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Discrete Event Simulation (Des) in Swapping/charging of Battery Electric Vehicles in Underground Mining

Albert Einstein Amponsem
Missouri University of Science and Technology

DISCRETE EVENT SIMULATION (DES) IN SWAPPING/CHARGING OF

BATTERY ELECTRIC VEHICLES IN UNDERGROUND MINING

by

ALBERT EINSTEIN AMPONSEM

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Approved by:

Dr. Samuel Frimpong, Advisor
Dr. Kwame Awuah Offei
Dr. Grzegorz Galecki

ABSTRACT

With climate change concerns escalating, international agreements such as the Kyoto Protocol, the US Presidential Policy, and the Paris Agreement aim to reduce greenhouse gas (GHG) emissions, targeting significant reductions by 2050. The mining sector, a notable contributor to GHG emissions primarily through diesel-powered material haulage, emits approximately 68 million tons of CO2 annually. Transitioning to Battery Electric Trucks (BETs) presents a viable mitigation strategy by replacing diesel trucks with electric alternatives, thus eliminating CO2 emissions.

However, the effectiveness of BETs hinges on optimized battery swapping and charging procedures. This study employs Discrete Event Simulation (DES), a computational methodology for simulating system operations as discrete events, to optimize these procedures in underground mining. The approach entails developing a DES model to evaluate and enhance battery swapping and charging efficiency, focusing on critical metrics like truck availability, charging unit utilization, queues generated during battery charging, and battery wait times post-charging.

Using Arena® software, a DES model was created to replicate the overall system and evaluate the key performance metrics. The base case scenario ensured 100% truck availability but had inefficiencies in charger utilization and battery waiting times. Scenario 53, involving eight batteries, four trucks, and four chargers, emerged as the most efficient, balancing charger utilization and battery waiting time while maintaining 100% truck availability without queues at the charging station. This finding is crucial for the mining industry as BETs gain prevalence, offering a sustainable solution for reducing GHG emissions.

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This thesis does not only reflect my efforts but is also a profound testament to the collective support and guidance of everyone who believed in this success. I dedicate this to myself as the beginning of an unending thirst for success.

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NOMENCLATURE

Symbol	Description
GHG	Greenhouse Gas
CO2	Carbon Dioxide
BEV	Battery Electric Vehicle
EV	Electric Vehicle
EPA	Environmental Protection Agency
DES	Discrete Event Simulation
ICMM	International Council of Mining and Metals
ICE	Internal Combustion Engine

1. INTRODUCTION

1.1. BACKGROUND

The world envisions a carbon-free environment that ends climate change and the associated consequences. Thus, all nations and companies around the globe are working towards achieving net-zero carbon emissions by the year 2050 [1]. The mining sector must contribute towards making this goal a reality. The industry contributes about 4-7% of greenhouse gas emissions (GHGs) [2]. Carbon capture and sequestration strategies for reducing GHGs have been difficult to implement by the mining industry [3]. Therefore, the mining industry is adapting to new ways of reducing these emissions[4], electric propelling vehicles [5].

Smith (1981) presented a paper on the potential and concerns of using diesel and electric trucks for haulage. The author noted that one of the significant concerns of diesel-powered trucks is the amount of carbon dioxide released into the atmosphere [6]. Moreover, the Environmental Protection Agency (EPA) (2012), under the Clean Air Act, noted that to cut down on GHG emissions and the use of petroleum fuels, all transportation fuels sold in the United States must have a certain percentage of renewable energy [6].

Over the years, various studies have been conducted on the emissions of toxic gases and heat produced during diesel equipment operation in both underground and surface mining environments. Exposure to these conditions has been associated with increased susceptibility to lung cancer and other airborne diseases in individuals [7]. As a result, the utilization of Battery Electric Vehicles (BEVs) is gaining much attention due to their use of renewable energy [8]. Implementing BEVs in underground mines reduces ventilation demands and associated costs, owing to their capacity to generate lower heat and fewer exhaust emissions [9]. This is illustrated below in Figure 1.1.

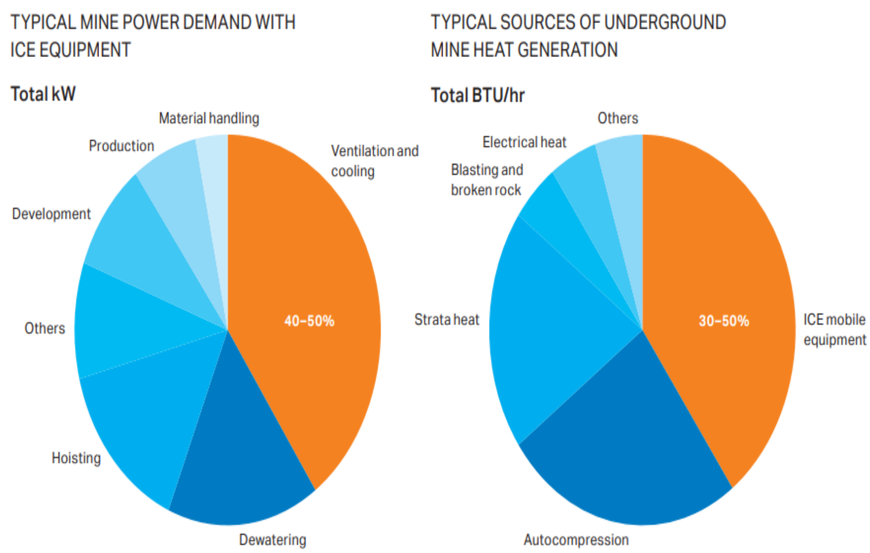


Figure 1.1. Typical sources of underground mine heat generation [10]

Using these equipment units reduces mining costs and dramatically improves efficiency with less maintenance [11]. BEVs, however, face challenges with battery capacities. The BEV technology also depends on the current charging infrastructures, locations, and availability [12]. That is why consumers rank BEV cost, driving range, and charging problems as their top concerns [13]. Various approaches have been adopted to improve on these drawbacks. Some of these include improvements in the charging processes, the utilization of new battery technologies, and the use of Artificial Intelligence (AI) for locating the charging infrastructure [14].

For a typical mining project, uncertainties exist in the various unit operations, such as drilling, blasting, loading, and hauling [15]. Thus, the introduction of the DES technique is a significant tool for modeling the stochastic processes of uncertainties associated with these unit operations. In addition to modeling uncertainties, the DES technique provides appropriate environments and platforms for virtual simulation experiments to mimic real-world experiments [16]. The DES technique has been used extensively to model several mining systems. These include mine planning and scheduling, material handling and logistics, optimizing equipment utilization and availability, modeling efficient scenarios regarding certain operations, and so on [17]. Other researchers have used the DES tool as a reference for a model-based system engineering framework [18]

In a BEV's operation, the battery swapping and charging processes occur at specific points in time, and the system state changes only at these events. Multiple events occur as these units go through these states of change. Figure 1.2 shows that events, such as the arrival of a BEV at a charging facility, its battery swapping or charging processes, and its departure after swapping and returning to the production stations occur at specific points in time and are subject to random fields. Thus, the DES technique is appropriate for modeling these BEV processes due to its ability to handle discrete, event-driven systems with uncertainties using probability distributions and random variables. These distributions can further be used to estimate the various procedures undergone by the batteries of BEVs.

As the mining industry dives towards adopting electrically powered vehicles, it is essential to understand the randomness surrounding its operation. This will not only assist in lowering carbon emissions but also enhance productivity. Critical aspects, such as energy management, charging infrastructure, repair, and maintenance need to be addressed for optimal BEV operations [14].

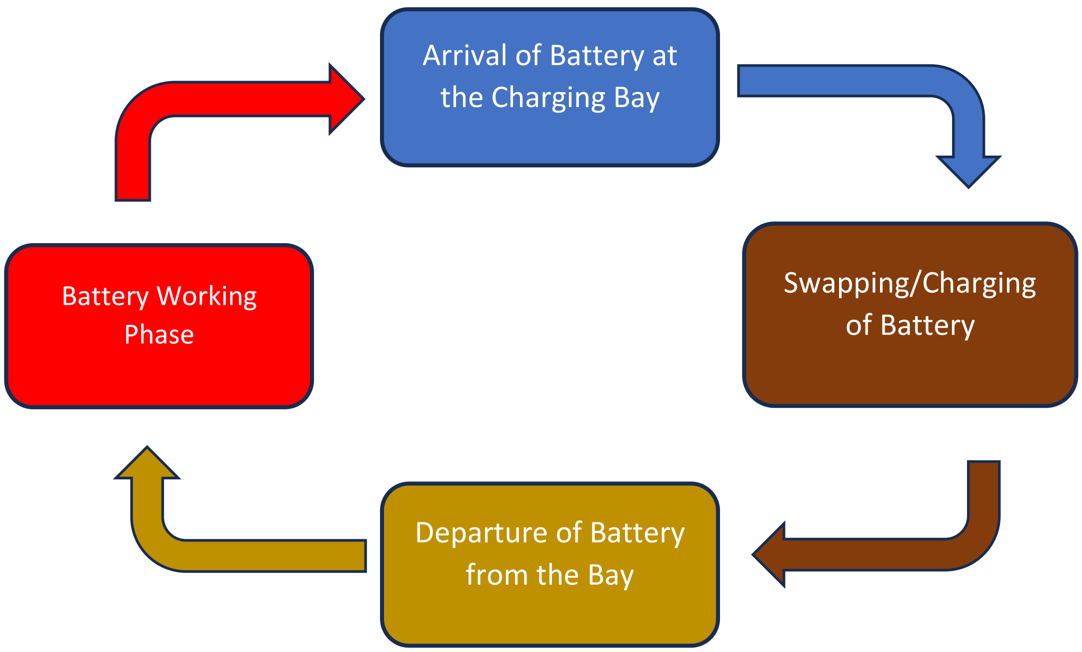


Figure 1.2. Nature of Events in Battery Swapping/Charging

Generally, since mining costs increase when trucks are parked for an extended period, it is essential to understand the various uncertainties surrounding this equipment battery charging and swapping procedures. The DES technique can be used to model the base case and multiple scenarios to replicate a natural system.

1.2. PROBLEM STATEMENT

The mining industry, traditionally a significant contributor to global GHG emissions, is increasingly under pressure to reduce its carbon footprints [19]. The 2015

Paris Agreement states that over 190 countries are committed to reducing GHG emissions [20]. This has triggered a global transition from fossil fuels to renewable energy. In October 2021, the International Council of Mining and Metals (ICMM) stated its engagement for achieving carbon neutrality by 2050 [21]. Following the ICMM's statement on engagement, major mining companies like BHP-Billiton, Rio Tinto, Anglo American, and Freeport McMoRan set ambitious goals to achieve net-zero emissions, underlining the strategic importance of GHG emissions reduction in their operations.

BHP-Billiton aims to achieve net-zero operational emissions by 2050, alongside a goal to reduce operational GHG emissions by 30% by 2030 [22]. Similarly, Rio Tinto aims for net-zero emissions by 2050 and aims to invest approximately $1 billion in climate-related projects over the next five years [23]. Anglo-American and Freeport-McMoRan, two prominent players in the global mining sector, have also set ambitious carbon neutrality goals, reflecting a strong commitment to environmental sustainability. Anglo-American aims to achieve carbon neutrality in Scope 1 and 2 emissions across its operations by 2040, specifically focusing on reducing direct and indirect greenhouse gas emissions [24]. Freeport-McMoRan, on the other hand, has set a target to reach net zero carbon emissions by 2050, detailed in their updated Climate Report, which includes comprehensive plans for reducing greenhouse gas emissions and improving energy efficiency [25]. Both companies are focused on innovative solutions and industry-wide collaborations to meet these challenges, signaling a significant shift towards sustainable and responsible mining practices in the industry, overall productivity, and efficiency of the mining operation [24], [25].

One key strategy to achieve these ambitious targets is decarbonization and electrification in most operations, especially trucks and shovels [26]. The strategic importance of BEVs in the mining industry is multi-faceted. Figure 1.3 shows that the application of BEVs reduces the dependence of mining operations on fossil fuels (diesel particulate matter), significantly reducing CO_2 and other GHG emissions [27]. These reductions can improve health and safety conditions by reducing air and noise pollution in the mining environment [28]. There is a potential reduction in operational costs in the long run with lower maintenance, ventilation, and fuel costs [29]. All these cost reductions will contribute to sustainability, a safe working environment, social license to operate, and mine economics [30].

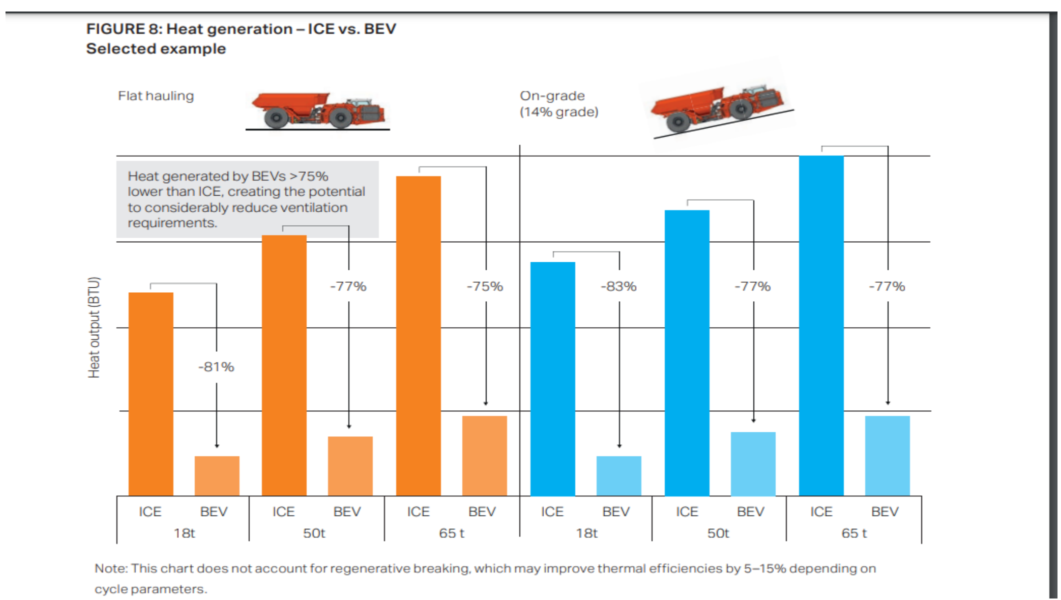


Figure 1.3. Heat Generated by ICE and BEV according to their payloads and travel grades [27]

However, the current state of BEVs in the mining sector still has several challenges. There is a significant concern about energy density, charging infrastructure, and requirements [31]. There is evidence that the batteries play a pivotal role in the operation of the trucks [32]. Hence the magnitude of the latter is significant since the technology is still in the nascent stages and requires complex techniques and infrastructure to overcome the associated challenges. Available literature recognizes the necessity to advance the frontier of battery technology [32]

As the mining sector embraces the idea of utilizing BEVs to reduce carbon emissions, it is critical to understand and optimize these trucks charging and swapping procedures. The industry must employ techniques that ensure their highest utilization without compromising the usage and efficiency of these batteries. However, the problem of battery depletion in BEVs is a multifaceted issue influenced by various factors that can significantly affect the performance and reliability of these vehicles. These factors include temperatures, humidity, travel range, terrain, speed, and even driving habits.

For this research case study, the process used by the manufacturer to swap and charge a BEV's battery in an underground mine involves allocating a truck with two batteries and a charging device to a single bay. The overarching goal is to determine which possible outcomes represent the optimal case scenario for this operation. A scenario is described as optimal when trucks are available close to 100% of the time for work and the system is devoid of queues. In such a scenario, the charger utilization should be substantially high with minimal battery waiting times post-charging. This is essential due to the cost of blasting and constructing a charging bay for each truck.

Again, certain complexities, such as battery replacement and charging, present a challenge that must be addressed to understand how those parameters affect truck availability. This is important since production loss is due to long queues at the charging facility. Other performance metrics, such as the charging system utilization, must be understood to improve the system.

Therefore, developing a DES model capable of replicating the system complexities, verifying the base case scenario, and adjusting the model to ascertain the optimized model for the decision-making process is essential. The potential of DES in replicating and modeling this system is the long-term goal of this research.

1.3. OBJECTIVES AND SCOPE OF RESEARCH

The primary research objective is to design an efficient multi-service bay for a BEV battery swapping and charging system that maximizes truck availability and utilization. The specific objectives include:

- Developing a DES model of a multi-service BEV battery swapping and charging system.
- Verifying and simulating the base case scenario.
- Evaluating critical performance metrics such as charging unit utilization, battery waiting time before being utilized, and truck availability to improve the base case scenario.
- Simulating several scenarios using the improved base case model to develop multiple maps of the multi-service BEV swapping and charging systems for optimal decision-making.

1.4. RESEARCH CONTRIBUTIONS

This research advances a pioneering effort to address challenging problems associated with BEV battery swapping and charging systems. The study also advances frontiers and knowledge in BEV haulage and emissions reduction within the mining industry. The solutions to these challenges and problems also meet the industry's need to use BEVs to reduce GHG emissions. These reductions also contribute to the drive towards meeting the Paris and Kyoto Accords and the US Presidential Policy for reducing GHG emissions by 52% by 2050. The research results also improve the efficiency of deploying BEVs for material haulage in the mining and transportation industries.

1.5. STRUCTURE OF THESIS

This introduction is the first of five sections that make up the thesis. Section 2.0 presents a detailed examination of all the relevant literature, an extensive assessment of Battery Electric Vehicles (BEVs), and a discussion of DES and its use in mining. This section also discusses the research gaps and a summary of each heading. Section 3.0 focuses on a framework for using DES for the charging/swapping procedures of BEVs in underground mining. Section 4.0 presents the discussion and analysis of the results from the experiments. Section 5.0 focuses on the conclusion and recommendations for future works.

2. REVIEW OF LITERATURE

This section of the thesis thoroughly analyzes the pertinent literature on relevant subjects relating to BEVs. The author discusses battery technology, which is crucial for BEVs, its challenges, and the charging technologies. The review examines, in greater detail, battery swapping and charging procedures as applied in the mining industry. The DES technique is also discussed, along with optimizing battery charging and swapping protocols.

Simulation comprises a wide range of techniques and tools used to replicate natural operating systems, typically using computer software [33]. It has been used extensively across many disciplines to understand and improve complex systems. In sectors ranging from manufacturing to healthcare and logistics to finance, as well as in system engineering to mining, their ability to replicate real-world processes without direct field interventions underscores the significance of their application [34], [35].

Continuity and characteristics of a system modification is usually used in the classification simulation [36]. The types include Monte Carlo Simulations, Agent-Based Modelling and Simulation and Discrete Event Modelling simulations [35].

Discrete Event Simulation focuses on systems where changes occur at specific points in time rather than continuously [34]. It has been applied in systems whose operations occur at discrete points in time, such as manufacturing, construction, healthcare, marketing, supply chain, and mining [34] [35], [37] – [39].

The rapid proliferation of BEVs has highlighted the challenges associated with efficient charging and energy management [40]. Traditional plug-in charging methods, while effective, may only sometimes cater to the demands of high vehicle utilization, considering time constraints [41], [42]. Battery swapping, where depleted batteries are swiftly replaced with fully charged ones, emerges as a potential solution [41]. However, this procedure brings its complexities: inventory management of charged batteries, prediction of demand surges, and scheduling and planning of swapping stations. With its ability to model and analyze sequential and interdependent events of complex systems, DES offers a pathway to address these challenges.

2.1. BATTERY ELECTRIC VEHICLES

BEVs are electric-based vehicles that generate energy from a battery pack without an internal combustion engine (ICE) [43]. They have existed for over a century, emerging as innovative technology after the Industrial Revolution. [44]. Parker (1834) crafted the first functional electric vehicle. The Porsche electric vehicle was launched in 1899 because of its advantages over its gasoline counterparts. They had even existed before the invention of Internal Combustion Engine Vehicles (ICEVs). After its dormancy for nearly 70 years, EVs regained popularity in the 1970s. The final decade of the 19th century marked a flourishing era for the initial growth of EVs [44]– [46]. However, their popularity began to wane in the second decade of the 20th century. This was because the ICEVs experienced significant advancement [46]. The price tag on ICEVs was very low as compared to EVs. Even the range at which they could drive was very low. This caused a decline in their commercialization.

In the 1970s, the resurgence of BEVs was driven by energy concerns stemming from the oil crisis in the Middle East, which was revived due to the energy [45]. Their revival was not just because of the latter but also for environmental conservation [46]. Their ability to recover the energy they use through braking makes them highly economical [40]. With the global focus on reducing carbon emissions, they play an instrumental role in shaping the sustainable future of transportation systems. Their implementation will aid in addressing the global energy crisis and environmental issues [47]. Also, their evolution over the years, aside from the above, is mainly due to technology advancements, policy requirements, and consumer acceptance [44], [48]. Even though certain countries deem it a pressure on their electric grid, many countries adapt their applications due to their advantages over ICEs [49],[44].

EVs can be categorized into three main types, namely: pure electric vehicles (PEVs), fuel cell electric vehicles (FCEVs), and hybrid electric vehicles (HEVs) [44], [50], [51]. They are differentiated according to the energy source provided to the vehicle, as their names imply. The purely electric vehicles are powered entirely by batteries. The hybrid usually will have a dual power source: an electric system and an ICE system. On the other hand, the FCEV is powered by fuel cells instead of batteries. The main components that form the powertrain of a pure EV include:

- Electric Machine
- Traction battery
- Gearbox
- Power electronics [48]

For this research, the vehicle under consideration was purely electric, and the onboard battery can be detached and charged separately. The simple architecture of a pure EV is illustrated in Figure 2.1.

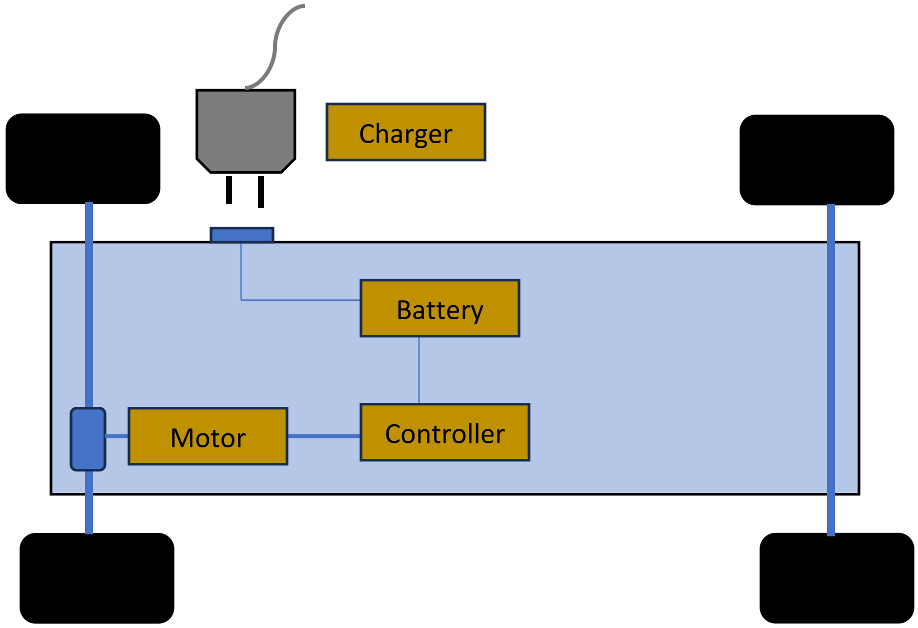


Figure 2.1. Architecture of a BEV

Despite the advantages of BEVs, literature indicates that they encounter significant challenges. Some of these include:

- Battery driving range.
- Charging infrastructure
- Vehicular and Battery costs
- Battery life and safety features
- Consumer acceptance and perceptions [40] [50], [52], [53]

From the above challenges, it is evident that the primary challenge of BEVs is related to their batteries. Thus, it is crucial to conduct in-depth research on BEV batteries, as their performance can significantly influence the success or failure of these vehicles in the transportation industry [49].

