is the **horizontal distance at which the SOC of the Mining Haulage Electric Truck (MHET) goes below 30%**, which was set as the threshold limit that the truck should not go under. The independent variables may have different impact in the performance of a MHET depending on the shape of the trajectory. However, this is an example that shows if the simulation is useful and shows the data requirements needed for the correct functioning of the simulation.

3.3.2 Experiment 1.2

The division of the load across trips and the choice of making several round trips with a lower load or fewer trips with a higher load is another experiment conducted to determine the more convenient (Fixed Charging Stations (FCS) cannot be place in any location) location of FCS in a particular trajectory. This is due to the belief that making more trips with less load can lead to a less energy consumptive scenario, or even a less time consumptive scenario if the load reduction finally implies the non-charging of the truck in the middle of the route.

In this experiment **the load** carried and the **number of trips** done by the MHET are the **independent variable**. The **dependent variables** of this experiment are **the positioning of the FCS** in the route, **the time** and **the energy spent** for each of the different options to transport one full unit of load.
Considering 1 unit of load the full dump box of a MHET, the different configurations that will be explored are:

- Load=1 ; 1 drive cycle
- Load=0.5 ; 2 drive cycles
- Load=0.33 ; 3 drive cycles

3.3.3 Experiment 2

In this case the simulation wants to offer a tool that is capable of optimizing the number of trucks given fixed trajectories, fixed load carried and fixed maximum velocity. The charging station only accepts one truck at a time for its battery recharge. This limits the amount of trucks that can be in movement at the same time. For this reason, when the total amount of time spent by a MHET in a single lap is divided out of the recharging time for a battery, the bottleneck in number of trucks is given (for the certain characteristics of the drive cycle and the machine parameters). The bottleneck would mean to have trucks in queue to enter the charging station. Then, for this experiment, the **dependent variable** are the **time** and the **energy** spent and the **independent variable the number of trucks circulating at the same time**.

To make correctly run the experiment the following steps should be done:

- Calculation of the max number of trucks; max nº trucks=$\lfloor \frac{TAT1L}{b} \rfloor$
- Selection of the quantity of load that wants to be transported; *load*
- Calculation of the time taken to transport all the load from different number of trucks; $TAT(n°trucks) = TAT1L \cdot \frac{load}{n°trucks}$
- Calculation of the amount of load transported in a certain amount of time by a given number of trucks; $load = n°trucks \cdot \frac{TAT}{TAT1L}$

Where TAT stands for Total Amount of Time, TAT1L Total Amount of Time for 1 Lap, b stands for the time the truck is stopped charging battery and $n°trucks \leq \lfloor \frac{TAT1L}{b} \rfloor$.

3.3.4 Experiment 3

This experiment analyses whether or not can Mobile Charging Stations (MCS) be useful in unfavourable conditions to refill batteries if trucks run out of it. These stations can go to the rescue and assist a specific vehicle that runs out of battery or is predicted to run out of battery at a specific point determined by the simulation tool.

In this case a rainy scenario will be simulated. This means that at a certain point a change in the friction coefficient will be implemented in the code. The **friction coefficient between the trucks wheel and the ground** will change from 0.014, which is the standard coefficient at which the simulation was fixed, to 0.22, simulating a muddy ground [27].

A comparison between the muddy and dry situations will be done in this experiment comparing **energy** and **time spent** in both situations.

3.4 Threats to Validity

There are different levels of validity threats that must be taken into account when reviewing this work. Internal validity, in our case, refers to the degree of confidence that the the simulation we are using is trustworthy. External validity, instead, refers to the extent to which results from our study can be applied (generalized) to other situations, groups, or events.

3.4.1 Internal Validity Threats

In the used simulation, the linear behaviour of battery charging and discharging does not exactly resemble real-world variations in operational conditions. This simplification could impact the outcomes. However, the State of Charge (SOC) is recalculated every horizontal meter the truck moves, meaning that the linearity assumption will not introduce significant errors because the frequent recalculations approximate real-world conditions over small distances. Despite this, the linear model might miss other non-linear behaviors of the battery under varying parameters, such as the temperature. Both low and high temperatures affect the charging efficiency slowing the time needed for a battery to recharge [28]. This deviation in the behaviour of the charging and discharging of batteries will be more accused when the battery temperature is distant from the peak performance temperature of the battery, that changes depending on the battery, but for some batteries of automobiles it usually is between 20 to 30 degrees [29].

Additionally, the energy conservation balance is calculated assuming the truck is a point object. In contrast, other simulation tools, like Simulink, consider the vehicle as a 3D model and include powertrains that simulate engine dynamics more accurately. This difference in modeling can lead to discrepancies in the simulation outcomes, affecting the validity of the conclusions extracted from this study.

Finally, the practical feasibility of assumptions made in the simulation shows another threat. For instance, the assumption that Fast Charging Stations (FCS) could be implemented at any point in the drive cycle is not always economically and energetically feasible. However, in real setups the charging station must be located close to the electric distribution panel to minimize high transmission losses. The implementation of Mobile Charging Stations (MCS) in a mining environment is also a concern, as there is limited literature on MCS, particularly regarding their use in mines, which adds uncertainty to the feasibility of such implementations.

3.4.2 External Validity Threats

External validity threats are related with the generalization of our study and the extent to other situations, groups, or events.. The results obtained for the specific fleet size and configuration used in the study might not scale linearly to larger or smaller fleets or different configurations. This is the reason why it has been chosen to keep the caterpillar size. However, the implementation of such a big truck powered by a battery supposes another threat to the validity. Although there are similar models of trucks implementing similar sizes of batteries right now, they probably have different power trains, and work differently from what it is coded in this simulation.

