An integrated stochastic multi-objective simulation and optimization framework for fuel-efficient truck dispatching in open-pit mines

by

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ABSTRACT

In the context of open-pit mining, the haulage system plays a pivotal role in the overall environmental impact of the operation, particularly concerning greenhouse gas (GHG) emissions and energy consumption. This impact stems from the heavy reliance on trucks for the transportation of materials within the mining site. However, recognizing the need for energy-efficient practices in today's world, there is a growing emphasis on optimizing truck dispatching strategies to enhance productivity while aligning mining operations with environmental and energy efficiency principles.

Traditionally, truck dispatching in open-pit mines has been centered on achieving production targets and maximizing operational efficiency, often overlooking the environmental implications of such practices. Nevertheless, the rising awareness of climate change and the call for responsible resource extraction have prompted a shift in focus towards adopting energy-efficient practices throughout the mining industry, including open-pit mining.

To address these environmental and economic concerns and optimize operations, this research introduces an innovative approach: an integrated simulation and optimization model. The primary objective of this study is to present a new truck dispatching framework that seeks to achieve a dual purpose: maximizing the economic benefits derived from open-pit mining while minimizing its environmental footprint. To accomplish this goal (or objective), the framework focuses on four interdependent goals: first, minimizing the deviations from target production rates established by strategic plans to ensure consistent and efficient mining operations; second, reducing shovel idle time to optimize the use of resources; third, minimizing the wait time for trucks, ensuring smooth material flow throughout the mining process; and finally, decreasing truck fuel consumption, directly contributing to the reduction of GHG emissions. Additionally, this research analyzes the impact of the number of available trucks and their types, degree of heterogeneity of the truck fleet, as well as truck failures.

To evaluate the performance and robustness of this novel framework, a case study was conducted at Gol-E-Gohar mine in Iran. The results were promising, showing a noteworthy accomplishment of achieving a reduction of up to 6% in fuel consumption per tonne of production. Over a ten-day

operation period with 12 hours of daily operation, this led to an impressive total reduction of up to 20,000 liters in fuel consumption.

In conclusion, the integration of an innovative simulation and optimization framework into the truck dispatching practices of open-pit mining offers a promising solution for the industry's environmental concerns. By simultaneously achieving economic advantages and minimizing the ecological impact, this approach sets a positive precedent for energy-efficient mining operations and responsible resource extraction in the future.

PREFACE

This thesis represents an original work by Mohammadreza Kazemi Ashtiani. Certain portions of this research have previously undergone submission for publication under the title: "A Stochastic Energy-Efficient Robust Truck Dispatching Framework for Simultaneous GHG Mitigation and Operational Excellence in Open-Pit Mines" by Kazemi Ashtiani, M., Moradi Afrapoli, A., Doucette, J., and Askari-Nasab, H. in the Journal of Cleaner Production. However, as of now, these parts remain unpublished. In this study, I took charge of designing the conceptual model, developing algorithms, conducting case studies, documenting and analyzing the outcomes, and preparing the manuscripts. The supervisory authors, Askari-Nasab, H., Doucette, J., and Moradi Afrapoli, A., played a role in conceiving the ideas and contributing to the manuscript's composition.

ACKNOWLEDGMENT

I am profoundly thankful to my advisor, Prof. Hooman Askari-Nasab, for his indispensable mentorship, encouragement, and backing, which have been crucial in the successful completion of this work. Under his guidance, I have not only acquired invaluable knowledge and skills in scientific research but have also witnessed the qualities of an exceptional mentor. I am truly grateful for his patience, accessibility, and insightful feedback, all of which have contributed significantly to my personal and academic growth. I am deeply thankful to Prof. John Doucette for serving as my co-supervisor and providing invaluable guidance and support throughout this journey.

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To my friends, particularly Soroush, I extend my heartfelt gratitude for their unwavering support during this research endeavor.

I will be forever grateful to my parents and sister, Mahnaz, Ali, and Farnaz, for their constant support and unwavering encouragement that has been a guiding light in every aspect of my life. Their presence has been a source of strength and inspiration, and I am deeply indebted to them for their unwavering love and support.

With utmost sincerity,

Mohammadreza Kazemi Ashtiani

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LIST OF ABBREVIATONS

DES	Discrete Event Simulation
MOO	Multi-Objective Optimization
SD	System Dynamics
TS	Truck and Shovel
IPCC	In Pit Crushing and Conveying
SMIPCC	Semi Mobile In Pit Crushing and Conveying
OPMOP	Open-Pit Mining Operational Planning
MILP	Mixed Integer Linear Programming
MOMIGP	Multi-Objective Mixed Integer Goal Programming
VRP	Vehicle Routing Problem
HVRP	Heterogeneous Vehicle Routing Problem
HazMat	Hazardous Materials
CAT	Caterpillar
KPI	Key Performance Indicator
MF	Match Factor
TPGOH	Tonne Per Gross Operating Hours
OTPGOH	Ore Tonne Per Gross Operating Hours
FC	Fuel Consumption
SIT	Shovel Idle Time
TWT	Truck Wait Time
PD	Production Deviation
GHG	Greenhouse Gas
CO_2	Carbon Dioxide
USD	United States dollar
Eq	Equation
Q	Queue
W	Weight
S	Scenario
Tri-Obj.	Tri Objective

Quad-Obj.	Quad Objective
Diff.	Difference of
Stdev	Standard Deviation
StdErr	Standard Error
P1	Plant 1
P2	Plant 2
WD	Waste Dump
SR	Stripping Ratio
Avg	Average
ConLev	Confidence Level
TP	Total Production
OP	Ore Production
SH	Shovel
Rep	Replication
Util.	Utilization
Dest.	Destination

Sec/s	Seconds
Mins/mins	Minutes
Hrs/hrs	Hours
T/t	Tons
KT/kt	Kilo Tons
L/l	Liters
KL/kl	Kilo Liters
#	Number

1 INTRODUCTION

1.1 Background

Several key challenges must be solved in open-pit mining. These challenges encompass various aspects, including mine design and sequencing, road network design and analysis, infrastructure location optimization, net present value (NPV) and production rate determination, fleet management, determination of the number of trucks, shovels, and crushers, optimization of truck terminals, maintenance centers, crusher locations, and allocation of trucks and shovels as well as the trucks dispatching. Additionally, uncertainties associated with these factors need to be evaluated.

Open-pit mining operations, as one of the main mining methods, require a substantial amount of equipment to extract minerals and waste materials from the Earth's crust and transport them. Trucks play a key role in this process, as they are responsible for transporting extracted material to processing sites and waste dumps. Effective dispatching of trucks is crucial for maximizing productivity and, consequently, the profitability of the operation. It also contributes to the reduction of negative environmental impacts. This research explores the problem of truck dispatching in open-pit mining and proposes a unique approach to optimize this process, considering various factors such as truck capacity, the distance between mining sites, the rate of material extraction, and the demand for processed material. The approach aims to find a solution that not only meets the operation's needs, enhances productivity, and reduces costs but also contributes to optimizing open-pit mining operations, promoting profitability, and reducing GHG emissions from truck fuel consumption.

Mining operations often entail equipment capital and operating costs that can reach hundreds of millions or even billions of dollars for large companies managing multiple mines. To optimize the return on these substantial investments, it is essential to ensure efficient utilization of the equipment through optimal scheduling to minimize operating costs and maximize utilization. The high operating costs associated with mining projects mean that even a slight increase in the productivity of mining equipment can result in significant savings, often in the millions of dollars (Topal and Ramazan, 2010). Achieving an optimized fleet size is essential for efficient dispatching in mining operations to meet production requirements while minimizing costs. The decision regarding the number and types of trucks to include in the fleet represents a significant financial investment, as it is not easily reversible (Salhi and Rand, 1993). In the mining system, an excess of trucks can lead to over-trucking, where trucks must wait for the shovel to become available. On the other hand, having too few trucks results in under-trucking, causing the shovel to wait for trucks to become available (Ataeepour and Baafi, 1999). An ideal fleet size is vital for effective dispatching in other industries as well. An inadequate or excessive fleet size may lead to delays and under-utilizations, resulting in lower productivity. Simulation and optimization models can provide guidance to avoid over- or under-trucking (Chaowasakoo et al., 2017).

This study delves into the truck dispatching problem in the open-pit mines, which involves a unique aspect where trucks are not locked or restricted to a specific pit or shovel. In traditional open-pit mining operations, trucks are typically allocated to specific dumping points or shovels based on predetermined assignments. However, in the dispatching problem addressed in this research, the assignment of trucks is highly dynamic and adaptable. Trucks can be assigned to different dumping points or shovels based on real-time conditions, such as shovel availability, target production rates, and transportation requirements. Additionally, various constraints and factors such as truck capacity, truck availability, shovel digging rate, and plant capacity can affect the truck dispatching decision-making. The dynamic truck dispatching approach ensures efficient utilization of trucks and maximizes overall productivity within the open-pit mining environment and simultaneously leads to lowered transportation cost and pollution. This may involve dynamically adjusting truck assignments as conditions change, and re-evaluating assignments as new information becomes available. The dispatching of trucks in open-pit mining operations is a complex optimization problem. The challenges of this problem include considering multiple objectives such as minimizing costs, maximizing productivity, and reducing environmental impact, while accounting for the inherent uncertainty in the mining process. To address these challenges, a multi-objective stochastic simulation and optimization framework can be applied. This approach utilizes mathematical modeling and computer simulations to optimize the dispatching of trucks in open-pit mines.

The importance of reducing fuel consumption and carbon emissions in open-pit mining operations has become increasingly relevant in recent years, as concerns about the environment and the need to reduce carbon footprints grow. The dispatching of trucks in open-pit mining operations have a noticeable impact on the fuel consumption and carbon emissions. Effective management of trucks can significantly reduce the consumption of fuel and the emissions of carbon, thereby reducing costs and environmental impact.

In conclusion, truck dispatching plays a critical role in the success of open-pit mining operations. By effectively dispatching trucks, mining companies can increase productivity, reduce costs, reduce the environmental footprints, and improve the overall efficiency of their operations. In this research, the focus is not only on achieving optimal truck dispatching but also on developing a comprehensive framework that emulates the dynamic nature of the mining operations. By leveraging advanced optimization techniques and real-time data integration, the study aims to provide practical solutions that optimize truck dispatching decisions while accounting for changing operational conditions and constraints.

1.2 Statement of the problem

A comprehensive haulage system that manages and optimizes the mining fleet operations plays a crucial role in real-time production activities. This system operates at different levels throughout the lifespan of a mine, making optimal decisions to meet short-/long-term production targets. However, there are several challenges and limitations that need to be addressed to enhance the efficiency and effectiveness of fleet operation in mining. One significant challenge revolves around the assignment of available shovels to mining faces. Currently, this responsibility lies with mine planners, who determine the best shovel allocation based on their expertise and experience following the long-term plans trying to minimize the shovels’ move. However, this manual approach can lead to variations in shovel allocation outcomes and may not fully optimize the utilization of available shovels. Another challenge is the identification of optimal routes for trucks within the mine site. Algorithms like Dijkstra's (Dijkstra, 1959) are commonly used to find the shortest path from a shovel to a destination, taking into account factors such as the shovel's current working face position. However, in large open-pit mines with complex road networks, varying numbers and types of trucks, and potential truck failures, the task of finding the most efficient routes becomes more intricate.

The truck dispatching problem that represents a significant and crucial challenge in mining fleet operations, is the main focus of this study, and refers to the task of dynamically assigning trucks to shovels as starting points and to dumping points as destinations in an efficient manner. Existing optimization algorithms typically focus on maximizing the utilization of either the truck fleet or the shovel fleet individually, rather than considering the utilization of both fleets. These approaches fail to account for the interdependence and synergies between both fleets, leading to suboptimal resource allocation. Current truck dispatching models often overlook the integration between mining and processing operations and do not consider the operational constraints effect on the truck dispatching. This limits their ability to accurately reflect real-world mining operations and hinders efficient dispatching. By overcoming the mentioned challenges and advancing the field of truck dispatching in mining, the efficiency of mining operations can be significantly improved, leading to productive mining.

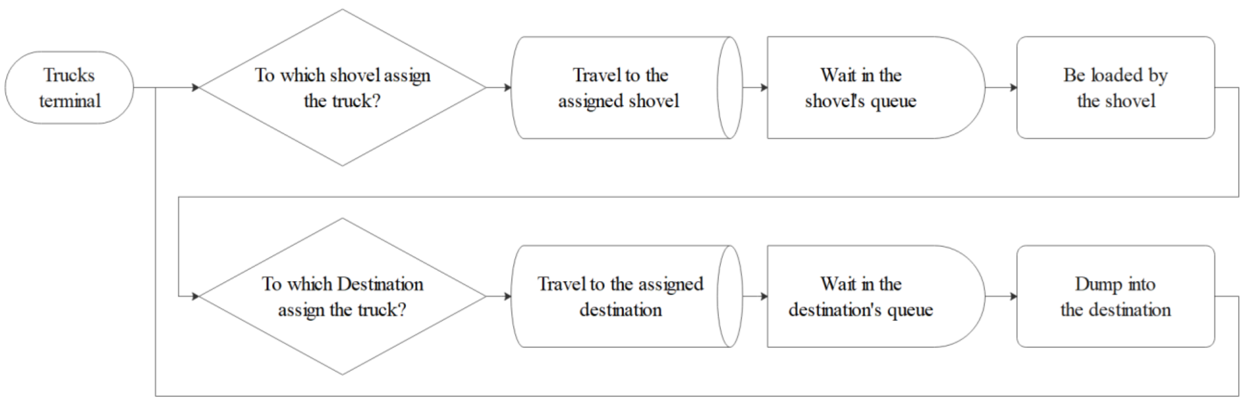

Figure 1.1. Truck assignment and operations

Figure 1.1 illustrates the hauling process conducted by trucks in open-pit mining. The process begins at the terminal, where trucks are assigned to either ore or waste shovels based on factors such as production targets, travel times, queue conditions, and processing times. Subsequently, the trucks travel to the waste dump or one of the crushers/plants, depending on the materials they carry and the capacities of the hoppers in each plant. Finally, the trucks are assigned to a new shovel according to the schedule and objective functions, and this cycle continues.

The following research question drives this dissertation.

*Can truck dispatching be optimized by considering processing limitations, resource utilization, and **environmental impacts** to achieve higher production levels with **reduced costs**?*

1.3 Significance of the study

The mining industry is crucial for the world economy and population growth as it provides raw materials, but this has led to increased energy consumption and emissions (Feng et al., 2022). The improvement of energy efficiency has become one of the most important concerns for mining companies in order to minimize their negative environmental impacts. However, there is a lack of research that has been conducted in this area, particularly in relation to the haulage activity at open-pit mines which consumes a significant amount of energy. Both industry and academia acknowledge the problem of poor energy efficiency in mines, emphasizing on the improvement of the energy efficiency as a necessary step for mines to take (Patterson et al., 2017). In addition, recently, the energy crisis and global warming have become major concerns worldwide. In response, many countries have introduced carbon policies, which include carbon cap and trade, carbon tax, and carbon quota, the European Union (EU) has had a cap and trade in place since 2005 and started to implement a carbon tax in 2012 (Li et al., 2018). Optimizing vehicle routing decisions is a way companies are working towards minimizing carbon emissions and fuel consumption (Li et al., 2018). The emissions from a heavy-duty mining truck, which has a capacity ranging from 15 to 360 tons, is hundreds of times higher than the emissions from a passenger vehicle (Feng et al., 2022). The mining industry is driven to seek cleaner solutions for trucks due to this substantial emissions burden, coupled with the ongoing challenge of global warming (Feng et al., 2022). In certain mining ventures, like iron, bauxite, and coal projects, loading and hauling operations contribute to 41% to 66% of the overall energy consumption and 37% to 54% of GHG emissions (Feng et al., 2022). Mining trucks, which are the main hauling equipment in open-pit mines, transport over 80% of metallic minerals and 40% of coal and are highly productive, reliable, low cost, and integrated (Feng et al., 2022). Nevertheless, Purhamadani et al. (2021) believe that in open-pit mining, the truck-based haulage system has been a significant contributor to energy consumption in the haulage sector. Apart from the considerable environmental impact caused by the mining haulage system, it also entails noticeable operational cost. The mining operational cost heavily relies on haulage expenses, estimated to make up about 50-60% of the total. Moreover, any disruptions in the materials handling system can lead to supplementary costs for the processing plant (Alarie and Gamache, 2002; Moradi Afrapoli et al., 2019; Moradi Afrapoli and Askari-Nasab, 2017; Upadhyay and Askari-Nasab, 2019).

Efficient truck dispatching in open-pit mining operations plays a critical role in reducing GHG emissions and minimizing operational costs. Through optimized truck dispatching, mining companies can attain cost savings, enhance profitability, and contribute to an eco-friendlier future. Lowering GHG emissions by reducing fuel consumption aligns with environmental concerns and boosts competitiveness. By prioritizing efficient truck dispatching practices, mining companies not only improve operational efficiency but also establish themselves as responsible industry leaders.

1.4 Summary of literature review

Chapter 2 of the thesis provides a comprehensive review of the existing literature. The literature review encompasses studies on dispatching, routing and allocation problems across various industries, including mining. The literature review is categorized into two main categories: publications with economical goals such as minimizing the total cost, and publications with environmental goals such as minimizing GHG emissions. The majority of the studies utilize various operations research and simulation techniques to offer decision makers the most optimal choices. Table 1.1, and Table 1.2 provide an overview and classification of numerous relevant mining studies.

Table 1.1. Summary of literature review part 1

Authors	**Year**	**Surface Mining**	**Environmental objective**	**Simulation**
Ataeepour and Baafi	1999	✓	×	✓
Gamache et al.	2005	×	×	×
Salama and Greberg	2012	×	×	✓
Topal and Ramazan	2010	✓	×	×
Souza et al.	2010	✓	×	×
Ta et al.	2013	✓	×	×
Zhang and Xia	2015	✓	×	×
Matamoros and Dimitrakopoulos	2016	✓	×	×
Chaowasakoo et al.	2017	✓	×	✓
Fadin and Moeis	2017	✓	×	✓
Shishvan and Benndorf	2019	✓	×	×
Moradi Afrapoli et al.	2019	✓	×	✓
Yu et al.	2016	✓	✓	×
Gonzalez et al.	2017	×	✓	✓
Patterson et al.	2017	✓	✓	×
Mohtasham et al.	2021	✓	✓	×
Mohtasham et al.	2022	✓	✓	✓
Vergara-Zambrano et al.	2022	✓	✓	×
Huo et al.	2023	✓	✓	×

Table 1.2. Summary of literature review part 2

Authors	Year	Features
Ataeepour and Baafi	1999	Homogenous fleet
Gamache et al.	2005	1. Undergraund mining 2. Took traffic into account
Salama and Greberg	2012	Undergraund mining
Topal and Ramazan	2010	1. Mixed integer programming 2. Considered truck age, maintenance costs, and operating hours to meet production targets
Souza et al.	2010	1. Developed a hybrid algorithm that combines elements of two metaheuristics, greedy randomized adaptive search procedure (GRASP) and general variable neighborhood search (GVNS) 2. Validated results by a mixed integer programming model based on goal programming
Ta et al.	2013	Employed CPLEX
Zhang and Xia	2015	1. Integer programming 2. Heterogeneous fleet 3. Considered production targets
Matamoros and Dimitrakopoulos	2016	1. Stochastic mixed integer programming 2. Handled uncertainties associated with input parameters
Chaowasakoo et al.	2017	1. Heterogenous fleet 2. Used match factor
Fadin and Moeis	2017	Utilized a "look-ahead algorithm" approach (Jang et al., 2001)
Shishvan and Benndorf	2019	Considered different types of overburdens
Moradi Afrapoli et al.	2019	1. Employed the weighted-sum method to convert the multi-objective problem into a single-objective problem 2. Mixed integer linear programming 3. Considered production targets
Yu et al.	2016	1. Mixed integer programming 2. Considered uncertainties related to equipment failure using a multi-scenario decision-aided system
Gonzalez et al.	2017	Underground mining
Patterson et al.	2017	1. Mixed integer linear programming 2. Employed a tabu search solution method 3. Heterogenous fleet
Mohtasham et al.	2021	1. Developed a goal programming model based on mixed integer linear programming 2. Solved with the CPLEX solver in the GAMS environment 3. Heterogenous fleet
Mohtasham et al.	2022	1. M-trucks-to-1-shovel strategy 2. Heterogeous fleet
Vergara-Zambrano et al.	2022	Applied a carbon tax
Huo et al.	2023	Implemented a reinforcement learning-based approach

In these studies, a method that accounts for environmental objective functions using simulation techniques to address uncertainty in an open-pit mine, while also considering factors such as truck failures and operating hours to achieve production targets, is lacking.

1.5 Objective of the thesis

This study aims to achieve three main goals:

- developing a framework for truck dispatching: Formulating truck dispatching optimization model, integrating it with a simulation model to capture uncertainty parameters and to display the robustness of the model.
- conducting a case study to show the performance of the developed truck dispatching model. It addresses questions regarding the feasibility of simulation and optimization for truck dispatching. Evaluating the performance of the proposed model by comparing it with benchmark dispatching methods.
- Engaging in sensitivity analysis involves introducing various scenarios to assess the model's response.

1.6 Context and scope of work

In this research, dispatching decisions are made based on the following objectives.

1. Minimizing the cumulative trucks' fuel consumption
2. Minimizing the cumulative trucks' queue time
3. Minimizing the cumulative shovels' idle time
4. Minimizing the deviation from the target flow rates

The decisions will be made whenever the status of a truck changes, including when a truck starts working, when it dumps its load, or when a failed truck is repaired. The mentioned objectives aim to achieve a balance between maximizing equipment utilization, maximizing production, and minimizing negative environmental impacts. A multi-objective optimization model is integrated with a simulation model, creating an integrated stochastic multi-objective simulation and optimization framework that accounts for:

1. Uncertainties in input random parameters such as truck's load tonnage, service times, and truck's speed
2. The processing/crusher capacity limitation
3. Failure (uptime and downtime) of trucks

However, the developed framework does not account for:

1. Variation in the equipment costs or product price
2. Weather conditions
3. Road closure
4. Changes in plant status or dump locations
5. Shovels failure
6. Presence of a stockpile

For the sensitivity analysis, several scenarios are conducted, including varying the weights of various objectives in the multi-objective optimization model (16 scenarios) and considering different numbers and types of trucks (40 scenarios).