Due to its contributions towards solving the global warming challenge, the mining industry is implementing BEV technologies in several mining operations [52]. Even though ICE trucks have remained the preferred choice for moving material due to the high energy demand of such an operation, BEVs have made significant advancements in this regard [49]. An extensive focus has been on enhancing BEV technologies, particularly the powertrain, battery, and charging infrastructure [53]. The battery endurance and range remain the primary focus even for this large equipment [52]. Battery technology, as the primary component of BEVs, is, therefore, an exciting research frontier for research and technological innovations.

Sen et al. (2018) investigated the necessary battery capacity for BEVs, considering the demands for long-distance transportation. Their study revealed that, typically, the battery in these vehicles would restrict the payload capacity to only 80% of what a standard ICE truck can transport. However, this might be deemed acceptable when considering average payload usage [54]. Burak et al. (2017) also emphasized the need for extensive research because electric-propelling heavy-duty equipment technologies are expected to grow exponentially [55].

The technological shift from ICE engines to EVs will impact economic, social, and political dimensions. The analytical survey of the literature will provide a comprehensive review of BEVs, including the challenges of battery technology and charging infrastructure, equipment battery swapping and charging procedures, and how they affect their availability.

2.1.1. Battery Technology. Battery technology is an essential component of BEVs since it influences the driving range, fuel economy, and overall performance of the vehicles [44], [48]. In automotive history, battery technology has evolved through research and innovations in electrochemistry, material science, and design to achieve unmatched energy density [46] [56]. Over the years, battery technologies have seen continuous advancements, with significant improvements [44].

The earliest EVs relied on lead acid batteries, a technology traced back to Plantes' 1859 innovation [44], [46]. While reliable for the era, their weight and energy constraints called for optimizing their energy density while managing their weight [44]. This drive for innovation paved the way for Nickel-metal weight Hydride (NiMH) batteries in the late 20th century, embodying advancements in energy storage and efficiency [44]. Battery technology has evolved from nickel-based to ZEBRA batteries, culminating in advanced lithium-based variants [57]. As BEVs rely solely on traction batteries for their propulsion systems, advancements in traction battery technology play a crucial role in shaping the electric vehicle industry [48], [58].

Figure 2.2 shows that the battery capacity for BEVs has increased over the years [58]. This is a result of high consumer demand and the need for manufacturers to improve their battery capacities [56]. As illustrated in Figure 2.2, the production and patronization of EVs are expected to increase with time [41].

However, these improvements come at a higher cost than a regular ICE vehicle [57]. Also, these batteries are usually bulky and take up space [59]. As we venture deeper into advanced energy storage solutions, the challenge is not just to improve EVs' mileage or limit the charging duration; it is also about understanding and manipulating the molecular and atomic interactions within the battery cells [56].

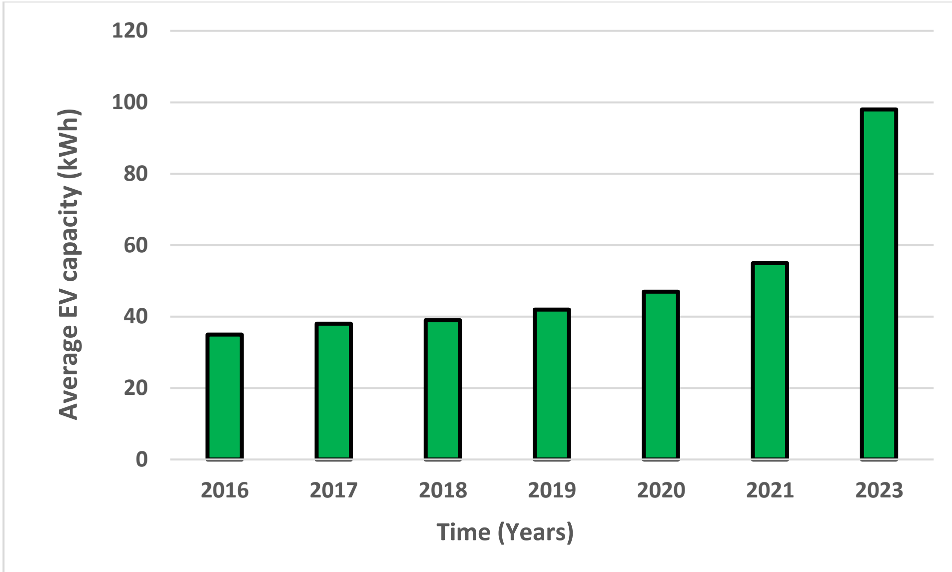


Figure 2.2. Evolution of Battery Capacity with Time [58]

2.1.1.1. Types of batteries. The evolution of battery technology, driven by the demand for more efficient and sustainable energy storage solutions, has led to the emergence of various types of batteries [44]. From the early lead-acid batteries that paved the initial path to the lithium-ion solutions powering most modern BEVs and the promising solid-state technologies on the horizon, each battery type has its strengths and limitations [44]. As illustrated in Table 2.1, their comparison is usually based on energy density, power density, cycle life, calendar life, and cost per kWh [49], [50]. As such, the BEV battery is typically determined by the energy needed to achieve a specific distance [40].

- **Lead-acid battery (Pb-PbO2).** This is one of the oldest batteries for powering electric vehicles [46], dating to the late 19th and 20th centuries [45], [46]. It features lead dioxide as the cathode and sponge lead as the anode, both submerged in a sulfuric acid electrolyte characterized by a low specific energy between 20 and 40 Wh/Kg [44], [49], [60]. While their simple construction and abundant availability of materials made them cost-effective, they posed significant challenges [44]. The heavy build and size contributed to a lower energy density, reducing driving range [49]. Also, the life cycle needed to be more stable, necessitating frequent replacements and making it less efficient for long-term vehicle usage [49].

Due to the detrimental effects of lead on the environment and human health in its production, use, and disposal, lead acid battery recovery and recycling rates have surged to 95-99% in Europe and the US [44]. This battery is not used on a large scale due to its environmentally unfriendly nature and low energy density [44].

Usually, the lifespan is influenced by factors such as overcharging, undercharging, operating temperature, and storage conditions [61] [56]. This makes the State of Charge (SOC) and Depth of Depletion (DOD) of these batteries critical features to analyze [61]. Horkos et al. (2015) demonstrated the different techniques for charging lead acid batteries. They discussed all the different techniques, such as the conventional method, the pulse method, the negative pulse technique, the superimposed pulse frequency technique, and the intermittent charge control, and their limitations and strengths. Interruptive charge control, the latest technique, ensures long battery life and reduces the effect on temperature during charge [61].

- **Nickel-Cadmium battery (Ni-Cd).** In the 20th century, nickel-cadmium (NiCd) batteries entered the market [50]. This battery was constructed with nickel oxide hydroxide as the cathode and cadmium as the anode, enveloped within an alkaline electrolyte [50]. It offered a superior energy density compared to its lead-acid counterparts, making it an attractive choice for early electric vehicles [50].

Its durable nature and ability to sustain high discharge rates were desirable features [57]. However, it had its challenges, including the memory effect, which gradually reduced its capacity. Additionally, the cadmium component posed environmental toxicity challenges, casting shadows over their sustainability [57].

- **Nickel-Metal Hydride Battery**. Following the Nickel-Cadmium era, the Nickel-Metal Hydride (NiMH) battery emerged as a beacon of hope for electric mobility [44], [50]. The positive electrode consisted of nickel hydroxide, while the negative electrode was composed of various materials, and the electrolyte used was a solution of potassium hydroxide. [62], [63] [44]. It was developed to provide a more environmentally friendly solution, integrating nickel oxide hydroxide as the cathode and a metal hydride for the anode [44] [64].

Widely adopted, especially for hybrid vehicles (Toyota Prius), it showcased a commendable energy density [49], [63]. The absence of memory effect made it superior to NiCd batteries [49]. However, its weight, bulkiness, and underperformance in high-temperature scenarios limited its efficiency [44], [50].

- **Lithium-ion battery**. The dawn of the Lithium-Ion (Li-ion) battery in the late 20th century marked a paradigm shift in BEV power sources [44]. Rapidly becoming mainstream in the 1990s and 2000s, this battery has dominated the electric vehicle landscape [44], [49]. Characterized by a lithium compound cathode, graphite anode, and a lithium salt in an organic solvent acting as the electrolyte, its lightweight and high energy density are unparalleled [56]. The most widely used material as the positive electrode include lithium cobalt oxide ($LiCoO_2$), lithium manganese oxide ($LiMn2O_4$), and lithium iron phosphate ($LiFePO_4$) [44], [65]

Vehicles powered by Li-ion batteries offer longer ranges, thus addressing a major limitation of earlier battery types [49]. Recently, they have been employed by BMW i3, and Tesla [44]. These batteries are renowned for a wide range of applications because of their benefits, which include high power density, extended lifespan, capability to operate at low temperatures, high voltage, and low volatility [56]. However, these batteries are limited due to safety concerns, mainly associated with overheating risks [66]. The industry's reliance on rare and potentially expensive materials for construction is a pressing issue [67].

They have been researched extensively in recent years as they suffer longevity, reliability, and charging rates [44]. Current research suggests that adding graphene can improve performance [50], [66],[67]. Also, Li-rich, Zn-air, and Li-sulfur systems are great frontiers to be advanced due to their cheaper rate and high energy density[57] [41], [67]. LiFePo4, employed as the cathode, has garnered attention recently owing to its superior power density, longer life cycle, and enhanced safety [57] [64]. Research into low-temperature plasma technology has been pursued, given its efficacy and eco-friendly nature [68].

- **Solid-state battery**. In the continuous quest for optimizing electric mobility, the solid-state battery has emerged as the next frontier [49].

Unlike conventional batteries, it replaces the liquid electrolyte with a solid variant, promising significant improvements in energy density. Preliminary results indicate that it could offer a safer experience by reducing fire risks inherent in some liquid electrolyte batteries. It also provides a greater energy density and quicker charging times [56]. Its limitations lie in streamlining manufacturing processes and navigating the economic landscape to make them cost-effective solutions for the masses [69].

- **Other emerging trends.** The horizon of battery technology for BEVs is expansive, with several emerging contenders. For instance, lithium-sulfur (Li-S) batteries harness sulfur as the cathode and have been projected to achieve higher energy densities than conventional Li-ion batteries [44]. Then there are the experimental Lithium-Air (Li-Air) batteries, which intriguingly utilize oxygen from the air as the cathode [57]. Their theoretical energy density approaches that of gasoline, though practical applications are still in their infancy [58]. Lastly, the Redox Flow Batteries present a novel approach by storing energy in a liquid electrolyte separated from the electrode, though their automotive applications remain in the exploratory stages [40].

In conclusion, the quest for reliable battery technology lies in the potential of the batteries to a) fully recycle, b) be environmentally and biologically friendly, and c) possess superior electricity generation and storage capabilities [40].

Table 2.1. Comparison of Battery Types

Battery Type	Energy density (Wh/Kg)	Nominal Voltage (V)	Specific Power (W/Kg)	Self-Discharge %) per month
Pb-acid	35	2	180	<5
Ni-Cd	50-80	1.2	200	10
Ni-MH	70-95	1.2	200-300	20
ZEBRA	90-120	2.6	155	<5
Li-ion	118-250	3.6	200-430	<5
LiPo	130-225	3.7	260-450	<5
LiFePO4	120	3.2	2000-4500	<5
Zn-air	460	1.65	80-140	<5
Li-S	350-650	2.5	-	8-15
Li-air	1300-2000	2.9	-	<5

2.1.1.2. Battery management systems: a tool for battery efficiency and safety. Battery Management Systems (BMS) form an integral part of the efficiency of BEVs [70]. Lee et al. (2021) emphasized how significant BMS algorithms impact the optimization of charging and discharging cycles [71]. The overall energy efficiency of BEVs directly correlates to optimizing the battery cycles [72]. Another critical aspect of the energy efficiency of BEV batteries is cell balancing [73]. In his study, Jian Qi (2014) pointed out how cell balancing technology within BMS is critical to maintaining the efficiency of the battery pack, which indirectly affects vehicle efficiency. This balance is critical in ensuring that all battery pack cells contribute equally, avoiding scenarios where inefficiencies in one cell diminish the overall system performance [74].

BMS is a tool that ensures the safety and reliability of BEV batteries [71]. There is currently extensive research in preventing thermal runaway, a dangerous condition that can lead to battery fires [75]. Qingsong et al. (2012) elaborated on advanced BMS capabilities to detect and mitigate conditions that could lead to thermal runaways. A system that monitors and keeps track of battery utilization and parameters like temperature, voltage, and current is essential for the safety and reliability of these batteries [76]. This will ensure that BEVs operate within safe limits. The longevity of batteries in such a system depends on BMS capabilities. Wang et al. (2020) demonstrated how advanced BMS algorithms can significantly prolong battery life. This is done by preventing scenarios such as deep discharge and overcharging, which contribute to the degradation of battery health [77]. The early detection of potential issues leads to a reduction in the frequency and the cost associated with BEV maintenance [76]. Despite the advancements, BMS faces significant technical challenges. Hossain et al. (2021) discussed the issues related to sensor accuracy and the complexity of BMS algorithms [78]. The effectiveness and responsiveness of the system are limited due to the challenge of real-time data processing, which is critical for immediate decision-making and system adjustments [78]. Again, the cost involved in setting up a sophisticated system can increase the overall cost of the vehicles.

This cost factor can be crucial for manufacturers, stakeholders, and consumers. Another technical hurdle is integrating the systems with the vehicular systems [79]. Cheng et al. and Johnson (2021) discussed ensuring seamless communication and coordination between these systems. They highlighted that this is important for the optimal performance of BEVs, but it is challenging to implement. Integrating AI and machine learning tools in BMS is an emerging technique [80]. Dapai et al. (2022) elaborated on how these technologies offer improved predictive analytics in BMS. They allow for more accurate forecasting of battery health and performance, which leads to better decision-making and efficiency of BEVs [81]. BMS tools are central to BEVs' performance, safety, and efficiency. While they have come a long way in terms of technology and functionality, challenges in sensor accuracy, system complexity, cost, and integration with other vehicle systems persist. However, there are emerging technologies with the advancements in AI, machine learning, and wireless technologies paving the way for more efficient, reliable, and intelligent BMS in BEVs.

2.1.2. Charging Technology and its Impact on Batteries. The revolution of charging technology is pivotal in the widespread adoption and efficiency of BEVs [82]. The advancements in charging technology have impacted battery performance and longevity, particularly in the context of BEVs used in mining operations. The current stage of charging technology has undergone significant transformations, with innovations focusing on increasing charging speed and efficiency while minimizing adverse effects on batteries [83]. As documented by Camilo Suarez (2019), rapid advancements in this field have led to the development of ultra-fast charging stations capable of charging BEV batteries to 80% within minutes. However, this technological leap brings inherent challenges related to battery health and the electrical grid capacity [82]. Fast charging, while advantageous in reducing downtime, imposes stress on BEV batteries, particularly lithium-ion cells. This stress can manifest in accelerated degradation, reducing battery life and efficiency [84]. Li and Zhang (2020) indicated that repeated fast charging can increase internal resistance and decrease energy capacity in lithium-ion batteries. Furthermore, thermal management becomes critical when rapidly charged batteries, as excessive heat generation can lead to safety risks and further degradation [77]. Researchers are exploring various solutions to mitigate the adverse effects of rapid charging. These include improved battery chemistry, advanced thermal management systems, and intelligent charging strategies that balance charging speed with battery health. For instance, Green et al. (2022) highlights the development of BMS that optimize charging parameters in real-time. This advancement aims to prolong battery life while ensuring efficient energy storage. Charging technology plays a vital role in battery health and performance, particularly in the deployment and operation of BEVs. This aspect becomes even more crucial in challenging environments, such as in the mining industry. Ongoing research and development in this field are essential to ensure that advancements in charging technology contribute positively to the efficiency, sustainability, and economic viability of BEV adoption in various sectors.

2.1.2.1. Charging infrastructure: the challenge. The transition to BEVs in various sectors, including mining, has necessitated the development of robust charging infrastructures. This section explores the multifaceted challenges of establishing such infrastructure, focusing on technological, economic, and logistics aspects. The primary technological challenge in developing charging infrastructure for BEVs is the need for high-powered charging systems. These systems require advanced electrical components and grid connections capable of handling high currents without compromising safety and reliability. Jones et al. (2020) showed the complexity of integrating high-powered charging systems into existing electrical grids, particularly in remote or off-grid mining locations. Furthermore, the harsh environmental conditions in mining areas demand robust and durable charging solutions that can withstand dust, moisture, and extreme temperatures. The economic aspect of charging infrastructure development includes the initial investment in equipment and installation and the ongoing costs associated with maintenance and electrical consumption. As Smith and Brown (2019) outlined, the return on investment for charging infrastructure in mining is complicated by the sporadic nature of mining operations and the potential for site relocation. Logistically, installing charging stations in remote or underground locations presents significant challenges. Limited space, extensive cabling, and ensuring consistent power supply are critical considerations highlighted by the case study in Doe and Andrews (2021).

Another dimension of the challenge is the impact of charging infrastructure on battery health and efficiency. Rapid charging technologies, while beneficial for reducing downtime, can adversely affect battery longevity and performance. Zhang et al. (2018) showed that frequent fast charging can lead to accelerated degradation of lithium-ion batteries, a common type in BEVs. This degradation reduces the overall life expectancy of batteries and impacts their efficiency and operational range.

Bespoke solutions are required to address these challenges from the mining perspective. Innovations in charging technology, such as modular and mobile charging stations, are being explored to offer flexibility and resilience in mining operations. As Taylor et al. (2022) discussed, these solutions provide scalable and adaptable charging options that can evolve with mining charging needs and locations.

Developing charging infrastructure for BEVs in mining is a complex undertaking, fraught with technological, economic, and logistical challenges. However, it is critical for successfully implementing and operating BEVs in this sector. Ongoing research and development are essential in overcoming these challenges and ensuring that the transition to electric vehicles in mining is both efficient and sustainable.

2.1.2.2. Consumer acceptance. The widespread adoption of BEVs heavily depends on consumer acceptance. This section examines the factors influencing consumer attitudes towards BEVs, barriers to acceptance, and strategies to enhance consumer adoption, especially in the mining industry context. Multiple factors influence consumer acceptance of BEVs, including perceived benefits and drawbacks. The key aspects include the initial cost of BEVs, range anxiety, charging infrastructure availability, and environmental consciousness. Thompson et al. (2020) have shown that while environmental benefits are significant motivators, concerns over range and lack of charging facilities can deter potential users. Moreover, the perceptions of the performance and reliability of BEVs play a role in shaping consumer attitudes.

The economic aspect, particularly the upfront cost and long-term savings, is critical to BEV acceptance. According to Kim and Choi (2021), consumers often weigh the higher initial purchase price against potential fuel savings and lower maintenance costs. Government incentives and subsidies also play a role in making BEVs more economically attractive. The availability of charging infrastructure is pivotal in influencing consumer acceptance. As highlighted by Evans and Ritz (2019), consumers are likelier to adopt BEVs if they have access to convenient and fast charging options. Therefore, developing widespread and efficient charging networks is critical to boosting consumer confidence in BEVs.

Range anxiety remains one of the primary barriers to BEV adoption. Efforts to address this concern include improving battery technology to extend driving ranges, enhancing the predictability of battery health and depletion monitoring, and range prediction, as by Lee (2022), which can help alleviate range anxiety. To improve consumer acceptance, improvements in the BEV charging technology and infrastructure can shift consumer perceptions. Additionally, policies and incentives to reduce the purchase price and expand charging infrastructure are essential, as indicated by the policy analysis by Green and Smith (2023).

In conclusion, consumer acceptance of BEVs is influenced by a complex interplay of factors, including economic considerations, technological advancements, and infrastructural developments. It is imperative to tackle these problems in their entirety in order to boost the adoption rate of BEVs, not only in the general consumer market but also in niche industries such as mining.

2.2. BATTERY ELECTRIC TRUCKS (BETs) IN MINING

BETs in the mining industry mark a significant shift towards sustainable and efficient operations. BETs offer several operational benefits in mining environments. Their electric drive systems provide high torque at low speeds, ideal for hauling heavy loads in rough terrain. As Jones and Murphy (2021) pointed out, BETs contribute to improved air quality in underground mines by eliminating diesel emissions, which is crucial for worker health and safety. The reduced noise level of electric trucks also enhances the working conditions in mines. While the upfront cost of BETs can be higher than traditional diesel trucks, their long-term economic benefits are compelling. As detailed by Lee and Watson (2022), BETs incur lower operating costs, attributed to their fewer moving parts, diminished maintenance needs, and reduced energy expenses. However, the economic viability of BETs also depends on factors like the cost of electricity, battery depletion rates, battery replacement costs, and the required charging infrastructure.

The transition to BETs in mining is not without challenges. One of the primary concerns is the need for a reliable and efficient charging infrastructure, as highlighted by

Patel and Kumar (2021). Additionally, concerns about battery life, performance under extreme mining conditions, and the need for specialized maintenance skills pose challenges to widespread adoption, as discussed by Moreno et al. (2021). The future of BETs in mining looks promising, with ongoing advancements in battery technology, charging solutions, and vehicle design. Innovations in battery technology that increase energy density and reduce charging times are particularly relevant. Furthermore, integrating renewable energy sources for charging BETs can enhance their environmental and economic benefits, as Zhang et al. (2023) explored.

In summary, BETs represent a transformative technology for the mining industry, offering operational, environmental, and economic advantages. While challenges remain in their widespread implementation, ongoing technological advancements and research pave the way for their successful integration into mining operations.

2.2.1. Factors Affecting Battery Depletion. The performance and longevity of BEVs are significantly influenced by various factors that contribute to battery depletion. The operational factors of BEVs contribute to battery depletion. These factors include driving habits, vehicle load, and frequency of use. Aggressive driving styles characterized by rapid acceleration and braking, as indicated by Patel and Kumar (2020), contribute to faster battery drainage. Similarly, heavy loads increase energy consumption, leading to quicker battery depletion. The distance covered by the equipment also dramatically affects the battery depletion rate. The greater the distance covered, the more the battery is depleted. Smith and Lee (2021) highlighted how the range of BEVs directly correlates with battery capacity and depletion rates. Long distances, particularly without convenient charging infrastructure, pose a significant challenge for BEV usage, especially in applications like long-haul transportation or extensive mining operations. Again, the speed at which a BEV is driven profoundly impacts battery depletion. Higher speeds require more power, leading to quicker battery drain. Zhao et al. (2022) showed that BEVs operating at higher speeds exhibit increased consumption per mile due to factors like air resistance and the efficiency of electric motors at different speeds. This is particularly relevant in highway driving scenarios compared to urban settings, where lower speeds are the norm.