Finally, another threat to the validity depends on the drive cycle. The physics model has been trained with real data recordings, as per the work of Lindgren et al. [26]. Therefore, if we introduce a significantly different drive cycle, deviations from reality may occur, leading to inaccurate results.

4

Results

Within the simulation tool, we have focused in three main use cases to explore and understand data requirements: managing the placement of electric chargers depending on the track and truck characteristics, presented in Section 4.1.1 and 4.1.2; determining the load split among vehicles under the throughput constraints of the system, as reported in Section 4.2; and finally investigating the effects on how does a change in the friction coefficient affect the performance of a truck.

4.1 Experiment 1

4.1.1 Experiment 1.1: Positioning Chargers

When simulating the position of the charger for a route without noise, the following results are obtained:

Table 4.1: Position for charger (m)

Velocity\load	**0.8**	**0.85**	**0.9**	**0.95**	**1**
15	3246	3168	3095	3027	2962
20	3212	3144	3079	3018	2960
25	3216	3147	3082	3021	2963
30	3219	3150	3085	3024	2966
35	3222	3153	3089	3027	2970

However, in real life, roads have bumps and get rougher with the passing of vehicles, as it has been proven in the data used to calibrate the simulation. Therefore that needs to be implemented. Different random noises that follow the same deviation than the calibration tests have been simulated in order to get a range for the position for the charger instead of a single position, the standard deviation for the positioning of the charging station is included as seen in Table 4.2.
Other world conditions (e.g., weather) could also introduce variations in the road (e.g., slipperiness).

Table 4.2: Position for charger (m) and standard deviation based on noise profile found in real data

Velocity\load	**80%**	**85%**	**90%**	**95%**	**100%**
15 km/h	3209 ± 7	3139 ± 9	3075 ± 10	3013 ± 5	2953 ± 4
20 km/h	3210 ± 10	3141 ± 8	3074 ± 4	3012 ± 9	2952 ± 6
25 km/h	3209 ± 4	3138 ± 11	3074 ± 6	3010 ± 11	2953 ± 5
30 km/h	3207 ± 10	3137 ± 7	3071 ± 7	3009 ± 10	2949 ± 4
35 km/h	3205 ± 5	3133 ± 6	3066 ± 4	3003 ± 2	2944 ± 8

The results reported in Tables 4.1 and 4.2 are extracted from a single drive cycle, represented in Figure 4.1, in which the first third features a steep slope. In this steeped parts the driving velocities of the MHET equalises no matter what the maximum velocity of the engine is. It is shown in Figure 4.1 and Figure 4.2 between positions 1000 and 3500m. This is due to the limitation of power that the MHET can provide.

The speed and the SOC across the route can be plotted against the position and the time to be able to visualise the results.

- **Max. speed Variation**

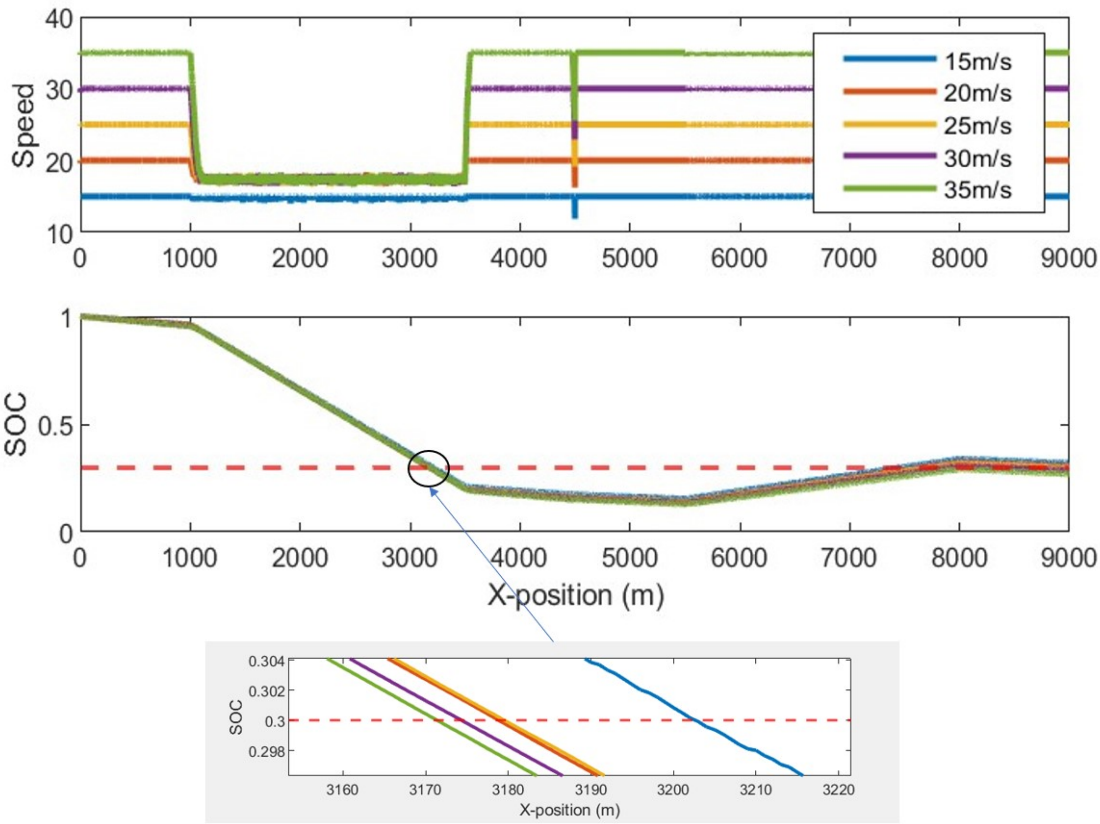

Figure 4.1: Speed & SOC vs X-position (fixed load), chargers should be positioned where the lines cross the red dashed line (30% SOC threshold)