1.7 Importance and application of simulation in the research

Simulation modeling is a powerful tool that can be used to experiment and test alternative courses of action, providing insight and the most favorable outcomes. In the mining industry, simulation models can be used to predict the impact of new ideas, procedures, and policy changes. The use of Monte Carlo Simulation techniques and special-purpose computer languages have greatly simplified the construction of discrete event models. These models can analyze production capacities, determine bottlenecks, and estimate resource utilization levels in mines (Knights and Bonates, 1999). Manríquez et al. (2019) emphasized the significance of utilizing discrete event simulation in designing mining systems, which includes determining transportation routes, loading points, and types of load equipment. Simulation methods have been a topic of interest for truck allocation and dispatching problems for many years. Maran and Topuz (1988) claimed that the discrete event simulation can be a valuable technique to evaluate and experiment truck allocation and dispatching problems, especially when traditional analytical methods are not appropriate. The use of discrete event simulation is widespread in optimizing truck and shovel systems in mining due to its ability to capture random behavior and model complex systems easily (Que et al., 2016).

1.8 Research methodology

This research has 5 main steps:

1. Preprocessing the historical input data and capturing the uncertainties by fitting appropriate random distributions
2. Developing a comprehensive multi-objective optimization model
3. Developing a proper simulation model and evaluating a real case problem
4. Integrating the simulation and optimization models and optimizing key performance indicator (KPI)s of the system
5. Adjusting parameters and developing diverse scenarios to improve fleet performance within the mining system

The probability distribution functions are fitted for each shovel type, including bucket tonnage and loading cycle time. Similarly, for each type of truck, distribution functions are fitted for empty velocity, loaded velocity, backing time, and dumping time. Additionally, for each combination of truck and shovel types, the probability distribution functions are fitted for the spot time and loading passes. All of these estimations are based on historical data and are applied to the simulation model (Figure 1.2).

Within the framework of this study, a simulation model is implemented to encompass the entire mining operation, including material flow through downstream processes. To facilitate effective communication and dynamic interaction, the optimization components are integrated with the simulation model using VBA® (Microsoft Corporation, 2013) and OPLrun (IBM, 2022) (Optimization Programming Language Integration). Figure 1.3 illustrates the dynamic interaction between the simulation model and the optimization models within the developed framework. For constructing the simulation model, Rockwell Arena simulation software (Rockwell Automation, 2019) is utilized, while the optimization models are created and solved using IBM CPLEX® (IBM, 2022).

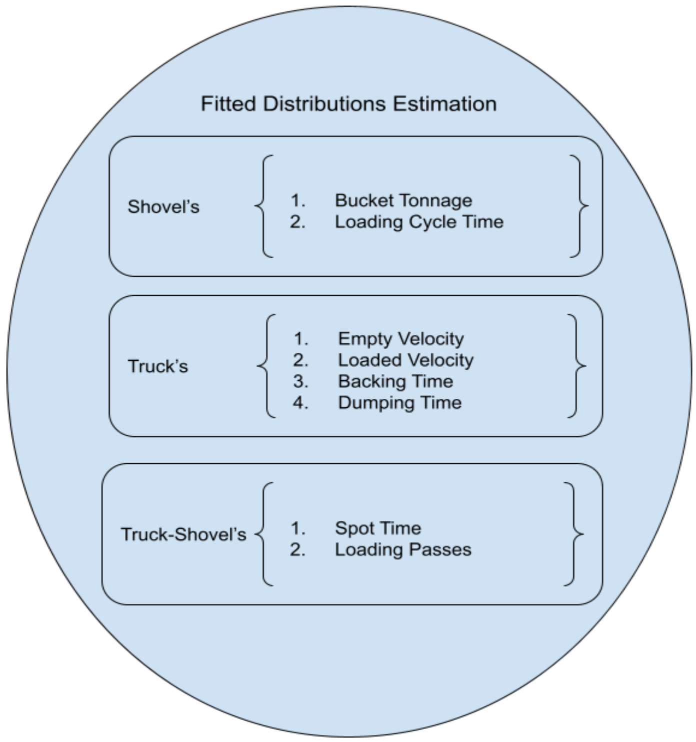

Figure 1.2. The required input parameters needed estimation

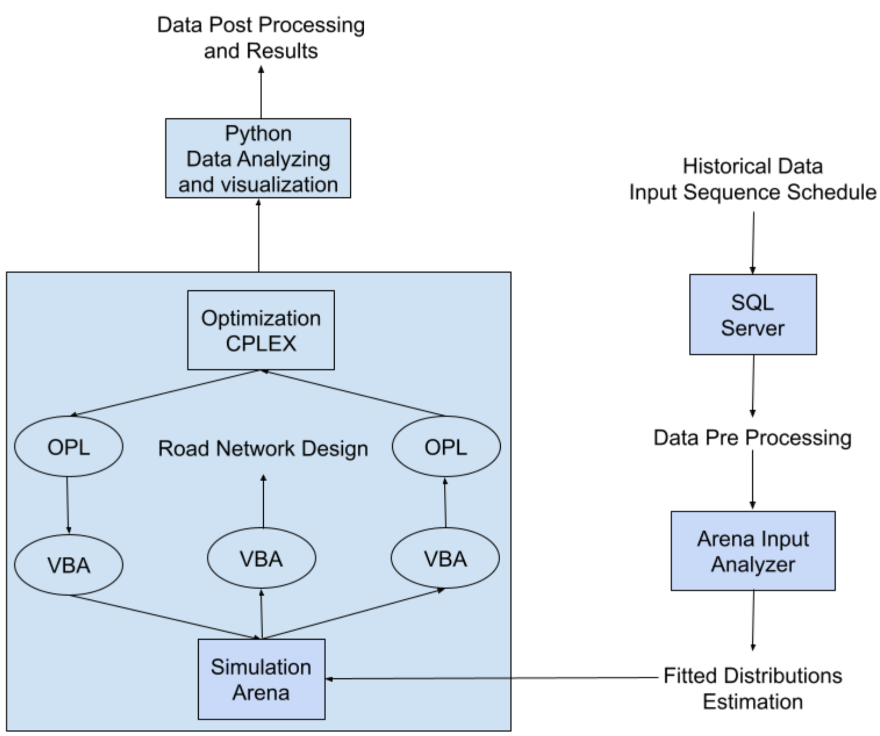

Figure 1.3. The different aspects of the study and how they interact with each other

1.9 Scientific contribution and industrial significance of the research

Compared to other industries, the mining and petroleum sector is the second largest consumer of energy after bulk chemicals sector (Worrell and Price, 2001). Trucks play a crucial role in the transportation of materials in open-pit mines and account for the highest energy consumption among all equipment and resources used in mining operations (Sahoo et al., 2014). The main novelty of this research lies in offering a practical approach to decrease fuel consumption and subsequently reduce the carbon footprint in open-pit mining operations by optimizing truck dispatching. The novel approach aims to enhance efficiency and productivity while prioritizing fuel efficiency. Additionally, the model developed in this research takes into account the dynamic stochastic uptimes and downtimes for each truck within the simulation model, making the model more realistic and reliable. The distinction between the method employed in this study and the previous benchmark method developed by Moradi Afrapoli et al. (2019) includes the following:

- Incorporating a fuel consumption minimization objective function in addition to meeting the production requirement objective.
- Taking into consideration the possibility of truck failures.

As per the National Energy Foundation's report (National Energy Foundation, 2015), the CO_2 emission rate stands at 3.05 ton CO_2 equivalent per liter of diesel fuel. Therefore, decreasing fuel consumption directly contributes to the reduction of GHG emissions. Fuel consumption of vehicles is commonly used as a substitute for the measurement of GHG emissions, which is influenced by factors such as vehicle speed, load, engine type, and the characteristics of the route traveled (Bula et al., 2019).

The approach applied in this research to the problem of truck dispatching in open-pit mining operations is deemed a significant contribution to the field of energy-efficient mining, offering valuable insights and advancements in promoting environmentally-friendly mining practices.

This study sets itself apart from prior research by introducing an integrated simulation and optimization framework that combines economic and environmental goals while addressing uncertainty parameters. Additionally, the approach incorporates production targets and accounts for potential truck failures.

1.10 Organization of the thesis

Chapter 1 serves as an introductory overview of the research, covering the background of the research topic, identifying the problem of concern, and presenting a concise summary of the literature review. It also outlines the objectives of the thesis, introduces the research methodology, and highlights the contributions made.

In Chapter 2, the literature review delves into mining transportation and hauling systems. It explores the application of simulation and optimization methods in allocation and dispatching Problems across mining and other industries. The chapter categorizes haulage systems from economic and environmental perspectives.

Chapter 3 first introduces a market-dominated benchmark truck dispatching approach and then outlines the proposed framework. The chapter provides a detailed explanation of how the simulation and optimization components of the framework function and communicate. It also elaborates on the key performance indicators (KPIs) and discusses the model's limitations.

Chapter 4 focuses on the implementation of the developed truck dispatching models and the simulation and optimization framework. It introduces the input data used in the simulation and optimization framework for the case study. Various scenarios are presented, including those related to objectives' weights determination where the model proposed in this research is compared with benchmark models. The chapter further explores scenarios involving the number and types of trucks, as well as scenarios considering truck failures and the impact of truck uptimes and downtimes on the major KPIs.

Finally, Chapter 5 serves as the concluding chapter, summarizing the thesis and presenting concluding statements. It restates the contributions and limitations of this research and offers recommendations for future studies in the field of truck dispatching in open-pit mining operations.

2 LITERATURE REVIEW

2.1 Introduction

Open-pit mining, as a well-known surface mining method, is preferable to the underground methods from technical and economic viewpoints, except for environmental desirability (Bakhtavar et al., 2012). The main production cycle in open-pit mining includes drilling, blasting, loading, and hauling (Figure 2.1).

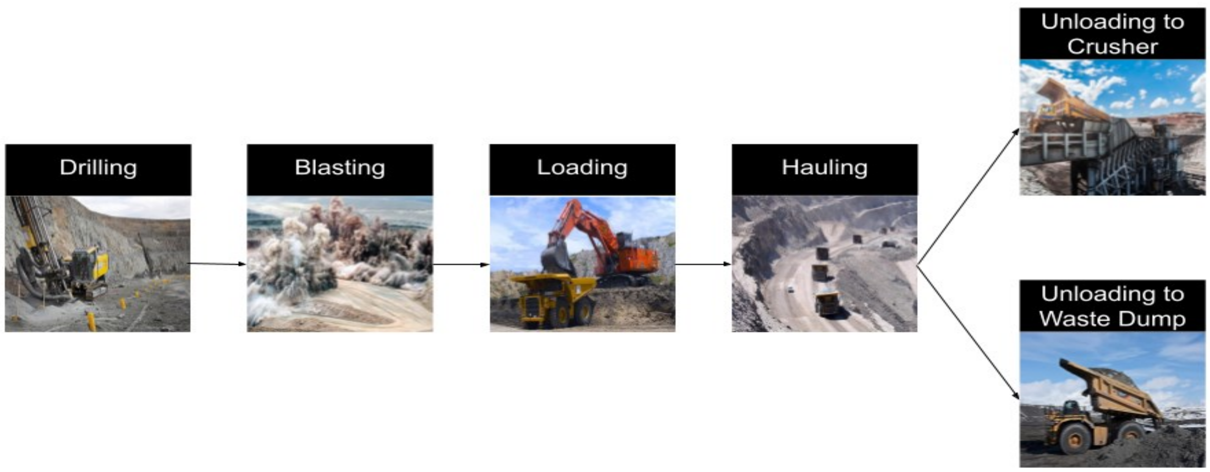

Figure 2.1. Production levels in open-pit mining

Figure 2.2 displays all levels of production planning in an open-pit mine. Production planning in open-pit mining incorporates a strategic level and a tactical level. The strategic level covers the long-term and medium-term production planning, while the short-term and operational planning are addressed in the tactical level. The operational plan consists of upper and lower stages. In the upper stage, there are tasks related to production optimization and allocations of trucks and shovels. Meanwhile, the lower stage is focused on truck dispatching (Mohtasham et al., 2021). An efficient operational plan takes into account the long-term objectives and optimizes the operations in such a way to meet those objectives. In operational planning, dynamic decision-making for truck dispatching is one of the most significant challenges. Minimizing human interferences in decision-making is one of the operational planning goals. However, it is rarely possible to automatically perform the entire process and eliminate human interference because of several constraints, including the complexity of operations, unforeseen events, safety concerns, and environmental regulations.

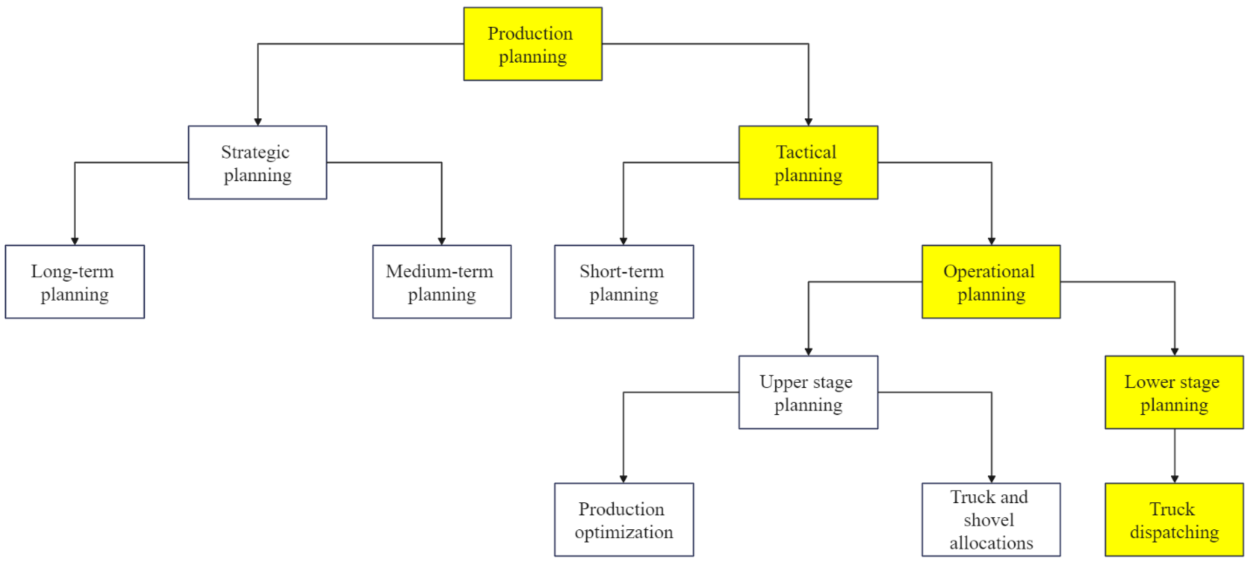

Figure 2.2. Open-pit mining production planning

This research centers on the optimization problem of truck dispatching. The model's crucial variables include shovel and truck capacities, available number of shovels and trucks, number of destinations (processing plants and waste dumps), and physical distances. Choosing the dispatching method depends on the mining operation's scope, particular objectives, road network, equipment condition, geological condition, and financial resources (Ahangaran et al., 2012). Industrial companies aim for cost-efficient dispatching methods, while governments and communities prefer eco-friendly dispatching methods. Past researchers have employed three approaches, namely operations research, queuing theory, and simulation techniques, to facilitate optimal decision-making in this context (Upadhyay, 2013). In what follows, several studies on dispatching, routing and allocation problems, based on the methods employed and their respective objectives, are reviewed and categorized under two perspectives: the economical perspective and the environmental perspective.

2.2 Economical perspective

Ataeepour and Baafi (1999) examined how a dispatching rule affects mine productivity using an ARENA simulation system. They considered all trucks in the mine to be identical and proposed a dispatching rule that aimed to maximize overall productivity by ensuring optimal utilization of available trucks and shovels. Topal and Ramazan (2010) introduced a novel method for scheduling mining trucks on a yearly basis, spanning multiple years, by employing mixed integer programming. Their method considered truck age, maintenance costs, and operating hours to meet production targets and optimize the truck schedule. Souza et al. (2010) addressed the problem of optimizing mineral extraction in open-pit mines through dynamic truck allocation. The goal was to minimize the number of mining trucks used in order to meet production goals and quality requirements. The authors presented a hybrid algorithm that combines elements of two metaheuristics, greedy randomized adaptive search procedure (GRASP) and general variable neighborhood search (GVNS) and validated their results using the CPLEX optimizer. The algorithm used a mixed integer programming model based on goal programming. However, Ta et al. (2013) introduced models for optimizing truck and shovel usage in oil sand surface mines. The objective was to minimize the number of trucks needed while meeting throughput and ore grade constraints. The models used a straightforward approximation to quantify the relationship between a shovel's idle probability and the number of assigned trucks and were capable of handling multiple truck sizes. The authors employed CPLEX (IBM, 2022) to solve the truck allocation problem. Zhang and Xia (2015) utilized integer programming to optimize truck dispatching in open-pit mines, reducing costs and achieving production targets. They also introduced an analytical method to determine the optimal fleet size based on the dispatching results. Furthermore, the experiments with a heterogeneous fleet demonstrated that well-mixed fleets lead to additional reductions in operating costs. Matamoros and Dimitrakopoulos (2016) presented an innovative technique for scheduling short-term mine production, which accounted for factors related to mining, production limitations, uncertain ore quantities, as well as the availability and parameters of the fleet. The approach optimized the allocation of the fleet and handled uncertainties associated with input parameters, leading to lower cost and more efficient fleet allocation compared to traditional methods, as demonstrated in a multi-element iron mine case study. Chaowasakoo et al. (2017) proposed a new approach for mixed-fleet optimization, using match factor to determine the optimal fleet size for different types of trucks. They conducted a simulation in an open-pit mine, focusing on minimizing shovel waiting time and saturation, as well as truck cycle time and wait time. However, the study had some limitations, such as not considering haul road profiles and varying velocities. Fadin and Moeis (2017) utilized a "look-ahead algorithm" approach (Jang et al., 2001) as a new method to solve the truck dispatch problem in open-pit mines. The proposed approach was developed through simulation and optimization models, using real data to address the truck dispatch problem effectively. The dispatching results aimed to determine the optimal truck routes and schedules to maximize production and provide significant operating cost savings to the mining industry. The study employed discrete event simulation to test several scenarios for truck dispatch. Shishvan and Benndorf (2019) explored a solution to optimize the dispatch of materials in coal mines where different types of overburden must be placed in specific patterns for safety. The authors proposed an approach that optimized dispatch decisions based on equipment capacity, performance, and availability. The method was evaluated and tested at the Hambach mine located in Germany. Gamache et al. (2005) studied the fleet management problem in an underground mine, including dispatching, routing, and scheduling the equipment. They considered criteria such as minimizing cycle time or waiting time, and taking traffic into account to improve the overall productivity. Salama and Greberg (2012) improved the efficiency of the haulage system in an underground mine by simulating the loading and hauling operations.

Newman et al. (2010) conducted a review of operations research in mine planning, which includes a discussion of survey articles on open-pit truck dispatching. They classify truck dispatching strategies, examine their underlying mathematical formulations, and identify the strengths and weaknesses of alternate approaches. To gain a thorough understanding of the economic enhancements in haulage systems within the mining industry, Moradi Afrapoli and Askari-Nasab (2017) reviewed and conducted an extensive assessment and documentation of models and algorithms employed in mine fleet management systems. Their focus encompassed three interconnected challenges: determining the shortest path, optimizing production processes, and facilitating real-time dispatching. The review delved into a variety of allocation issues, including queuing theory, the Li transportation approach, linear programming, goal programming, and stochastic programming. Additionally, the study reviewed the algorithm underpinning the Modular Mining Dispatch (MODULAR MINING), which was developed by White and Olson (1993; 1986) for the purpose of real-time truck dispatching.

The dispatching or allocation of trucks can be classified as a type of vehicle routing problem. Several relevant research works have addressed this issue in various industries, such as hazardous material handling. Androutsopoulos and Zografos (2012) discussed the solution to a vehicle routing and scheduling problem for hazardous materials distribution that has multiple objectives. They employed the weighted-sum method to convert the multi-objective problem into a single-objective problem. Bula et al. (2016) presented a mathematical model that utilizes mixed integer linear programming (MILP) to solve the Heterogeneous Vehicle Routing Problem (HVRP) in the context of hazardous materials transportation. Bula et al. (2019) proposed a bi-objective heterogeneous fleet vehicle routing problem for the transportation of hazardous. Two solution methods were presented: a multi-objective neighborhood dominance-based algorithm and an epsilon-constraint meta-heuristic algorithm. Ghaderi and Burdett (2019) examined the best approach for routing hazardous materials through a two-stage stochastic programming model. Tasouji Hassanpour et al. (2021) solved a hazardous material routing problem by an augmented epsilon-constraint method. Wang et al. (2023) introduced a multi-objective optimization model that used epsilon constraint method and a mixed integer linear programming to determine robust and stable transportation solutions for hazardous materials. Villegas et al. (2013) proposed a straightforward yet effective two-phase metaheuristic for the truck and trailer routing problem. Bélanger et al. (2020) introduced a solution for the Ambulance Location and Dispatching Problem (ALDP) by employing a recursive simulation-optimization framework that balances location and dispatch decisions using mathematical formulation and simulation modeling. Hua et al. (2022) introduced an approach to ascertain the minimal fleet size and ideal vehicle allocation in bike sharing, taking into account uncertainties in future demand. To sum up, there are numerous vehicle dispatching studies in other industries. Besides the mentioned research, other studies also focus on topics such as dispatching design for customized hybrid bus vehicles, energy or electric vehicle dispatch problems, emergency vehicle dispatching and routing, automated guided vehicles dispatching, dispatching in transit systems, autonomous trucks and lorries dispatching for parcel deliveries, and commercial vehicles dispatching (Cheng et al., 2005; Chowdhury and Chien, 2001; Duan et al., 2015; Goel and Gruhn, 2006; Jiang et al., 2019; Kassai et al., 2020; Liang et al., 2020; Xi et al., 2021; Zhou et al., 2016). These investigations underscore the significance of efficient dispatching practices across different sectors.

2.3 Environmental perspective

Green vehicle routing is a subdomain of Vehicle Routing Problems (VRPs) with the primary goal of minimizing fuel consumption, carbon emissions, total distance, or costs when making routing decisions (Turkensteen, 2017). Due to the growing concern about global warming, most of the large organizations are investing more resources and effort into reducing energy consumption and emission of pollutants (Ganji et al., 2020). Due to the challenges posed by global climate change and the increasing levels of GHG emissions, numerous countries, including Canada and the United States in North America, have taken action by adopting diverse carbon pricing policies or regulatory measures (Abdi and Taghipour, 2018). In an effort to make industries responsible for their carbon emissions, governments have introduced carbon tax policies, leading to a growing focus on enhancing energy efficiency within the mining sector. The most promising areas for improvement in this regard are loading and hauling operations. Nevertheless, despite endeavors to curtail energy consumption, numerous mines encounter obstacles in achieving optimal energy efficiency (Awuah-Offei, 2016). As mentioned in (Awuah-Offei, 2016) energy efficiency is a measure of the ratio between the amount of useful work performed and the energy input. In the context of mining, the volume of product produced (such as tonnes of rock or grams of metal) is often used as a proxy for useful work. This can be represented by factors such as payload or the product of payload and distance traveled (Motlogelwa and Minnitt, 2013; Odhams et al., 2010; Oskouei and Awuah-Offei, 2014). Government of Canada (2016) emphasized the urgent requirement to decrease GHG emissions in line with the obligations of the Paris Agreement in 2016 (Paris Agreement, 2016). Nonetheless, the transportation sector, particularly heavy-duty freight trucks, has witnessed a notable rise in GHG emissions, accounting for 70% of the overall emissions growth between 1990 and 2019 (Government of Canada, 2021a).