The terrain and driving conditions also play a critical role in battery depletion. During uphill or rough terrain, common in mining and off-road applications, more energy is depleted faster. Conversely, driving downhill can aid in battery regeneration through regenerative braking systems. Johnson and Kumar (2020) showed that BEVs used in hilly or mountainous regions may have a reduced range compared to those operated on flat terrain. Again, environmental conditions, such as temperature, humidity, and weather, significantly affect battery performance. Extreme hot and cold temperatures can reduce battery efficiency and increase the depletion rate. Patel and Wang (2019) have demonstrated how cold temperatures can increase the internal resistance of batteries leading to faster depletion, while high temperatures can cause overheating and accelerated degradation.

2.2.2. Battery Swapping and Charging and Its Effect on BET Availability.

The availability and operational efficiency of BETs are significantly influenced by battery swapping and charging strategies. Battery swapping offers a rapid solution to replenish a BET's energy source, substantially reducing downtime compared to traditional charging. Battery swapping can be a game-changer in mining operations where continuous vehicle availability is crucial. Wang and Zhang (2021) demonstrated how battery swapping stations can facilitate quick turnaround for BEVs, thereby increasing their availability and operational efficiency. This system, however, requires a significant initial investment in infrastructure and a pool of charged batteries, which might be challenging in remote mining areas.

While battery swapping offers speed, traditional charging infrastructure is still prevalent due to its lower initial cost and widespread applicability. The charging (slow or fast charging) plays a crucial role in determining the availability of BEVs. Li et al. (2022) showed that fast charging technologies could reduce downtime but may impact the battery’s longevity and overall vehicle availability in the long term due to faster degradation. Integrating battery swapping with traditional charging systems can provide a balanced approach to maintaining BEV availability. Such integration allows the flexibility to choose between rapid swapping or slower, more battery-preserving charging methods based on operational demands and constraints. Feyijimi et al. (2019) pointed out the importance of designing an autonomous battery-swapping system due to the range anxiety problem encountered by these units. However, Ahsanul et al. (2022) argued that while battery swapping is critical to solving that problem, it can cost about 48% more than the fast-charging technique, even though it gives higher productivity.

Due to the energy demands of BEVs, innovation in battery technology that allows for faster charging with minimal degradation and improvements in swapping station design for quicker and safer batteries is crucial. As a result, the long-term savings in operational costs need to be weighed against the initial setup and maintenance costs.

2.3. DISCRETE EVENT SIMULATION AND ITS MINING APPLICATIONS

DES models in mining can include variables like equipment availability, workforce schedules, and environmental conditions, allowing for a comprehensive operational efficiency analysis. This section explores the application of DES in mining, highlighting its advantages, applications, and challenges.

2.3.1. Simulation. Simulation is a practical method for replicating the behavior of real-world systems and employs symbolic or mathematical representations [85]. Its cornerstone of problem-solving and optimization is applied across various fields, such as energy, healthcare, public services, and mining [35]. The use of computer simulations for complex systems problem-solving has become prevalent [86]. A robust simulation model effectively mirrors the actual system, providing reliable insights into system queries [87]. Creating such models involves defining the system's state variables for thorough evaluation and analysis [85]. These variables can be categorized as discrete or continuous, static or dynamic, and deterministic or stochastic [88]. In discrete event models, variable changes occur at specific moments, whereas continuous models see variables evolving steadily over time in a continuous process [85].

Simulations offer several benefits, such as understanding system operations, testing concepts before implementation, and gathering vital data without disrupting the natural system [89]. They enable rapid experimentation with system alternatives [90]. Computer simulations facilitate system analysis with minimal analytical input, handling complex elements like stochastic variables and time delays that are challenging in analytical approaches [35]. Simulations can address both qualitative and quantitative aspects of problems unresolvable through qualitative methods alone [91]. However, they cannot provide the optimal solution independently and rely heavily on the accuracy of input data [92]. As such, repetitive iterations are essential in testing the sensitivity of the results.

There are several kinds of simulation. These include:

- **Agent-based simulations**. This type of simulation is a technique where individual agents, each with their intelligence, memory, and rules, are created to interact among themselves and with their environment. This interaction leads to behaviors, patterns, and structures emerging over time. These outcomes, derived from the complex interplay of agents, are utilized for various purposes [35], [93].
- **System dynamics simulation.** This kind of simulation uses feedback loops and time delays to represent the interactions and dynamics of system components. It focuses on understanding and modeling complex systems over time. It is mainly applied in strategic planning and policy development, especially in social, economic, and ecological systems[86] [93].
- **Discrete Event Simulations.** In this type of simulation, the state variables undergo changes at specific, discrete moments in time. [35] [87].
- **Hybrid Modelling**. This often combines DES and system dynamics to model complex models more comprehensively. Its primary advantage lies in combining various simulation techniques and incorporating empirical data from multiple sources to achieve comprehensive results [93].

This research uses DES to enhance BEVs' battery swapping and charging procedures in underground mining operations as they are becoming prevalent in the mining industry.

2.3.2. Discrete Event Simulation. DES is a sophisticated modeling method that can replicate complicated systems like natural systems [35], [94]. This computer-based approach ensures the creation, simulation, and examination of complex systems into a series of events. DES originated in the post-World War II era with advancing operations research and computer technology. The early applications arose from the need to simulate complex military and telecommunications systems. This allowed for the development of the core concepts of DES, such as the representation of such systems as a series of distinct events whose states change with time. The General-Purpose Simulation System (GPSS) is the oldest simulation language. It was developed by Geoffrey Gordon in the 1960s. This was a milestone in providing a standardized approach to DES modeling [95]. GPSS mainly was utilized for models involving queues. Compared to other languages, it lacked the flexibility and capability to alter the system's state [96]. Some other popular simulation languages include:

- **SIMAN**. This is the shortened form for SIMulation ANalysis and is mainly utilized in modeling discrete event simulation systems [96]. Arena, the software utilized in this research, uses this simulation language to model a discrete, continuous, or hybrid of both[96] [91]. In Siman, users can model various experiments yielding multiple results [91]. The downside of this language is its demanding feature in demand-driven modeling systems [97]. **SLAM**. Simulation Language for Alternative

Modelling, as the name implies, aids analysts in modeling in multiple paradigms for flexibility and problem requirements [91]. A more significant advantage of this language is its ability to construct integrated models encompassing different system orientations, such as discrete-event, process-oriented, and object-oriented [98]. It has quite a steeper learning curve due to its hybrid nature [98], [99]

- **SIMSCRIPT**. The original version was by Markowitz under the U.S. Air Force [100]. This is often used for discrete event simulation systems using the object-oriented approach [96], [99]. This language, however, imposes higher constraints on the process definitions [96]. It incorporates object-oriented programming concepts, which allow for the creation of modular, reusable, and scalable simulation models [85], [99]
- **AnyLogic.** This language supports seamless switching between 2D and 3D modeling [101]. It has advanced statistical analysis and experimentation tools, making it easier to analyze and interpret the results of simulated experiments [101]. These are its significant advantages over the other simulation languages.

In typical DES modeling, a system is under study, and a model is developed to replicate the system [102]. In a detailed context, activities and events determine entities' processes. Entities may have different attributes depending on the system under consideration. They are modeled to go through the system as the state variables change [87], [94], [103]. Current DES models use simulation languages like GPSS, SIMAN, and SLAM [96].

In developing a DES model, four conceptual frameworks have been applied since the evolution of DES models [95],[100]. These include:

- **Event scheduling.** This framework offers a localized concept of time with a complete focus on an event occurrence [100]. The events occur when entities allocated for an activity are released by resources or processes. The analyst is thus required to monitor the current and future events by making changes in the model once these processes and activities are defined for the DES model [91].
- **Activity scanning.** This framework offers a localized concept of state, emphasizing the conditions and actions of entities. The model assumes a different state with the probability of a particular condition occurring [100]. The framework requires analysts to ensure that all appropriate conditions are feasible before taking the required actions. Usually, this framework is prolonged since analysts usually perform numerous simulations at specific intervals [100].
- **Process interaction.** This framework offers a localized concept of an object with emphasis on model specifications. The overall action sequence of the object in question is monitored as it moves through the various processes in the model [100].
- **Three-phase approach**. This multiple approach focuses on the stages that entities advance through events, activities, and resources. In the first phase, a state change is acknowledged only when there has been a change in time. The second phase ensures that resources scheduled for an activity

are released after performing their schedules. The last phase completes the process as activities are marked as completed when resources avail themselves to be used by entities [99].

2.3.3. DES Application in Mining. The quest to build a DES model requires expertise and training, which can be costly and time-consuming [85]. Various industries apply DES models to develop optimal designs and configurations of real-world systems [104], [105]. The cheap and easy ways of modeling complicated systems using DES have made their application prevalent [102].

The application of DES has been extensively applied in the mining industry to optimize operations and advance several making processes [103], [106], [107]. The early stages of its application focused on streamlining mining operations and logistics. Material handling, equipment scheduling, and process optimization are the key areas where their implementation has been highlighted according to relevant literature [84], [85], [63]. It has been applied primarily on surface mines compared to its underground counterparts [108]. According to the reviewed literature, DES has not been used extensively for BEVs, which is gaining an audience in mining.

In summary, integrating BEVs in the mining environment presents promising opportunities and significant challenges, as highlighted in the thesis' comprehensive literature review. Central to these challenges is the effective management of battery technology, where limitations such as restricted life spans and prolonged charging times pose operational constraints. The impact of various charging technologies on battery health and efficiency introduces further complexities. Moreover, as discussed in the literature, the driving range of BEV is a significant factor worth probing into. Since harsh conditions and fluctuating demands characterize mining, these challenges are accentuated, necessitating robust and adaptive charging and swapping technologies. This is where DES becomes crucial. DES offers a dynamic tool to model, simulate, and analyze the complex interplay of these factors.

By simulating diverse scenarios, DES can inform the development of optimized charging protocols that align with the unique operational needs of mining, evaluate the efficiency and practicality of different battery swapping methods, and assess the overall impact of these strategies on the productivity and sustainability of BEV use in mining operations. DES serves as a bridge between the challenges identified in the literature and the practical solutions, providing a platform to test and refine BEV battery management strategies to enhance operational efficiency and demands.

3. DISCRETE EVENT SIMULATION (DES) IN SWAPPING/CHARGING OF BATTERY ELECTRIC VEHICLES IN UNDERGROUND MINING

3.1. INTRODUCTION

This Section deals with the specific framework utilized for this study. A detailed DES model, with a comprehensive case study, has been developed, focusing on the assumptions. This Section investigates the application of DES for evaluating the critical performance metrics of BEVs' battery swapping and charging procedures, such as charging unit utilization, battery waiting time before utilization, availability of trucks, and the frequency of queues with a change in the number of trucks and/or batteries. An existing underground BEV was used as a case study to showcase the application of DES for solving the associated problems.

Understanding the processes that the BEV's battery experiences throughout the working phase is critical. A continuous flow of events within such a system without queues was the optimal goal. A longer waiting time for trucks at the charging bay for batteries will lead to lower productivity. Moreover, a charged battery sitting at the charging bay will imply the under-utilization of batteries. The maximum utilization of the charging unit is also a key component for an optimal system for this case study.

This study also assessed the possible queues that the system can generate during the working phase. This was used to develop multiple maps of the multi-service BEV swapping and charging systems for optimal decision-making. The DES model can determine the utilization of the charging unit, trucks, and batteries and the time a charged battery is idle after charging.

3.2. DES MODEL FRAMEWORK

Advancements in computer simulation have significantly reduced the intricacy and time required to tackle significant optimization challenges. In underground mining, integrating BEV technologies demands robust frameworks for efficient operations. DES is an indispensable tool for modeling and analyzing BEVs' swapping and charging mechanisms.

The ultimate goal of this thesis is to optimize the battery swapping and charging processes of battery electric trucks, particularly in underground mines. With the battery being a pivotal contributor to the powertrain of the equipment [44], it is significant to examine the series of events it undergoes before, during, and after each shift. If we can understand the sequence of events the battery undergoes throughout a shift, we can model those uncertainties as a series of events.

The methodology applied in this study aims to:

1. Build a DES model of the base case scenario to replicate the natural system.
2. Examine the performance metrics of the base model.
3. Build other experiments and compare them with the base case scenario.
4. Select the optimal scenario.

3.3. MODEL ASSUMPTIONS

This thesis makes fundamental assumptions for the DES model to be functional and reliable. Some of the critical assumptions are highlighted below:

1. The underground mine maintains constant operational hours, and the BEVs operate within the specified time frames without unscheduled halts or failures except for battery depletion.

2. BEVs have uniform battery lifespan and depletion rates. Battery degradation over time is not considered in this study.
3. The speeds of BEVs differ depending on the terrain in which they move. The gradient of the haul roads was not considered in the model.
4. The model did not consider the status of BEVs, either loaded or unloaded, while visiting the charging bay. The bay can be accessed by the truck even in its loaded state.
5. The model assumes a single charging bay for the base case and all other scenarios.
6. The model did not incorporate the shift breaks. As such, the base model assumes a 20-hour per day shift.

3.4. CASE STUDY

A case study of a BEV used in an underground mine is presented in this section to highlight the approach discussed in Section 3.2. Kelton et al. (2003) stated that a typical simulation study has seven major components [33]. The subsequent discussions will, however, be explicitly based on the battery and charging model of the BEVs in the underground working environment.

3.4.1. Build DES Model. The study delves into the approach and procedures used to build the Arena model. It discusses the model specifics, including the entities' processes, variables, and attributes.

3.4.1.1. Problem formulation. The primary objective of this research is to examine and optimize the battery swapping and charging procedures used by Battery Electric Vehicles (BEVs) in an underground mining setting. To achieve this, a Discrete Event Simulation (DES) model was developed utilizing Arena® software. This model meticulously mirrors the actual operational environment, incorporating various attributes and variables representative of a real-world system.

The core functionality of the DES model is to forecast the utilization of trucks, chargers, and batteries within the mine. This is achieved by analyzing and predicting the formation of queues in the system, which is a key indicator of process efficiency. This approach is particularly relevant in addressing the primary concern of the study, i.e., assessing and enhancing the efficiency and effectiveness of the battery swapping and charging procedures for BEVs in underground mining scenarios.

A critical outcome of this study is determining the ideal number of batteries to be assigned to a specific number of trucks and chargers. This is not a straightforward calculation, as the model seeks to establish the most efficient scenario that balances operational demands with resource availability. This is highly relevant due to the cost of establishing a single bay for each truck, which is the current setup.

Furthermore, an essential aspect of this study is the cost implications of the battery charging process. The charging procedures must not lead to a surge in operational costs. This concern introduces an additional layer of complexity into the model, as it must identify the optimal intervals for charging and swapping batteries. The goal is to predict and mitigate potential bottlenecks in these processes, thereby ensuring a smooth and cost-effective operation.

In summary, the DES model in this study is an intricate tool designed to optimize battery charging and swapping of BEVs for underground mining. It does so by balancing the need for efficiency in battery swapping and charging to maintain a system with fewer queues, which will increase production.

3.4.1.2. System and simulation specification. The study focuses on an underground mine that employs the sub-level stoping method for ore extraction. This mining operation utilizes Battery Electric Vehicles (BEVs) to transport materials. These materials are moved from the mining areas, known as stopes, to designated ore passes. The materials are conveyed to the surface through a hoist shaft system from these ore passes. The model only considers the truck's movement from the stope to the ore passes.

A noteworthy aspect of this mining operation, as shown in Figure 3.1, is the logistics surrounding the BEVs. Each truck is allocated a specific set of resources: one charging bay, an individual charger, and a pair of batteries. This setup is crucial for the efficient functioning of the transport system within the mine. The precise distances these trucks travel, starting from the loading stations to the ore passes and then to the charging stations, have been methodically tabulated in Table 3.2.

The study also incorporates a model designed to simulate and verify the efficiency of this system. This model is not merely a theoretical construct; it includes a basic animation feature visually representing the system’s operation. Data was sourced directly from the manufacturer of the equipment and vehicles used in the mine to construct this model. The various fields in the data were cleaned using box plots in Excel.

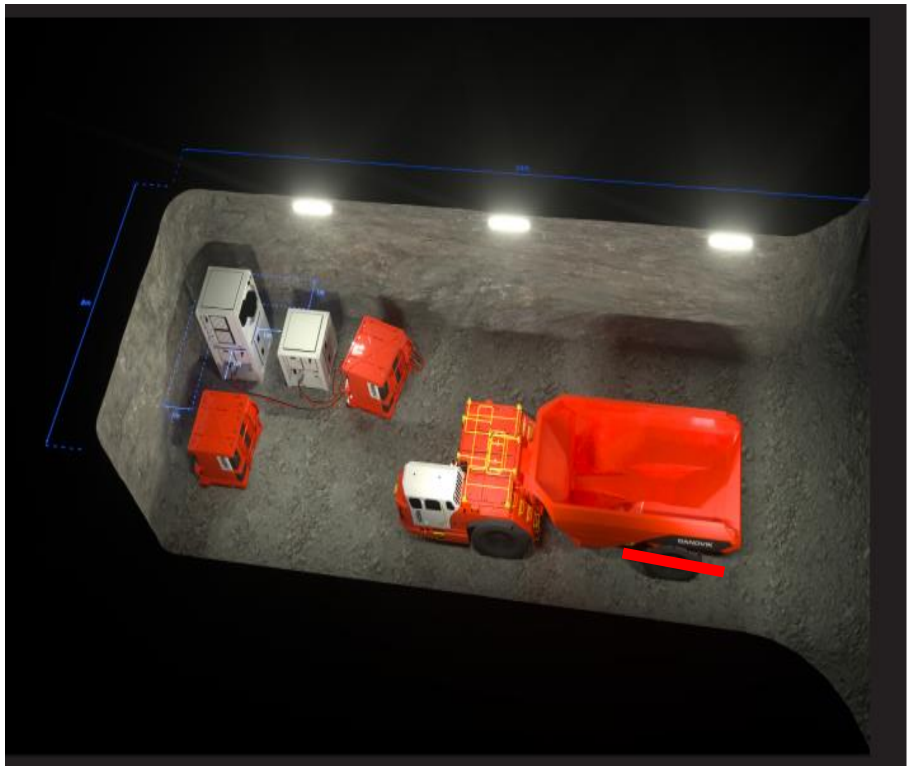


Figure 3.1. Typical Charging Bay Setup

This raw data underwent a thorough analytical process using the Input Analyzer tool in the Arena software. The purpose of this analysis was to formulate distributions for all the parameters that are essential to the model. The Input Analyzer employs statistical techniques such as the Chi-squared and Kolmogorov-Smirnov (KS) tests, leveraging their strengths to enhance the robustness and precision of distribution fitting in the simulation models. The rationale behind this dual approach is rooted in the complementary nature of these tests. With its non-parametric foundation, the KS test offers flexibility in assessing the fit of a wide range of data types without pre-assuming any specific distribution [109]. This is highly efficient since the data distributions were unknown. On the other hand, the fact that the Input Analyzer tool utilizes the Chi-squared test, which is parametric, makes it worth implementing [110]. By incorporating both tests, Arena's Input Analyzer caters to a comprehensive spectrum of data analysis scenarios, from general explanatory assessments to specific distribution fits [33]. This dual methodology ensured that the chosen distributions were not only statistically valid but also the most representative of the real-world scenarios being modeled, thereby enhancing the credibility and effectiveness of the simulation results. These tests are critical in evaluating each distribution's suitability or 'goodness of fit.' The input parameters are highlighted in Figures 3.2 – 3.8.

Some of the critical data pivotal to the model include the duration of battery charging, the time taken for battery swapping, and the average speeds of the BEVs traveling over different terrains. Table 3.1 comprehensively presents these specific details.