- **Load Variation**

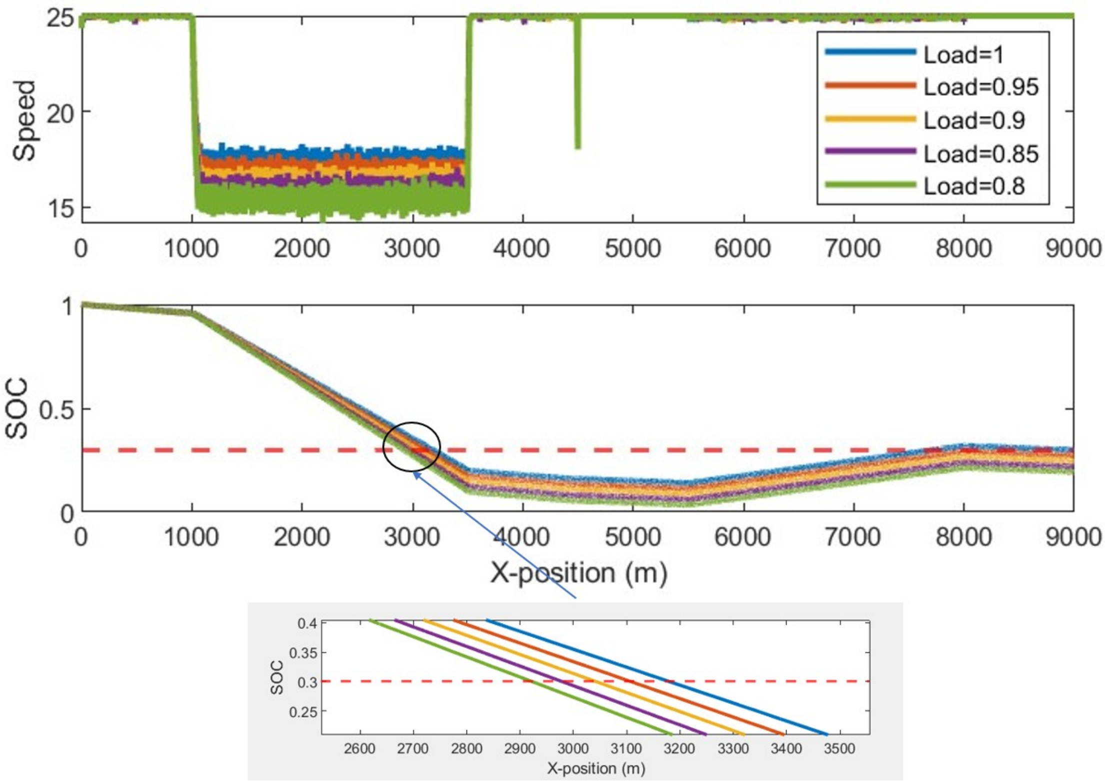

Figure 4.2: Speed & SOC vs X-position (fixed max. vel), chargers should be positioned where the lines cross the red dashed line (30% SOC threshold)

In Figures 4.1 and 4.2 the speed and the SOC of the MHET are plotted against the horizontal distance covered. The red dashed line references the battery threshold, being established in the 30% place where the FCS should be installed. Figure 4.1 plots the studied variables for different maximum velocities fixing a certain load. Instead, Figure 4.2 plots the studied variables for different loads fixing a maximum velocity (25km/h).

As it has been previously commented there is a limitation in the steep part of the drive cycle in both graphs. Nonetheless in Figure 4.2 there is a certain variability in the speed in this steeped part, ranging from 18 to 15 km/h. This is caused by the change in the load, supposing less weight resistance and an increase in the velocity.

4.1.2 Experiment 1.2: Splitting The Load Across Trips

The simulation of these parameters has been carried out to transfer one unit of load to determine the impact that splitting the load have on where the FCS is placed. Nonetheless, a sample path for a mining site has been selected, as stated earlier. Depending on the trajectory's shape these attributes (load and number of drive cycles) may affect an MHET's performance differently. The results are shown in Table 4.3

Table 4.3: Positioning of the FCS, time and energy consumption to finish 1 unit of load transportation

Laps \ load	33%	50%	100%
		FCS POSITION	
1 lap			2843m
2 laps		4364m	
3 laps	-		
		TIME SPENT	
1 lap			38'
2 laps		61'	
3 laps	83'		
		ENERGY CONSUMPTION	
1 lap			0.9
2 laps		1.2	
3 laps	1.5		

When evaluating the time spent in each of the three different load options, the fastest truck in transporting 1 unit of load is the one going fully loaded (38'). The truck carrying the load in two round trips is the following truck when it comes to time spent taking (61') minutes to get all the material transported. Finally, the third round trip is the one taking more time, spending (83') Table 4.3.

Elevation, speed and the SOC of the battery have been also plotted as a function of the time and the horizontal position in Figure 4.3 and Figure 4.4. In Figure 4.3 where the variables are plotted against time, the duration of the different loaded trucks can be appreciated. The blue line corresponding to the thirdly loaded truck should end the circuit in the 1145 seconds (19'), however when adding the recharge of the battery to the cycle it ends at 1672 seconds (28'), multiplying this result by 3 times the 83' are reached. The other lines corresponding to the half and full loaded trucks end at 61' and 38' minutes respectively. In the elevation graphic the altitude at which the FCS is installed for the half and the fully loaded MHET can be elucidated. The half loaded truck stays a long time in the peak of the circuit meaning that it recharges all his battery in that point. Instead, the fully loaded truck remains the recharging battery time before reaching the peak of the route at an elevation around 280 meters.