Several research works in green vehicle routing problems have been conducted in diverse industries, including bus routing, healthcare supply chain, winter service vehicle management, garbage truck scheduling, carsharing systems, and more. Some of the notable studies include those by Li et al. (2021), Ganji et al. (2020), Erdinç et al. (2019), Abdi and Taghipour (2018), Li et al. (2018), Lukman et al. (2018), Kumar and Rahman (2014), and Upreti et al. (2014). These studies reflect a growing interest in developing eco-friendly transportation solutions across various sectors. The literature on green vehicle routing problems in various industries shows significant depth and breadth, highlighting a strong emphasis on environmental considerations. Also, extensive research has been conducted to introduce various methods and approaches in different industries for green vehicle routing and transportation. For example, Cao et al. (2022) investigated the green routing problem using smart internet of things (IoT) (Ashton, 2009). In contrast, the mining sector's research on eco-friendly vehicle routing is relatively limited. As the mining industry faces increasing pressure to adopt greener practices, further exploration and investigation of green vehicle routing strategies could pave the way for more energy-efficient transportation solutions and reduced environmental impact.

Awuah-Offei (2016) conducted an extensive review of the ongoing research related to energy efficiency in the mining industry, placing special emphasis on the importance of operators in optimizing energy efficiency during loading and hauling operations. This research claimed that increasing payloads leads to more fuel consumption, but it improves fuel efficiency, as it increases the productivity. However, beyond a certain point, higher payloads results in lower fuel efficiency due to slower travel velocity and potential mechanical damage from exceeding the maximum load limits. Yu et al. (2016) introduced a decision-support model to maximize surface coal mining productivity through efficient operational planning. Their model, based on mixed integer programming, optimized shovel production plans and truck allocations to minimize operational costs, fuel consumption, and GHG emissions. Additionally, it considered uncertainties related to equipment failure using a multi-scenario decision-aided system. Gonzalez et al. (2017) presented a simulation-based methodology for evaluating the sustainability in underground mining projects. The simulation took into account various factors, including the trucks' speed, loading and unloading time, time between failures, and time to repair, which were modeled using statistical distributions. Their goal was to determine the optimal balance between carbon emissions and operational costs. Patterson et al. (2017) introduced a novel MILP optimization model to schedule mining haulage activity, aiming to minimize energy consumption. They applied this model in a case study conducted in an open-pit coal mine located in Queensland, Australia. A constructive algorithm and tabu search solution were used to solve the model. The model considered heterogeneous equipment and four equipment activities: trucks traveling, trucks idle, shovels loading, and shovels idle. Mohtasham et al. (2021) developed a goal programming model based on mixed integer linear programming for optimizing truck and shovel scheduling in open-pit mines. The primary objectives of this model were to maximize production while minimizing deviations in head grade, tonnage, and fuel consumption. The model was implemented with a case study of the Sungun copper mine in Iran, using a fleet of trucks and shovels, and was solved with the CPLEX solver in the GAMS environment (GAMS Development Corporation, 2019). In a subsequent study to address uncertainty in fleet cycle times, Mohtasham et al. (2022) proposed a multi-stage approach for optimal materials handling in open-pit mines, including simulation-based optimization and a novel heuristic algorithm for operational real-time decision-making. The approach aimed to minimize the production loss, deviations in head grade and tonnage, and fuel consumption of mining trucks. Vergara-Zambrano et al. (2022) developed a model that minimizes annual costs and GHG emissions in a copper mining industry. In an effort to minimize emissions in their model, a carbon tax was applied with a price range of 100 to 1,000 USD per ton of CO_2-equivalent. They established an optimization model considering dispatch carbon cost, transportation cost, and various dispatch constraints. Amiri et al. (2023) proposed a new bi-objective programming model for transportation problem using trucks. They considered two objectives: minimizing total transportation costs and minimizing total GHG emissions. They integrate three multi-objective solution methods: weighted-sum, epsilon constraint, and hybrid methods with the Adaptive Large Neighborhood Search algorithm and test the model using real-world locations in Canada. The bi-objective model provides a promising solution to the challenge of balancing cost efficiency and GHG mitigation in the trucking industry. They proved that, even a slight rise in transportation expenses can yield substantial reductions in GHG emissions, through their case study. Huo et al. (2023) focused on enhancing truck fleet dispatching in open-pit mining operations through the implementation of a reinforcement learning-based approach. The main goal of their study was to achieve smarter fleet management and reduce GHG emissions.

3 THEORETICAL FRAMEWORK

3.1 Introduction

This chapter delves into the theoretical foundations of integrated simulation and optimization framework for truck dispatching in open-pit mines. Within the framework, the mining operation, processing plants, and operational decision-making tools establish communication channels. The framework is utilized to address not only the truck dispatching problem but also truck fleet selection and sizing problem in open-pit mines.

Whitin the development of the integrated simulation and optimization framework for open-pit mining operation, this chapter places emphasis on constructing a multi-objective mixed integer goal programming (MOMIGP) model to solve the truck dispatching problem in the optimization part of the framework. The MOMIGP truck dispatching model aims to optimize production by minimizing equipment idle time, deviations from planned production requirements, and total GHG emissions resulting from trucks fuel consumption. This model effectively tackles the truck dispatching decision-making problem, considering uncertain input parameters.

3.2 Benchmark models

One of the most widely used truck dispatching systems in the entire mining industry, catering specifically to open-pit mines, is the Modular Mining Dispatch (MODULAR MINING) developed by White and Olson (1993; 1986). This system provides real-time truck dispatching, which is a critical aspect of efficient mining operations. In the Modular Dispatch system, the truck dispatching decision-making process relies on two main lists: "needy shovels" and "available trucks." The "needy shovels" list consists of shovels that are in need of a truck, and these shovels are prioritized based on the urgency of truck assignments. On the other hand, the "available trucks" list is prioritized according to the trucks' next availability. The dispatching process involves assigning the first available truck to the shovel at the top of the "needy shovels" list, and this process is repeated until all trucks have been dispatched. Due to its effective and widespread implementation, Modular Dispatch has become the dominant mining fleet dispatching system in the market. It boasts a substantial number of installations, with over 400 successful deployments in large-scale open-pit mines worldwide. To assess the effectiveness of the proposed robust framework presented in this thesis, the Modular Dispatch system is used as a benchmark for comparison. This decision is based on its reputation and proven track record as a reliable and efficient mining fleet dispatching solution.

For the purpose of real-time truck dispatching in open-pit mines, Moradi Afrapoli et al. (2019) developed a tri-objective transportation model to minimize shovel idle times, truck wait times, and deviations from path production requirements, simultaneously. The model can handle heterogeneous fleets of different sizes and types and requires no human intervention to meet the target production rate. The model is to be solved every time a truck requires a new assignment and considers operational parameters such as stripping ratio requirements, available transporter capacity, required plant throughput, and shovel digging rate. Achieving full processing plant capacity with 14% fewer trucks compared to the desired fleet obtained via the Modular Mining Dispatch method, their tri-objective model fulfills production requirements using only 86% of the designated fleet size. Since this model has satisfied the predetermined production rate requirement, it is considered as another benchmark model.

3.3 Quad-objective optimization model (covering the fuel consumption)

This section introduces a new mathematical model for real-time truck dispatching, which serves as an optimization model for this research. It is an extended version of the mathematical model presented in (Moradi Afrapoli, 2018; Moradi Afrapoli et al., 2019) that is the benchmark model of this research. The primary contribution of the model in this research lies in its consideration of the environmental impacts of the dispatching process by adding another objective function to minimize the total trucks' fuel consumption and consequently minimize the GHG emissions. There are various formula to calculate the fuel consumption and the equivalent carbon emission (Li et al., 2018). In this research, the formulation of the fuel consumption objective function is derived from the equation introduced in the study conducted by Dindarloo and Siami-Irdemoosa (2016). They applied regression analysis in their case and formulated the fuel consumption for the truck type CAT 785C. Equation (1) provides the formula:

$$F\left(\frac{l}{cycle}\right) = 1.37071 + 0.00483 \times PL + 0.00398 \times LT + 0.00499 \times ES + 0.01471 \times ETR + 0.00278 \times LS + 0.0519 \times LTR \tag{1}$$

Following is a list of variables that are represented in Equation (1):

F: fuel consumption per cycle (liters)

PL: payload (tonnes)

LT: loading time (seconds)

ES: empty idle time (seconds)

ETR: empty travel time (seconds)

LS: loaded idle time (seconds)

LTR: loaded travel time (seconds)

In the case study presented in Chapter 4, as there are two types of trucks available including CAT 785C, and CAT 793C, let's introduce the fuel consumption formula used for CAT 793C trucks as well. The fuel consumption for the CAT 793C truck type in the scenarios is calculated using Equation (1), where a specific coefficient, derived from the Caterpillar handbook (Caterpillar Performance Handbook Edition 29, 1999), is multiplied with it. This coefficient takes into account various factors like normal load and haul time, varying load and haul road conditions, some adverse grades, and some high rolling resistance. The resulting fuel consumption for CAT 793C is approximately 1.59 times higher than that of CAT 785C. Thus, Equation (2) presents the formula used to calculate the fuel consumption for the CAT 793C truck type in each cycle.

$$F(\frac{l}{cycle}) = 2.17943 + 0.00768 \times PL + 0.00633 \times LT + 0.00793 \times ES + 0.02339 \times ETR + 0.00442 \times LS + 0.0825 \times LTR \quad (2)$$

Within the optimization model, numerous indices, parameters, and decision variables are available. Following is a list of the indices:

t	Index for set of trucks: $t = \{1, \dots, T\}$
s	Index for set of shovels: $s = \{1, \dots, S\}$
d	Index for set of dumping points: $d = \{1, \dots, D\}$
d'	Index for set of locations where trucks are required to dump their load before traveling to the new shovel: $d' = \{1, \dots, D\}$

w — Index for set of weights assigned to individual goals: $w = \{1, 2, 3, 4\}$

g — index for the group of trucks that are currently waiting in a queue of the shovel: $g = \{1, \ldots, NTWS\}$

Following is a list of the decision variables:

x_{tsd} — Binary variable equals to 1 if truck t assigns to the path of shovel s to dumping point d , and 0 otherwise

y^{-}_{sd} — Negative deviation of the met path flow rate and the desired path flow rate for the path between shovel s and dumping point d

y^{+}_{sd} — Positive deviation of the met path flow rate and the desired path flow rate for the path between shovel s and dumping point d

Following is a list of the parameters:

IT_{tsd} — Idle time for shovel s if truck t is assigned to transport material from shovel s to the dumping point d

WT_{tsd} — Wait time for truck t if it is assigned to transport material from shovel s to the dumping point d

N_w — Normalized weights of individual goals based on priority

AF — A factor balancing available trucks with the required capacity of plants

PC_d — Capacity of the plant d: $d = \{1, \ldots, P\} \subset \{1, \ldots, \mathrm{D}\}$

SC_s — Production capacity of shovel s

MP_{sd} — Path flow rate for the path from shovel s to the dumping point d that the production operation has met so far

TC_t — Actual capacity of truck t (tonne)

NTC_t — Nominal capacity of truck t (tonne)

P_{sd} — Path flow rate for the path from shovel s to the dumping point d

TR_{tsd} — Next time truck t reaches shovel s, if truck t is assigned to transport material from shovel s to the dumping point d

SA_{tsd}	Next time shovel s is available to serve truck t, if truck t is assigned to transport material from shovel s to the dumping point d
TNOW	Current time of the operation/simulation
$LD_{td'}$	The distance truck t must travel to reach the dumping point d' to dump its load
$ED_{td's}$	The distance truck t must travel from the dumping point d' to the next expected shovel s
ALT_t	Average loading time of truck t
APL_t	Average payload of truck t
$LV_{td's}$	Average loaded velocity of truck t traveling to dumping point d' and will travel to shovel s after dumping its load
$EV_{td's}$	Average empty velocity of truck t traveling from dumping point d' to the next expected shovel s
$DQ_{td'}$	Queue time for truck t in the queue of the dumping point d'
$DT_{td'}$	Dump time for truck t to dump its material in dumping point d'
$NTWS_s$	Number of trucks waiting in queue at shovel s
ST_g	Spotting time for the truck g in the queue
LT_g	Loading time for the truck g in the queue
α_t	Intercept of truck t for the fuel consumption
β_t	Payload coefficient of truck t for the fuel consumption
γ_t	Loading time coefficient of truck t for the fuel consumption
τ_t	Idle time coefficient of truck t for the fuel consumption
ω_t	Empty traveling time coefficient of truck t for the fuel consumption
φ_t	Loaded traveling time coefficient of truck t for the fuel consumption
SIT_{tsd}	Shovel idle time coefficient, by assigning truck t to the path of shovel s to dumping point d

TWT_{tsd}	Truck wait time coefficient, by assigning truck t to the path of shovel s to dumping point d
F_{tsd}	Truck fuel consumption coefficient, by assigning truck t to the path of shovel s to dumping point d

Equation (3) is utilized for determining the arrival time of each truck t to be loaded by shovel s. Meanwhile, Equation (4) is employed to calculate the shovel availability, representing the next time shovel s is available to load truck t.

$$TR_{tsd} = TNOW + \frac{LD_{td'}}{LV_{td's}} + DQ_{td'} + DT_{td'} + \frac{ED_{td's}}{EV_{td's}} \tag{3}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\} \;\&\; \forall d' \in \{1, \dots, D\}$$

$$SA_{tsd} = TNOW + \sum_{g=1}^{NTWS_s} \left(ST_g + LT_g\right) \tag{4}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\}$$

Equations (5), (6) and (7) are utilized to compute the coefficients for three objectives within the optimization problem. These coefficients correspond to the shovel idle time, truck wait time, and fuel consumption objective functions, respectively.

$$SIT_{tsd} = \max\,(0, TR_{tsd} - SA_{tsd}) \tag{5}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\}$$

$$TWT_{tsd} = \max\,(0, SA_{tsd} - TR_{tsd}) \tag{6}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\}$$

$$F_{tsd} = \alpha_t + \beta_t \times APL_t + \gamma_t \times ALT_t + \tau_t \times TWT_{tsd} + \omega_t\,\frac{ED_{td's}}{EV_{td's}} + \varphi_t\,\frac{LD_{td'}}{LV_{td's}} \tag{7}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\} \;\&\; \forall d' \in \{1, \dots, D\}$$

The model uses the following objective functions:

- Shovel idle time minimization (Eq. 8)
- Truck wait time minimization (Eq. 9)
- Target path flow rates' deviations minimization (Eq. 10)
- Fuel consumption minimization (Eq. 11)

$$f_1 = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{d=1}^{D} SIT_{tsd}x_{tsd} \tag{8}$$

$$f_2 = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{d=1}^{D} TWT_{tsd}x_{tsd} \tag{9}$$

$$f_3 = \sum_{s=1}^{S}\sum_{d=1}^{D} (y_{sd}^{-} + y_{sd}^{+}) \tag{10}$$

$$f_4 = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{d=1}^{D} F_{tsd}x_{tsd} \tag{11}$$

By employing the normalization process outlined in the work of Grodzevich and Romanko (2006), the values of $\bar{f_i}, i = \{1, 2, 3, 4\}$ are calculated for the objectives. This research aims to optimize the weighted sum of the objectives that have been normalized (Equation (12)).

- Weighted sum objective function (Eq. 12)

$$f = N_1\bar{f_1} + N_2\bar{f_2} + N_3\bar{f_3} + N_4\bar{f_4} \tag{12}$$

The constraints used in the model are as follows:

- Truck capacity constraint (Eq. 13)
- Plant production requirement constraint (Eq. 14)
- Shovel digging rate constraint (Eq. 15)
- Deviation of the path flow rate constraint (Eq. 16)
- Truck's assignment binary decision variable (Eq. 17)

- Non-negativity for deviations below the target path flow rate (Eq. 18)
- Non-negativity for deviations above the target path flow rate (Eq. 19)
- Production adjustment factor constraint (Eq. 20)

$$\sum_{s=1}^{S}\sum_{d=1}^{D} TC_t x_{tsd} \leq NTC_t \qquad \forall t \in \{1, \dots, T\} \tag{13}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S} TC_t x_{tsd} \geq AF \times PC_d \qquad \forall d \in \{1, \dots, P\} \tag{14}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D} TC_t x_{tsd} \leq SC_s \qquad \forall s \in \{1, \dots, S\} \tag{15}$$

$$\sum_{t=1}^{T} TC_t x_{tsd} + MP_{sd} + y_{sd}^{-} - y_{sd}^{+} = P_{sd} \quad \forall s \in \{1, \dots, S\} \ \& \ \forall d \in \{1, \dots, D\} \tag{16}$$

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

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

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

$$AF = \frac{\sum capacity\ of\ available\ trucks}{\sum required\ flow\ rate\ at\ paths} \tag{20}$$

The optimization model comprises four distinct objectives, each serving a specific purpose. The first objective aims to minimize the idle time of active shovels by utilizing Equation (8) to calculate the summation of this value. The second objective seeks to minimize the wait time of trucks during operation by computing the summation of this value through Equation (9). As for the third objective, it follows a goal programming approach with the objective of minimizing the deviation from the flow rates of the paths, as calculated in Equation (10). Finally, the fourth objective function targets the minimization of total fuel consumption by active trucks in the system, employing Equation (11) for this purpose. These objectives have different scales and exert varying levels of influence on the system. The model is also characterized as a MILP (Mixed Integer Linear Programming) model and requires a non-preemptive mixed integer linear weighted sum goal programming approach for solving.

To solve the model, the four objectives are transformed into dimensionless objectives by utilizing Nadir (N_i) and Utopia (U_i) points, as proposed in (Grodzevich and Romanko, 2006). In this approach, the Utopia point sets a lower bound for individual objectives, while the Nadir point sets an upper bound. By determining these points, the lower and upper bounds of the interval within which the objective functions will vary in the Pareto optimal set can be established. In case of considering only one objective, the optimization will lead to the Utopia point, which provides the minimum values for individual objectives. The upper bounds, on the other hand, are determined using the components of a Nadir point. The normalization of objectives is achieved by employing Nadir and Utopia points, which scales them within the range of 0 to 1 (Equation (21)). To determine the priority weights necessary for the weighted sum method, each component of the objective function described in Equation (12) is a weighted and normalized version of an individual objective from Equations (8) to (11).

$$\bar{f_i} = \frac{f_i - U_i}{N_i - U_i} \qquad \forall i \in \{1,2,3,4\} \tag{21}$$

A number of constraints are imposed upon the system in order to ensure its efficient operation. A truck is limited to its maximum nominal capacity in terms of the amount of tonnage it can transport in one payload under constraint (13). In regard to constraint (14) it is taken into consideration that the material hauled to the processing plants using all the trucks must meet a portion equal to AF times the processing target required by each plant. The adjustment factor, AF, is calculated using Equation (20), and it is used to adjust the amount of material required at each processing facility. In other words, it is only possible to meet the AF portion of the plant's requirements. Constraint (15) imposes a restriction on the total haulage capacity directed to a shovel, limiting it to the nominal digging rate at that specific shovel. For each path connecting a source to a destination point, constraint (16) calculates the deviation of the path flow rate from the desired path flow rate.

Lastly, constraint (17) assures that the first set of decision variables is binary, and constraints (18) and (19) ensure that the goal programming variables are not negative. To ensure that the system operates efficiently, trucks will be dispatched to shovels after the model has been solved.

3.4 Integrated simulation and optimization Model

The simulation section of the framework incorporates a step-by-step process, as depicted in Figure 3.1. Initially, the model checks for active trucks in need of assignment to active shovels and destinations. Subsequently, the multi-objective optimization model comes into play, efficiently assigning all unassigned trucks. This step ensures that every available truck is efficiently assigned to its appropriate tasks. During the simulation, the optimization model is re-run whenever certain events occur, such as a truck starts working, a truck completes its dumping, or a truck reactivates after a failure. These events trigger the need to reassess the best assignment decision for the truck. The optimization process for assigning available trucks continues throughout the simulation runtime until it reaches the specified time period designated for the simulation.

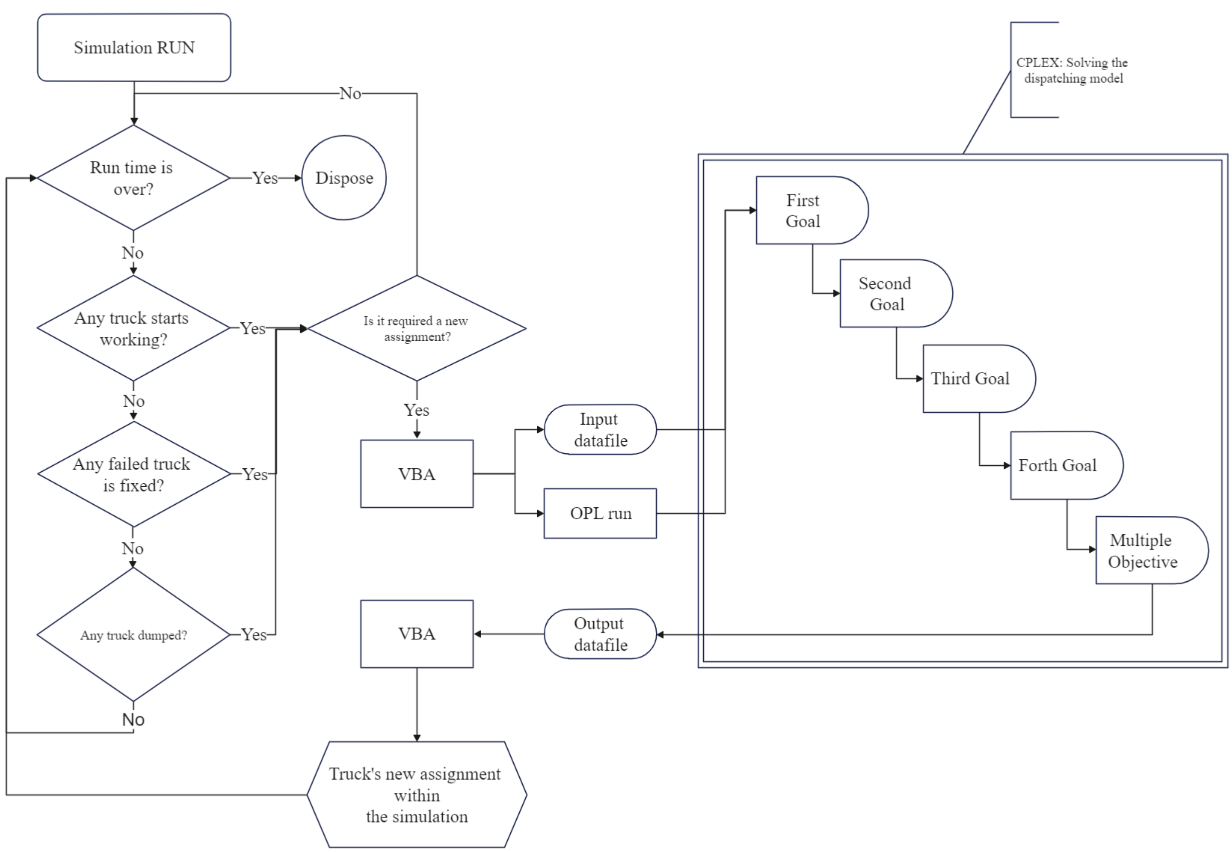

Figure 3.1. Flowchart of the simulation and optimization framework

3.5 Integrated simulation and optimization Model's assumptions

Although the developed dispatching model for trucks in open-pit mines was designed to be comprehensive, there are certain aspects that were not considered in this study. These assumptions include:

- The road network remains unchanged throughout the simulation period, without any reconstruction or maintenance.
- The exclusion of equipment maintenance from the simulation time and optimization model.
- The exclusion of equipment failures for the shovel fleet.
- The mine operates continuously for 12 hours a day.