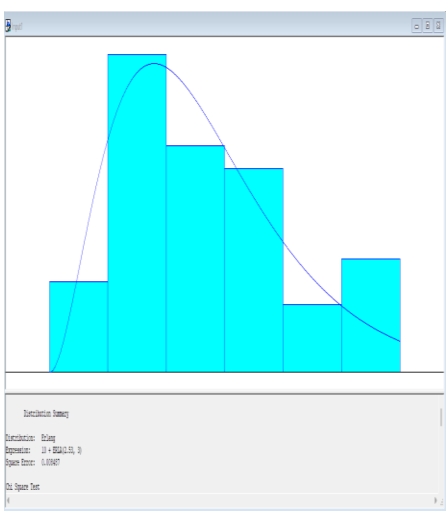


Figure 3.2. Average battery swapping time

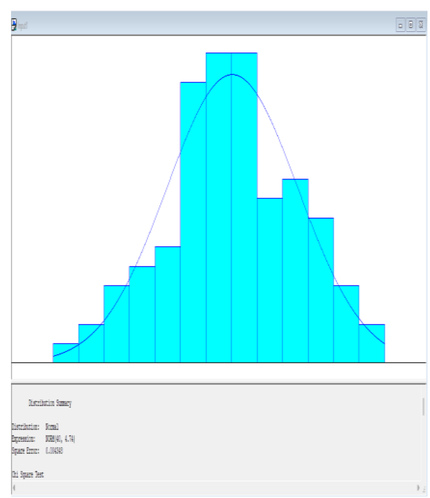


Figure 3.3. Average payload

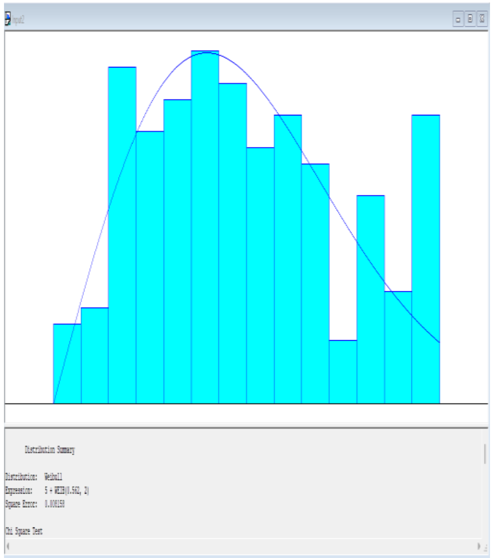


Figure 3.4. Total distance traveled

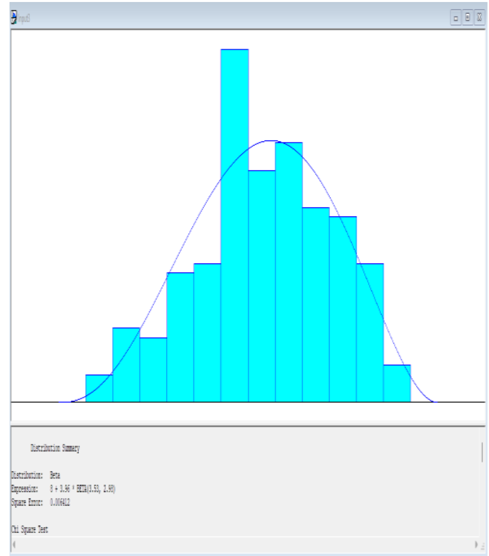


Figure 3.5. Average speed uphill

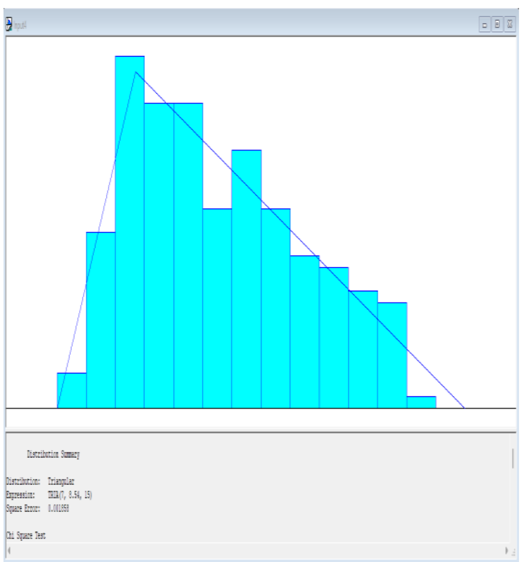


Figure 3.6. Average speed level

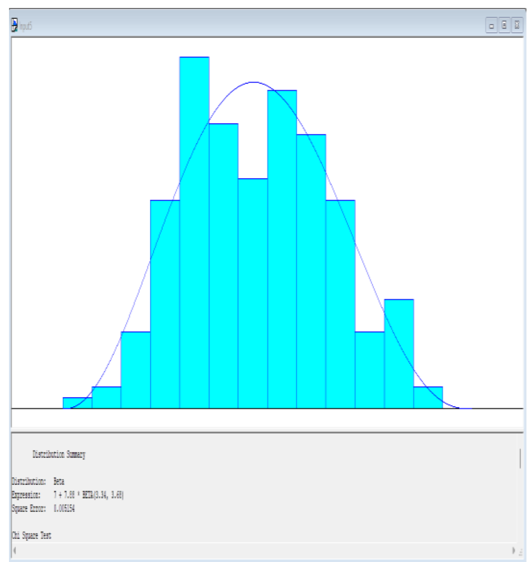


Figure 3.7. Average speed downhill

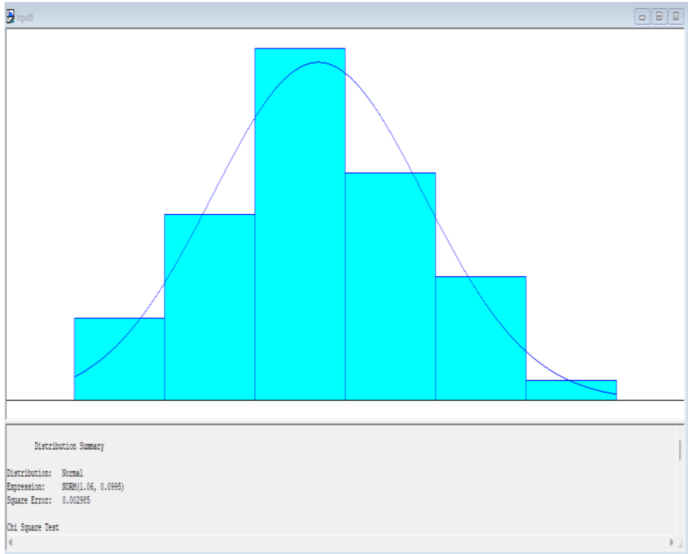


Figure 3.8. Average charging duration

Table 3.1. Input data

Activity	**Distribution(s)**	**P-value**
Loading time (min)	TRIA (7, 11,12)	<0.005
Dumping time (min)	TRIA (5, 8, 10)	<0.005
Speed level (Km/h)	TRIA (7, 8.54, 15)	<0.005
Speed Uphill (Km/h)	8 + 3.96 * BETA (3.53, 2.98)	<0.005
Speed Downhill (Km/h)	7 + 7.88 * BETA (3.34, 3.68)	<0.005
Cycle time (hrs)	From model	
Payload (tons)	NORM (40, 4.74)	<0.005
Battery swapping time (min)	10 + ERLA (2.53, 3)	<0.005
Charging (hrs)	TRIA (0.82, 0.965, 1.4)	<0.005

3.4.1.3. Model formulation. The DES modeling framework is structured around a detailed specification of the entities, resources, and processes constituting the system under examination. This specification is critical for the analyst, who must accurately define and integrate these components to create a realistic and functional model. Entities are the distinct items or units that move through the system. They are central to the simulation as their movements and interactions represent the operational dynamics of the system. In this model, the BEV's batteries were modeled as entities. These entities have attributes that change as they move about in the model. An example is the attribute state of charge (SOC), which determines how low the battery is and asks it to be recharged if it falls below a certain threshold.

Resources in the DES model are elements entities required to complete various processes. The charging unit is modeled as a resource for this model implementation. The charging unit as a resource seizes the battery when it enters the charging process for the duration shown in Table 3.1 and releases it after charging to be transported by a truck. The availability and utilization of these resources significantly impact the efficiency and effectiveness of the system.

Processes are the sequence of steps or actions entities undergo within the system. The DES model must logically define these processes to reflect real-world operations. In this model, the batteries (entities) go through the loading, dumping, and charging process. The modeling considers the battery swapping time during the charging process, as shown in Table 3.1. The model incorporates several designated stations to accommodate these processes, each tailored to facilitate a specific part of the battery's journey through the system.

For an entity to move from one station to another, it requests to be transported by a Transporter. Transporters, in a DES model, are mobile entities used to simulate the movement of items between locations in the model. For this study, BETs are modeled as Transporters. As shown in Table 3.1, the transporter changes its speed based on the entities between terrain and its direction of travel. The distance traveled by the Transporter to moving stations is highlighted in Table 3.2.

Table 3.2. Distance between stations

Station Names		**Distance (km)**
From	**To**	
Loading	Ore pass	0.1
Charging bay	Ore pass	0.02
Charging bay	Loading	0.03

- **Analysis of battery depletion in BEVs using multiple regression:** The model required analysis of the raw data to ascertain how the various fields correlate with battery depletion. Table 3.3 shows the correlation between battery depletion and the remainder of the variables in the input data.

A comprehensive approach was adopted in the initial stage of the multiple regression analysis for this project. This involved considering the entire spectrum of variables available in the raw data set provided by the manufacturer. The multiple regression model is represented in Equation 3.1.

- $$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots\dots + \beta_p x_p \quad (3.1)$$

- Dependent variable (y) = Battery depletion (kWh Used);
- Multiple variables ($x_1, x_2, x_3, \dots x_p$) = All the independent variables.
- β_0 = intercept.

The raw data was systematically divided into two distinct sets: training and testing datasets. This division followed the standard practice of using a larger portion for training (70%) and a smaller portion for testing (30%). Such a split was relevant in developing a robust, well-trained model on most of the data and effectively validated against an independent dataset. The purpose of the more extensive training set was to train the regression model, which improves the model's parameters (coefficients) to fit the dataset best. The testing data will further validate the model's performance.

The data presented in Figure 3.9 and Figure 3.10 indicate that the regression model is highly effective in predicting the rate at which the battery depletes. This high level of accuracy and certainty in the predictions made by the model lends credibility to the assumption that the equation derived from the regression model can be reliably used to represent the battery depletion rate within the Arena simulation model.

Furthermore, the efficacy and performance metrics of the regression model are comprehensively detailed in Table 3.4 and Table 3.5. These tables present the model's accuracy on the training and testing data sets. The strong performance of the regression model on the test data, as shown by the metrics in Table 3.5, reinforces the validity of employing its derived equation in the Arena model to simulate and understand the battery depletion dynamics realistically.

For the specific requirements of this project, the multiple regression model was adapted to focus on a subset of six variables deemed most critical in predicting the battery depletion rate in BEVs. This decision was based on the preliminary data analysis and Arena compatibility of certain input variables. An important aspect of this process was selecting the variables that were highly correlated to battery depletion according to

Table 3.3. As highlighted in Section 2.2.1 of the literature, only four main variables were selected after critical evaluation. In this model, battery depletion depends on:

- ✓ Cycle time.
- ✓ Payload.
- ✓ Average speed (uphill, downhill, or level terrain).
- ✓ Distance of travel.

Table 3.3. Correlation between Battery Depletion (kWh Used) and the independent variables

kWh Used	**1.000000**
Cycle Time	0.425157
Distance Traveled	0.472540
Avg. Machine Speed	-0.101398
Max Machine Speed	-0.132704
Avg. Speed Uphill	-0.580605
Avg. Speed Downhill	-0.259224
Avg. Speed Level	-0.568464
Tons	0.325817
TKPH	-0.055498
Tons/Hr	-0.146593
kWh/Ton	0.461023
Uphill kWh	0.979949
kWh/km Uphill	0.657516
Downhill kWh	-0.704163
kWh/km Downhill	-0.288437
Max of Max Front ATF Temp	0.239708
Max of Max Rear ATF Temp	0.190569
Max Hydraulic Tank	0.255842
Max Front Cell Temp	0.155283
Max Rear Cell Temp	0.086404

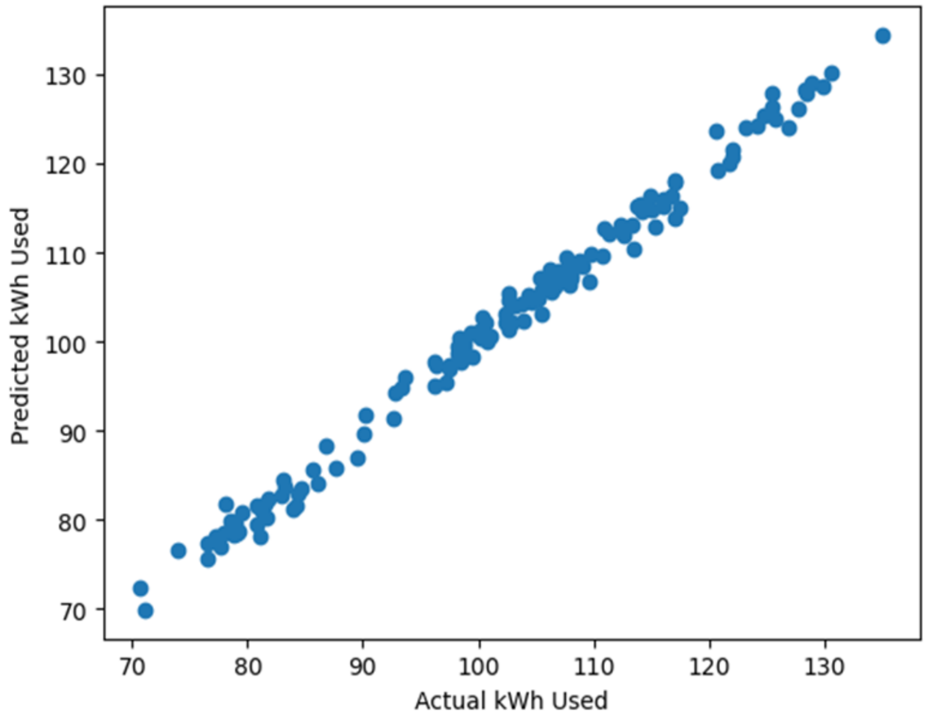


Figure 3.9. Plot of the regression model’s performance on training data

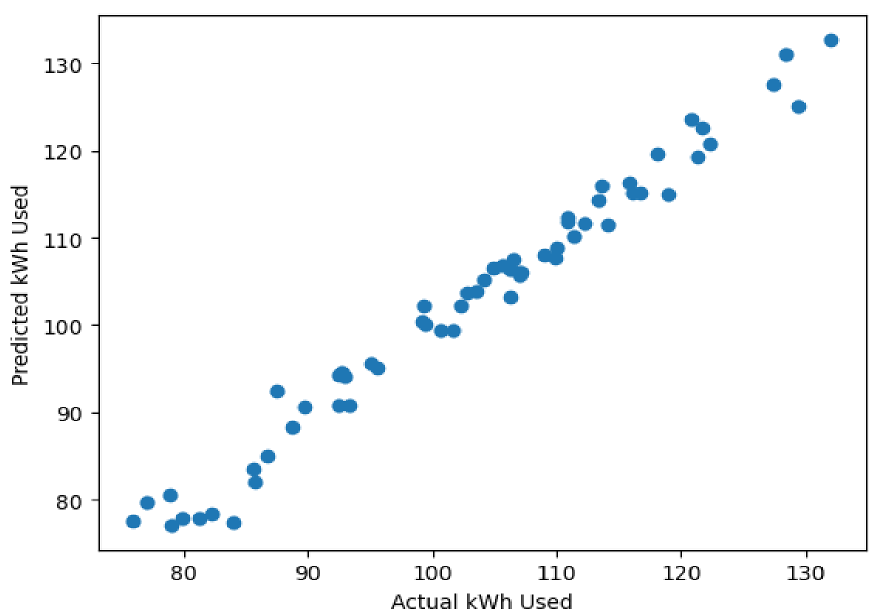


Figure 3.10. Plot of the regression model’s performance on testing data

Table 3.4. Performance of the regression model

Metric	Training data	Test data
R-squared	0.99	0.97
MAE	N/A	1.74
MSE	N/A	4.61
RMSE	N/A	2.14

The revised form of Equation 3.1 is presented in Equation 3.2 for this model. Estimating the coefficient of the variables using regression techniques is what the model tends to predict [87].

$$\begin{aligned} &Battery\ Used\ (kWh) \\ &= \beta_0 + \beta_1 \times Cycle\ Time + \beta_2 \times Tons\ (Payload) \\ &+ \beta_3 \times Average\ Speed\ Uphill + \beta_4 \times Average\ Speed\ Downhill \\ &+ \beta_5 \times Average\ Speed\ Level \\ &+ \beta_6 \\ &\times Distance\ Traveled \end{aligned} \quad (3.2)$$

The statistical analysis involved fitting the regression model on the proposed variables. The model's performance on the training and testing data of the proposed variables is presented in Figure 3.11 and 3.12.

Table 3.5. Performance of the regression model

Metric	Training	Test
R-squared	0.99	0.97
MAE	N/A	1.74
MSE	N/A	4.61
RMSE	N/A	2.14

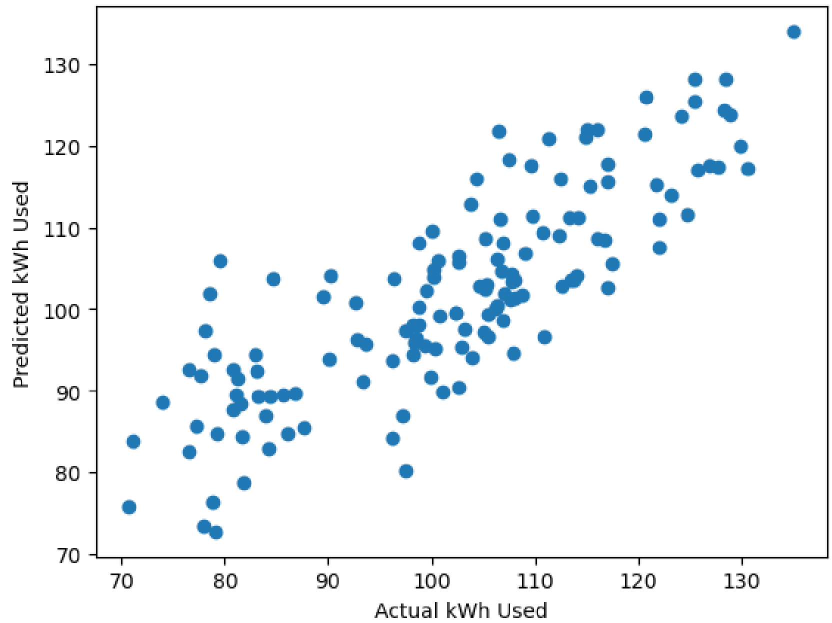


Figure 3.11. Plot of the regression model’s performance on training data

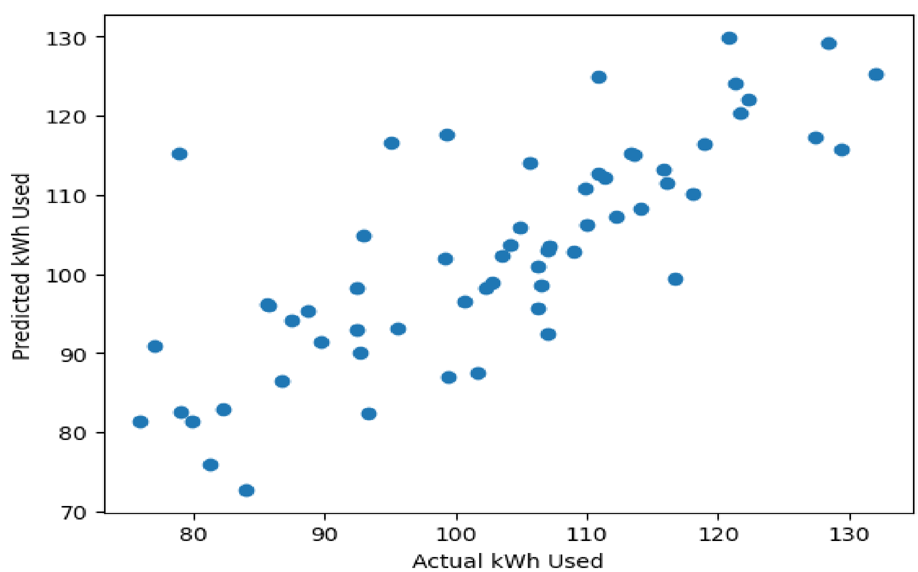


Figure 3.12. Plot of the regression model’s performance on testing data

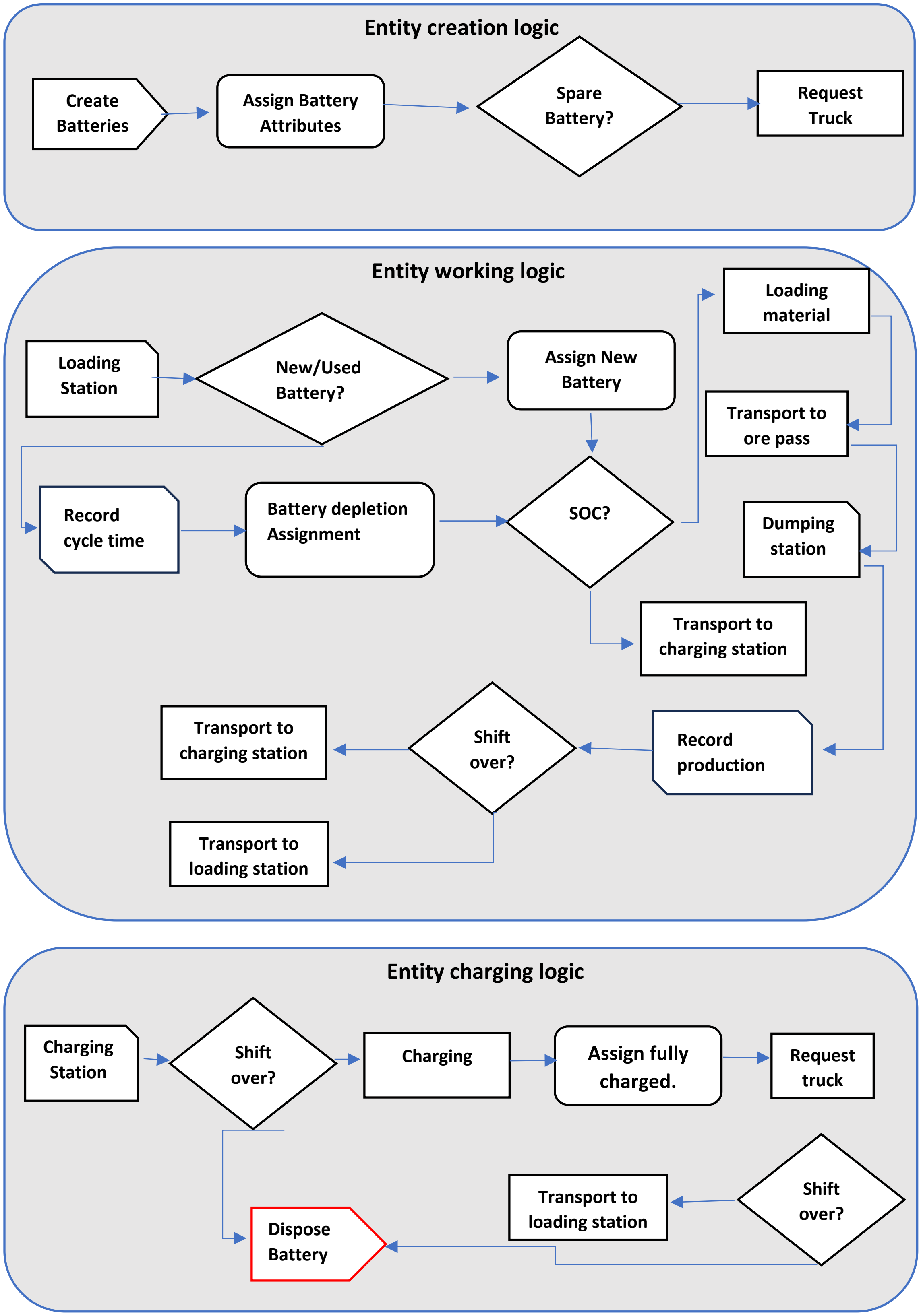


Figure 3.13. Flowchart of DES model logic

3.4.1.4. Verification and validation. For the verification of the model, an animation of the system was built to ensure that the model was performing as expected in its theoretical compositions. In detail, the model tracked some system and user-defined variables, such as a graphical representation of the battery depletion after each cycle. Again, the model was verified by identifying the charger utilization and frequency of queues generated at the charging bay when there is an increase or decrease in the number of batteries and/or trucks.

Since the model aims to predict the number of queues generated when the number of entities and transporters changes, the subsequent sections will discuss how the variations affect the performance metrics discussed earlier.

In the context of this project, the model will not undergo the traditional validation approach. This is because the data utilized in constructing the model lacks corresponding real-world data for our specific output deliverables. This limits the ability to validate the simulation results directly against actual operational outcomes.

Half-width represents the range on either side of the estimated mean within which the population's true mean will likely fall. This implies that the lesser the half-width, the lesser the uncertainty, indicating the model’s performance [87]. The main outputs of the simulation were charger utilization, truck availability, frequency of queues, and battery waiting time post-charging. The output's functions are the cycle time, payload, average speed, and distance traveled. However, since the simulation results only present cycle time and payload, we considered these two metrics and the outputs in determining the relevant metrics of the half-width. As such, we chose the number of replications such that their half-widths were less than 3% of the mean. After the examination, we discovered that 240 replications were required to achieve the required half-width.

$$Half - width = t_{n-1,1-\alpha/2*} \frac{s}{\sqrt{n}}, \tag{3.3}$$

where $t_{n-1,1-\alpha/2}$ = tables values, n = number of replications, s = standard deviation.

3.4.2. Evaluating the Key Performance Metrics. As highlighted earlier, the model needs to evaluate specific key parameters, such as charger utilization, truck utilization, and the frequency of queues. The results of the simulation yield numerous outputs. However, discussions will focus on only the key performance metrics.