The variables evaluated in this experiment are plotted in the following graphs.

- As a function of X-position (s)

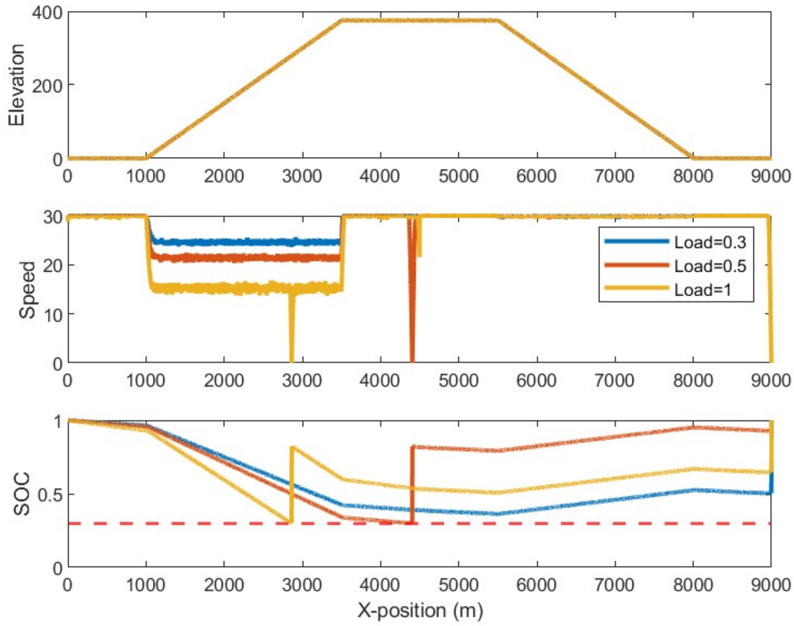

Figure 4.3: Elevation, Speed & SOC vs X-position (for three different loads)

- As a function of time (s)

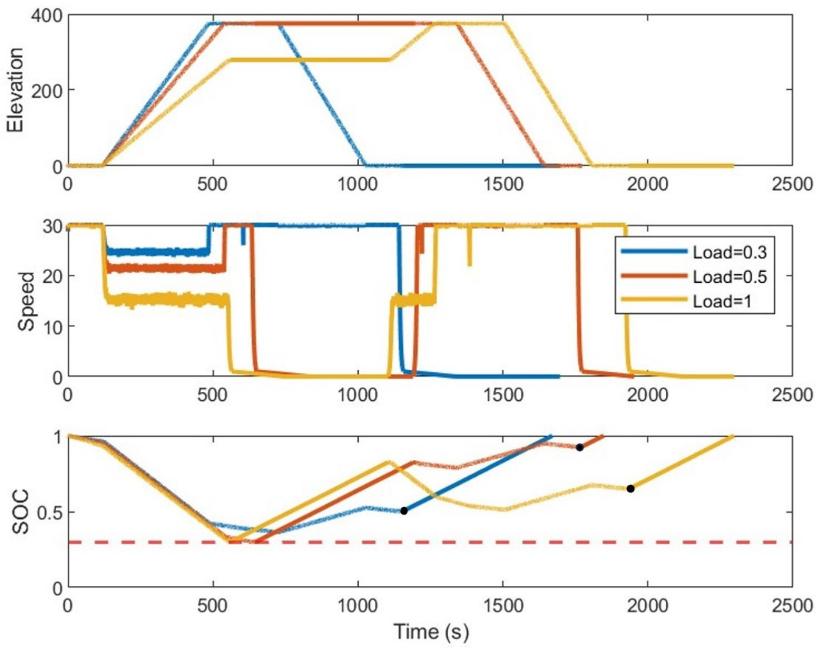

Figure 4.4: Position, Speed & SOC vs time (for three different loads)

The graph of the velocity vs time in Figure 4.3 shows the different trends in the velocities during the trajectories. The maximum speed in this path is fixed to 30km/h, meaning that whenever the power required for moving the truck is lower or equal to the power that can be achieved by its motor the truck will be moving at 30km/h. In the steep part of the circuit the limitation of velocities according to the weight of the freight they are carrying is shown. For the thirdly filled truck the limitation is around 25km/h, for the half fully truck around 21 km/h, and 15 km/h for the full loaded truck. While the battery charging the speeds go down to 0km/h and finally they retake the 30km/h in the downhill part of the route.

Finally, in the plot of the SOC vs time the life of the batteries is plotted. The positive slope of the lines mean a recharge of the battery. When this positive charge starts exactly from the battery threshold, meaning that it is charged from a FCS, instead when this positive slope starts from above the 0.3 SOC means that the source of this battery recharge comes from regenerative braking and not a charging station, except for the recharge after the black point, this recharge refers to the one done by the FCS in the beginning of the route to start the circuit again with the full battery. In blue the thirdly loaded truck does not reach the battery threshold and therefore it will only have to recharge at the end of each route not needing the installation of any FCS. The totally loaded truck has been proved to return better results than having partially loaded trucks, both in energy consumption and time spent.

In Figure 4.4 elevation, speed and SOC are plotted but in this case as a function of the position and not the time. In the central graphic the limitation of velocities according to the weight of the freight can be appreciated, also the stop in the charging points (in 2860m and 4395m). In the last graphic the evolution of the SOC as a function of the position is shown. The recharging of the batteries are represented as vertical lines since there is no movement while the MHET are charging.

4.2 Experiment 2: Using Multiple Vehicles Simultaneously

The optimal number of trucks used in a certain circuit is dependent on many variables. In this experiment, we show how the addition of trucks affect the productivity and the energy consumed by the whole fleet. To do so, a theoretical analysis has been elaborated and the results are presented in this section.