These assumptions should be taken into consideration when interpreting the results of this study.

3.6 Key performance indicators (KPI)s

One necessary task is to distinguish the independent and dependent variables in the system. The dependent variables measure the performance criteria, while the independent variables represent the system parameters. Modifying the independent variables significantly impacts the dependent variables. Independent and dependent variables also aid in recognizing critical events and controlling them over time (Upreti et al., 2014). The variables listed below are all important key performance indicators (KPIs) in truck dispatching:

1. Total ore tonnage production: This indicates the overall quantity of ore delivered to the plants, which directly impacts the profitability and productivity of the mining operation.
2. Total ore and waste tonnages mined and delivered: Monitoring the total tonnages of both ore and waste materials provides insights into the efficiency of the mining process and helps optimize resource utilization.
3. Utilization of ore and waste shovels: Assessing the utilization of shovels dedicated to handling ore and waste materials helps to ensure their optimal usage and identify potential bottlenecks or underutilized equipment.
4. Total and average queue times for trucks: Tracking the queue times for trucks waiting to be loaded or unloaded provides information on operational efficiency and helps identify areas where delays may occur.

5. Fuel consumption of trucks: Managing fuel consumption is crucial for cost control and energy efficiency. Monitoring and optimizing fuel usage helps minimize operational expenses and reduce carbon emissions.
6. Fuel consumption of a truck per tonne of production: This metric provides insights into the fuel efficiency of trucks in relation to the quantity of material they transport. It helps identify opportunities for improving fuel efficiency and reducing operational costs.
7. Ore TPGOH (tonne per gross operating hour): This indicator measures the productivity of the mining operation by calculating the amount of ore extracted per hour of equipment operation. Higher TPGOH values indicate better efficiency and productivity.
8. Stripping ratio: The stripping ratio compares the volume of waste material removed to the volume of ore extracted. It provides insights into the balance between ore production and waste removal.
9. Trucks' availabilities and their down times: Monitoring the availability of trucks and tracking their down times helps identify potential equipment failure, planned maintenance activities, and minimize disruptions to the mining operation. Also, it can affect the TPGOH significantly.

Overall, these variables play a significant role in evaluating and optimizing truck dispatching in mining operations, enabling better decision-making, improved operational efficiency, and enhanced profitability.

3.7 Limitations of the model

While the developed models in this study encompass several important objectives and constraints, it is essential to acknowledge that actual open-pit mining operations involve numerous additional factors that must be taken into account. Some of these factors include:

- Shovels’ failures
- Presence of stockpile
- Dynamic changes in dump locations
- Road development

Especially, shovel’s failure and the presence of stockpile have noticeable impact on the haul fleet selection, sizing, and dispatching. Shovel’s failure can noticeably decrease the production rate and directly impact the number of trucks required and their dispatching decisions. The presence of stockpiles can improve hauling efficiency by providing a buffer between the excavation and processing stages. Stockpiles allow for continuous material flow, especially during equipment shutdowns. Consequently, decision-making processes in real-world mining scenarios must consider these complex variables to ensure more accurate and effective decision-making in the truck dispatching problem.

Another limitation of this study is the assignment of a 5% optimality gap in the optimization process. While this parameter was necessary to ensure computational feasibility, it's important to note that a lower optimality gap is generally considered better for achieving more accurate results. A smaller optimality gap indicates that the solution obtained by the optimization model is closer to the theoretical optimal solution. This limitation might affect the precision of the results and their comparison with other methods in this thesis. Ideally, a smaller optimality gap would allow for a more accurate evaluation and comparison of the method with others in the field. However, due to computational constraints or other practical considerations, the 5% optimality gap was chosen. It's essential to keep this limitation in mind when interpreting and generalizing the findings presented in this thesis.

4 DESIGN OF EXPERIMENTS, VERIFICATIONS, AND RESULTS

4.1 Input data and case study

The Gol-E-Gohar iron ore mine, located in Iran's Kerman Province, employs a truck and shovel material handling system to carry out its mining operations in one of its 12 ore deposits. In Figure 4.1, the layout of loading and dumping points, as well as the road network for the 11th year of operation at the Gol-E-Gohar iron ore mine, is illustrated. The operation involves five shovels, with two allocated for extracting ore materials and three for removing waste. Trucks hauling waste materials have only one destination option to transport their loads. On the other hand, trucks carrying ore materials from each ore shovel have two destination options available to them for unloading their loads in either of the plants 1 or 2. Figure 4.2 provides a clearer depiction of the variations in elevation between the ore and waste materials.

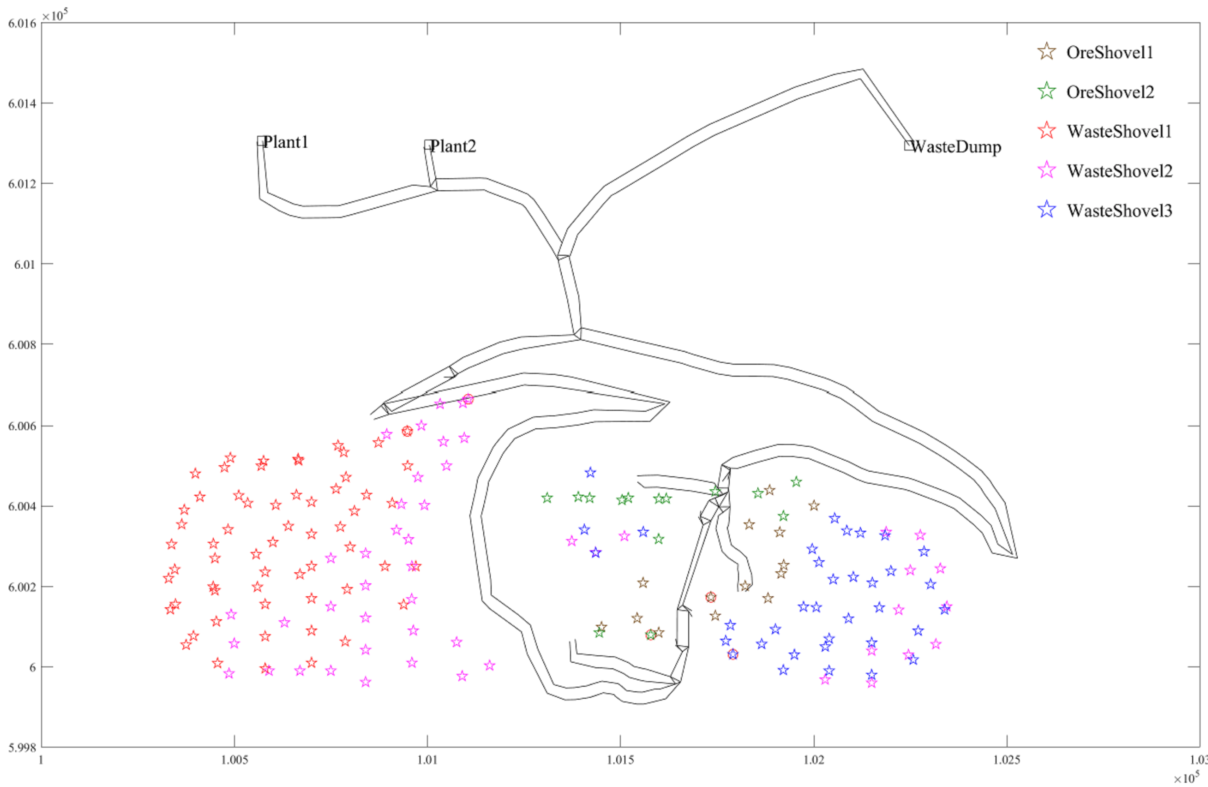

Figure 4.1. Gol-E-Gohar iron ore mine road network with loading and dumping locations

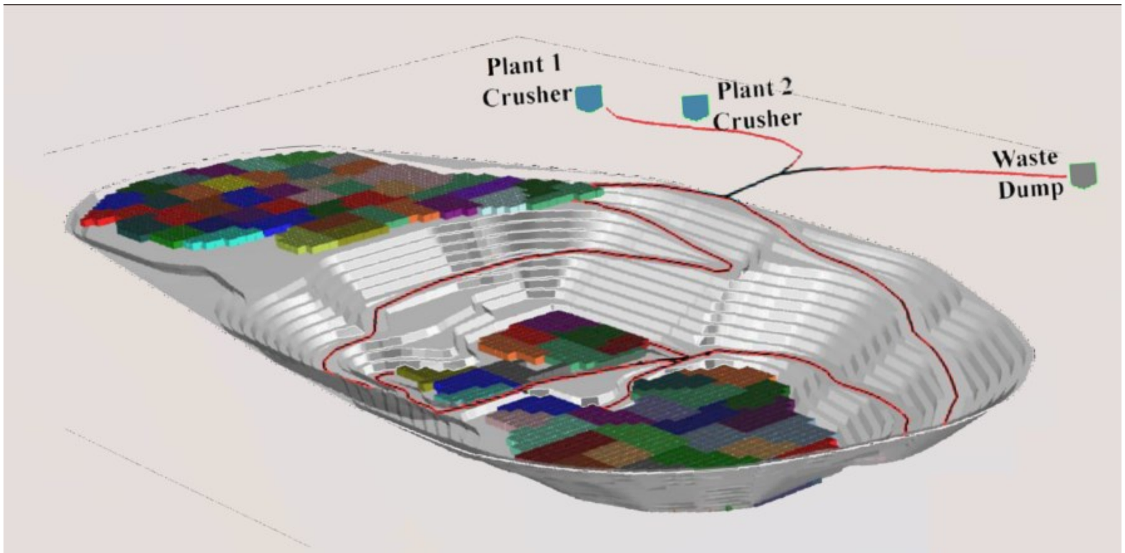

Figure 4.2. Gol-E-Gohar iron ore pit and road network (Moradi Afrapoli, 2018)

In the evaluation, Hitachi EX2500 and Hitachi EX5500 excavators were encountered, as well as Cat 785C and 793C trucks for the hauling process. The mining operation has three destination locations: two processing plants, each having two hoppers, and one waste dump with multiple dumping points. Table 4.1 presents the allocation of shovels and trucks to the digging and dumping points.

Table 4.1. Available destinations and fleet specification

Origin	Destinations	Shovel Type	Possible Truck Types
Shovel 1	Plant 1 Plant 2	Hitachi EX2500	Cat 785C Cat 793C
Shovel 2	Plant 1 Plant 2	Hitachi EX2500	Cat 785C Cat 793C
Shovel 3	Waste Dump	Hitachi EX5500	Cat 785C Cat 793C
Shovel 4	Waste Dump	Hitachi EX5500	Cat 785C Cat 793C
Shovel 5	Waste Dump	Hitachi EX2500	Cat 785C Cat 793C

Table 4.2 illustrates the distances, measured in meters, between each shovel and corresponding dumping point. It is important to note that each value represents the average distance from the origin points to the specific destination point.

Table 4.2. Distances in meters

	Plant 1	**Plant 2**	**Waste Dump**
Shovel 1	**4311**	**3808**	4397
Shovel 2	**3972**	**3469**	4058
Shovel 3	2308	1805	**2394**
Shovel 4	2892	2389	**2978**
Shovel 5	4243	3740	**4329**

The input data for the case study comprises both deterministic and stochastic data. Stochastic input distributions (retrieved from (Moradi Afrapoli, 2018)) were determined using historical data through the Arena Input Analyzer tool (Rockwell Automation, 2019). Incorrect analysis of collected data and choosing the wrong distribution can lead to an unrealistic representation of the system in a simulation model (Upreti et al., 2014).

Table 4.3, and Table 4.4 display the characteristics for each shovel type and each truck type, respectively.

Table 4.3. Shovels characteristics

Shovel Type	**Maximum digging rate (tph)**	**Capacity (t)**	**Cycle time (s)**
HIT 2500	2300	NORM(14, 1)	NORM(17, 0.5)
HIT 5500	1850	NORM(21, 2)	NORM(16, 1)

Table 4.4. Trucks characteristics

Truck Type	**Capacity (t)**	**Backing time (s)**	**Dumping time (s)**	**Empty velocity(m/s)**	**Loaded velocity(m/s)**
CAT 785C	140	9.5 + GAMM(7, 1)	NORM(60, 27)	NORM(10.4, 3.5)	7 + GAMM(0.8, 1.6)
CAT 793C	240	0.5 + ERLA(5, 3)	NORM(52, 21)	NORM(10.2, 3.2)	2.3 + LOGN(5.2, 2.1)

Table 4.5 showcases the spot time in seconds for every combination of truck type and shovel type.

Table 4.5. Spot time distributions

Spot Time (s)	HIT 2500	HIT 5500
CAT 785C	LOGN(32, 26)	LOGN(69, 94)
CAT 793C	LOGN(42, 41)	LOGN(79, 114)

Table 4.6 demonstrates the best fitted distribution on the number of loading passes of each shovel type loading each truck type.

Table 4.6. Number of loading passes distributions

Number of Loading Passes	HIT 2500	HIT 5500
CAT 785C	DISC(0.34,9,0.69,10,1,11)	DISC(0.49,5,1,6)
CAT 793C	DISC(0.24,14,0.53,15,0.79,16,1,17)	DISC(0.36,9,0.72,10,1,11)

The mine has two processing plants, each equipped with a crusher that has two hoppers to ensure a constant supply of material. 2300 tonnes of ore material per hour is the target feed rate for each crusher (Table 4.7). Waste material mined from the mining faces is transported by trucks to a waste dump, where scrapers are actively working to accommodate simultaneous dumping by trucks.

Table 4.7. Target feed rates of the active processing plants

Dumping point	Target feed rate (tph)
Plant 1 Crusher	2300
Plant 2 Crusher	2300

The simulation run time and the number of replications employed in this case study are presented in Table 4.8. The model is designed to simulate a 10-day operation with 12 hours of operation per day. The precision and reliability of the outcomes are influenced by the suitable runtime and the number of replications. By running the simulation multiple times, the effects of randomness and variability can be reduced, leading to more robust outcomes. This is particularly crucial when dealing with complex systems or scenarios with uncertainty. Additionally, a higher number of replications enhances the statistical validity of the results, allowing for better inference and generalization to real-world situations. It also enables the analysis of rare events or low-probability scenarios. Overall, a higher number of replications increases confidence in the simulation results and improves decision-making.

Table 4.8. Simulation runtime and operation time period

Number of simulation replications	Operational planning duration (days)	Daily operating hours
5	10	12

The operational planning time frame in this case was set to 10 days with 12 daily operating hours. By computing statistics, particularly confidence intervals, around the KPIs, we assess the precision and reliability of the results from the 5 replications. The narrow confidence intervals and consistent estimated values of the KPIs across the replications suggest that the simulation model's outcomes are stable and reliable with 5 replications.

The requirements for the productions of ore and waste material within 10 operating days are listed in Table 4.9.

Table 4.9. 10 days production requirements

Total material (kt)	Ore material (kt)	SR
1270	552	1.3

The input data used in this research is identical to the input data utilized in the study conducted by (Moradi Afrapoli, 2018; Moradi Afrapoli et al., 2019).

The rest of this chapter is divided into three subsections: scenarios involving modifications of objective weights, scenarios examining fleet size and truck types, and scenarios considering truck failures. However, the benchmark models are compared with the selected scenario from the first part, which involves adjusting the weights of objectives, and the fleet consists of 30 CAT 785C trucks without any occurrences of truck failures.

4.2 Objectives' weights

Selecting appropriate weights for the objective function is a critical aspect of multi-objective optimization problems that demands a deep comprehension of the problem domain and optimization objectives. One approach to determine the weights involves seeking insights and preferences from subject matter experts or stakeholders about the relative significance of different objectives. Another method involves conducting sensitivity analysis to observe changes in the objective function values resulting from varying the weights of the objectives. The choice of weights should stem from a thorough comprehension of the problem, taking into account stakeholder preferences, and carefully analyzing the trade-offs among different objectives. In the Table 4.10 and Table 4.11, various scenarios have been defined with different weights for the objective functions and their corresponding KPIs.

Table 4.10. Weights of the objective functions

Scenario	W1(SIT)	W2(TWT)	W3(PD)	W4(FC)
S1	0.1	0.25	0.55	0.1
S2	0.3	0.1	0.5	0.1
S3	0.1	0.2	0.5	0.2
S4	0.1	0.1	0.4	0.4
S5	0.1	0.3	0.4	0.2
S6	0.2	0.3	0.4	0.1
S7	0.25	0.25	0.25	0.25
S8	0.1	0.1	0.7	0.1
S9	0.1	0.1	0.2	0.6
S10	0.6	0.1	0.2	0.1
S11	0.1	0.6	0.2	0.1
S12	0.1	0.35	0.55	0
S13	1	0	0	0
S14	0	1	0	0
S15	0	0	1	0
S16	0	0	0	1

Table 4.11. Weighted scenarios' KPIs

Scenario	Utilization Ore (%)	Utilization Waste (%)	Q Time (Mins)	FC (KL)	Ore Tonnage (KT)	Total Tonnage (KT)	OTPGOH (T)
S1	81.18	55.98	3.66	415.71	552.29	1272.61	4602.46
S2	81.23	56.07	3.73	413.80	552.36	1273.03	4602.97
S3	81.19	56.22	3.75	412.53	552.18	1277.73	4601.48
S4	81.14	56.38	3.66	414.88	552.26	1279.06	4602.19
S5	81.19	56.23	3.68	414.85	552.36	1277.72	4602.99
S6	81.28	56.19	3.71	414.05	552.28	1275.51	4602.32
S7	81.17	56.23	3.66	415.53	552.36	1276.74	4602.97
S8	81.03	56.31	3.66	415.43	552.44	1276.66	4603.70
S9	81.16	56.22	3.85	410.04	552.39	1277.51	4603.23
S10	81.28	56.19	3.61	416.56	552.30	1276.54	4602.49
S11	81.17	56.26	3.62	416.41	552.35	1278.04	4602.93
S12	81.23	55.86	3.62	417.11	552.33	1270.68	4602.77
S13	81.23	56.16	3.64	416.17	552.33	1274.78	4602.71
S14	81.15	55.32	3.59	419.69	552.35	1263.39	4602.88
S15	81.15	50.95	4.16	416.98	552.37	1205.09	4603.08
S16	81.08	55.70	4.18	402.65	552.36	1269.25	4602.96

The results presented in Table 4.11 demonstrate the consistency and stability of Key Performance Indicators (KPIs) across different scenarios, which can be attributed to the constraints of the mathematical model. As a result, most of these KPIs show relatively minor fluctuations within a narrow range, regardless of any adjustments made to the weights of objective functions. Notably, the Total Tonnage and Fuel Consumption indicators exhibit the most significant variations. Particularly, the weight of the fuel consumption objective function (W4) has a strong negative correlation of -0.91 with the total fuel consumption in the simulation model. Additionally, other objective functions' weights also demonstrate correlations with their corresponding KPIs. It is worthy to note that the correlation coefficient between Total Fuel Consumption and Average Queue Time of Trucks is -0.63, suggesting a negative relationship between these two variables.

Considering that the main goal of this research is to minimize fuel consumption while ensuring an acceptable production rate within the 10-day period, we have chosen weight scenario number 9 for further examination and comparison with the benchmark models. Total production, Average truck queue time, and total fuel consumption are displayed for all of scenarios in Figure 4.3, and Figure 4.4.

Figure 4.3. Total production for different scenarios

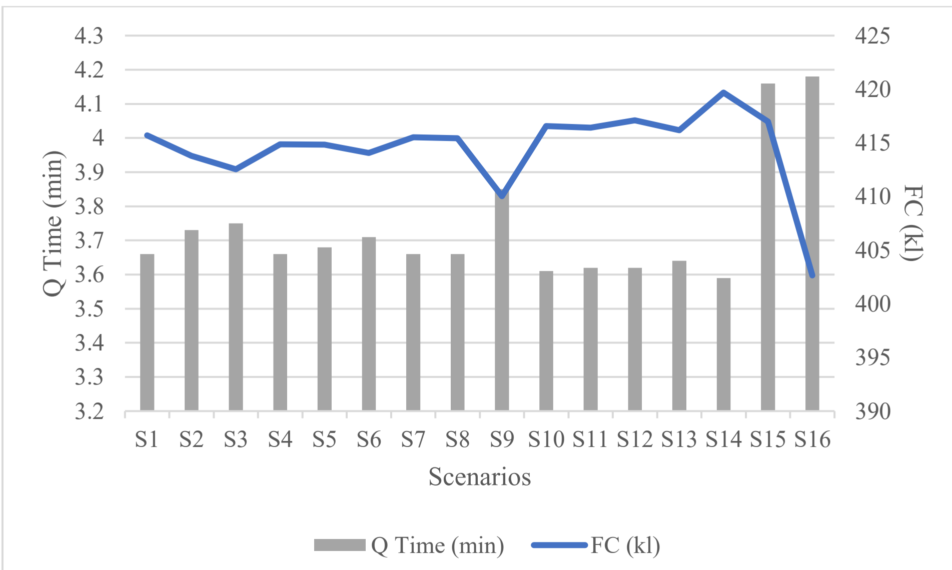

Figure 4.4. Fuel consumption and queue time in each scenario

4.2.1 Comparison with the benchmark models

In this section, the Quad-Obj. model (model number 3) (the proposed model in this research) is compared with the Modular Mining Dispatch model (model number 1) and Tri-Obj. model (model number 2) (both models retrieved from (Moradi Afrapoli et al., 2019)), examining various key performance indicators (KPIs) such as tonnages transported to different destinations, stripping ratio, Ore TPGOH (tonne per gross operating hour) on a daily basis, waste tonnage per operating day, total fuel consumption, fuel consumption per tonne of production, shovels' utilization, shovels' queue time, tonnages extracted by each shovel, and plants' queue time. Statistical data including mean, standard deviation, median, standard error, and confidence level are provided for these KPIs. It is worth considering that, on average, each experiment consisting of 5 replications had a runtime of 60 minutes for the Quad-Obj. model and 50 minutes for the Tri-Obj. model.