The charging bay has zero queues for the base case scenario, which is always the case since only a single truck is in the base model. This verified the performance of the DES model for the base case scenario. The average utilization of the charging unit, as shown in Figure 3.13, was very low. This clearly demonstrates how the charging unit is generally under-utilized. The high efficiency of the charger is attributed to the cycle time of the trucks and the battery charging duration.

It is evident from Figure 3.14 that the operational efficiency of truck was maximized, with trucks being readily available for use at any given time, signifying an optimal state of vehicle utilization within the system. However, a contrasting situation is observed regarding the battery charging and utilization process, as depicted in Figure 3.15. Even though the batteries were charged and ready for deployment, they remained in the charging bay for an extended duration of approximately 5 hours post-charging as shown in Figure 3.16.

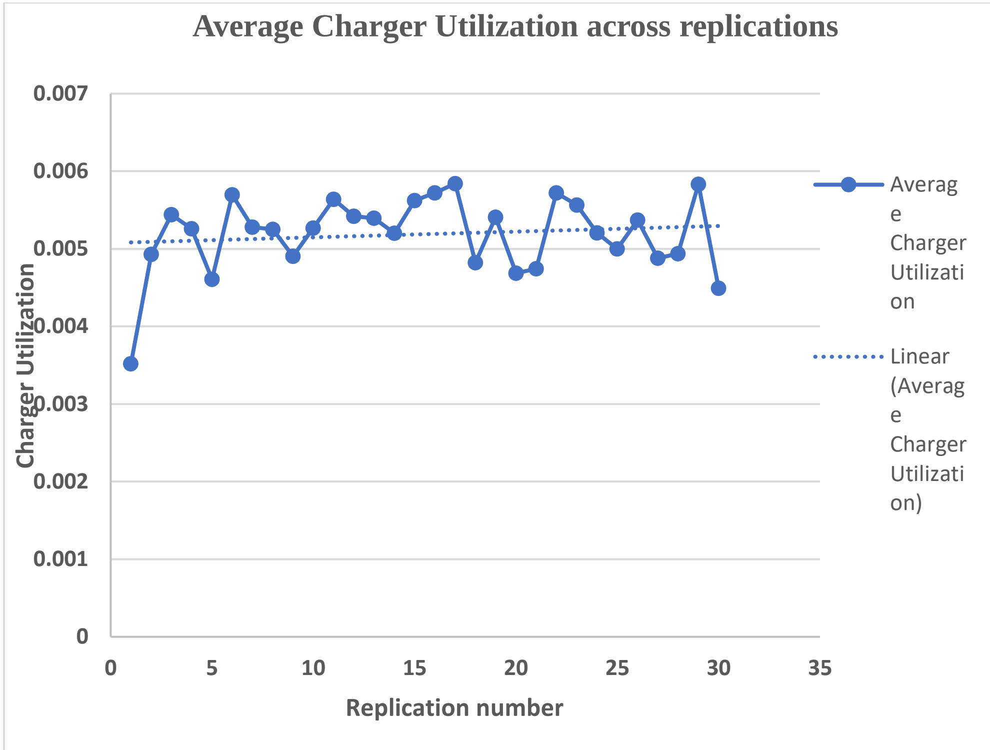


Figure 3.14. Average charger utilization across 30 replications

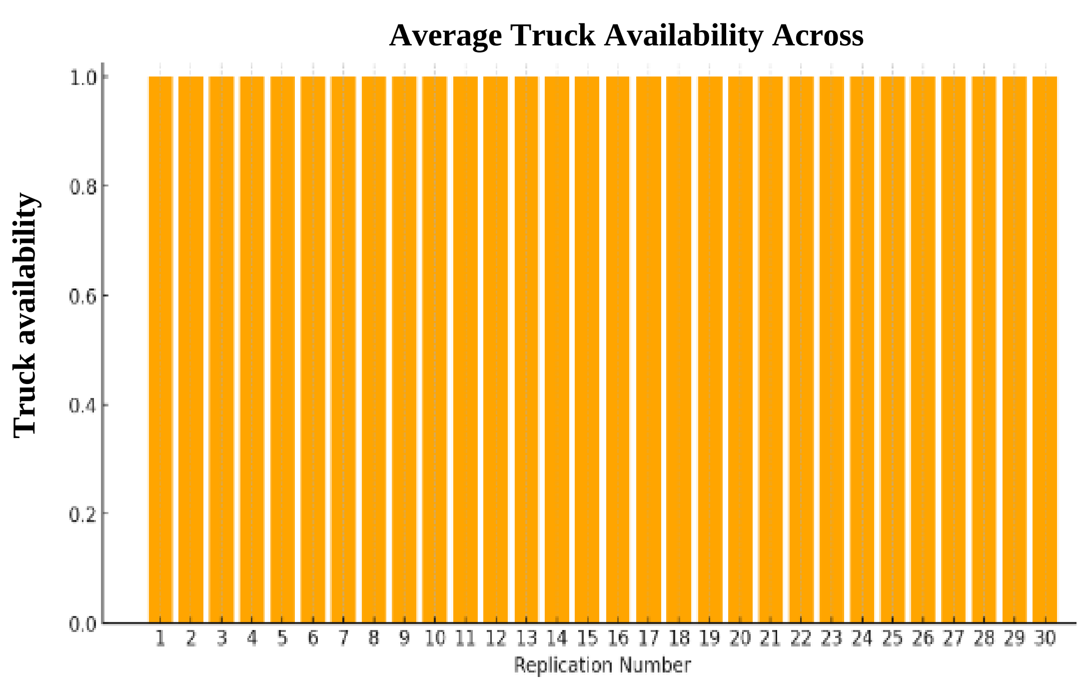


Figure 3.15. Average truck availability across 30 replications

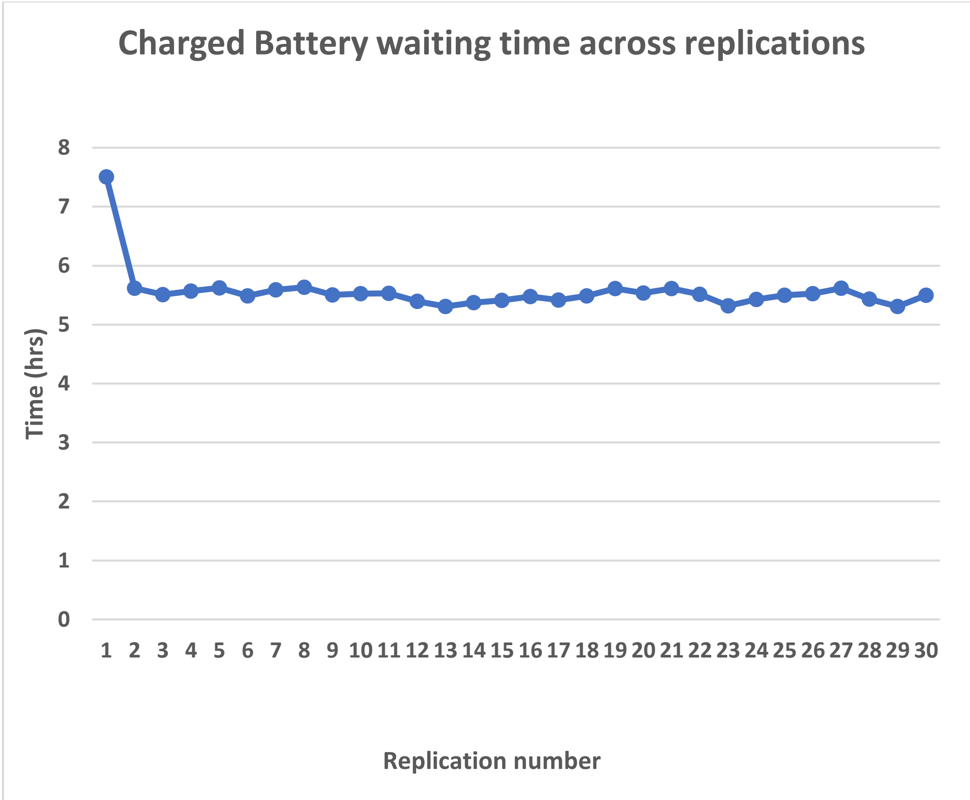


Figure 3.16. Average battery waiting time after charging

Table 3.6. Average of averages of the replications

Metric	**Average of 240 replications**
Charging queue (hrs)	0
Battery waiting time (hrs)	5.55
Charger Utilization (%)	0.524
Truck Availability (%)	100

3.5. SUMMARY

This project analyzed the potential of DES for optimizing the battery swapping and charging procedures of battery electric vehicles (BEVs) in underground mining operations. Data from a BEV manufacturer was used as input parameters for the DES model.

The DES model can be used to assess performance metrics, such as charger utilization, truck availability and utilization, and the number of queues generated with a change in the number of entities and transporters. The overall result of the base case scenario is presented in Table 3.6. Therefore it can be gihlighted that model has successfully been verified for the base case scenario. From the base case study, the following conclusions can be drawn:

- The simulation results from this case study showcased the capability of DES to model the complexities and uncertainties surrounding such an operational system. Although comprehensive validation of the model was constrained due to the absence of specific comparative data, the successful verification of the model underscores its reliability and effectiveness.
- The model's significant strength lies in its adaptability. It allows for modifications for critical input variables without redeveloping the entire model. This means that adjustments for variables, such as the trucks' speed, can be made relatively easily, offering a high degree of flexibility.
- The base case scenario guaranteed 100% truck availability but significantly under-utilized charger and had batteries waiting the longest

to be used after charging. This insight points to potential areas for optimizing charger and battery usage to enhance overall operational efficiency.

4. EVALUATING THE RESPONSE OF THE INPUT PARAMETERS

4.1. OVERVIEW

This section focuses on the DES model's experimentation. It explores how changing critical input parameters, such as the number of trucks, batteries, and chargers, impacts critical metrics in the DES model. These metrics include queue frequency, charger utilization, truck availability, and battery wait times post-charging.

The study aims to identify an optimal combination model that minimizes queues and battery wait times while maximizing truck availability and charger utilization. To achieve this, different scenarios developed during the experiment design phase will be thoroughly evaluated.

Subsequent subsections provide detailed insights into each experiment, focusing on various parameter combinations tailored to the specific mining setup under study. These experiments will show how alterations in input variables influence performance metrics, as discussed in Subsection 3.4.2. The author leverages Arena, a simulation modeling software, specifically its Process Analyzer tool, to conduct these experiments, showcasing the effectiveness of DES in addressing the problem at hand.

4.2. DESIGN OF EXPERIMENTS

Design of experiments (DoE) is a methodological and thorough approach, used in improving and optimizing processes. It enables researchers and practitioners to evaluate the changes in output variables in response to alterations in input factors, thereby establishing cause-and-effect relationships.

Full factorial design. The study utilized the full factorial experimental design approach to determine the effects of multiple factors and their interactions on the response variables. In this design approach, experiments are conducted considering all possible combinations of factors and their levels. The factors considered were the number of trucks, batteries, and chargers. Even though it is crucial to understand the interactions between these factors and the output parameters, it will be an exhaustive approach to rebuild the model for each scenario.

The maximum number of factors to be considered was selected after consultation with experts of the mine under consideration (anon, personal communication, December 3, 2023). The maximum number of trucks and chargers was equal to four. The maximum number of batteries was equivalent to eight. Thus, a truck is roughly assigned to two batteries. The possible combinations based on the above were determined using Equation 4.1.

$$\begin{aligned}\text{Total combinations} \\ = \text{Levels of trucks} * \text{levels of batteries} * \text{levels of chargers}\end{aligned} \tag{4.1}$$

The possible number of combinations could be 112 experiments. After careful review, based on the maximum number of factors and ignoring certain combinations, only 53 experiments were conducted, as shown in Table 4.1 (Run Experiments) and Table 4.2 (Ignore Experiments). These experiments were evaluated to ascertain how their effects contributed to the various performance metrics, trucks availability for work, battery waiting times post-charging, charging queues, and the chargers' utilization.

Arena's process analyzer was used to build and run the experiments. The tool allows the user to create controls (same as factors) and responses (same as key output

Table 4.1 Run Experiments

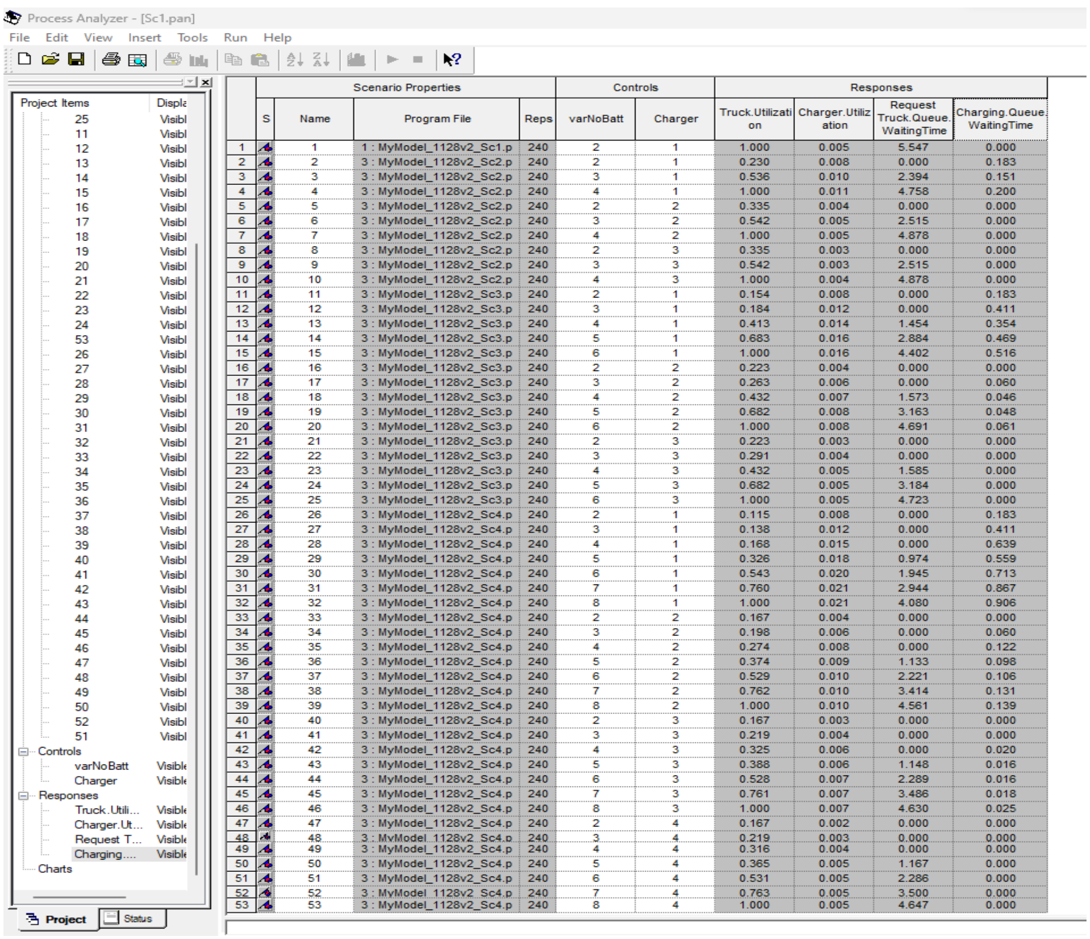
Run Experiments				Run Experiments			
Scenario	Trucks	Batteries	Chargers	Scenario	Trucks	Batteries	Chargers
1	1	2	1	29	4	5	1
2	2	2	1	30	4	6	1
3	2	3	1	31	4	7	1
4	2	4	1	32	4	8	1
5	2	2	2	33	4	2	2
6	2	3	2	34	4	3	2
7	2	4	2	35	4	4	2
8	2	2	3	36	4	5	2
9	2	3	3	37	4	6	2
10	2	4	3	38	4	7	2
11	3	2	1	39	4	8	2
12	3	3	1	40	4	2	3
13	3	4	1	41	4	3	3
14	3	5	1	42	4	4	3
15	3	6	1	43	4	5	3
16	3	2	2	44	4	6	3
17	3	3	2	45	4	7	3
18	3	4	2	46	4	8	3
19	3	5	2	47	4	2	4
20	3	6	2	48	4	3	4
21	3	2	3	49	4	4	4
22	3	3	3	50	4	5	4
23	3	4	3	51	4	6	4
24	3	5	3	52	4	7	4
25	3	6	3	53	4	8	4
26	4	2	1				
27	4	3	1				
28	4	4	1				

Table 4.2 Ignored Experiments

Ignored Experiments				Ignored Experiments			
Scenario	Trucks	Batteries	Chargers	Scenario	Trucks	Batteries	Chargers
1	1	3	1	31	2	8	1
2	1	4	1	32	2	5	2
3	1	5	1	33	2	6	2
4	1	6	1	34	2	7	2
5	1	7	1	35	2	8	2
6	1	8	1	36	2	5	3
7	1	2	2	37	2	6	3
8	1	3	2	38	2	7	3
9	1	4	2	39	2	8	3
10	1	5	2	40	2	2	4
11	1	6	2	41	2	3	4
12	1	7	2	42	2	4	4
13	1	8	2	43	2	5	4
14	1	2	3	44	2	6	4
15	1	3	3	45	2	7	4
16	1	4	3	46	2	8	4
17	1	5	3	47	3	7	1
18	1	6	3	48	3	8	1
19	1	7	3	49	3	7	2
20	1	8	3	50	3	8	2
21	1	2	4	51	3	7	3
22	1	3	4	52	3	8	3
23	1	4	4	53	3	2	4
24	1	5	4	54	3	3	4
25	1	6	4	55	3	4	4
26	1	7	4	56	3	5	4
27	1	8	4	57	3	6	4
28	2	5	1	58	3	7	4
29	2	6	1	59	3	8	4
30	2	7	1				

parameters). Each of the 53 experiments, guided by the run experiments in Table 4.1, was scrutinized based on key performance metrics outlined in Section 3.4.2. These experiments and their configuration are further illustrated in Figure 4.1.

The model underwent modifications to establish experimental controls, enabling input factors to be variables. This approach differed from the base case scenario, where inputs were initially hard-coded and fixed. This change allowed for flexibility and adaptability in experimenting with different combinations of input factors in Process Analyzer. The outputs (response) were based on the average of averages after the 240 runs, as highlighted in Section 3.4.1.4.



	Scenario Properties				Controls		Responses			
	S	Name	Program File	Reps	varNoBatt	Charger	Truck.Utilization	Charger.Utilization	Request Truck.Queue.WaitingTime	Charging.Queue.WaitingTime
1		1	1 : MyModel_1128v2_Sc1.p	240	2	1	1.000	0.005	5.547	0.000
2		2	3 : MyModel_1128v2_Sc2.p	240	2	1	0.230	0.008	0.000	0.183
3		3	3 : MyModel_1128v2_Sc2.p	240	3	1	0.536	0.010	2.394	0.151
4		4	3 : MyModel_1128v2_Sc2.p	240	4	1	1.000	0.011	4.758	0.200
5		5	3 : MyModel_1128v2_Sc2.p	240	2	2	0.335	0.004	0.000	0.000
6		6	3 : MyModel_1128v2_Sc2.p	240	3	2	0.542	0.005	2.515	0.000
7		7	3 : MyModel_1128v2_Sc2.p	240	4	2	1.000	0.005	4.878	0.000
8		8	3 : MyModel_1128v2_Sc2.p	240	2	3	0.335	0.003	0.000	0.000
9		9	3 : MyModel_1128v2_Sc2.p	240	3	3	0.542	0.003	2.515	0.000
10		10	3 : MyModel_1128v2_Sc2.p	240	4	3	1.000	0.004	4.878	0.000
11		11	3 : MyModel_1128v2_Sc3.p	240	2	1	0.154	0.008	0.000	0.183
12		12	3 : MyModel_1128v2_Sc3.p	240	3	1	0.184	0.012	0.000	0.411
13		13	3 : MyModel_1128v2_Sc3.p	240	4	1	0.413	0.014	1.454	0.354
14		14	3 : MyModel_1128v2_Sc3.p	240	5	1	0.683	0.016	2.884	0.469
15		15	3 : MyModel_1128v2_Sc3.p	240	6	1	1.000	0.016	4.402	0.516
16		16	3 : MyModel_1128v2_Sc3.p	240	2	2	0.223	0.004	0.000	0.000
17		17	3 : MyModel_1128v2_Sc3.p	240	3	2	0.263	0.006	0.000	0.060
18		18	3 : MyModel_1128v2_Sc3.p	240	4	2	0.432	0.007	1.573	0.046
19		19	3 : MyModel_1128v2_Sc3.p	240	5	2	0.682	0.008	3.163	0.048
20		20	3 : MyModel_1128v2_Sc3.p	240	6	2	1.000	0.008	4.691	0.061
21		21	3 : MyModel_1128v2_Sc3.p	240	2	3	0.223	0.003	0.000	0.000
22		22	3 : MyModel_1128v2_Sc3.p	240	3	3	0.291	0.004	0.000	0.000
23		23	3 : MyModel_1128v2_Sc3.p	240	4	3	0.432	0.005	1.585	0.000
24		24	3 : MyModel_1128v2_Sc3.p	240	5	3	0.682	0.005	3.184	0.000
25		25	3 : MyModel_1128v2_Sc3.p	240	6	3	1.000	0.005	4.723	0.000
26		26	3 : MyModel_1128v2_Sc4.p	240	2	1	0.115	0.008	0.000	0.183
27		27	3 : MyModel_1128v2_Sc4.p	240	3	1	0.138	0.012	0.000	0.411
28		28	3 : MyModel_1128v2_Sc4.p	240	4	1	0.168	0.015	0.000	0.639
29		29	3 : MyModel_1128v2_Sc4.p	240	5	1	0.326	0.018	0.974	0.559
30		30	3 : MyModel_1128v2_Sc4.p	240	6	1	0.543	0.020	1.945	0.713
31		31	3 : MyModel_1128v2_Sc4.p	240	7	1	0.760	0.021	2.944	0.867
32		32	3 : MyModel_1128v2_Sc4.p	240	8	1	1.000	0.021	4.080	0.906
33		33	3 : MyModel_1128v2_Sc4.p	240	2	2	0.167	0.004	0.000	0.000
34		34	3 : MyModel_1128v2_Sc4.p	240	3	2	0.198	0.006	0.000	0.060
35		35	3 : MyModel_1128v2_Sc4.p	240	4	2	0.274	0.008	0.000	0.122
36		36	3 : MyModel_1128v2_Sc4.p	240	5	2	0.374	0.009	1.133	0.098
37		37	3 : MyModel_1128v2_Sc4.p	240	6	2	0.529	0.010	2.221	0.106
38		38	3 : MyModel_1128v2_Sc4.p	240	7	2	0.762	0.010	3.414	0.131
39		39	3 : MyModel_1128v2_Sc4.p	240	8	2	1.000	0.010	4.561	0.139
40		40	3 : MyModel_1128v2_Sc4.p	240	2	3	0.167	0.003	0.000	0.000
41		41	3 : MyModel_1128v2_Sc4.p	240	3	3	0.219	0.004	0.000	0.000
42		42	3 : MyModel_1128v2_Sc4.p	240	4	3	0.325	0.006	0.000	0.020
43		43	3 : MyModel_1128v2_Sc4.p	240	5	3	0.388	0.006	1.148	0.016
44		44	3 : MyModel_1128v2_Sc4.p	240	6	3	0.528	0.007	2.289	0.016
45		45	3 : MyModel_1128v2_Sc4.p	240	7	3	0.761	0.007	3.486	0.018
46		46	3 : MyModel_1128v2_Sc4.p	240	8	3	1.000	0.007	4.630	0.025
47		47	3 : MyModel_1128v2_Sc4.p	240	2	4	0.167	0.002	0.000	0.000
48		48	3 : MyModel_1128v2_Sc4.p	240	3	4	0.219	0.003	0.000	0.000
49		49	3 : MyModel_1128v2_Sc4.p	240	4	4	0.316	0.004	0.000	0.000
50		50	3 : MyModel_1128v2_Sc4.p	240	5	4	0.365	0.005	1.167	0.000
51		51	3 : MyModel_1128v2_Sc4.p	240	6	4	0.531	0.005	2.286	0.000
52		52	3 : MyModel_1128v2_Sc4.p	240	7	4	0.763	0.005	3.500	0.000
53		53	3 : MyModel_1128v2_Sc4.p	240	8	4	1.000	0.005	4.647	0.000

Figure 4.1. Interface of Arena’s Process Analyzer

Table 4.3 Average of averages of the simulation experiments

	Controls			Responses			
Scen-ario	No. of Trucks	No. of Batteries	No. of Chargers	Truck Availability (%)	Charger Utilization (%)	Charged battery waiting time (hrs)	Charging Queue (hrs)
1	1	2	1	100	0.5	5.547	0
2	2	2	1	23	0.8	0	0.183
3	2	3	1	53.6	1	2.394	0.151
4	2	4	1	100	1.1	4.758	0.2
5	2	2	2	33.5	0.4	0	0
6	2	3	2	54.2	0.5	2.515	0
7	2	4	2	100	0.5	4.878	0
8	2	2	3	33.5	0.3	0	0
9	2	3	3	54.2	0.3	2.515	0
10	2	4	3	100	0.4	4.878	0
11	3	2	1	15.4	0.8	0	0.183
12	3	3	1	18.4	1.2	0	0.411
13	3	4	1	41.3	1.4	1.454	0.354
14	3	5	1	68.3	1.6	2.884	0.469
15	3	6	1	100	1.6	4.402	0.516
16	3	2	2	22.3	0.4	0	0
17	3	3	2	26.3	0.6	0	0.06
18	3	4	2	43.2	0.7	1.573	0.046
19	3	5	2	68.2	0.8	3.163	0.048
20	3	6	2	100	0.8	4.691	0.061
21	3	2	3	22.3	0.3	0	0
22	3	3	3	29.1	0.4	0	0
23	3	4	3	43.2	0.5	1.585	0
24	3	5	3	68.2	0.5	3.184	0
25	3	6	3	100	0.5	4.723	0
26	4	2	1	11.5	0.8	0	0.183
27	4	3	1	13.8	1.2	0	0.411
28	4	4	1	16.8	1.5	0	0.639
29	4	5	1	32.6	1.8	0.974	0.559
30	4	6	1	54.3	2	1.945	0.713
31	4	7	1	76	2.1	2.944	0.867
32	4	8	1	100	2.1	4.08	0.906
33	4	2	2	16.7	0.4	0	0
34	4	3	2	19.8	0.6	0	0.06

Table 4.3 Average of averages of the simulation experiments (cont.)