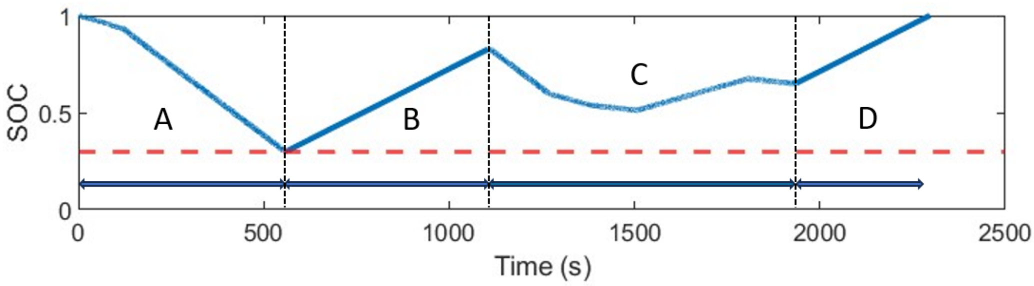

Figure 4.5: SOC vs time (for load = 1)

Since the best load split configuration in terms of energy consumption and time spent is to carry the maximum amount of load in the truck (as it has been proven in the last experiment) this situation has been considered for the trucks involved in this experiment. Four different sections can be distinguished in the drive cycle in Figure 4.5 : the first one moving towards the first charging station (A), the second one staying in the charging station (B), the third one moving towards the end of the drive cycle (C) and the forth one recharging the battery in the start of the drive cycle (D). At that point the truck will have completed a full round to the circuit.
To get results and be able to see how those evolve, the trajectory of the fully loaded truck in the previous experiment has been studied. In that case the parameters needed for the correct analysis of the impact of the addition of trucks in the route are the following ones:

Table 4.4: Data needed for the study of the influence in the number of trucks

TAT1L	b	$\frac{TAT1L}{b}$	$\lfloor\frac{TAT1L}{b}\rfloor$	Load
2300s	540s	4.26	4	500

In Table 4.4 'load' makes reference to the amount of freight carried in the dump boxes of the MHET. In order to know the total amount of load carried, the number of loads will have to be multiplied by the weight of 1 fully loaded dump box.
The values for the time in hours in Table 4.5 comes from the expression in section 3.3.3. The denominator of the fraction has to be changed for the number of trucks that wants to be calculated. However there is a limit which is established in $\frac{TAT1L}{b}$. Reason why $TAT(5) = TAT(6)$, since there will not be a reduction of time when adding a truck to the trajectory if there is already a truck in the queue of a charger. The account of time in days has been calculated having 24 hours of work a day,

Table 4.5: Time spent for different number of trucks transporting 500 units of load, and load transported in 75 hrs by different number of trucks

	time(hrs)	time(days)	load(75hrs)
TAT(1)	319.5	13.3	117
TAT(2)	159.8	6.7	234
TAT(3)	106.5	4.4	352
TAT(4)	79.9	3.3	469
TAT(5)	75.0	3.1	500
TAT(6)	75.0	3.1	500

since having autonomous electric trucks.

The results in Table 4.5 are plotted in the following graphs Figure 4.6 and Figure 4.7. In those graphs the inversely proportion of the time with respect to the number of trucks is shown as well as the ascendant proportion between the load carried and the number of trucks. In both graphs, the tendency stagnates in a certain threshold due to the limitations appearing when the FCS is implemented and trucks have to stop to recharge their batteries .

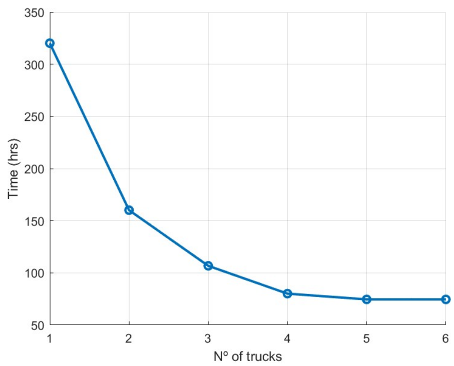

Figure 4.6: Time spent to transport 500 units of load as a function of the number of trucks

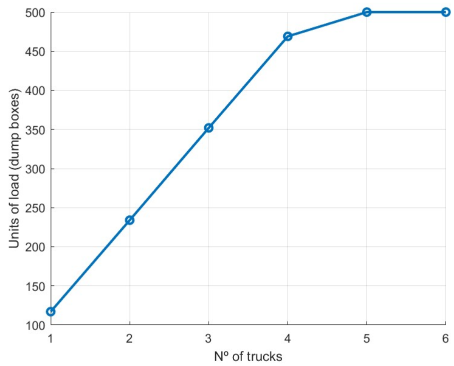

Figure 4.7: Transported load (in terms of dump boxes) transported in a period of 75 hours

4.3 Experiment 3: Change on the performance when changing the friction coefficient

The appearance of adverse circumstances is a possible factor to take into account when simulating the behaviour of MHET in mines. In this experiment the results of changing the friction coefficient simulating a muddy situation between the ground and the wheels is performed.

The variables evaluated in this experiment are plotted in the following graphs.