4.2.1.1 Production Tonnages Statistics

The data in the Table 4.12, Table 4.13, and Table 4.14 represents tonnages statistics for three different destinations of Plant 1, Plant 2, and the Waste Dump respectively. Regarding plant 1, the Modular Mining Dispatch model has a mean tonnage of 237.64 kt, while the Tri-Obj. and Quad-Obj. models have means of 276.19 kt and 276.22 kt, respectively. The Tri-Obj. and Quad-Obj. models show an increase of approximately 16.23% compared to the Modular Mining Dispatch model. Regarding plant 2, the Modular Mining Dispatch model has a mean tonnage of 248.79 kt, while the Tri-Obj. and Quad-Obj. models have means of 276.21 kt and 276.19 kt, respectively. The Tri-Obj. and Quad-Obj. models exhibit an increase of around 11.01% compared to the Modular Mining Dispatch model. Regarding waste dump, the Modular Mining Dispatch model yields a mean tonnage of 857.56 kt, while the Tri-Obj. and Quad-Obj. models have means of 698.95 kt and 725.12 kt, respectively. The Tri-Obj. and Quad-Obj. models show a decrease of approximately 18.5%, and 15.44% compared to the Modular Mining Dispatch model. The standard deviations and standard errors are relatively small for all models, indicating consistency in tonnage estimates. The confidence levels are also reasonably low, suggesting high reliability in the model results.

Table 4.12. Plant 1 Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	237.64	1.73	237.47	0.77	2.15
Tri-Obj.	276.19	0.03	276.18	0.02	0.04
Quad-Obj.	276.22	0.03	276.24	0.01	0.03
Diff. 2 to 1 (%)	16.22	-98.06	16.3	-98.06	-98.06
Diff. 3 to 1 (%)	16.23	-98.4	16.33	-98.4	-98.4
Diff. 3 to 2 (%)	0.01	-17.62	0.02	-17.62	-17.62

Table 4.13. Plant 2 Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	248.79	0.49	248.77	0.22	0.61
Tri-Obj.	276.21	0.04	276.23	0.02	0.05
Quad-Obj.	276.17	0.05	276.17	0.02	0.06
Diff. 2 to 1 (%)	11.02	-91.55	11.04	-91.55	-91.55
Diff. 3 to 1 (%)	11.0	-90.74	11.02	-90.74	-90.74
Diff. 3 to 2 (%)	-0.02	9.62	-0.02	9.62	9.62

Table 4.14. Waste Dump Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	857.56	3.68	858.08	1.65	4.57
Tri-Obj.	698.95	3.8	697.89	1.7	4.72
Quad-Obj.	725.12	1.23	725.32	0.55	1.53
Diff. 2 to 1 (%)	-18.5	3.36	-18.67	3.36	3.36
Diff. 3 to 1 (%)	-15.44	-66.6	-15.47	-66.6	-66.6
Diff. 3 to 2 (%)	3.74	-67.68	3.93	-67.68	-67.68

Figure 4.5 illustrates the quantities of materials transported to plant 1, plant 2, and the waste dump across all models. Despite the Modular Mining Dispatch model transferring larger overall tonnages, it falls short in meeting the capacity of the plants, resulting in less ore being transported and a higher amount of waste being moved. In contrast, both the tri-obj. and quad-obj. models effectively meet the plants' capacity requirements, as shown in Figure 4.6. However, the quad-obj. model transports a higher volume of waste materials, surpassing the tri-obj. model by 3.74% (equivalent to 26.17 kt).

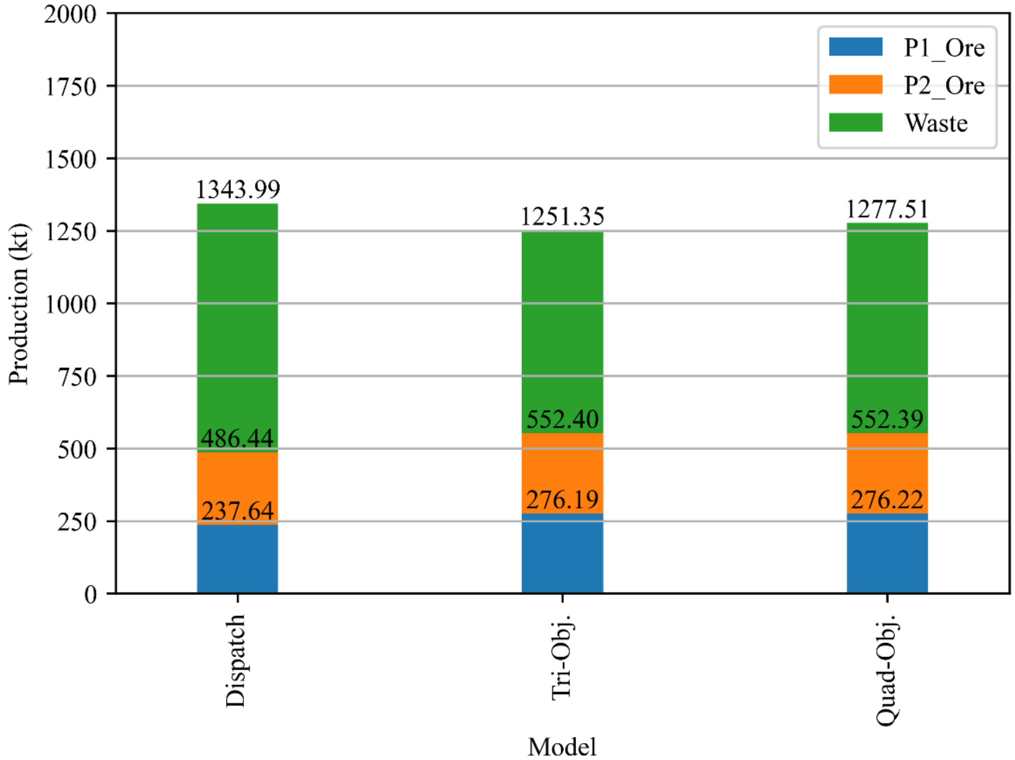

Figure 4.5. Tonnage Statistics for Plant1, Plant2, and Waste Dump for all modelss

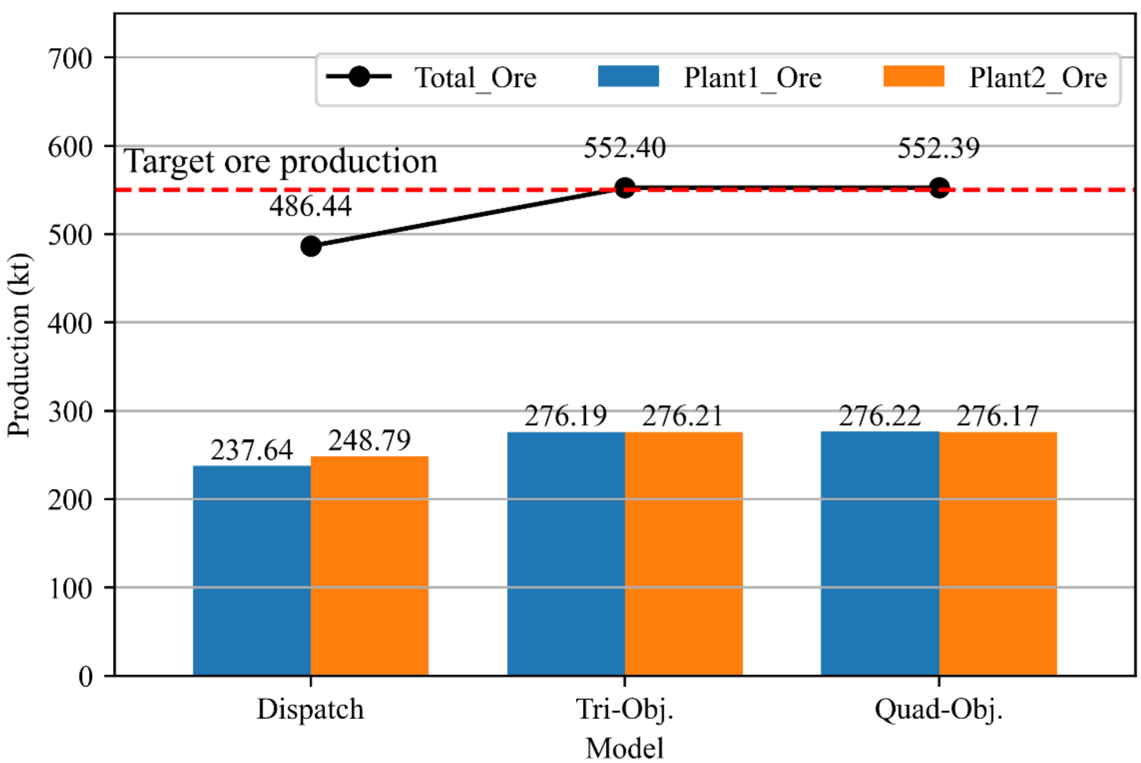

Figure 4.6. Production statistics for plant1, and plant2

The Tri-Obj. Model has the lowest average stripping ratio of 1.27, indicating a relatively lower waste-to-ore ratio compared to the other models. The Quad-Obj. Model has slightly higher average stripping ratio of 1.31, that is because of the higher waste production. The Modular Mining Dispatch model average stripping ratio is 1.76 which is significantly higher than other models. The absence of standard deviation and standard error values suggests that there is no significant variability or uncertainty associated with the mean value of stripping ratio. Table 4.15 and Figure 4.7 compare models regarding the stripping ratio.

Table 4.15. Stripping Ratio Statistics

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	1.76	0.0	1.76	0.0	0.01
Tri-Obj.	1.27	0.01	1.26	0.0	0.01
Quad-Obj.	1.31	0.0	1.31	0.0	0.01
Diff. 2 to 1 (%)	-28.23	69.6	-28.29	69.6	69.6
Diff. 3 to 1 (%)	-25.51	12.21	-25.51	12.21	12.21
Diff. 3 to 2 (%)	3.79	-33.84	3.87	-33.84	-33.84

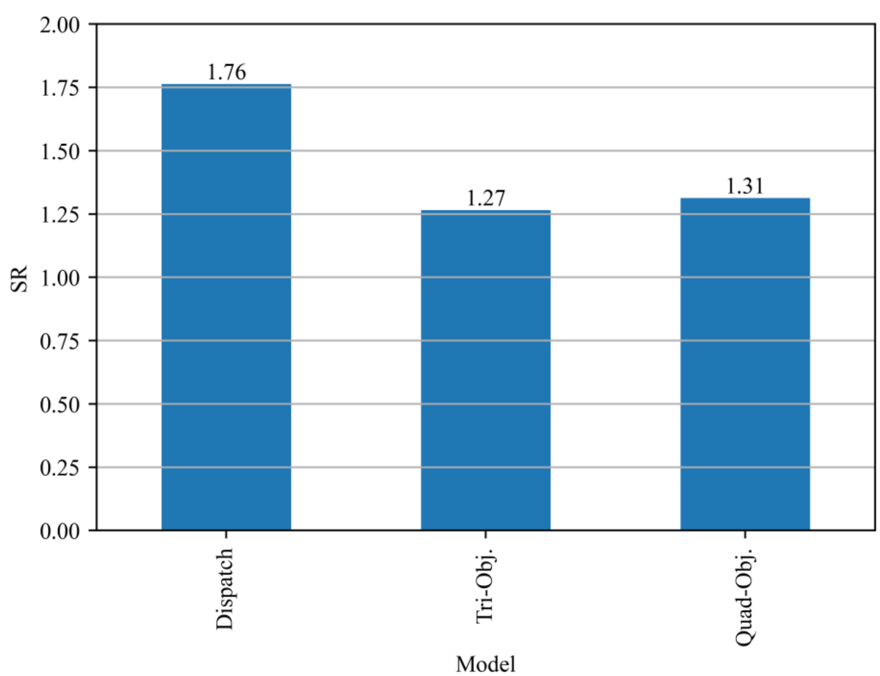

Figure 4.7. Stripping Ratio of all models

The Tonne per Gross Operating Hour (TPGOH) is a key performance indicator that holds significance across industries such as manufacturing, mining, and transportation. It is crucial because it measures operational efficiency, tracks performance, and optimizes costs. By evaluating the amount of material or product produced per hour of operation, organizations can identify inefficiencies, improve productivity, reduce costs, and compare their performance against industry standards. TPGOH serves as a valuable tool for driving operational excellence and resource optimization. The Modular Mining Dispatch model has the lowest average TPGOH of 4053.63, while the Tri-Obj. and Quad-Obj. models have similar averages TPGOH of 4603.34 and 4603.23, respectively. Both the tri-obj. and quad-obj. models utilize the entire hopper capacity, which is set at 2300 tonnes per hour for each plant. This utilization of the full hopper capacity contributes to the increased ore production in both models. Table 4.16 presents the TPGOH statistics for all models. Figure 4.8 shows the average TPGOH levels of all models for 10 days simulation run time.

The average TPGOH statistics for each operating day, including the average values from all replications (Avg) and their corresponding confidence levels (CL), are displayed in Table 4.17 and Figure 4.9. Higher TPGOH values are exhibited by the Tri-Obj. and Quad-Obj. models compared to the Modular Mining Dispatch model. Additionally, the average TPGOH levels remain relatively consistent across all the days.

Table 4.16. TPGOH Statistics

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	4053.63	14.86	4054.47	6.65	18.45
Tri-Obj.	4603.34	0.21	4600.05	0.09	0.26
Quad-Obj.	4603.23	0.41	4601.15	0.18	0.5
Diff. 2 to 1 (%)	13.56	-98.59	13.56	-98.59	-98.59
Diff. 3 to 1 (%)	13.56	-97.27	13.55	-97.27	-97.27
Diff. 3 to 2 (%)	0.0	-93.52	-0.01	93.52	93.52

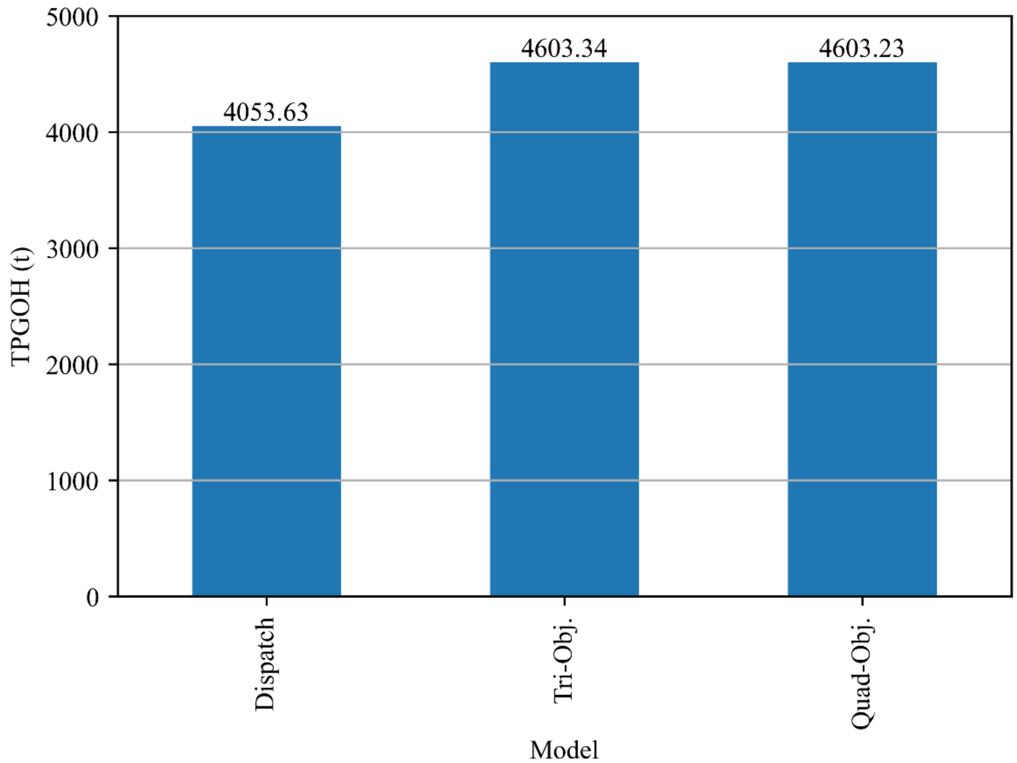

Figure 4.8. TPGOH Comparison

Table 4.17. TPGOH Statistics for 10 operating days

Day	Dispatch (Avg)	TriObj (Avg)	QuadObj (Avg)	Dispatch (CL)	TriObj (CL)	QuadObj (CL)
1	4012.86	4629.99	4625.3	120.67	141.13	127.78
2	4076.25	4601.35	4600.16	78.58	43.15	63.83
3	4038.46	4591.63	4601.78	80.97	35.3	37.91
4	4073.57	4612.03	4603.89	69.19	41.89	39.56
5	4015.35	4598.24	4591.76	78.68	38.82	42.23
6	4053.8	4599.2	4608.87	70.86	37.16	51.77
7	4075.8	4598.71	4587.45	75.12	49.5	43.51
8	4100.51	4597.2	4610.56	58.43	36.58	53.68
9	4034.97	4604.05	4600.06	78.55	36.92	44.82
10	4054.77	4601.03	4602.51	70.4	37.37	36.27

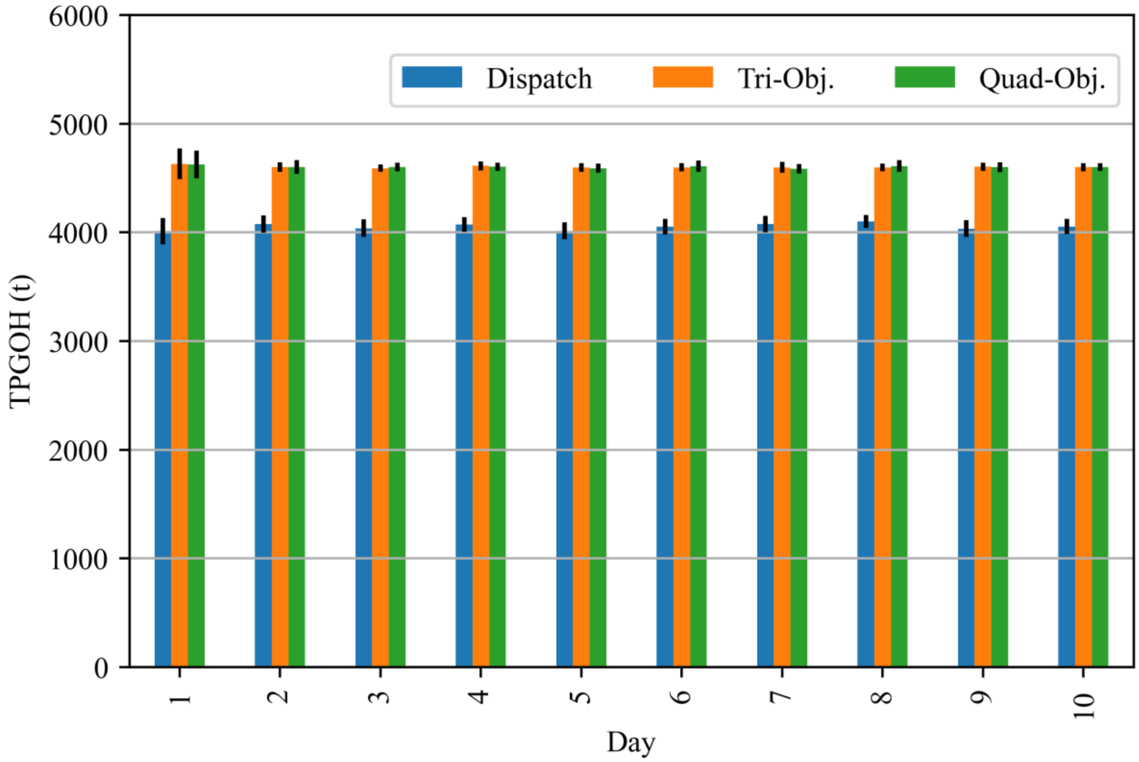

Figure 4.9. TPGOH for 10 operating days

In terms of delivered tonnages, the Quad-Obj. model demonstrates its superiority over the Tri-obj. model in the transportation of waste materials. Waste tonnage Statistics for 10 operating days is shown in Table 4.18.

Figure 4.10 clearly indicates that the Quad-Obj. model consistently achieves higher waste delivery compared to the Tri-Obj. model on each day. However, it is worth noting that the Modular Mining Dispatch model surpasses both models in waste delivery, with significantly higher values than the Quad-Obj. model, within each day. Despite this, it is important to highlight that the Modular Mining Dispatch model fails to meet the required ore tonnages delivery for each plant.