35	4	4	2	27.4	0.8	0	0.122
36	4	5	2	37.4	0.9	1.133	0.098
37	4	6	2	52.9	1	2.221	0.106
38	4	7	2	76.2	1	3.414	0.131
39	4	8	2	100	1	4.561	0.139
40	4	2	3	16.7	0.3	0	0
41	4	3	3	21.9	0.4	0	0
42	4	4	3	32.5	0.6	0	0.02
43	4	5	3	38.8	0.6	1.148	0.016
44	4	6	3	52.8	0.7	2.289	0.016
45	4	7	3	76.1	0.7	3.486	0.018
46	4	8	3	100	0.7	4.63	0.025
47	4	2	4	16.7	0.2	0	0
48	4	3	4	21.9	0.3	0	0
49	4	4	4	31.6	0.4	0	0
50	4	5	4	36.5	0.5	1.167	0
51	4	6	4	53.1	0.5	2.286	0
52	4	7	4	76.3	0.5	3.5	0
53	4	8	4	100	0.5	4.647	0

4.3. EFFECT ON TRUCK AVAILABILITY: RESULTS AND DISCUSSION

The efficiency and productivity of mining operations heavily rely on the availability and effective utilization of trucks. This study delved into how the various combinations of the controls affected the BEV's availability and how it could be maximized for production operations. The designed experiments were examined to determine the BEV's availability. The results of these experiments are presented in Table 4.3.

Figure 4.2 shows the experimental results for the 53 combinations in Table 4.1. The results show a range of truck availability across different scenarios. This variability indicated that combining the control variables significantly impacts truck availability. As indicated in Figure 4.2, some scenarios resulted in trucks being available 100% of the time for work, while others were as low as 11%. These fluctuations could be due to delays at the charging bay and scheduling conflicts. Scenarios 1, 4, 7, 10, 15, 20, 25, 32, 39, 46 and 53 had the highest truck availability. Moreover, Scenario 26 had the least truck availability since four trucks used two batteries and a single charging unit.

High truck availability scenarios suggest an optimal balance of resources, leading to enhanced productivity and reduced downtime. However, low truck availability scenarios imply potential bottlenecks, such as trucks competing for resources like batteries and chargers, which leads to queues and reduced productivity. These insights are pivotal for mining operations, guiding strategic decisions in resource allocation, infrastructure investment, and scheduling optimizations. Moreover, they align with the broader objectives of maximizing efficiency, reducing operational costs, and adhering to sustainable mining practices.

The correlation matrix illustrated in Figure 4.3 shows a weak negative correlation between truck increment in the model and truck availability. This suggests that increasing the number of trucks decreases truck availability for work and vice versa. This results from trucks competing for limited resources, leading to longer waiting times and, hence, reduced availability and utilization in the long run. Understanding and addressing the underlying reasons for this weak correlation is crucial for optimizing truck availability and mining operations in general. It is, therefore, vital to consider other factors like resource allocation, scheduling, and infrastructure capacity to improve truck availability in this sense to boost the overall mine's productivity.

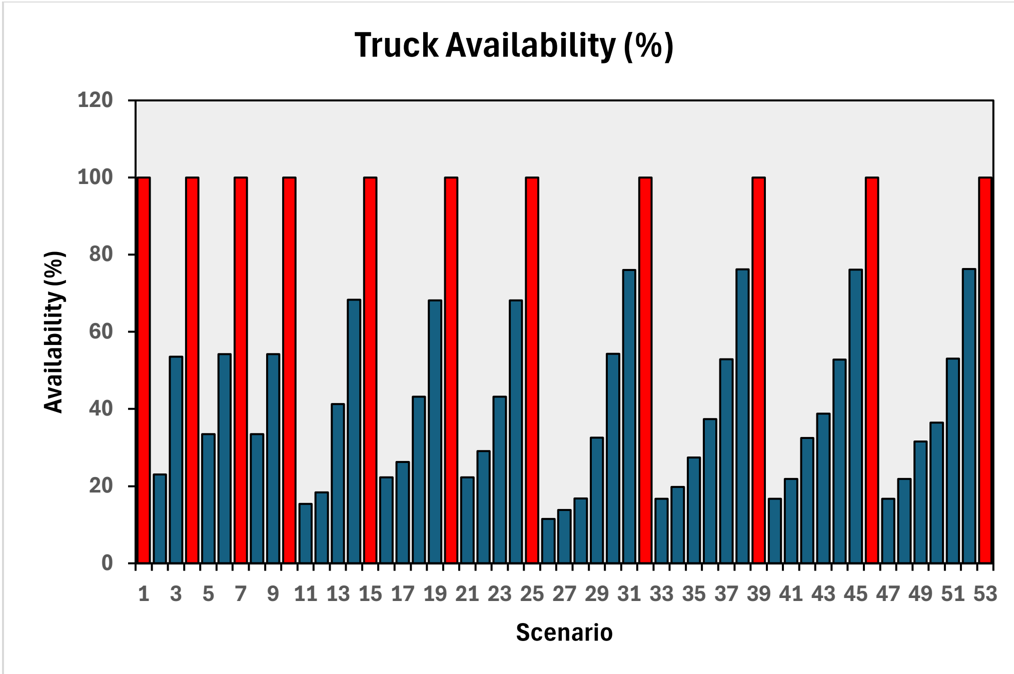


Figure 4.2. Truck availability of the experiments

Moreover, as illustrated in Figure 4.3, the results show a strong positive correlation between the number of batteries and truck availability, suggesting that introducing more batteries in the model significantly enhances truck availability. This highlights the contribution of adequate battery availability and management to BEV availability. The number of chargers shows no correlation to truck availability, suggesting that the number of chargers doesn't have a straightforward impact on truck availability.

The strong positive correlation between the number of batteries and truck availability, as shown in 4.3, emphasizes battery availability's critical role in maintaining high truck availability. The findings indicate that increasing the number of batteries in the model significantly improves the availability of trucks for work. This strong correlation with the number of batteries underscores their importance in maintaining high truck availability. Efficient battery management contributes a critical factor in achieving this optimality. This includes the availability of batteries and how they are managed- such as through effective charging strategies and battery swapping systems. These management practices will ensure that batteries are always available when needed, minimizing truck downtime.

Additionally, even though the number of chargers did not have a strong relationship with truck availability, the impact of the charging duration on truck availability contributes to the higher availability of batteries in the model. It suggests that the time it takes to charge batteries is a crucial factor influencing the effectiveness of the chargers. Shorter charging durations can significantly enhance truck availability, as trucks spend less time idle at charging stations. This finding points to the importance of investing in fast charging technology or optimizing charging schedules to reduce charging times, which would positively impact truck availability and the overall mining operation.

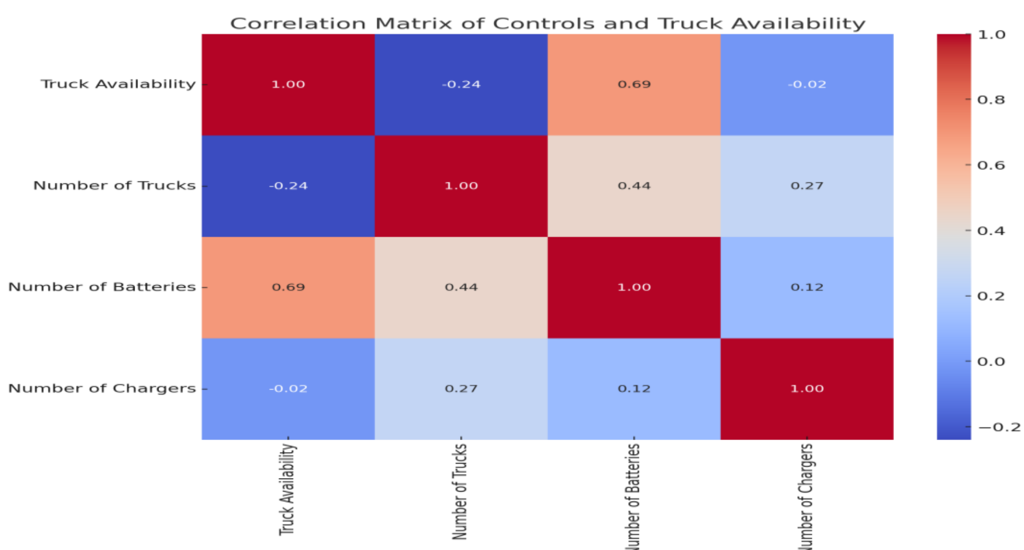


Figure 4.3. Correlation matrix of the factors and truck availability

4.4. EFFECT ON CHARGER UTILIZATION: RESULTS AND DISCUSSION

Ensuring adequate utilization of the charging unit for mining operations is critical. This will minimize downtime and charging queues and maximize operational efficiencies. This study assessed how the various combinations contribute to the charger's utilization. The multiple experiments conducted, and their respective charger utilizations are shown in Figure 4.4.

The results showed that the charger utilization changes across the various scenarios, significantly affected by the factors outlined in Section 4.2. From Figure 4.4, the highest and lowest charger utilization was around 2% and 0.2%, respectively, showing a very low utilization rate of the charging unit. This extremely low utilization of the charging units implies that the charger has the potential to handle more batteries, provided it won't lead to queuing in the system.

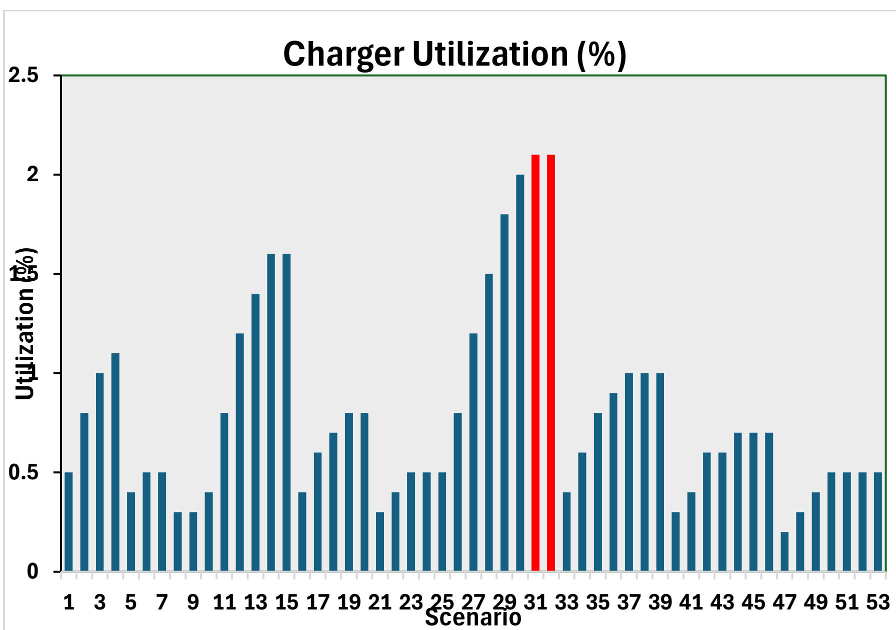


Figure 4.4. Charger Utilization across scenarios

Scenarios 31 and 32 made the best use of the charging unit, recording the highest charging utilization. These scenarios recorded the highest utilization due to the higher number of batteries in the experiments. This means that having a more significant number of batteries relative to charging units leads to more efficient use of the charging infrastructure. If the ultimate goal of the mine is to increase the utilization of the charging infrastructure, then it should consider increasing the number of batteries.

On the other hand, scenario 47, which recorded the lowest charger utilization, presents a contrasting situation. The experiment involved four charging units but only two batteries in this scenario. This disproportion between the number of chargers and batteries resulted in the extreme underutilization of the charging unit. With fewer batteries to charge, the chargers were left idle for more extended periods, indicating an imbalance in the resource allocation within this scenario.

Figure 4.5 shows a weak positive correlation between the number of trucks. This correlation suggests that an increase in the number of trucks is slightly associated with higher charger utilization. This is due to more frequent charging needs as the number of batteries increases.

This finding is essential for planning and optimizing resource allocation in an underground mining operation. It suggests that adding more trucks only marginally improves the charger's utilization. Thus, a balanced approach considering the number of trucks, batteries, and chargers, along with efficient scheduling and management strategies, is necessary to optimize the use of the charging infrastructure and enhance operational efficiency.

However, a moderate positive correlation exists between the number of batteries and the charger's utilization. This indicates a significant relationship where increasing the number of batteries leads to higher utilization of chargers. This is logical, as more batteries in such a system would naturally require more frequent charging, increasing the demand for charging units. The moderate strength of this correlation suggests that while the number of batteries is an essential factor worth considering in such a system, it is not the sole determinant of charger utilization. Factors such as the charging duration, battery capacity, and operational scheduling might also influence this relationship.

Conversely, there exists a strong negative correlation between the number of chargers and their utilization, according to Figure 4.5. This implies that as we add more chargers to the system, the utilization of each charger decreases significantly. It is therefore critical for the mining operation to consider a reasonable number of chargers to ensure optimal charging infrastructure utilization.

These correlations are essential for optimizing resource allocation and infrastructure planning in underground mining operations. They suggest that simply increasing the number of batteries or chargers is not a straightforward solution to improving operational efficiency. A more nuanced approach is essential, considering the balance between the number of trucks, batteries, and chargers, along with efficient scheduling.

4.5. EFFECT ON CHARGED BATTERY WAITING TIME: RESULTS AND DISCUSSIONS

The optimal utilization of charged batteries is achieved when they are utilized as soon as possible after being fully charged. This practice ensures the stored energy is used.

productively, minimizing the time batteries remain idle post-charging. Monitoring this output is crucial as it is a key indicator of effective energy management and operational efficiency within the system. This focus on prompt battery utilization underscores the importance of streamlining energy usage and workflow processes. As a result, the author assessed this metric for all the scenarios in Table 4.1.

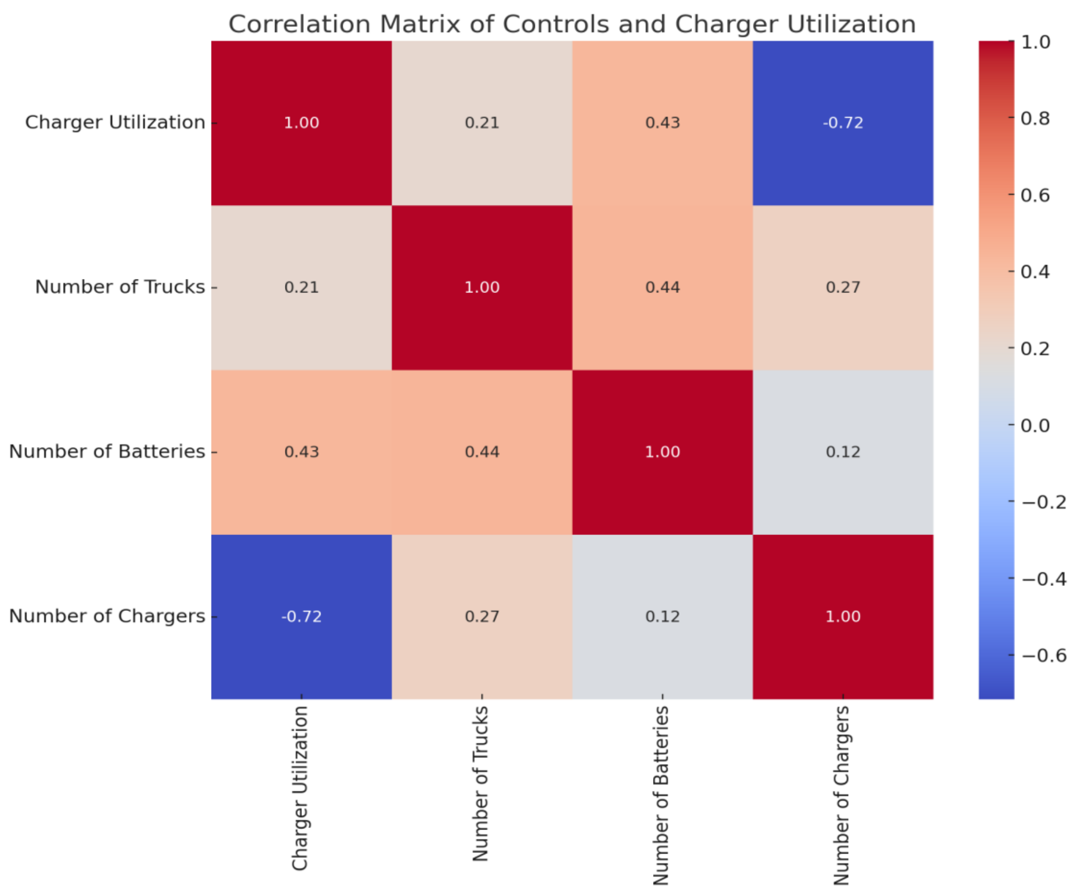


Figure 4.5. Correlation matrix of the factors and charger availability

As illustrated in Figure 4.6, there is a noticeable variability in battery waiting times across different scenarios. This implies that the various configurations of trucks, batteries, and chargers significantly impact battery waiting times post-charging. For instance, in scenario 1, batteries experienced over 5 hours of waiting time post-charging, suggesting low utilization. This is regarded as an inefficiency since batteries that remain idle post-charging could have been used to keep trucks operational, thereby enhancing the overall throughput of the mining operation.

There is an opportunity for the mine to consider increasing the number of trucks in such cases to ensure that batteries are deployed within the shortest possible time after charging. Addressing this inefficiency would require a more balanced and strategic approach to matching the number of trucks with the appropriate number of batteries, considering the operational demands and charging infrastructure. Optimizing this balance is crucial to reducing battery waiting times, ensuring that batteries are used effectively and contribute positively to the operational efficiency of the mining system.

Conversely, scenarios such as 2 and 5 recorded zero hours of waiting times, indicating more efficient usage where charged batteries were promptly deployed. These scenarios suggest an optimal alignment between the number of trucks, batteries, and the charging infrastructure. In such cases, the operational flow is seamless, with minimal downtime for trucks waiting for batteries. This efficient usage not only maximizes the productivity of the mining operation but also ensures that the energy storage resources (batteries) are utilized to their fullest potential, contributing to overall energy management efficiency. This contrast underscores the significance of aligning resource availability with operational demands to optimize energy management and workflow.

This contrast in different scenarios reveals the significance of strategic planning in resource allocation and scheduling within underground mining operations. It emphasizes the need for a holistic approach to managing trucks, batteries, and chargers, considering the quantity of each resource and how they interact and are synchronized to support continuous and efficient operation. By fine-tuning these elements, a mining operation can achieve optimized energy management and improved workflow, leading to enhanced productivity and reduced operational costs.