- As a function of X-position (s)

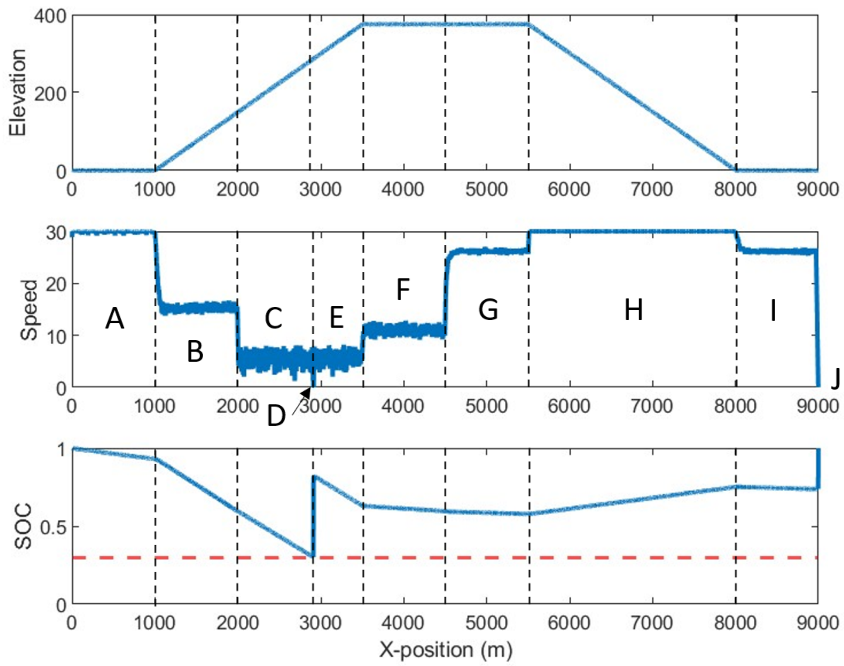

Figure 4.8: Elevation, Speed & SOC vs X-position

- As a function of time (s)

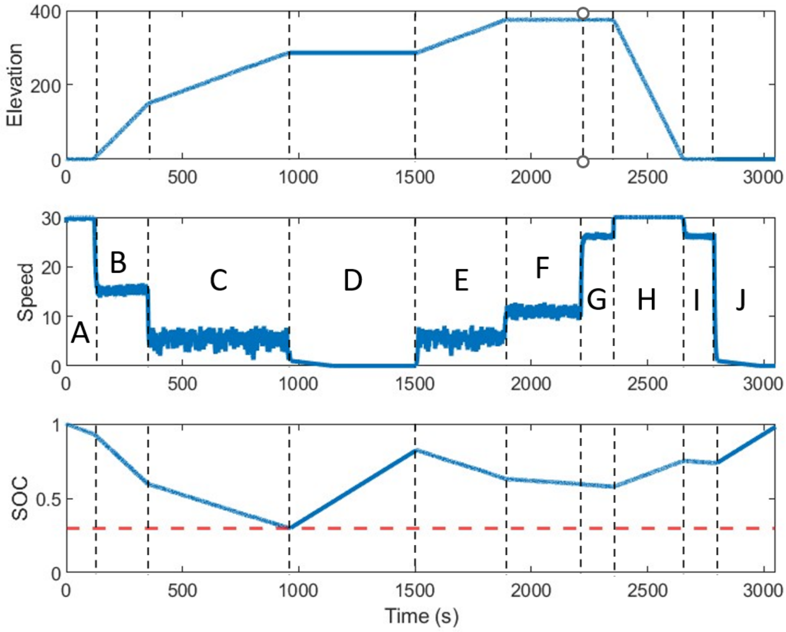

Figure 4.9: Position, Speed & SOC vs time

Each of the sections compressed in between dashed lines in images 4.8 and 4.9 represent different states and behaviours of the trucks.

- **A:** In this section, speed is considered 30km/h (max allowed speed) and the truck is driving over a flat surface.
- **B:** In this section speed is reduced to around 15km/h, due to the increase in the steepness.
- **C:** The MHET is still circulating in a steep part of the circuit and the friction coefficient is increased. This provokes a speed decrease, reducing the velocity to a value fluctuating around 5km/h.
- **D:** The MHET is reached by the MCS and they recharge the battery of the MHET. The recharging of the battery is made while the truck is not moving.
- **E:** There is still some ramp to climb, with the same steepness and velocity as before the stop.
- **F:** In this case the MHET has arrived to the top of the hill. However it has less velocity than in section A, because of the friction with the mud.
- **G:** The unloaded truck weigths less than before, therefore there is a speed increase despite the muddy ground.
- **H:** Another increase in the speed occurs in this zone, this happened because of the change in the slope of the trajectory, now the truck goes downwards.
- **I:** In this part of the track the characteristics of the truck are the same as in section G, truck moving over a flat surface with a muddy ground.
- **J:** In this last part of the track the battery is recharged while the truck is stopped in the same place where the circuit began (circular circuit)

In this experiment the time spent to complete one full lap is 3077 seconds. Instead, in the experiment 1.1 the fully loaded truck spent 38' (2280s) in completing the round. When referring to the SOC, in the increased friction coefficient situation the energy consumed is less, 0.79 batteries, while in the regular friction situation the energy consumed is 0.9 batteries.

5

Discussion

Through the simulation of diverse scenarios, including various tracks and truck characteristics, we explored the data requirements needed for using simulations as a tool for: (i) planning charger layouts for electric mining vehicles (i.e., the MHET), (ii) managing the usage of a fleet of such vehicles and (iii) know the effect that climate can cause to the track and its performance.