Table 4.18. Waste tonnage Statistics for 10 operating days (kt)

Day	Dispatch (Avg)	TriObj (Avg)	QuadObj (Avg)
1	85.83	73.48	75.15
2	85.55	69.68	72.49
3	84.77	68.93	72.17
4	85.72	69.22	71.9
5	86.34	69.6	72.67
6	85.83	69.7	72.57
7	86.02	70.31	70.94
8	86.66	68.87	72.67
9	85.5	68.92	72.33
10	85.33	70.23	72.21

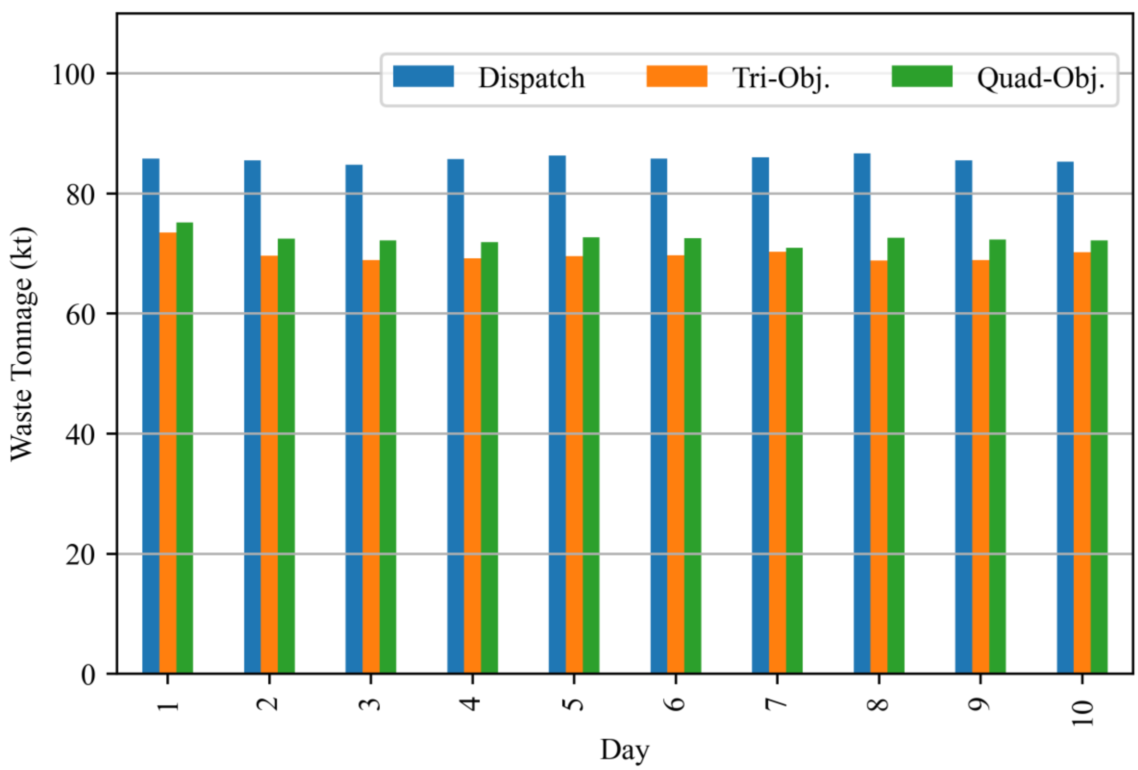

Figure 4.10. Waste tonnage for 10 operating days

4.2.1.2 Fuel Consumption Statistics

fuel consumption is crucial in mining fleet management due to its impact on cost efficiency, GHG mitigation, operational efficiency, and overall competitiveness. In this research, the primary emphasis is on minimizing fuel consumption, making it the most significant Key Performance Indicator (KPI) after achieving satisfaction in ore tonnages production.

As shown in Table 4.19, the fuel consumption of Quad-Obj model is 12190 liters lower than the previous model (Tri-Obj. benchmark model). Based on the table provided, it can be observed that there is low variability in average fuel consumption across all models.

Table 4.19. Fuel Consumption Statistics (kl)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	370.08	0.85	370.17	0.38	1.05
Tri-Obj.	422.23	2.14	421.97	0.96	2.66
Quad-Obj.	410.04	4.53	410.27	2.03	5.63
Diff. 2 to 1 (%)	14.09	153.34	13.99	153.34	153.34
Diff. 3 to 1 (%)	10.8	436.03	10.83	436.03	436.03
Diff. 3 to 2 (%)	-2.89	111.58	-2.77	111.58	111.58

The Modular Mining Dispatch model exhibits the lowest fuel consumption, primarily attributed to its focus on selecting the shortest path for each truck and delivering more waste materials rather than ore materials. This is influenced by the shorter distances between waste polygons and the waste dump in comparison to the distances between ore polygons and plant 1 and plant 2. Figure 4.11 is the fuel consumption plot for Dispatch, Tri-Obj., and Quad-Obj. models.

Purhamadani et al. (2021) considered the amount of energy consumed for the transportation of a certain quantity of minerals extracted as a criterion to evaluate and compare models in term of fuel efficiency. The liters of diesel utilized by each model to transport one tonne of ore materials is depicted in Figure 4.12. The Quad-Obj. model was found to exhibit the lowest fuel consumption per tonne of ore production, resulting in a reduction of about 2.88% compared to the Tri-Obj.

model (equivalent to approximately 22050 liters deduction). When total production, including waste materials, is taken into account, this reduction in fuel consumption is increased to 4.88%.

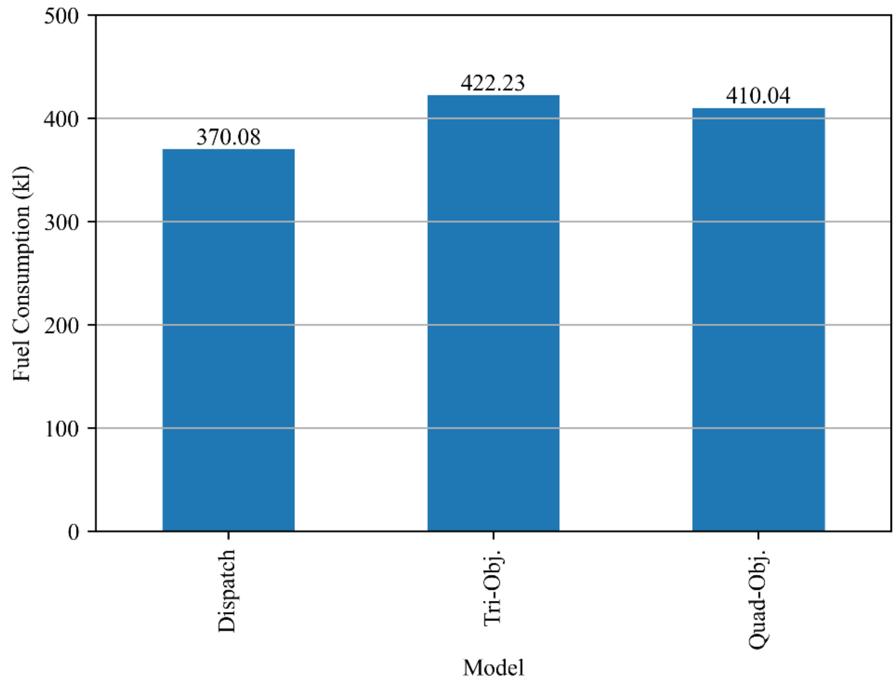

Figure 4.11. Fuel Consumption

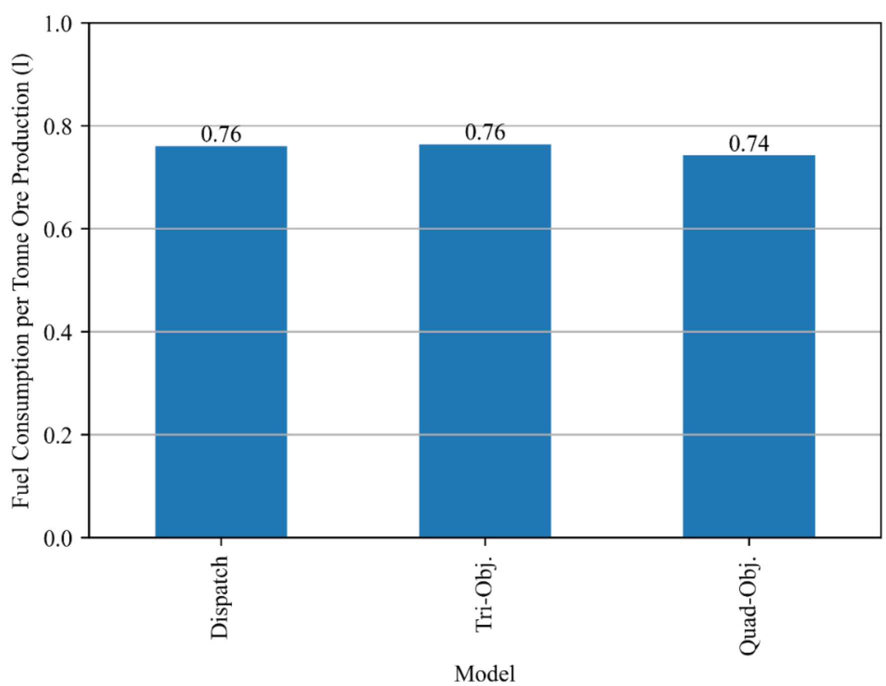

Figure 4.12. Fuel Consumption Per Tonne Ore Production

Figure 4.13 shows the quantity of liters utilized by each model to generate 1000 tonnes of ore materials as well as a bar chart for the total fuel consumption for each model.

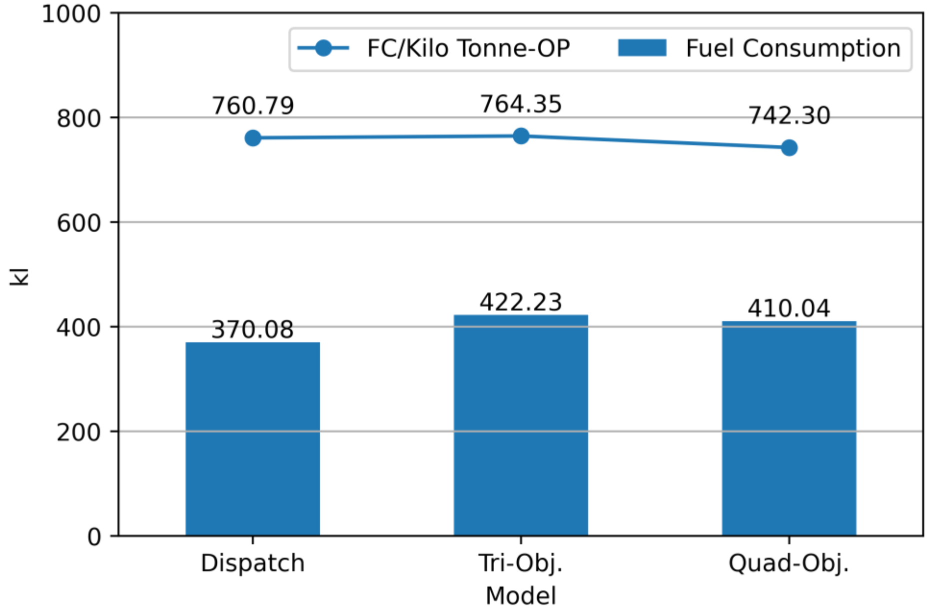

Figure 4.13. Fuel consumption per a kilo tonne ore production

4.2.1.3 Shovels utilization statistics

Efficient utilization of shovels is crucial in mining operations for various reasons:

- Enhanced Productivity: Shovels are instrumental in the excavation and loading process, particularly in open-pit mining. Maximizing shovel utilization results in efficient material handling, leading to increased productivity and the achievement of production targets.
- Improved Equipment Efficiency: Shovel utilization directly impacts equipment performance. Optimized utilization minimizes downtime and idle periods, ensuring that the equipment remains active and productive. Effective utilization strategies, such as reducing waiting times and optimizing maintenance schedules, contribute to overall equipment efficiency.
- Cost Optimization: Shovel utilization directly affects operational costs. By maximizing utilization, mining operations can reduce fuel consumption, maintenance expenses, and labor requirements. Smart planning and scheduling of shovel activities optimize resource allocation, resulting in cost savings.

- Streamlined Time Management: Shovels often serve as critical bottlenecks in mining operations. Efficient utilization of shovels minimizes delays and facilitates the smooth flow of materials, enabling effective time management. This minimizes production disruptions caused by shovel-related issues.
- Safety and Risk Mitigation: Proper shovel utilization ensures a safe working environment. Effective utilization practices, including operator training and adherence to safety protocols, reduce the risk of accidents and equipment failures. Well-managed shovel utilization enhances operational control and reduces the potential for incidents.
- Operational Planning and Optimization: Shovel utilization data provides valuable insights for operational planning and optimization. Monitoring and analyzing utilization patterns help identify areas for improvement, optimize resource allocation, and enhance operational efficiency. Utilizing this data-driven approach supports informed decision-making and continuous improvement efforts.

In summary, optimizing shovel utilization is essential for mining operations, driving productivity, equipment efficiency, cost optimization, time management, safety, and operational planning. By maximizing shovel utilization, mining operations can enhance performance, increase productivity, control costs, and achieve long-term success.

Table 4.20 presents the average utilization data for five different shovels (Shovel 1, Shovel 2, Shovel 3, Shovel 4, and Shovel 5) across three different models. Shovel 1 and shovel 2 extract ore materials while shovel 3, shovel 4, and shovel 5 extract waste materials.

Table 4.20. Shovels Utilization (%)

Model	Shovel 1	Shovel 2	Shovel 3	Shovel 4	Shovel 5
Dispatch	73.25	69.88	57.26	56.82	84.56
Tri-Obj.	81.11	81.28	44.59	44.94	74.19
Quad-Obj.	81.22	81.1	44.93	49.89	73.84
Diff. 2 to 1 (%)	10.73	16.31	-22.13	-20.91	-12.26
Diff. 3 to 1 (%)	10.88	16.06	-21.53	-12.2	-12.68
Diff. 3 to 2 (%)	0.14	-0.22	0.76	11.01	-0.47

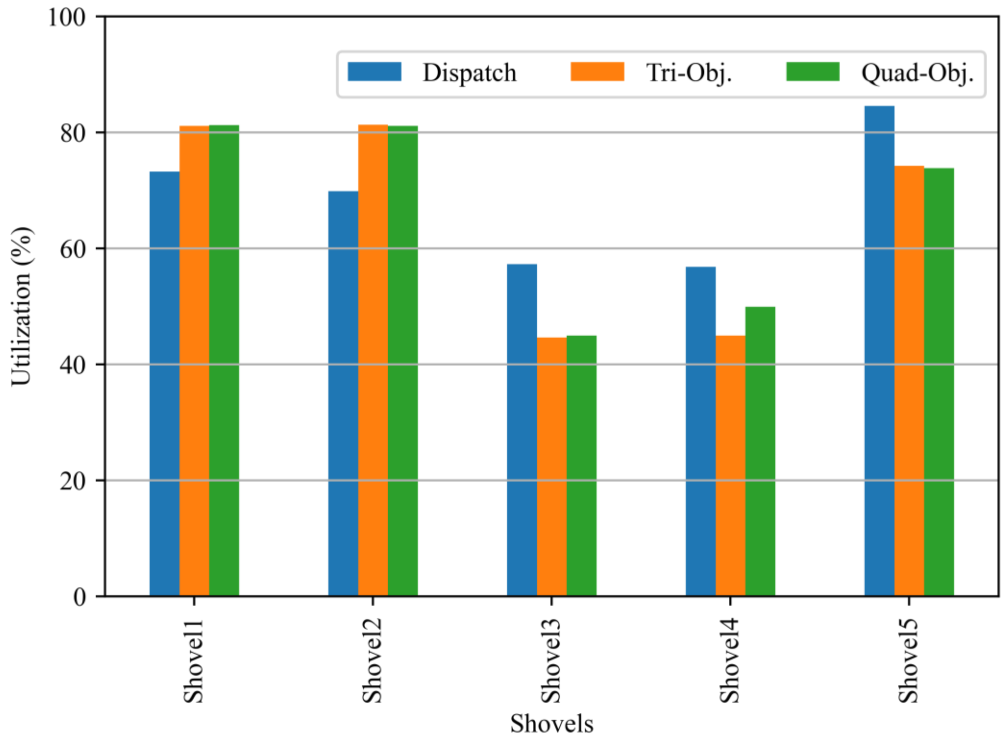

Figure 4.14. Shovels Utilization

Figure 4.14 illustrates the average utilization patterns of ore and waste shovels in the Dispatch, Tri-Obj., and Quad-Obj. models. The higher average utilization for ore shovels is observed in the Tri-Obj. and Quad-Obj. models, while the average utilization for waste shovels is lower when compared to the Modular Mining Dispatch model. When comparing the Tri-Obj. model and Quad-Obj. model, it is apparent that the average utilization rates for ore shovels including shovel 1 and shovel 2, are quite similar in both models. Additionally, in both models, shovel 1 and shovel 2 operate at similar rates, with their average utilization hovering around 81%. However, in the Modular Mining Dispatch model, the average utilization values for shovel 1 and shovel 2 are approximately 73% and 70% respectively, indicating a lower utilization compared to the Tri-Obj. and Quad-Obj. models. In terms of waste shovels, shovel 5 exhibits higher utilization in all models due to its higher capacity and digging rate. The average utilization of shovel 5 in the Tri-Obj. and Quad-Obj. models is around 74%, which is more than 10% lower than its average utilization in the Modular Mining Dispatch model. Considering the overall utilization of the shovels, the Quad-Obj. model demonstrates its superiority by increasing the utilization rate of shovel 4 (50%) compared to the Tri-Obj. model (45%).

4.2.1.4 Queue Time Statistics

Trucks waiting time, also known as Queue Time, is a vital aspect of a mining fleet system that significantly impacts operational efficiency and productivity. The importance of trucks waiting time can be understood from the following perspectives:

- Material Flow Optimization: Trucks queue time directly affects the flow of materials within the mining operation. When trucks experience longer wait times in queues before being loaded, it leads to disruptions in the material transport chain. Minimizing trucks queue time ensures a smooth and continuous flow of materials, optimizing the overall material handling process and maximizing production efficiency.
- Equipment Utilization: Longer trucks waiting time results in underutilization of trucks within the fleet. Idle trucks waiting in queues are not actively transporting materials, leading to decreased equipment utilization. By minimizing wait times, more trucks can be actively engaged in material transport, maximizing the utilization of the fleet and improving overall operational efficiency.
- Production Output: Delays in truck loading caused by longer queue times can have a direct impact on the production output of the mining operation. When trucks experience excessive wait times, it disrupts the loading sequence, leading to bottlenecks and reduced production. Minimizing trucks queue time ensures timely loading of trucks, maintaining a continuous material flow, and maximizing production output.
- Resource Planning: Trucks queue time provides valuable data for resource planning and allocation. By analyzing queue time information, mining operations can identify areas of congestion and optimize the allocation of resources such as shovels, and trucks. This optimization improves overall operational efficiency, reduces inefficiencies in resource utilization, and enhances the profitability of the mining fleet system.
- Cost Efficiency: Reducing trucks' waiting time helps to minimize operational costs associated with idle equipment and fuel consumption. When trucks wait for extended periods in queues, it increases fuel consumption and labor costs. By minimizing wait times, the operation can reduce fuel consumption and optimize labor utilization, leading to cost savings and improved cost efficiency.

- Safety Considerations: Excessive wait times for trucks in queues can create congestion and potential safety hazards, such as collisions or accidents. Minimizing trucks queue time reduces the risk of accidents and enhances overall operational safety within the mining fleet system.

In summary, Trucks waiting time plays a critical role in optimizing material flow, maximizing equipment utilization, enhancing production output, improving resource planning, reducing operational costs, and ensuring a safe working environment in mining fleet systems. By efficiently managing trucks queue time, mining operations can enhance their overall efficiency, productivity, and profitability.

Table 4.21 provides information on the total waiting time in hours for trucks in the queue for three different models: Dispatch, Tri-Obj., and Quad-Obj. The waiting times for each shovel are given as follows:

Table 4.21. Trucks Total Queue Time at Each Shovel (Hours)

Model	Shovel1	Shovel2	Shovel3	Shovel4	Shovel5
Dispatch	75.22	61.98	163.2	141.25	410.08
Tri-Obj.	155.5	160.69	71.39	79.56	96.53
Quad-Obj.	165.9	166.72	68.96	130.03	90.69
Diff. 2 to 1 (%)	106.73	159.26	-56.26	-43.67	-76.46
Diff. 3 to 1 (%)	120.55	168.99	-57.75	-7.94	-77.88
Diff. 3 to 2 (%)	6.69	3.75	-3.4	63.44	-6.05

The Modular Mining Dispatch model has relatively lower waiting times for Shovels 1 and 2 compared to the other models. However, Shovels 3, 4, and 5 experience significantly higher waiting times, with Shovel 5 having the longest waiting time of 410.08 hours. This suggests that the dispatching system may not be efficient in managing the queue for shovels. Since it does not consider queue times, the system simply allocates trucks to shovels based on the shortest available path and digging rates. The Tri-Obj. model shows higher waiting times across ore shovels compared to the Modular Mining Dispatch model. Shovels 1 and 2 have more than double the waiting times compared to Dispatch. However, Shovels 3, 4, and 5 experience lower waiting times compared to the Modular Mining Dispatch model, indicating potential improvements in the queue management for those shovels. The Quad-Obj. model generally exhibits higher waiting times compared to the Tri-Obj. model. Shovels 1, 2, and 4 experience higher waiting times, with Shovel 2 having the longest waiting time of 166.72 hours. Shovels 3 and 5 have slightly lower waiting times compared to the Tri-Obj. model. Overall, the table highlights variations in truck waiting times for different shovels and models. It indicates the potential for optimizing the queue management system to reduce waiting times and improve operational efficiency. By analyzing and addressing the specific bottlenecks causing longer waiting times, mining operations can enhance the productivity and effectiveness of their fleet systems. Figure 4.15 shows the average total trucks' waiting time in hours for each shovel in each model.