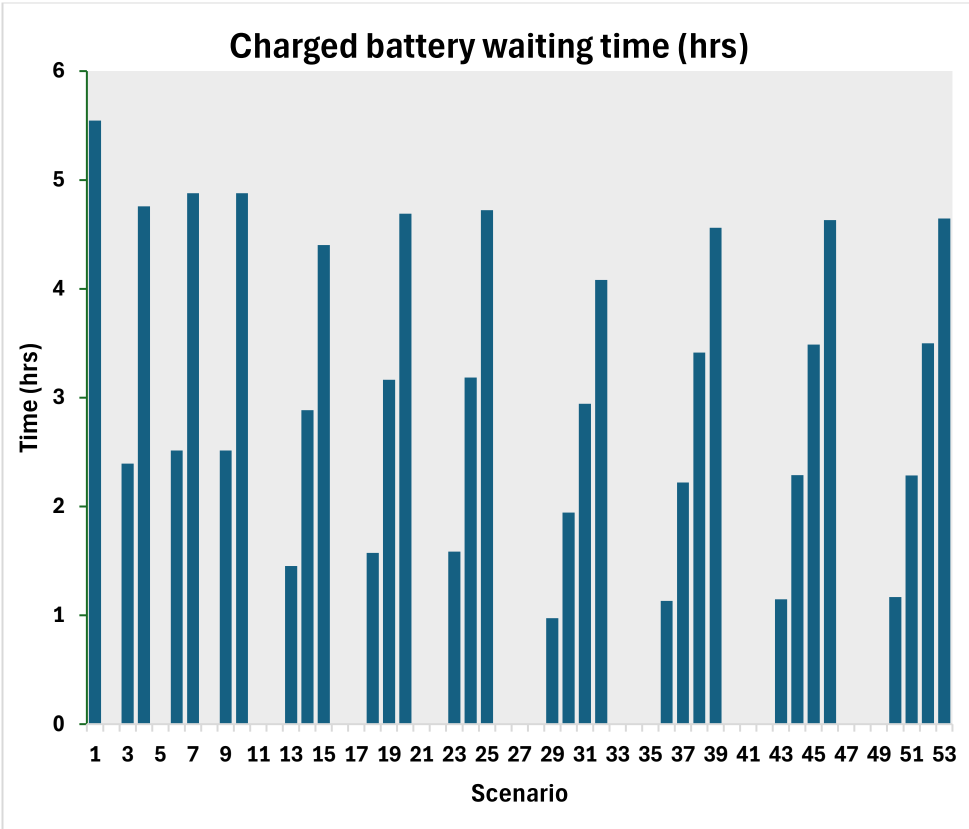


Figure 4.6. Charged battery waiting time across scenarios

The results in Figure 4.7 depict a weak negative correlation between the number of trucks and battery waiting time post-charging. This indicates that an increased number of trucks slightly reduces the waiting time for charged batteries. Essentially, more trucks in the system lead to more efficient and quicker deployment of charged batteries. The weak nature of the correlation also suggests that the number of trucks is just one of several factors influencing battery waiting times. Therefore, to ensure that battery waiting times are minimal, it is important to investigate other factors such as the efficiency of the charging system and the number of batteries in the system.

A strong positive correlation exists between this metric and the number of batteries, as shown in Figure 4.7. This indicates that more batteries in the system result in longer waiting times for charged batteries. This shows that as the number of batteries increases in the model, managing them becomes more challenging due to the rate at which the batteries charge, leading to longer waiting times for the batteries. As a result, it depicts that there is an imbalance system since the number of batteries exceeds the operational demand or capacity of the trucks. In such scenarios, even though batteries are available and charged, they may have to wait longer due to a lack of trucks ready to receive them. As such, if the charging infrastructure or the scheduling system is not scaled or optimized in tandem with the increase in battery numbers, it leads to bottlenecks where batteries, despite being charged, await deployment.

It is critical to address these challenges, which require an increase in the number of batteries and a strategic approach to enhance the overall management of these resources. This may include optimizing charging schedules, improving the efficiency of battery swapping, and ensuring that the growth in battery numbers is proportionate to the operational capacity and demand of the mining trucks. By effectively aligning these factors, the mining operation can achieve a balanced system where the battery increase contributes positively to operational efficiency rather than creating additional waiting time and potential inefficiencies.

The number of chargers show a very weak correlation, suggesting that the number of chargers minimally impacts the waiting time for the charged batteries. This indicates that the critical factor to this metric is the charging duration, not the number of chargers, due to the fast rate at which batteries are charged. This means that the existing charging infrastructure is already sufficient to handle the charging needs of the batteries efficiently or that the operational bottleneck lies elsewhere in the system.

In practical terms, this finding indicates that efforts to reduce battery waiting times in such a mining operation would be better focused on optimizing other aspects of the system rather than merely increasing the number of chargers. This could include enhancing the efficiency of battery swapping procedures, improving scheduling and coordination for battery usage, or even further exploring ways to reduce charging times. Understanding and addressing these factors can lead to a more streamlined operation where the waiting time for batteries is minimized, thereby enhancing the overall productivity and efficiency of the mining operation.

These insights from the results point to the importance of effective battery management, especially in scenarios with many batteries. Optimizing battery charging schedules, turnaround times, and swap strategies could be more effective.

4.6. EFFECT ON CHARGING QUEUE: RESULTS AND DISCUSSIONS

Effective charging queue management directly influences the operational efficiency of BEVs in material handling within the mining environment. It determines the readiness of trucks, thereby affecting productivity, energy utilization, and operational scheduling. When queues within such a system are poorly managed, they lead to extended downtimes, decreased equipment utilization, and potential bottlenecks in the material handling process. Thus, this project evaluated this critical metric to determine what the optimal scenario will look like.

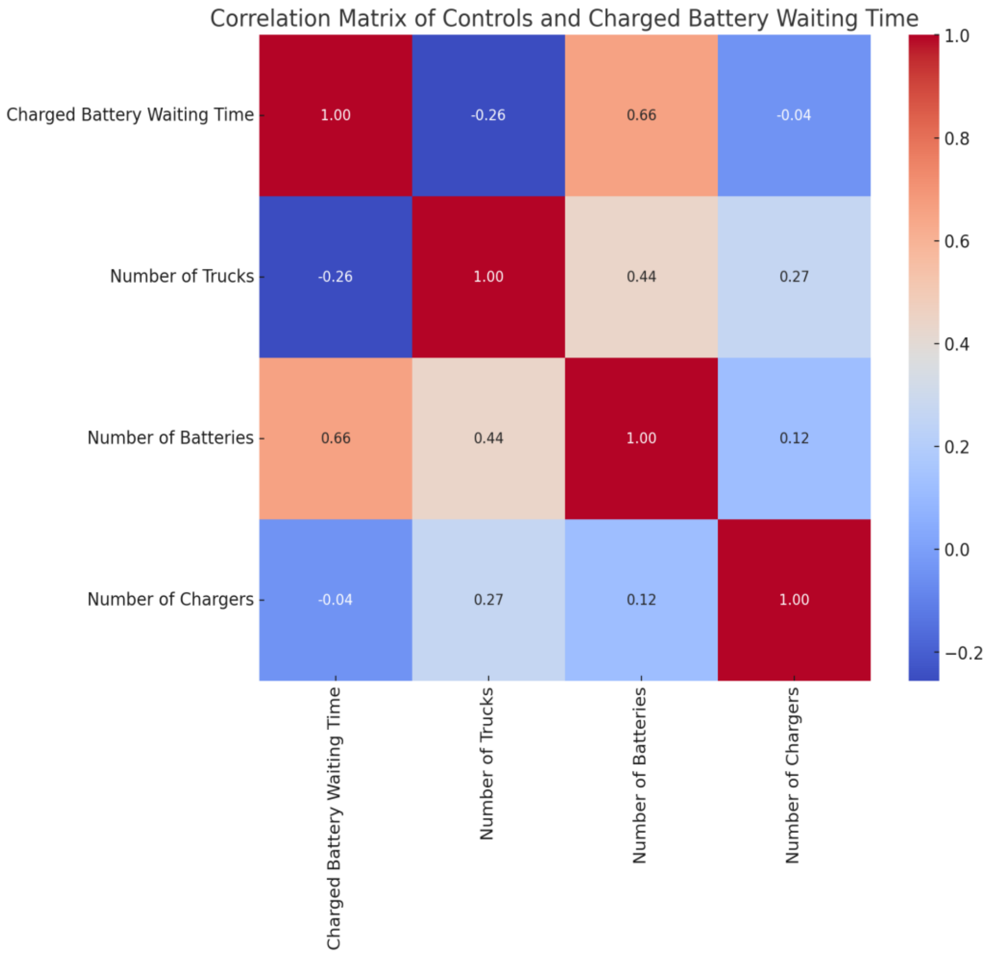


Figure 4.7. Correlation matrix of the factors and charged battery waiting time

Figure 4.8 shows a noticeable variation in charging queue times across the scenarios, indicating that the configuration of trucks, batteries, and chargers substantially impacts queuing. Scenario 32 was seen to generate the highest frequency of queues at the charging bay. From Table 4.1, this scenario had four trucks, eight batteries, and a single charger, which means the charger is highly correlated to this performance metric. There were quite a few scenarios that resulted in no queues. For instance, scenarios 5-7 had zero queue frequency. In these scenarios, enough chargers were available to recharge the batteries whenever they reached the bay.

These observations highlight the critical role of charger availability in managing charging queues and overall operational efficiency in mining operations. Ensuring a proper balance between the number of trucks, batteries and chargers is key to minimizing queuing times and maximizing the productivity of the mining operation.

The heat map in Figure 4.9 shows that an increase in the number of trucks is associated with longer charging queues. This implies that more trucks lead to increased demand for charging, resulting in longer queues. A moderate positive correlation exists between the number of batteries and the frequency of the charging queue. The correlation suggests that having more batteries in the system can lead to longer charging queues. The frequency of charging sessions due to the battery increment is the reason for this correlation.

A strong negative correlation exists between the number of chargers and the charging queue’s frequency, as shown in Figure 4.9. The relationship indicates that an increase in the number of chargers significantly reduces the length of the charging queue. This effectively will reduce the bottlenecks at the charging bay, leading to a smoother and more efficient charging process. It suggests that even though the charger’s utilization is low across all the scenarios, investing in additional chargers can significantly enhance operational efficiency, particularly where the number of trucks and batteries creates a high demand for charging. The costs and physical space are constraints worth considering in that regard.

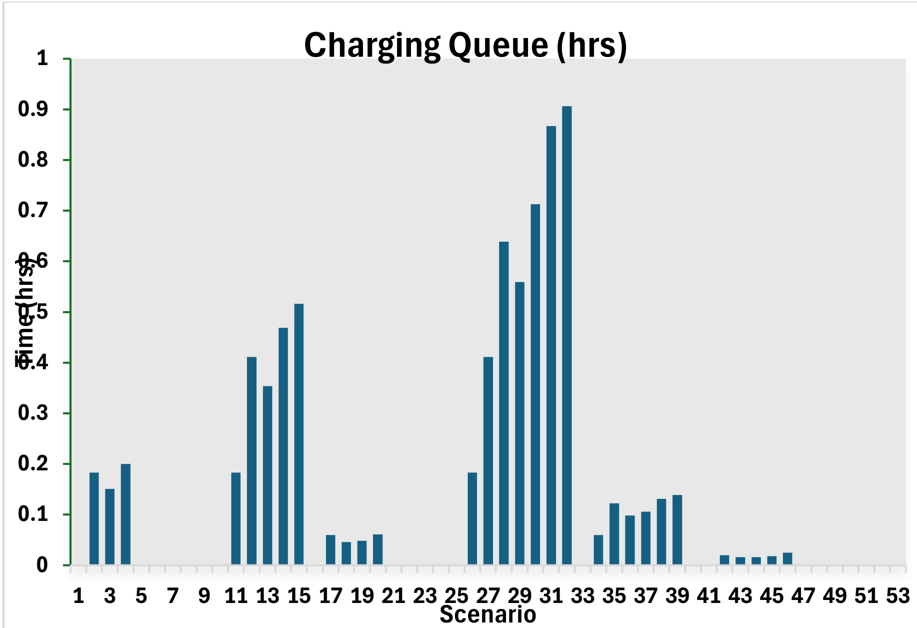


Figure 4.8. Frequency of charging queues across scenarios

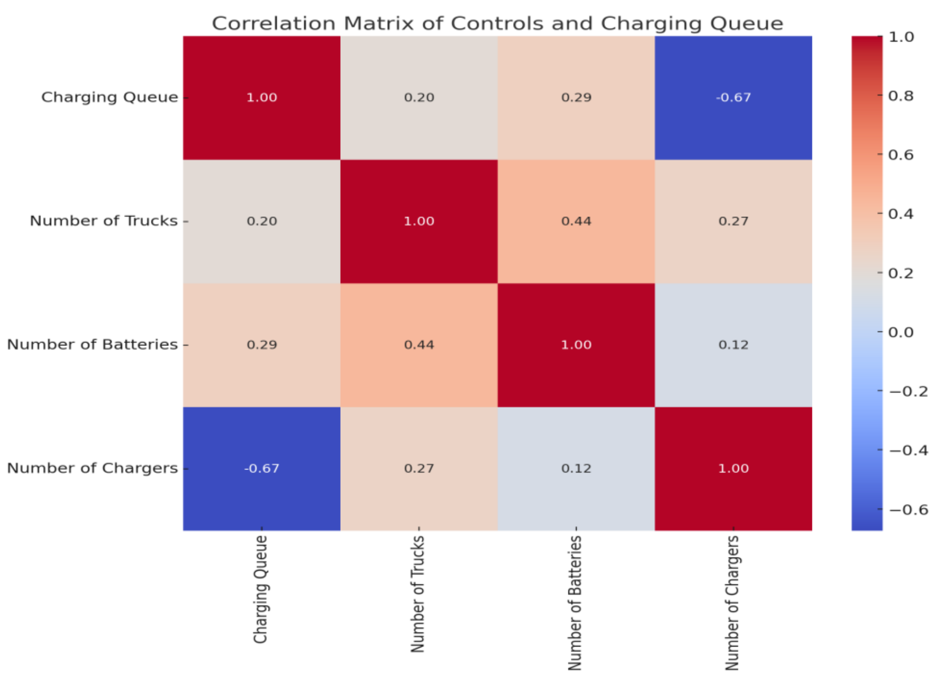


Figure 4.9. Correlation matrix of the factors and charging queue

4.7. SELECTING THE OPTIMAL AND CRITICAL CONFIGURATIONS

4.7.1. Optimal Configuration. A crucial aspect of this project was determining the optimal scenario: maximizing the use of factors such as the charging unit, trucks, and batteries. The analysis focused on this aspect, exploring various configurations of these factors to identify the most effective setup. All 53 scenarios were critically evaluated based on the performance metrics. The optimal scenario is selected based on the combination that offers the best balance regarding truck availability, charger utilization, battery waiting time post-charging, and charging queue time.

The objective was to select the scenario with 100% truck availability, ideally close to 100% charger utilization, lower charging queues, and the least charged battery waiting times.

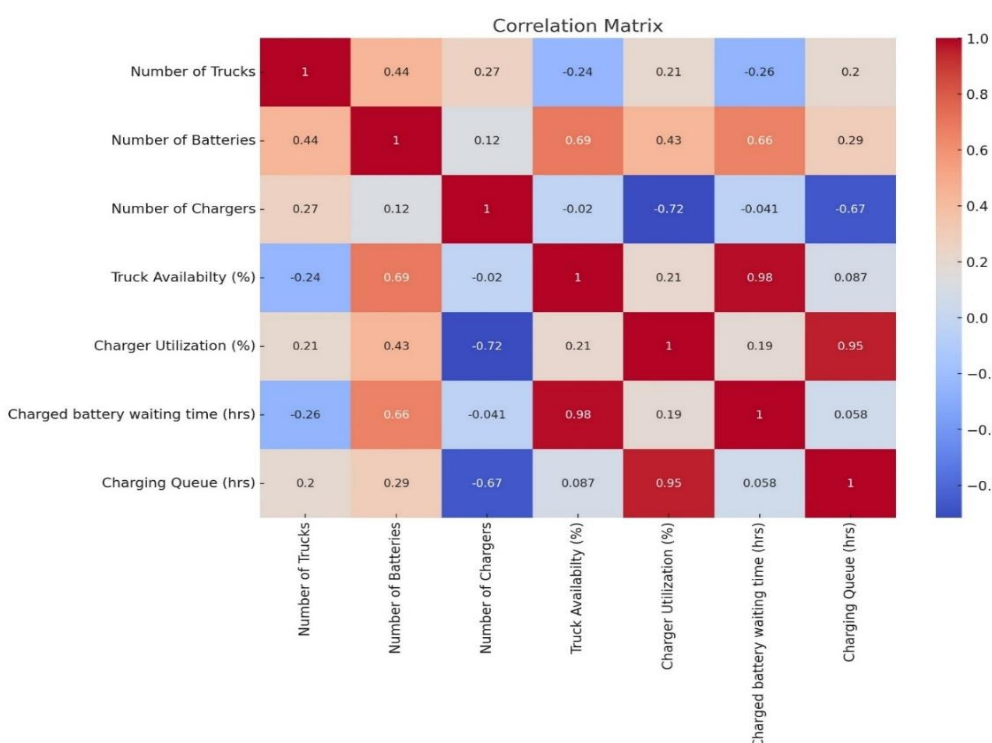


Figure 4.10. Correlation matrix of the factors and performance metrics

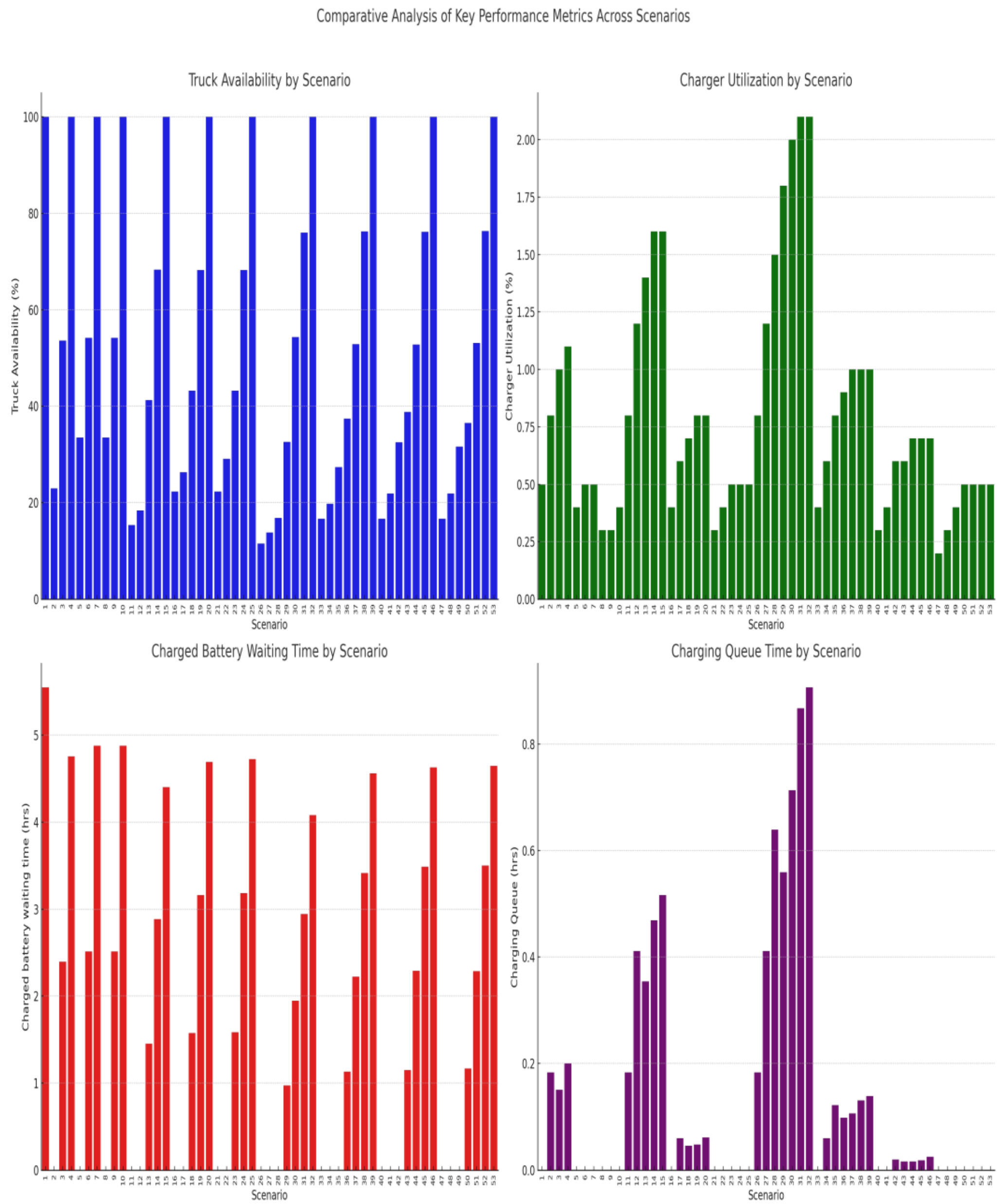


Figure 4.11. Comparative analysis of the performance metrics

Figures 4.10 and 4.11 showed that considering all four metrics makes selecting a single scenario as optimal difficult. Therefore, we prioritized truck availability and charging queues. These metrics were believed to be the key contributors to production. Based on the prioritized criteria, several scenarios emerged as optimal. Table 4.4 presents a list of the possible scenarios that were considered optimal. It can be observed that all scenarios had trucks available 100% of the time and zero charging queue hours.

Finally, scenario 53 was selected as the most optimal since it had the lowest battery waiting post-charging rate at a high charger utilization rate.

Table 4.4 Optimal scenarios

Scenario	**Number of Trucks**	**Number of Batteries**	**Number of Chargers**	**Truck Availability (%)**	**Charger Utilization (%)**	**Charged Battery Waiting Time (hrs)**	**Charging Queue (hrs)**
1	1	2	1	100	0.5	5.547	0
7	2	4	2	100	0.5	4.878	0
10	2	4	3	100	0.4	4.878	0
25	3	6	3	100	0.5	4.723	0
53	**4**	**8**	**4**	**100**	**0.5**	**4.647**	**0**

4.7.2. Critical Configurations. The essence of this investigation is rooted in the hypothesis that a strategy in resource allocation can significantly enhance fleet operations, reducing downtimes and ensuring a higher rate of truck availability. We contend that additional resources may not benefit these performance metrics proportionally beyond a certain threshold, potentially leading to diminishing returns. The research further study is pioneering in its approach, offering a comprehensive analysis that could guide fleet managers in making informed decisions, thus fostering more sustainable and efficient logistics operations.

At this stage, our analysis was segmented based on the number of trucks within the fleet, considering scenarios with 2,3 and 4 trucks to reflect a range of operational scales from small to moderately large fleets. By employing heatmaps, we provide a visual and analytical representation of how varying the number of batteries and chargers influences the aforementioned performance metrics. This methodical examination not only identifies the optimal configurations for different fleet sizes but also highlights the point at which the addition of more batteries or chargers ceases to yield significant improvements, marking a critical juncture in resource allocation strategy.

4.7.2.1. Results and discussion: truck availability. Truck availability remains relatively high across various configurations, suggesting that with 2 trucks, the system is less prone to bottlenecks caused by insufficient batteries or chargers. However, the highest availability is observed with a moderate battery increase, indicating that having a surplus ensures trucks are seldom idle due to charging constraints. The heatmap in Figure 4.12 suggests that 2 trucks' availability diminishes when the number of batteries is reduced to 3 with a single charger. The optimal charger-to-battery ratio for 2 trucks appears to be 1 charger to 4 batteries.

When there are 3 or 4 trucks, the optimal threshold for truck availability changes, moving away from 100% when the battery count is less than double the number of trucks. However, adding extra chargers for the same number of batteries increases the truck's availability. While adding chargers also plays a role, the number of batteries consistently emerges as a critical factor in ensuring high truck availability across all scenarios.

4.7.2.2. Results and discussion: charger utilization. This metric reflects the balance between the availability of charging resources and their actual use, offering insights into how well the charging infrastructure supports the operational demands of the fleet. As the fleet size varies from 2 to 4 trucks, the study meticulously identifies the optimal number of chargers that can service the fleet without leading to underutilization or overextension. Figure 4.13 shows how adding batteries and chargers affects the charger's utilization. The dark blue regions in the heatmap show the peak utilization of the chargers.