5.1 Experiment 1

5.1.1 Simulation tool to plan charger positions: input data (RQ1)

As previously discussed, simulations could assist mining site managers in determining the optimal placement of FCSs along specific tracks. As a proof-of-concept, we conducted a number of experiments aimed at predicting the charging needs of vehicles as they advance along a pre-defined track. Each experiment considers different configurations for the MHET and the drive cycle. Based on the findings from these experiments, we conclude that the simulation would require the following input data:

Drive cycle data:
- Slope of the route
- Air density (in kg/m^3)
- Friction coefficient
- Bumps size / road roughness
- Horizontal driving distance (in m)

Heavy duty truck data:
- Truck's empty mass
- Equivalent inertia drive (in tons)
- Maximum load to carry
- Maximum acceleration/deceleration rate (in km/h/m)
- Losses from engine to wheels
- Battery capacity
- Cross section area of the truck (air resistance)
- Traction power
- Regenerative breaking efficiency rate
- Battery threshold (acceptable lower bound)

This information is needed in order to parameterise the simulation models within the simulation. The simulation can, with this information, provide information about (i) the drive cycle and (ii) the performance of the setup. On the one hand, the information about the drive cycle is related to its configuration, and this input data is needed to determine the positioning of the electric charging station. Figures 4.1 and 4.2 are representations of how the different input values can impact the final configuration of the drive cycle depending on the charging needs of the MHETs.

On the other hand, the simulation can lay information about the performance of the fleet of MHETs and their operation: e.g., the energy consumed by the MHETs, the time spent, and the load transported.

5.1.2 Interpreting the simulations insights (RQ1)

Tables 4.1 and 4.2 report the distance to the origin position (i.e., the start of the drive cycle) at which a FCS is needed, given an arbitrary SOC threshold of 30%. With this information, computed for different maximum velocities of the truck and loads, the positioning of the first FCS could be decided.

From these tables some valuable information can be extracted. On the one hand, how the variation of load affects the location of the FCS, since there is a difference of almost 300m in the position of the FCS when carrying the maximum capacity of truck or the 80% of it (first column). Contrary to expectations, this study did not find a significant differences in the positioning of the FCS due to differences in the maximum speed of the MHET: the position of the FCS only varies by approximately 10 meters across velocities (rows).

The data presented in Tables 4.1 and 4.2 originate from a single drive cycle, shown in Figure 4.1. The results suggest that in this drive cycle, characterised by a 15% slope, increasing the maximum velocity of the MHET does not significantly affect the placement of the FCS. This is because, no matter what the maximum velocity is, there is a limitation in the power that the electric engine can provide. These differences are reflected in Figures 4.1 and 4.2, that visually represent that there is greater variance in the position in which the FCS is needed, given the selected SOC threshold, when changing the load rather than changing the maximum velocity.

However, it is possible that these results are not reproducible using a different simulation engine paired with different vehicle models. The input data for the simulation to estimate the optimal placement of the FCS, reported in Section 5.1.1, would nevertheless remain a requirement independently of the selected simulation tools. Similarly, Tables 4.1 and 4.2 could be a useful tool for the managers of an electrified and connected transport systems to decide on the placement of said FCSs.

5.1.3 Multiple trips with different loads (RQ1)

To calculate the best way to distribute the load among various laps around the drive cycle, as reported in Table 4.3, additional input data for the simulation is required. Several helpful parameters that will help for the decision taking of how to split the load in trucks are obtained as a consequence of the simulation. The comparison of time, energy consumed and the positioning of the FCS is shown in Table 4.3. In the upper part of this table the position of the charging station in each of the three loading situations is shown. In order for the simulation to calculate these results, the following data inputs, extracted from *Experiment 1.1*, are needed:

Charger data:
- Power rate
- Time to connect/disconnect vehicle to the charger
- Time to load/unload MHET

These input data complements the requirements reported in Section 5.1.1. These extra requirements were not needed previously since the simulation of the truck was only being taken into account from the beginning of the route until the first charging station (without taking into account the recharge of the battery). Another factor which was not taken into account was the freight loading and unloading periods of time of the truck, which is now needed to estimate the optimal distribution of the load among laps, as reported in Table 4.3.

From the results, it can be highlighted that when lowering down the load to only the 33% of its maximum capacity, the energy consumption to carry the load until the end of the route decreases, never reaching the battery threshold and therefore the MHET does not have the need to stop and charge until the end of the lap. This can be preferred by the managers of the mining site or the managers of the fleet of vehicles, given that installing FCSs can be challenging for different reasons. On the other hand, the MHET would need to stop, according to the results reported in Section 4.1.2, when the MHET's dump bed is full (2860m) and in a later position when the truck is at its half load capacity (4395m) as it can be seen in Table 4.3.

Finally, when referring to the energy consumption, the fully loaded truck uses less energy for the transport of 1 unit of load rather than the other partially loaded options. What is remarkable is that completing three laps with a lighter load only uses 7% more energy than a single lap with a fully loaded truck. However, making two laps approximately doubles the energy consumption compared to the first scenario. This result is surprising because although you need less energy to transport the same amount of freight, in each of the rounds the weight of the truck is transported back and forth supposing an extra energy consumption which raises it.

In the end, it is important to guarantee the overall throughput of the mine. Therefore, these insights could guide decision making for the mine managers.

5.2 Experiment 2

5.2.1 Simulation tool to plan usage of vehicles in the fleet (RQ2)

In order to know how many trucks to deploy in a specific drive cycle, the time spent and the load transported as a function of the number of trucks has been written down in Table 4.5. The following data inputs, extracted from *Experiment 2*, are needed in addition to the input data reported in subsection 5.1.1:

Site goals:
- Throughput goals (tons per hour)

Heavy duty truck data:
- Fleet size (maximum)

Charging station data:
- Time interval between charging sessions

In Figure 4.6 and Figure 4.7 the different trends for time and load transported (when fixing the load and the time respectively) are shown. On the one hand, the relation between the time consumed and the number of trucks is inversely proportional and tending to 75 hrs which is the fastest time in which 500 dump boxes can be transported from the lower to the upper part of the mine. However 75hrs is not the most optimal result. The most optimal result is 79.9hrs since this would mean having 4 trucks working at full power during all the time. Meanwhile if it is decided to add another truck this will not be working all the time and will provoke queue in the charging stations.