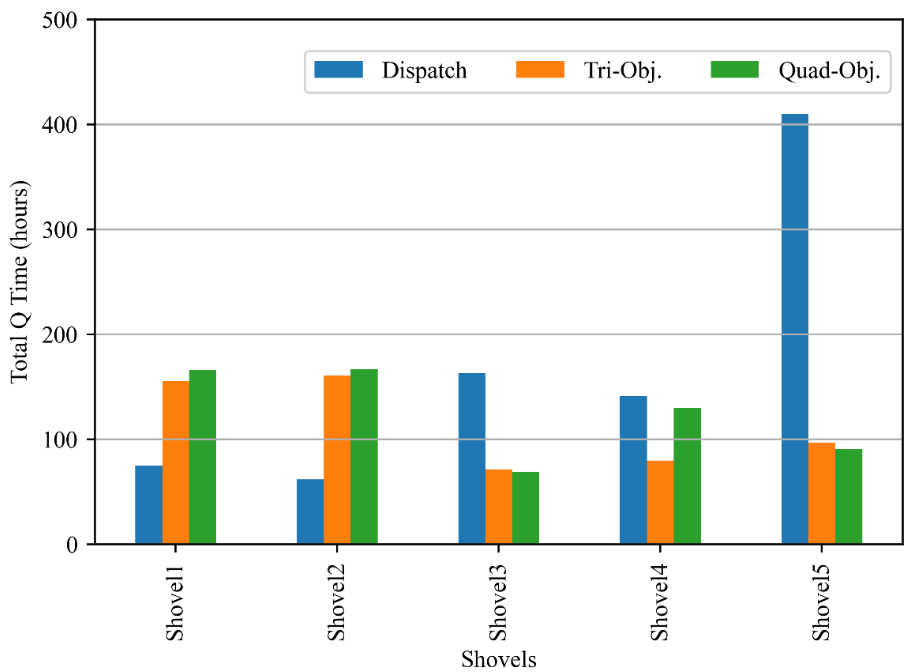

Figure 4.15. Trucks Total Queue Time at Each Shovel (Hours)

The average queue time in mining systems quantifies the waiting period encountered by each truck, enabling focused enhancements and efficient dispatching. Conversely, the total queue time signifies the cumulative waiting time for all trucks, offering a comprehensive evaluation of system efficiency and congestion levels. Both metrics are vital for appraising and enhancing mining system performance. The average queue time emphasizes individual truck productivity, while the total queue time evaluates overall congestion within the system. Table 4.22 presents the average truck waiting time, measured in minutes, for each shovel in three different models: Dispatch, Tri-Obj., and Quad-Obj. Here is a brief discussion of the table:

In the Modular Mining Dispatch model, the average truck waiting times for each shovel vary. Shovel 2 has the lowest waiting time of 1.27 minutes, followed by Shovel 1 with 1.47 minutes. Shovel 4 has a waiting time of 1.97 minutes, Shovel 3 has a waiting time of 2.23 minutes, and Shovel 5 has the highest waiting time of 5.49 minutes. In the Tri-Obj. model, the average truck waiting times for each ore shovel are generally higher compared to the Modular Mining Dispatch model. However, the average truck waiting times for each waste shovel are generally lower compared to the Modular Mining Dispatch model. Shovel 1 has an average waiting time of 2.52 minutes, Shovel 2 has 2.60 minutes, Shovel 3 has 1.35 minutes, Shovel 4 has 1.69 minutes, and Shovel 5 has 1.83 minutes. The Quad-Obj. model shows similar trends to the Tri-Obj. model, with slightly higher average waiting times. Shovel 1 has an average waiting time of 2.67 minutes, Shovel 2 has 2.69 minutes, Shovel 3 has 1.28 minutes, Shovel 4 has 2.09 minutes, and Shovel 5 has 1.74 minutes.

Table 4.22. Trucks Average Queue Time at Each Shovel (Minutes)

Model	Shovel1	Shovel2	Shovel3	Shovel4	Shovel5
Dispatch	1.47	1.27	2.23	1.97	5.49
Tri-Obj.	2.52	2.6	1.35	1.69	1.83
Quad-Obj.	2.67	2.69	1.28	2.09	1.74
Diff. 2 to 1 (%)	71.43	104.72	-39.46	-14.21	-66.67
Diff. 3 to 1 (%)	81.63	111.81	-42.6	6.09	-68.31
Diff. 3 to 2 (%)	5.95	3.46	-5.19	23.67	-4.92

Figure 4.16 depicts the average queue duration, expressed in minutes, for each shovel across different models.

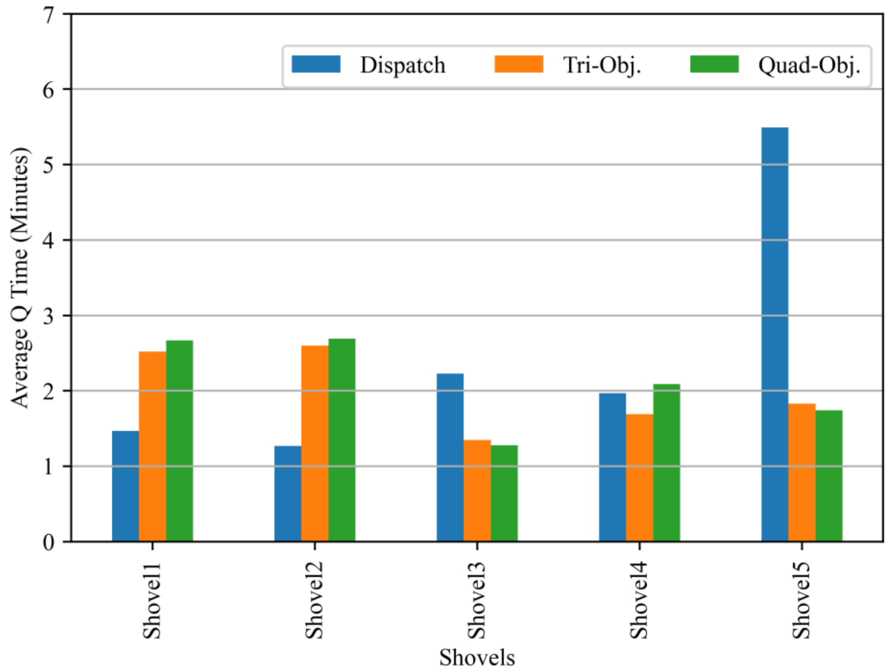

Figure 4.16. Trucks Average Queue Time at Each Shovel (Minutes)

In the case of shovel 4, the Quad-Obj. model exhibits a higher average queue time compared to the Tri-Obj. model. Also, the total queue time is higher for the Quad-Obj. model. This can be attributed to the fact that in the Quad-Obj. model, shovel 4 handles a greater number of cycles and loads a higher total number of trucks. As a result, shovel 4 experiences an increased average truck waiting time and total truck waiting time compared to the Tri-Obj. model.

Trucks in the mining fleet do not experience any waiting time when unloading waste materials into the designated waste dump. This is because multiple unloading spots are available, ensuring efficient waste disposal. In the Modular Mining Dispatch model specifically, trucks predominantly transport waste materials and a smaller quantity of ore materials. As a result, there is a lower influx of trucks heading towards the processing plants, consequently minimizing, or eliminating any queue time for trucks at the plants. Trucks waiting time in plant's queue is much lower than the truck waiting time in shovel's queue. The reason is that truck's loading time is higher than truck's dumping time. The average total waiting times of trucks in the queue at Plant 1 and Plant 2 in the Quad-Obj. model are approximately 41% and 39% lower, respectively, compared to these key performance indicators (KPIs) in the Tri-Obj. model. Also, the average mean waiting times of trucks in the queue at Plant 1 and Plant 2 in the Quad-Obj. model are approximately 29% and 28% lower, respectively, compared to these key performance indicators (KPIs) in the Tri-Obj. model.

Table 4.23, and Figure 4.17 display destinations average total queue time in hour for each model. Table 4.24, and Figure 4.18 display destinations average mean queue time in minutes for each model.

Table 4.23. Destinations Total Queue Time (Hours)

Model	Plant1	Plant2	Waste Dump
Dispatch	0.0	0.0	0.0
Tri-Obj.	47.0	67.46	0.0
Quad-Obj.	27.6	41.43	0.0
Diff. 3 to 2 (%)	-41.28	-38.59	0.0

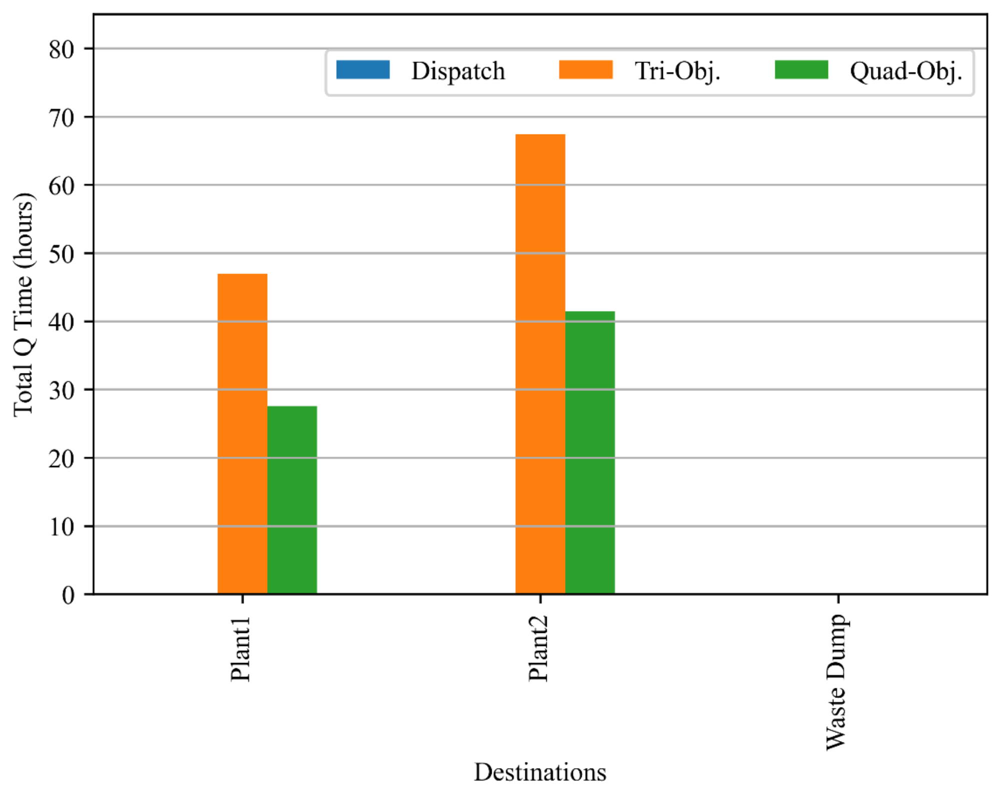

Figure 4.17. Destinations Total Queue Time

Table 4.24. Destinations Average Queue Time (Minutes)

Model	Plant1	Plant2	Waste Dump
Dispatch	0.0	0.0	0.0
Tri-Obj.	0.83	1.05	0.0
Quad-Obj.	0.59	0.76	0.0
Diff. 3 to 2 (%)	-28.92	-27.62	0.0

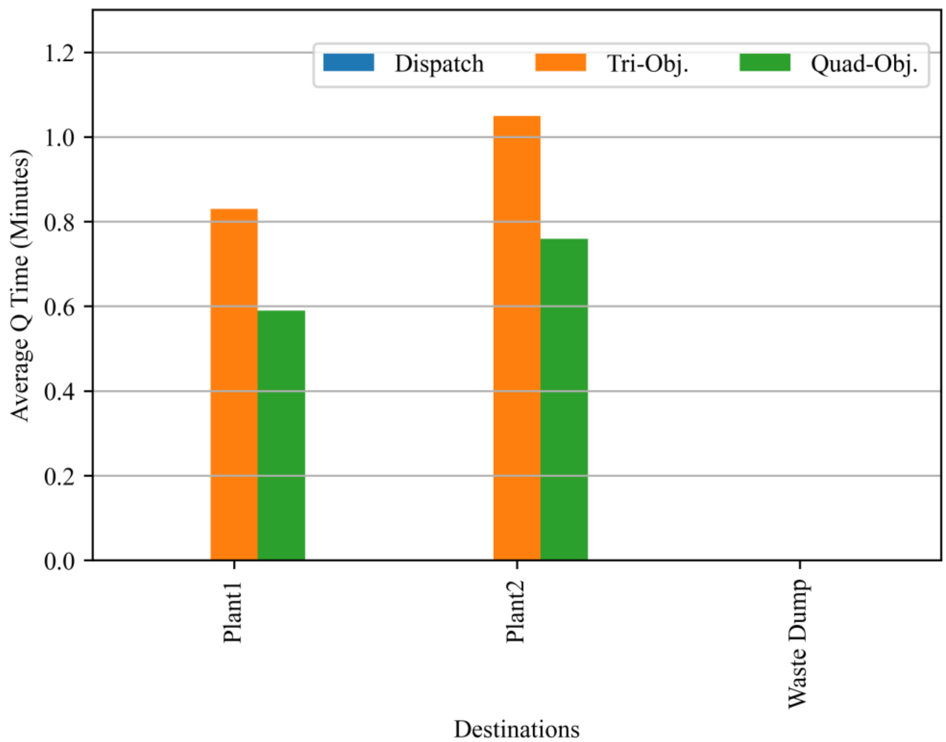

Figure 4.18. Destinations Average Queue Time (Minutes)

4.2.1.5 Hauled Tonnages Statistics

Hauled tonnages from each shovel to each destination are crucial in open-pit mining fleet management. They are important for production planning, material balance, efficiency analysis, equipment utilization, performance evaluation, and cost analysis. Tracking tonnages helps estimate materials extracted, reconcile inventory, optimize fleet deployment, and evaluate productivity. Overall, hauled tonnages data enables effective truck allocation and dispatching, improves operational efficiency, reduces costs, and maintains a safe working environment.

Table 4.25, and Figure 4.19 present the average total extracted tonnages, measured in kilotonnes, from each shovel in three different models: Dispatch, Tri-Obj., and Quad-Obj. Here is a discussion of the data:

In the Modular Mining Dispatch model, the average total extracted tonnages vary for each shovel. Shovel 1 has an average total extracted tonnage of 248.89 kilotonnes, Shovel 2 has 237.55 kilotonnes, Shovel 3 has 286.45 kilotonnes, Shovel 4 has 283.51 kilotonnes, and Shovel 5 has 287.60 kilotonnes. In the Tri-Obj. model, the average total extracted tonnages for each shovel show different values compared to the Modular Mining Dispatch model. Shovel 1 has an average total extracted tonnage of 275.72 kilotonnes, Shovel 2 has 276.68 kilotonnes, Shovel 3 has 222.45 kilotonnes, Shovel 4 has 224.28 kilotonnes, and Shovel 5 has 252.22 kilotonnes. The Quad-Obj. model exhibits similar trends to the Tri-Obj. model, with slight variations in the average total extracted tonnages. Shovel 1 has an average total extracted tonnage of 276.49 kilotonnes, Shovel 2 has 275.9 kilotonnes, Shovel 3 has 224.4 kilotonnes, Shovel 4 has 249.3 kilotonnes, and Shovel 5 has 251.42 kilotonnes. In Quad-Obj. model trucks deliver about 1% more waste materials from the shovel 3, and 11% more waste tonnages from shovel 4 compared to Tri-Obj. model.

Table 4.25. Shovels Total Hauled Tonnages (kt)

Model	Shovel1	Shovel2	Shovel3	Shovel4	Shovel5
Dispatch	248.89	237.55	286.45	283.51	287.60
Tri-Obj.	275.72	276.68	222.45	224.28	252.22
Quad-Obj.	276.49	275.9	224.4	249.3	251.42
Diff. 2 to 1 (%)	10.78	16.47	-22.34	-20.89	-12.3
Diff. 3 to 1 (%)	11.09	16.15	-21.66	-12.07	-12.58
Diff. 3 to 2 (%)	0.28	-0.28	0.88	11.16	-0.32

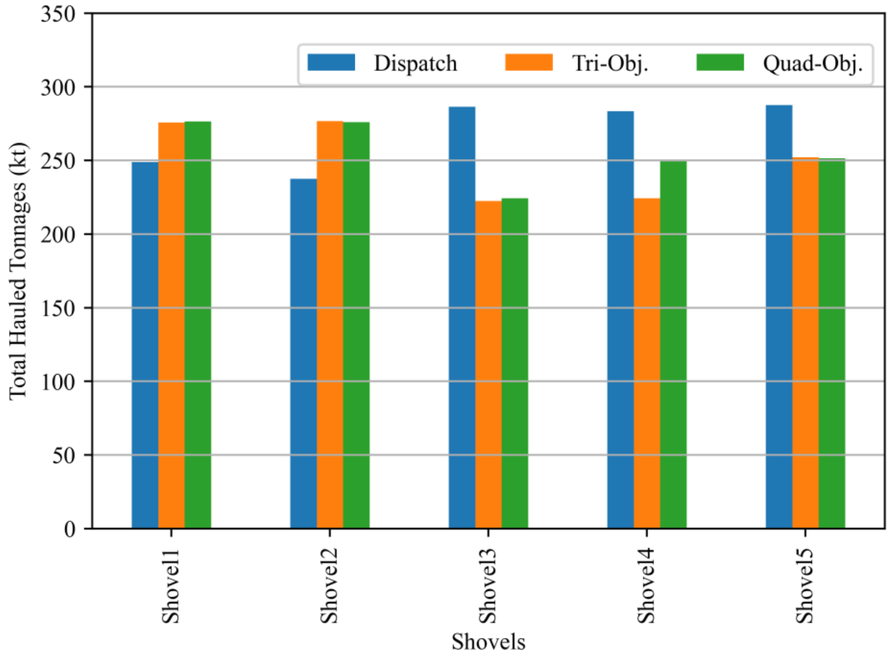

Figure 4.19. Shovels Total Hauled Tonnages (kt)

Table 4.26, and Figure 4.20 present the total Hauled Tonnages of ore and waste materials to each plant and waste dump for each model.

Table 4.26. Destinations Hauled Tonnages (kt)

Model	Plant1	Plant2	Waste Dump
Dispatch	237.64	248.79	857.56
Tri-Obj.	276.19	276.21	698.95
Quad-Obj.	276.22	276.17	725.12
Diff. 2 to 1 (%)	16.22	11.02	-18.5
Diff. 3 to 1 (%)	16.23	11.0	-15.44
Diff. 3 to 2 (%)	0.01	-0.02	3.74

Waste materials hauled is around 3.74% higher in Quad-Obj. model compared to Tri-Obj. model that is about 53.17 kilotonnes of waste materials.

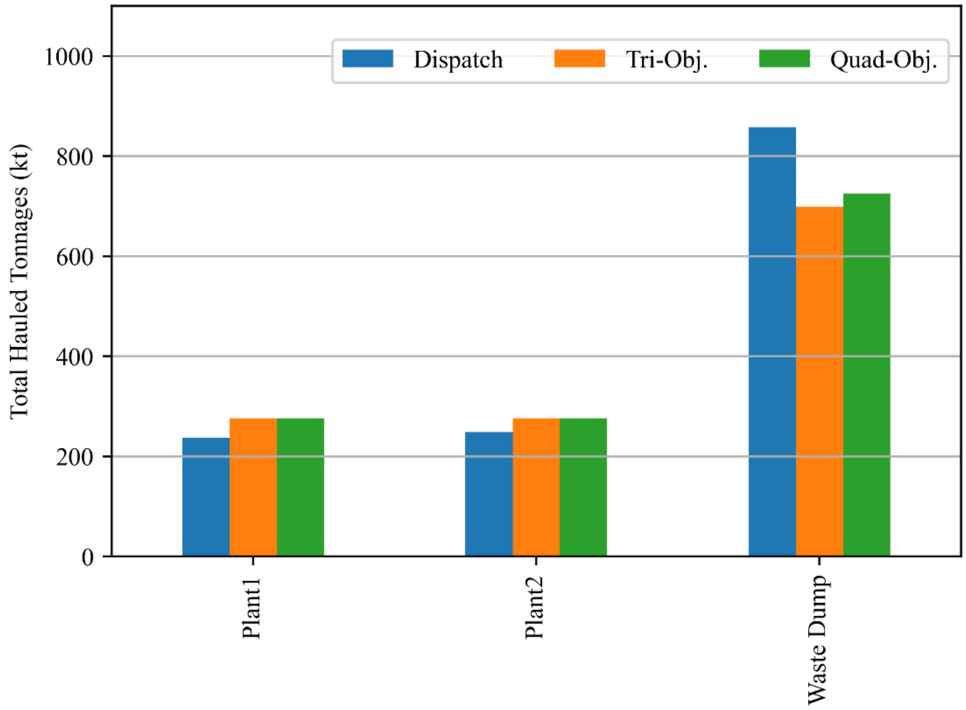

Figure 4.20. Destinations Hauled Tonnages (kt)

The comprehensive statistical data pertaining to the utilization of each shovel, queue times, extracted tonnages, queue times at each destination, and hauled tonnages can be found in the APPENDIX A. The detailed information is available in Table A. 1 through Table A. 27. These statistical measures provide insights into the central tendencies, variability, and differences between the models, allowing for a better understanding of their performance characteristics.

4.2.1.6 Comprehensive Fuel Consumption Comparison

Table 4.27 presents the average fuel consumption, average tonnage production, and average fuel consumption per tonne production for each destination, namely plant 1, plant 2, and the waste dump, in both the Tri-Obj. and Quad-Obj. models. For Plant 1 (P1), the Quad-Obj. model shows a total fuel consumption of 112.11 kl, representing a 7.02% decrease compared to the Tri-Obj. model. The total production in P1 is 276.22 kt, with a negligible difference between the models. The fuel consumption per tonne production in P1 is 0.41 l/t in the Quad-Obj. model, reflecting a 7.03% decrease compared to the Tri-Obj. model. Similarly, for Plant 2 (P2), the Quad-Obj. model exhibits a total fuel consumption of 111.91 kl, which is 7.90% lower than the Tri-Obj. model. The total production in P2 is 276.17 kt, with a slight difference between the models. The fuel consumption per tonne production in P2 is 0.41 l/t in the Quad-Obj. model, showing a 7.88% decrease compared to the Tri-Obj. model. Moving to the Waste Dump (WD), the Quad-Obj. model demonstrates a total fuel consumption of 186.01 kl, indicating a 3.26% increase compared to the Tri-Obj. model. The total production in the Waste Dump is 725.12.95 kt, showing a 3.74% increase compared to the Tri-Obj. model. The fuel consumption per tonne production in the Waste Dump is 0.26 l/t in both models, with a slight decrease in the Quad-Obj. model. Considering the total values for all destinations, the Quad-Obj. model has a total fuel consumption of 410.04 kl, representing a 2.89% decrease compared to the Tri-Obj. model. The total production in the Quad-Obj. model is 1277.51 kt, showing a 2.09% increase compared to the Tri-Obj. model. The fuel consumption per tonne production is 0.32 l/t in the Quad-Obj. model, reflecting a 4.88% decrease compared to the Tri-Obj. model. The greatest reduction in fuel consumption occurs at Plant 1 and Plant 2 destinations. This can be attributed to the fact that trucks have the flexibility to choose between these two locations. On the other hand, the Waste Dump has only one designated location, limiting the potential for fuel consumption reduction in that area.

Table 4.27. Fuel Consumption on each of the Destinations

Dest. Model	Total FC (kl)	Diff (%)	Total Production (kt)	Diff (%)	FC/Production (l/t)	Diff (%)
P1Tri	120.58	-7.02	276.19	0.01	0.44	-7.03
P1Quad	112.11		276.22		0.41	
P2Tri	121.51	-7.90	276.21	-0.02	0.44	-7.88
P2Quad	111.91		276.17		0.41	
WDTri	180.14	3.26	698.95	3.74	0.26	-0.46
WDQuad	186.01		725.12		0.26	
TotalTri	422.23	-2.89	1251.35	2.09	0.34	-4.88
TotalQuad	410.04		1277.51		0.32	

Table 4.28 presents the findings of the S16 model, identified as the most efficient model in terms of fuel consumption, and its comparison with the Tri-Objective benchmark model. The results indicate that this scenario in the Quad-Obj. model achieves a 4.64% reduction in total fuel consumption, a 1.43% increase in total production, and a 5.98% decrease in fuel consumption per tonne of production.