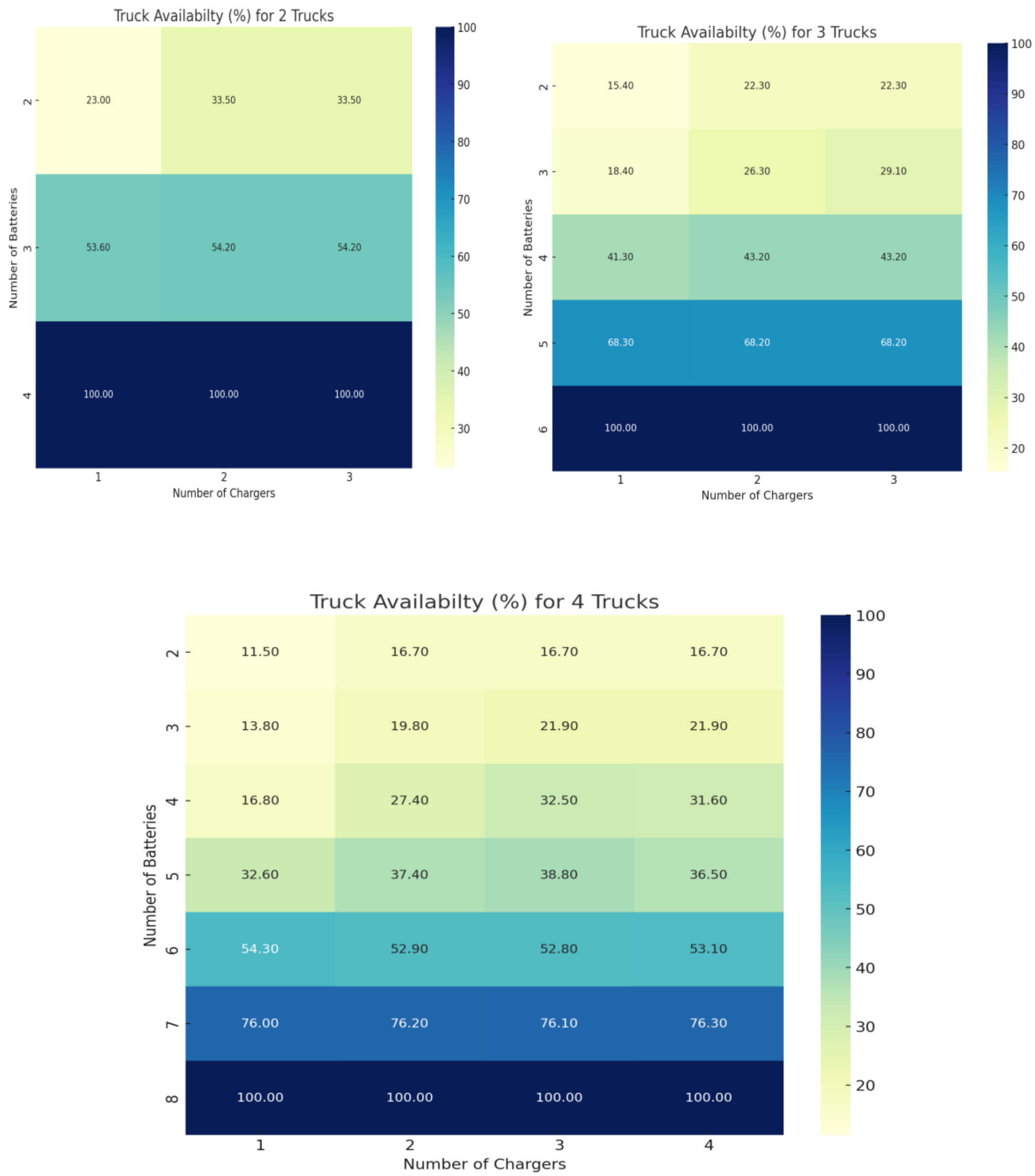


Figure 4.12. Critical effect of increasing the number of factors on truck availability

The results from the heatmap suggest that the charger's utilization is reduced when more chargers are introduced into the system. For 2 trucks, there appears to be high charger utilization when there are 4 batteries and a charger in the system. Reducing the number of batteries and incrementing the number of chargers tends to reduce the chargers' utilization. On the other hand, for 3 trucks, 6 or 5 batteries result in the exact charger utilization but reduce when there are 4 batteries in the system. These results remain the same considering 4 trucks.

4.7.2.3. Results and discussion: charged battery waiting time. This analysis sheds light on how variations in the number of batteries and chargers relative to the fleet size influence the downtime of the trucks and underutilization of the batteries. Ideally, batteries should not remain idle in the charging bay after charging. Therefore, we examined the configurations beyond which introducing more factors (batteries and chargers) increased or decreased battery waiting times post-charging. Figure 4.14 shows a heatmap of the various trucks and their combinations, as highlighted in Section 4.2. For 2 trucks, as the number of chargers reduces for the same number of batteries, charged batteries spend less time at the charging bay. The charged battery waiting times for 3 and 4 trucks are also reduced when the number of chargers is reduced for the same number of batteries.

4.7.2.4. Results and discussion: charging queue. The research also identified the crucial thresholds at which adding more batteries and chargers increased or decreased queues at the charging facility.

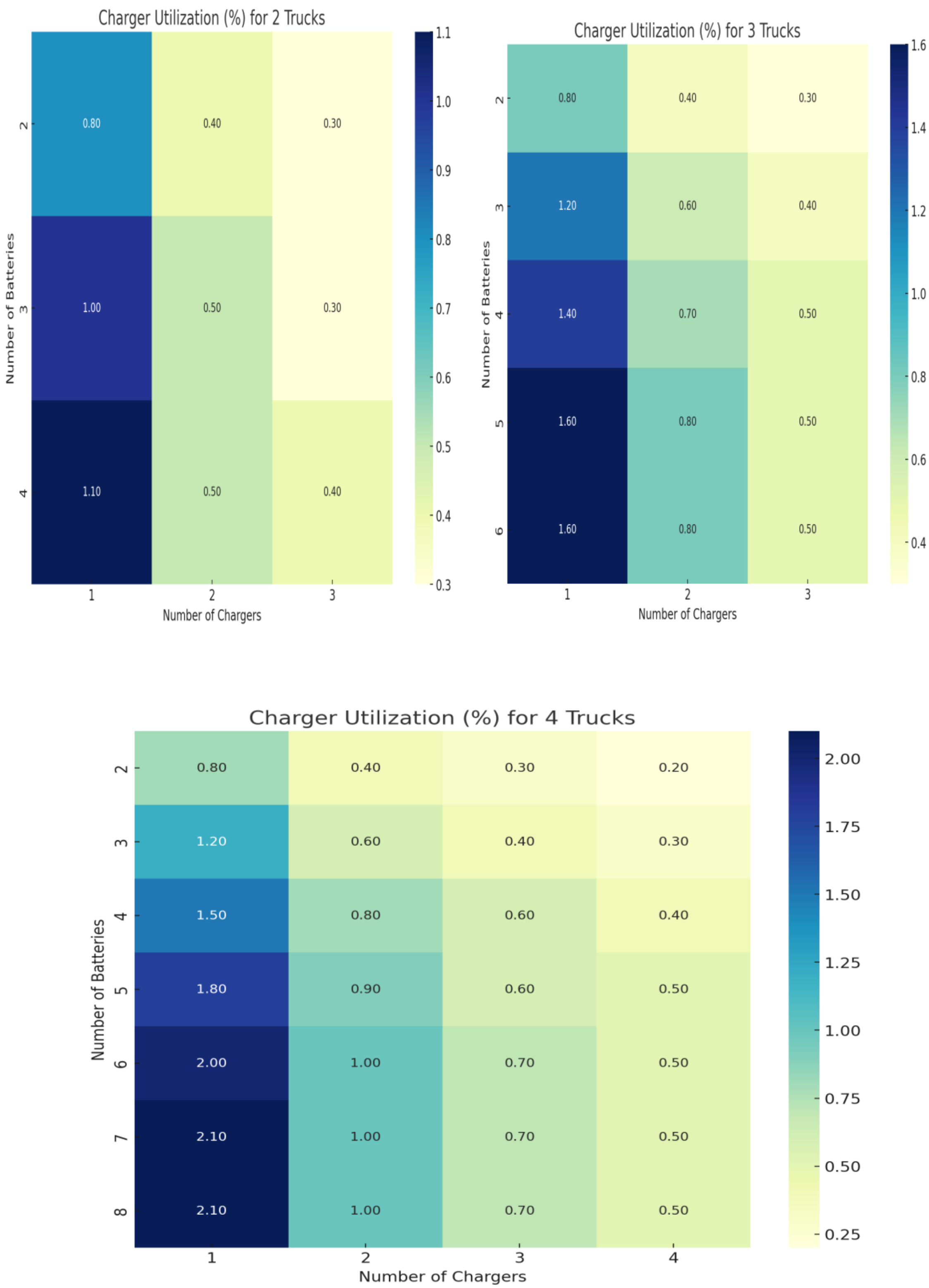


Figure 4.13. Critical effect of increasing the number of factors on charger utilization

This analysis is crucial in assessing how much time trucks wait to swap or charge batteries. A minimized charging queue directly translates to reduced vehicle downtime, ensuring that essential mining operations can proceed with minimal interruption.

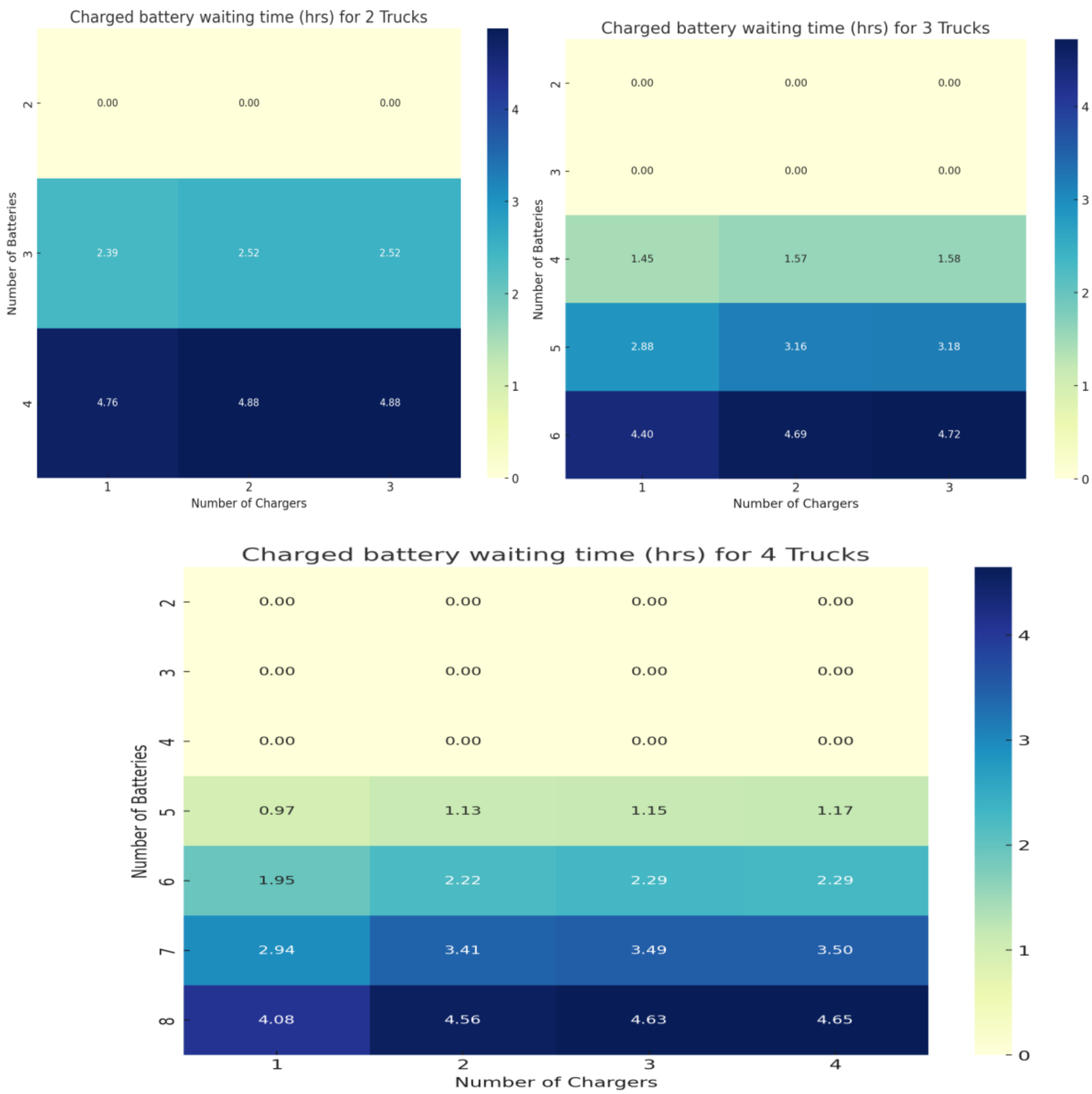


Figure 4.14. Critical effect of the increasing number of factors on charged battery waiting time

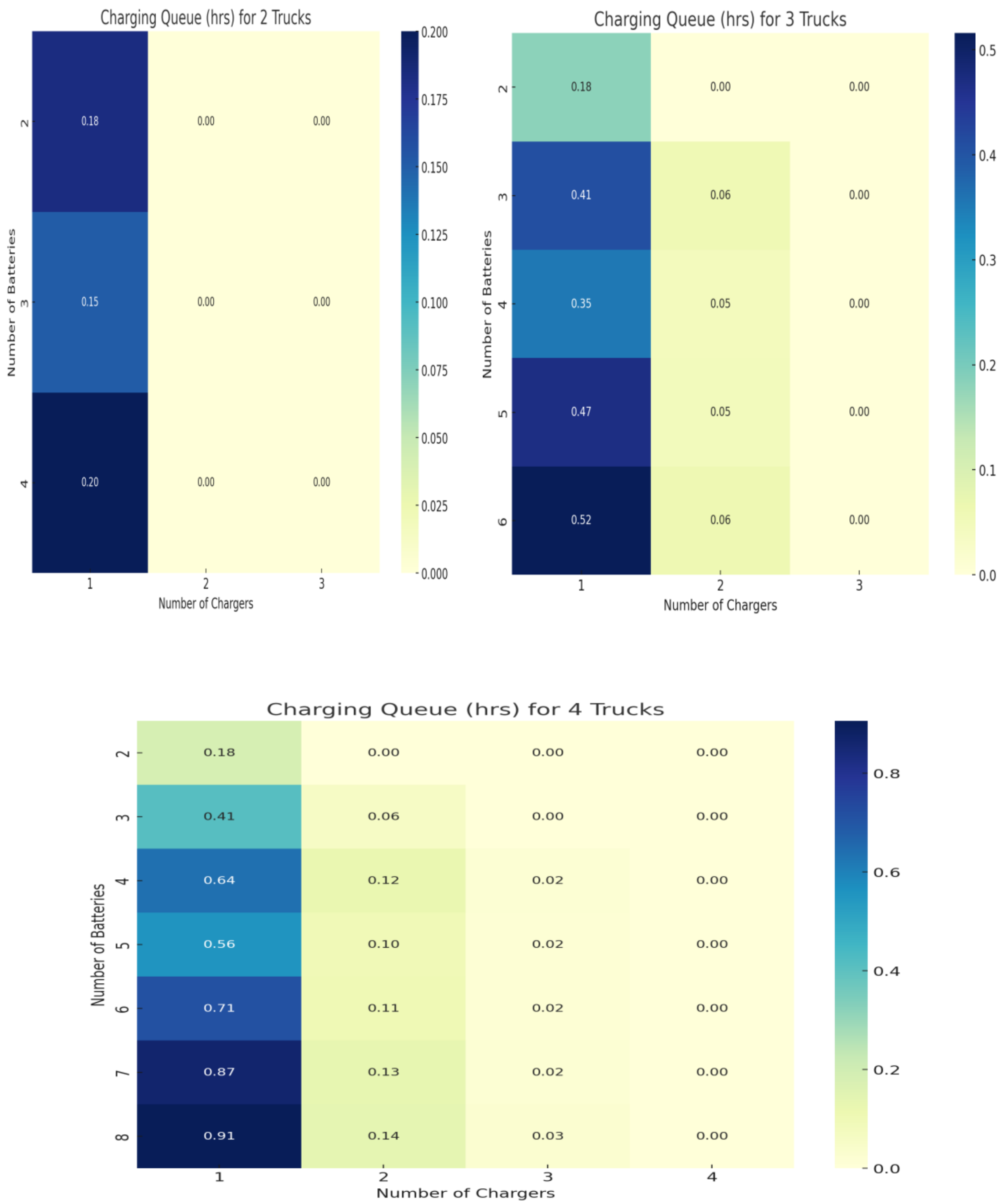


Figure 4.15. Critical effect of the increasing number of factors on charging queue

The results highlighted in Figure 4.15 show that, across all truck quantities, charging queue times improve as the number of batteries and chargers increases up to a specific threshold. For 2 trucks, this point is at 2 chargers, aligning with the optimal battery count of 4. However, for 3 and 4 trucks, the critical point moves slightly higher, suggesting that 3 chargers are sufficient to minimize queue times without leading to resource underutilization. The results highlighted in Figure 5.3 show that, across all truck quantities, charging queue times improve as the number of batteries and chargers increases up to a specific threshold. For 2 trucks, this point is at 2 chargers, aligning with the optimal battery count of 4. However, for 3 and 4 trucks, the critical point moves slightly higher, suggesting that 3 chargers are sufficient to minimize queue times without leading to resource underutilization.

These insights show that balancing the number of batteries and chargers can substantially decrease charging queue times, thus reducing vehicle downtime and enhancing fleet availability and efficiency.

4.8. SUMMARY

This thesis section presented experiments to evaluate the model performance to input parameters. In this Section, the author designed experiments using the full factorial approach. Certain experiments were rejected based on industrial recommendations on the maximum number of trucks, batteries, and chargers. Arena’s Process Analyzer tool was used to evaluate the experiments' configuration.

The findings of the experiments are highlighted below:

- The DES model can evaluate the performance of such a system. The critical metrics, such as truck availability, charger utilization, charging queue, and battery waiting times post-charging, were ascertained for all the scenarios.

- The DES model is sensitive to input variables such as the number of trucks, batteries, and chargers. As these factors change, the response variables change substantially.
- The optimal scenario was selected by prioritizing truck availability and charging queue metrics. Based on the configuration of the mine under study and the metrics prioritized, scenario 53 was selected as the optimal combination.
- The specific thresholds for which the model ceases to contribute significantly to operational efficiencies across the various metrics were highlighted.

5. CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

5.1. OVERVIEW

This project represents a rigorous study focused on enhancing the operational efficiency of battery electric vehicles (BEVs) in underground mining by optimizing their battery swapping and charging procedures. As such, we sought to bridge the gap between theoretical modeling and practical engineering solutions, employing a discrete event simulation (DES) approach to navigate the complexities of this mining operation.

The central objective was to design a multi-service bay system for BEVs that would effectively minimize truck wait times and queue lengths at the charging station without compromising truck availability and utilization. This goal resulted from a pressing need for more sustainable and efficient operation in loading and hauling material in the underground environment as BEVs are becoming prevalent in the industry.

To achieve this goal, a DES model was built to replicate the mining environment and the overall processes of the BEVs. The base case model utilized data provided by the manufacturer of the BEV, and the mine architecture was based on input from mining experts (anon, personal communication, December 3, 2023) and mining practice. This model allowed comprehensive mining experiments with analysis of the existing operational scenarios and experimentations with different trucks, batteries, and chargers configurations. This approach enabled the quantification of the impact of these variables on key operational metrics, such as charger utilization, truck availability, battery waiting times post-charging, and frequency of queues generated at the charging station. The model's adaptability to input variables was a significant advantage, allowing for real-time modifications and updates without necessitating a complete rebuild, making it highly applicable in practical mining scenarios.

In the experimentation phase, we applied the full factorial experimental design. This phase was critical in determining the most effective operational configuration, considering the interplay between the number of trucks, batteries, and chargers. The outcome was a refined understanding of the operational dynamics of BEVs in underground mining operations, surpassing simple analytic models to offer a multi-faceted view of the system's capabilities and limitations.

5.2. CONCLUSIONS

This research makes the following conclusions based on the analysis of the base case and the experimentations:

- With respect to the first and second objectives (building and verifying the DES model of BEVs battery swapping and charging procedures):
  - ✓ The DES model effectively showcased its capability in optimizing battery swapping and charging processes for BEVS, a critical component in underground mining operations. The model was successfully developed to accurately replicate the specific procedures involved in battery swapping and charging for BEVs, demonstrating the practical applicability potential of DES in enhancing operational efficiencies in this domain.
  - ✓ The base model demonstrated the capability of Arena's Input Analyzer to determine the distributions that best fit the various input parameters. The model's animation verified the model's prowess in depicting the processes the BEVs undergo from one station to the other.

- With respect to the third objective (evaluating the critical performance metrics):
    - ✓ The base case scenario verified that the truck will be available for work 100% of the time, as evidenced by the absence of queues at the charging station. However, this scenario had batteries sitting at the charging bay for about 5 hours post-charging, showing the underutilization of the spare battery. This served as the basis for building the other experiments.
- With respect to the final objective (simulating several experiments to determine the optimal configuration for the decision-making process):
    - ✓ The model evaluated several scenarios to ascertain the optimal scenario. This was done by altering factors, such as the number of trucks, batteries, and chargers and determining their effect on the key performance metrics. The author used the full factorial experimental design approach to determine the various combinations of the factors.
    - ✓ A key strength of the DES model was its adaptability and flexibility, allowing for modifications in input variables as per the experimental design phase without rebuilding the model entirely.
    - ✓ From the experimentation, scenario 53 emerged as the most optimal configuration, offering the best balance regarding truck availability, charging queue generated, and battery waiting times post-charging.
    - ✓ The threshold configurations for the model were also analyzed to fully comprehend the critical points beyond which the addition of any of the factors become inefficient.

5.3. RECOMMENDATIONS FOR FUTURE WORK

The following recommendations for future work will enhance the DES model performance and advance the frontiers of this research:

- A proposition is made for continuous improvement and refinement of the DES model to accommodate better complexities and variations, such as failures and breaks of the BEVs.
- The author proposes that optimization techniques should be utilized to improve the regression model performance. The regression model must incorporate more input variables for future research. This can approximate the battery depletion rate to a higher degree.
- Future work should take into consideration the size of the charging facility. This ensures the model can be applied to different fleet sizes.
- Finally, the DES model should be applied to different mining environments and conditions to test its applicability and adaptability in varied scenarios.

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VITA

Albert Einstein Amponsem was born in Ghana, West Africa, where he completed his Bachelor of Science degree in Geomatics Engineering in 2018 at the Kwame Nkrumah University of Science and Technology. After his first degree, he worked with AngloGold Ashanti Obuasi Gold Mines as a Geomatic Engineer until December 2021. In December 2021, he moved to the USA to further his education at the Missouri University of Science and Technology. During his pursuit of the MS degree, Albert maintained active membership with the Society for Mining, Metallurgy, and Exploration (SME), the National Society of Black Engineers (NSBE), and the African Students' Association (ASA). In May 2024, he received his master's degree in mining engineering from Missouri University of Science and Technology.