The number of trucks working is obtained from the ratio between the amount of time in doing one lap and the amount of time being stopped charging the battery back. This last value gives the output rate at which the MHETs should be getting off the start of the trajectory. All of this values are shown in Table 4.5. In this case the amount of time is 4.26 meaning that when having 4 trucks there will be a gap of 1.26 times the recharging time (b) between the first and the last truck. In case the number of trucks was increased the fifth truck would have to wait for 0.74times the recharging time creating a queue.

On the other hand, when plotting the amount of load transported in a fixed amount of time (75hrs in this case), the result shows us a linear increasing tendency with the number of trucks, until arriving to the 5th truck stagnating the load in 500 dump boxes. As it has been discussed previously, it is because of this 5th truck when the operation of the overall trucks stops being optimal and therefore the increase in the load transport is less. In the sixth truck scenario no load transportation is increased with respect to the fifth, because a queue is already formed. In this scenario another MHET will be joining this queue without increasing the overall productivity.

5.3 Experiment 3

5.3.1 Use of DTs to predict the change in the performance of vehicles in view of real time data changing weather (RQ3)

Key findings of the comprehensive review of existing literature highlighted the importance of real-time data sharing between physical systems and their digital counterparts to enable better decision-making processes.

Drive cycle real-time data:
- Weather conditions (e.g., ice, rain, wind, dust, etc.)

Heavy duty truck real-time data:
- Position
- State Of Charge (SOC)

Charging station real-time data:
- Occupation (binary: occupied, not occupied)

Charging station data:
- Alternatives to static charger (emergency, MCS)

This experiment focused on reviewing the impact of adverse conditions, specifically the effect of a muddy surface on the performance of MHET in a mining environment. The friction coefficient between the ground and the truck wheels is changed, the experiment simulates a rainy scenario and compares it to a dry condition. The primary variables evaluated included speed, SOC, and energy consumption.

The results show that the increased friction coefficient due to muddy conditions significantly impacted the truck's performance. Specifically, the maximum speed was reduced in steep sections of the track, with velocities dropping to around 5 km/h compared to higher speeds in dry conditions. This speed reduction was evident in sections where the slope is positive, leading to slower movement and higher energy consumption to maintain movement.

Interestingly, despite the adverse conditions, the energy consumption in the muddy scenario was less than in the dry scenario. The truck consumed 0.79 batteries in terms of energy in the muddy conditions compared to 0.9 batteries in dry conditions. This lower energy consumption in muddy conditions could be attributed to the reduced speed, leading to lower power despite the higher friction.

The experiment demonstrated the importance of considering climate factors in planning and optimizing the usage of MHETs in mining operations. The use of MCS proved beneficial, allowing the trucks to recharge on the go and maintain operational efficiency despite the challenging conditions. This flexibility is crucial for maintaining productivity and minimizing downtime in variable and unpredictable mining environments.
Nonetheless, with the data from external source and the baseline simulation tool,

there are still some assumptions that might make the numerical results not fit into reality. This can be due to the inaccuracy of the simulation or missing information that might be needed (e.g., we consider air friction but not temperature or atmospheric pressure, etc.).

5.4 Future Work

Despite the mining industry faces significant challenges related to emissions, the advancement of DTs offers a promising option for reducing environmental impact and improving operational efficiency.

Future work should focus on improving the existing simulation models to further study the operational efficiency of mines. This can be achieved by collaborating with mining companies to implement and validate the simulation-based recommendations in real-world scenarios, providing practical feedback for further model improvement, or using other more complex simulations that consider the integration of the limitations appearing in the actual simulation.

Other future research directions could be related with the analysis of the long-term environmental impacts of transitioning to electric fleets and the effectiveness of DTs for managing them.

6
Conclusion

The mining industry is a significant contributor to global emissions, and it is in the need of solutions to mitigate its environmental impact [4]. Despite the critical role that mining haul trucks play in this industry, there is a notable lack of literature on using simulations to study their behaviour. Moreover, the availability of real-world data is often restricted due to privacy concerns from industry, presenting a challenge for modelling and analysis [25] , [26].

The present study investigates the application of a simulation tool for heavy mining vehicles to guide decisions related to the charging infrastructure for electric vehicle fleets. The research method used to complete the thesis has been based on an iterative engineering research, reviewing the improvements each time until the desired results were achieved. This research was followed by the approach of the 3 research questions that would highlight the data requirements essential for designing the virtual tools, these research questions were approached with 4 experiments:

- Planning charger layouts as a function of the mining site and vehicle characteristics, as reported in subsection 4.1.1.
- Considering the impact of load distribution and spreading out charging times on charger placement, as reported in subsection 4.1.2.
- Analysing the use of multiple vehicles and how varying the fleet number influences the results, as reported in section 4.2.
- Utilising real-time data to adapt to changing environmental conditions, such as rain, to maintain the mine operations, as reported in section 4.3.

From each of the questions addressed by the simulation tool, critical input data requirements have been identified. These data requirements have been key in improving the effectiveness of simulation tools and digital twins (DTs) for the electrification of mines. These virtual tools provide environments for testing and optimization, contributing significantly to the reduction of emissions. However, the effectiveness of these virtual tools is heavily dependent on the availability and accuracy of data. Ensuring comprehensive data availability is crucial for simulation tools and digital twins to work effectively, leading to more efficient and sustainable mining operations.

As a summary, despite the mining industry faces significant challenges related to emissions, the advancement of simulation tools and digital twins offers a promising option for reducing environmental impact and improving operational efficiency. The insights from this thesis highlight the importance of specific data and adaptable strategies in achieving these goals.

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