Table 4.28. Fuel consumption comparison for the lowest fuel consuming scenario

Model	Total FC (kl)	Total Production (kt)	FC/Production (l/t)
Model S16	402.65	1269.25	0.32
Diff (%)	-4.64	1.43	-5.98

4.3 Number of trucks and their type

Monitoring the total number of trucks and their types is essential for effective fleet management and resource allocation. It ensures the availability of adequate equipment for the operational needs of the mine. It is considered as an independent variable in this study and it can meaningfully change the values of all other KPIs that are dependent variables. Determining the total number of trucks and their types is indeed crucial in finding the optimal values for the combination of other key performance indicators (KPIs) in mining. The number of trucks and their types within a mining fleet wield a distinctive influence on the dispatching of trucks, thereby significantly impacting operational efficiency, productivity, and cost-effectiveness. To begin with, the quantity of trucks directly governs the fleet's efficiency and productivity. Augmenting the number of trucks has the potential to amplify productivity by enabling a greater volume of material transportation. However, a careful balance must be struck to prevent congestion, operational delays, and inefficient resource utilization that may arise from an excessive fleet size. Hence, judicious consideration is imperative to align the fleet's scale with the specific operational demands. The mining industry faces a significant challenge in optimizing its equipment selection and utilization to minimize materials handling costs and keep up with the trend of technology usage. The efficiency of the equipment depends on factors such as utilization, availability, and age. Effective use of technology will play a crucial role in shaping the future of the mining industry (Samatemba et al., 2020). When selecting trucks for mining operations, fuel efficiency is a critical factor that requires careful consideration.(Gonzalez et al., 2017). To avoid the risks of not meeting ore demand due to operational uncertainties, mine operators usually assign more trucks than necessary, leading to inefficient truck usage and long truck queues at dump locations and shovels. This approach limits trucks available for other tasks such as transporting overburden, and short-term truck shortages are usually addressed by costly truck rentals. Even small reductions in the total number of available trucks can result in substantial savings. Using simulation instead of approximation can improve accuracy, and having multiple truck sizes can increase flexibility and efficiency, reducing the total number of trucks assigned and matching the mine's total throughput rate (Ta et al., 2013). In addition, the selection of truck types employed in the fleet is pivotal in determining its capacity and throughput. Diverse truck types exhibit distinctive payload capacities and capabilities. For instance, larger trucks possess superior load-carrying capacities, thereby elevating the mining operation's throughput. Conversely, smaller trucks excel in navigating restricted or challenging mining areas. Consequently, the deliberate choice of appropriate truck types, based on precise payload requirements, becomes paramount in optimizing the fleet's capacity and maximizing operational efficiency. Moreover, comprehensive cost analysis should underpin the decision-making process concerning fleet size and truck types. Expanding the fleet by introducing additional trucks incurs costs related to acquisition, maintenance, fuel consumption, and personnel requirements. Consequently, a meticulous cost-benefit evaluation is indispensable to strike an optimal balance between fleet size aspirations and associated financial implications. By managing costs effectively, mining enterprises can achieve resource utilization optimization while minimizing financial burdens. Furthermore, the diversity of truck types within the fleet endows it with operational versatility. Embracing a varied fleet composition allows mining companies to adapt to diverse mining conditions and operational demands. To exemplify, smaller trucks are particularly well-suited for the transportation of constrained tonnages of material, given their comparatively lower capacity. This characteristic confers enhanced flexibility, allowing them to be allocated effectively to capacitated dumping areas. Moreover, their reduced size results in lower fuel consumption and decreased carbon emissions, making them environmentally advantageous. Conversely, larger trucks excel in the transportation of larger volumes of materials. With their greater capacity, they are capable of efficiently handling substantial loads, especially in situations where there are no limitations on dumping or unloading capacity. The utilization of larger trucks in such scenarios can significantly contribute to improved productivity and streamlined operations, facilitating the efficient movement of bulk materials within the mining environment. This adaptability enhances fleet flexibility and augments its ability to execute a broad spectrum of mining tasks with utmost efficiency.

In conclusion, the quantity and types of trucks comprising a mining fleet exert a profound influence on operational efficiency, productivity, and cost-effectiveness. Achieving an optimal number of trucks, truck selection, and dispatching is pivotal to cultivate a productive and economically sustainable fleet system. By diligently deliberating these aspects and implementing robust fleet management strategies, mining enterprises can optimize operations, enhance productivity, and mitigate costs.

Table B. 1, provided in the APPENDIX B, presents a comprehensive overview of key performance indicators (KPIs) for a total of 40 distinct truck type and quantity scenarios. The first nine scenarios involve a homogeneous fleet composed solely of CAT 785C trucks. Following that, the subsequent eight scenarios utilize a homogeneous fleet of CAT 793C trucks, with different quantities of these vehicles. The rest of scenarios involve a heterogeneous fleet configuration composed of both CAT 785C and CAT 793C trucks as part of the system. In reality, a heterogeneous fleet composition can lead to better results than a homogeneous one (Salhi and Rand, 1993).

The findings presented in the table indicate that among the different scenarios analyzed, scenario 6 comprising 30 CAT 785C trucks in a homogenous fleet, scenario 13 with 18 CAT 793C trucks in a homogenous fleet, and scenario 24 involving a combination of 20 CAT 785C trucks and 5 CAT 793C trucks in a heterogeneous fleet exhibit the most favorable performance in terms of meeting production targets and minimizing fuel consumption. These results hold true when considering the specific fleet configurations of homogenous CAT 785C, homogenous CAT 793C, and a mixed fleet consisting of both CAT 785C and CAT 793C trucks, respectively. The ore production tonnages higher than 550000 tonnes is considered satisfactory in our research.

Considering the primary goal to maximize production, scenario 24 proves to be the optimal choice as it meets the production rates and minimizes fuel consumption and reduces carbon emissions. This scenario entails a fleet composition of 20 small trucks (CAT 785C) and 5 larger trucks (CAT 793C). By adopting this configuration, the need for high productivity can be effectively balanced with the imperative to minimize fuel consumption and environmental impact, thus aligning with the GHG mitigation objective of this study. Scenario 6 exhibits the highest utilization of ore and waste shovels, followed by scenario 24. Scenario 13 has the lowest shovels' utilization among the three scenarios. Scenario 6 has the highest average trucks queue time, followed by scenario 24. Scenario 13 exhibits the lowest average trucks queue time among the three scenarios. All three scenarios exhibit acceptable ore tonnage, with scenario 6 having the slightly higher ore tonnage and scenario 13 having slightly lower ore tonnage. Scenario 13 demonstrates the highest total tonnage, followed closely by Scenario 6. Scenario 24 has a slightly lower total tonnage compared to the other two scenarios. All 3 models have acceptable Stripping ratios. Comparing the fuel consumption of Scenario 6 and Scenario 13 to the lowest fuel consumption of Scenario 24, it is evident that Scenario 6 has a ratio difference of 5.83% higher fuel consumption, while Scenario 13 has a significantly higher ratio difference of 17.35%.

In Figure 4.21, the data presents the ore and waste productions for different scenarios, along with the total fuel consumption. Scenarios where the ore production meets the acceptable threshold are distinguished by a border in green color. On the other hand, scenarios with ore production falling below the acceptable threshold are indicated by a border in red color.

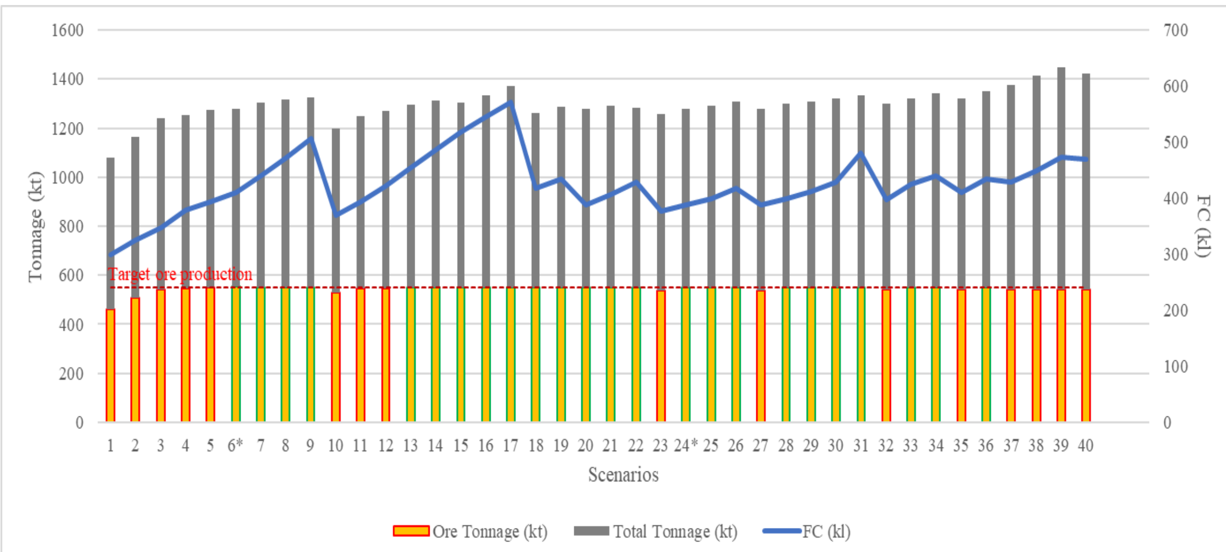

Figure 4.21. Production and fuel consumption in fleet scenarios

Another heterogeneous scenario, namely Scenario 20, consisting of 22 CAT 785C trucks and 4 CAT 793C trucks, demonstrates commendable key performance indicators (KPIs) that closely rival those of Scenario 24. Scenario 20 exhibits slightly higher average shovels' utilizations and average and total trucks' waiting times due to its larger fleet size compared to Scenario 24. Moreover, it consumes a slightly greater amount of fuel and handles higher total tonnages of ore and waste, albeit transporting less ore tonnage compared to Scenario 24.

Table 4.29 presents the average number of cycles from each shovel and the number of cycles to each destination for every truck in the system of scenario 24. Additionally, it includes the percentage of times a truck transports ore material over the total number of cycles (referred to as OreCycles %) and the percentage of times a truck transports waste material over the total number of cycles (referred to as WasteCycles %). Similarly, Table 4.31 offers the corresponding data, specifically for Scenario 20.

Table 4.29. Heterogenous fleet cycles of scenario 24

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

Table 4.30 provides the average percentage of cycles for each truck type in Scenario 24, while Table 4.32 displays the corresponding information for Scenario 20. Both tables present insights into the distribution of cycles across different truck types within their respective scenarios.

Table 4.30. Truck Type's cycles Comparison of scenario 24

Truck Type	SH1 Cycles (%)	SH2 Cycles (%)	SH3 Cycles (%)	SH4 Cycles (%)	SH5 Cycles (%)	P1 Cycles (%)	P2 Cycles (%)	WD Cycles (%)
785C	22	21	20	22	15	21	22	57
793C	16	20	17	14	33	20	16	64

Table 4.31 Heterogenous fleet cycles of scenario 20

Truck Type	Truck#	SH1	SH2	SH3	SH4	SH5	P1	P2	WD	OreCycles (%)	WasteCycles (%)
785C	1	88.8	74.6	52	53.8	55	82.2	81.2	160.8	50	50
	2	83.4	78.2	57.2	59	50.8	84	77.6	167	49	51
	3	78.8	77.2	53.2	59.6	57.8	77.6	78.4	170.6	48	52
	4	74.4	75.6	59.8	67	56.4	74.8	75.2	183.2	45	55
	5	77.8	75.6	58.2	66.4	54.4	77.2	76.2	179	46	54
	6	79.2	70	62.6	66.2	57.8	76	73.2	186.6	44	56
	7	72.4	68	65.6	73.4	60.6	60.6	79.8	199.6	41	59
	8	77.6	66	64.6	74.8	57.4	66.8	76.8	196.8	42	58
	9	78.2	64.8	63.8	83.4	53.4	69.2	73.8	200.6	42	58
	10	75.4	64.2	68.8	75.4	59.2	65.6	74	203.4	41	59
	11	75.2	66	75.6	73	53.8	60.6	80.6	202.4	41	59
	12	73.8	63.8	73	76	59	64	73.6	208	40	60
	13	68.4	66	81	78.8	53.8	64.6	69.8	213.6	39	61
	14	66	69	74.6	83.2	54.8	64	71	212.6	39	61
	15	71.6	66.4	81.8	82.8	50.2	61.4	76.6	214.8	39	61
	16	73.6	62.8	76.6	84.6	52	68	68.4	213.2	39	61
	17	74.6	67.8	71.8	80.6	51.8	68.2	74.2	204.2	41	59
	18	71.4	69.6	74.4	78.2	53.2	67.2	73.8	205.8	41	59
	19	70.4	72.6	73.8	83.4	47.6	69.4	73.6	204.8	41	59
	20	82.4	66.8	71	78.4	48.6	71.4	77.8	198	43	57
	21	74.8	71.4	75.4	72.8	48.8	69.6	76.6	197	43	57
	22	75.6	76.6	70.8	70.2	46.4	75	77.2	187.4	45	55
793C	23	42.8	60.8	49	38.4	108.6	60.2	43.4	196	35	65
	24	42.4	54.6	46.8	41.2	114.4	54.8	42.2	202.4	32	68
	25	46.8	60	52.2	33.8	104.8	60.2	46.6	190.8	36	64
	26	38.8	67	51.2	34.2	106.8	67.2	38.6	192.2	36	64

Table 4.32. Truck Type's cycles Comparison of scenario 20

Truck Type	SH1 Cycles (%)	SH2 Cycles (%)	SH3 Cycles (%)	SH4 Cycles (%)	SH5 Cycles (%)	P1 Cycles (%)	P2 Cycles (%)	WD Cycles (%)
785C	22	20	20	22	16	20	22	57
793C	14	20	17	12	36	20	14	65

Based on the findings, it can be observed that each CAT 793C truck transports greater quantities of waste compared to each CAT 785C truck. This can be attributed to the higher capacity of CAT 793C trucks. Also, it is important to note that while there is no hourly capacity limitation for waste dumping, the plants have specific hourly hopper capacities. Trucks with lower capacity make more flexibility in transferring of ore materials in the system and they are more appropriate choice to be assigned to ore shovels.

In terms of ore shovels, it is preferable to assign larger trucks to shovel 2 due to its shorter cycle distance compared to shovel 1. This selection criterion also applies to waste shovels, where shovel 3 is chosen as it is closest to the waste dump. However, there is a notable difference in the assignment of large trucks to waste shovel 5 compared to small trucks. This is primarily due to shovel 5 having a higher digging rate and capacity compared to the other waste shovels. As a result, trucks with higher capacities are required for efficient operations at shovel 5.

4.4 Trucks' uptime and downtime

As open-pit mining equipment becomes larger and more complex, equipment failure can result in significant repair costs and production loss. Improving equipment reliability can help mitigate these impacts, and the first step is collecting and analyzing the necessary data (Hall and Daneshmend, 2003). The effective management of trucks' uptime and downtime plays a pivotal role in the fleet management and dispatching of trucks in open-pit mining. It is essential to consider these factors in order to enhance the overall productivity and operational efficiency of the mining fleet.

Uptime refers to the duration when trucks are operational and available for hauling tasks. Maximizing uptime is of utmost importance as it directly influences the mining operation's ability to meet production targets and ensure timely material delivery. Efficient maintenance practices, regular inspections, and timely repairs are crucial in minimizing unplanned downtime and ensuring prolonged operational periods for trucks. Conversely, downtime pertains to the periods when trucks are out of service due to planned maintenance, repairs, or unexpected failures. Effective management and minimization of downtime are critical in reducing disruptions in mining operations, avoiding costly delays, and enhancing overall operational efficiency. Implementing efficient maintenance planning, proactive troubleshooting, and maintaining an inventory of readily available spare parts are key strategies in reducing downtime and optimizing truck availability.

By closely monitoring and managing trucks' uptime and downtime, fleet managers can make informed decisions regarding truck dispatching. Understanding the maintenance requirements and failure patterns of trucks enables the effective dispatching of trucks, ensuring that trucks are assigned to tasks based on their availability and reliability.

In the mine dispatching model, considering trucks' failure is essential due to its significant impact on key performance indicators (KPIs). Failure events can disrupt productivity, increase idle times, and decrease overall performance. By incorporating failure into the model, fleet managers can make more accurate decisions that mitigate disruptions and optimize KPIs.

Truck failures directly affect KPIs such as production rate, utilization, operating costs, and equipment availability. Unplanned downtime leads to decreased production rates and lower truck utilization, negatively impacting overall efficiency. The dispatching model must account for potential failure rates, maintenance needs, and repair times to optimize fleet performance.

By taking truck failures into account, proactive maintenance planning and scheduling can be implemented, thereby minimizing the impact on production. Anticipating failures enables the development of contingency plans to cover the missed tonnages that would have been transported by the failed trucks during planned downtime. These plans optimize resources and minimize unexpected reductions in the production rate. They may involve strategies such as having substitute trucks readily available in case of failures, utilizing stockpiles to feed the plant with the missed tonnages, or incorporating conveyors into the fleet system. These measures ensure that the mining operation can maintain a steady flow of materials, mitigate the effects of truck failures, and optimize overall production efficiency.

Uptimes and downtimes for trucks in the system are assumed to be in random time windows based on the distributions in Table 4.33.

Table 4.33. Trucks' Uptime and Downtime Distributions

Truck Type	**Up Time (Hours)**	**Down Time (Hours)**
CAT 785C	LOGNORMAL (90, 30)	WEIBULL (17,8)
CAT 793C	LOGNORMAL (100, 40)	WEIBULL (30,5)

LOGNORMAL (90, 30):

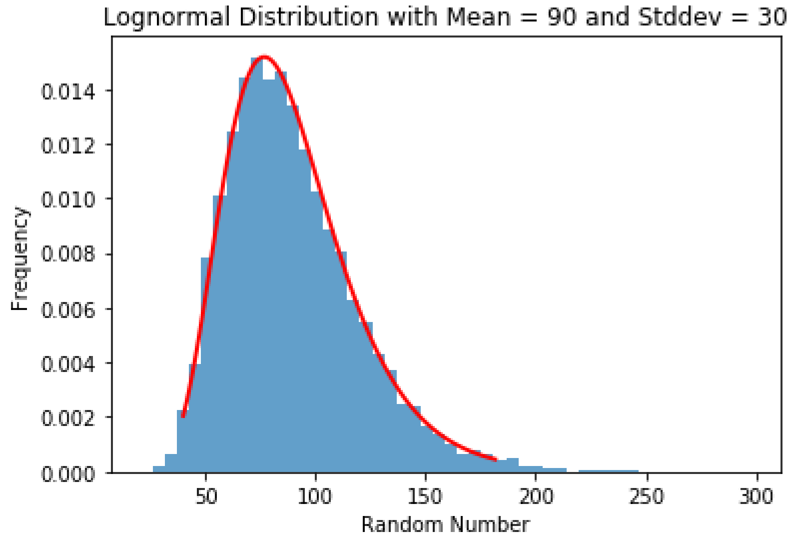

Figure 4.22. CAT 785C Up Time (Hours) Distribution

The mean of this distribution should be 90 with the standard deviation of 30. Figure 4.22 is the frequency plot for this distribution. This lognormal distribution is skewed to the right.

WEIBULL (8, 17):

The scale of this distribution should be 17 with the shape of 8. Figure 4.23 is the density plot for this distribution.

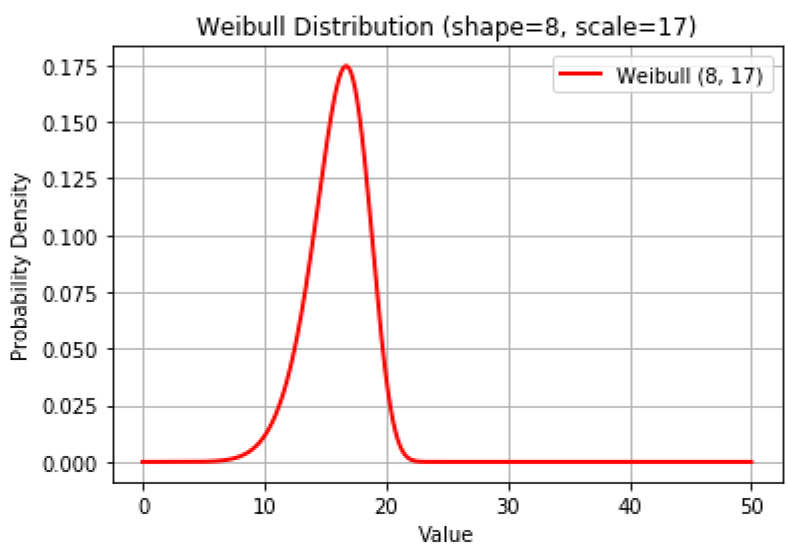

Figure 4.23. CAT 785C Down Time (Hours) Distribution

LOGNORMAL (100, 40):

The mean of this distribution should be 100 with the standard deviation of 40. Figure 4.24 is the frequency plot for this distribution. This lognormal distribution is skewed to the right.

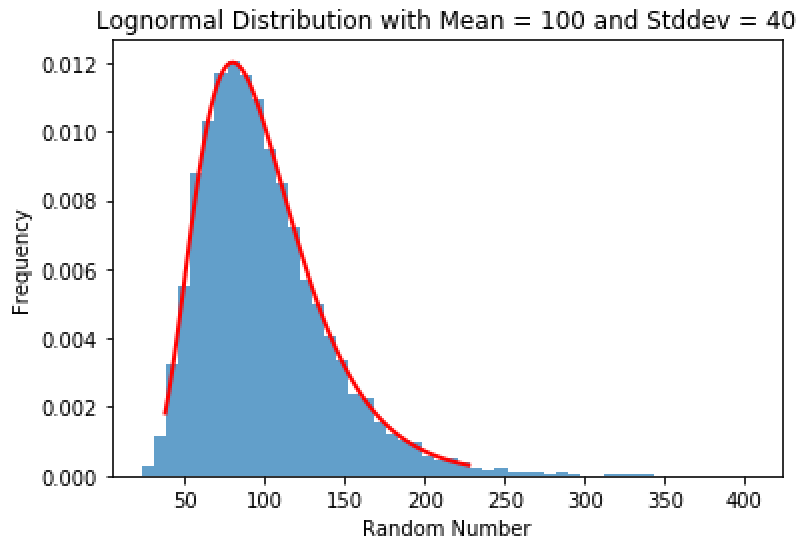

Figure 4.24. CAT 793C Up Time (Hours) Distribution

WEIBULL (5, 30):

The scale of this distribution should be 30 with the shape of 5. Figure 4.25 is the density plot for this distribution.

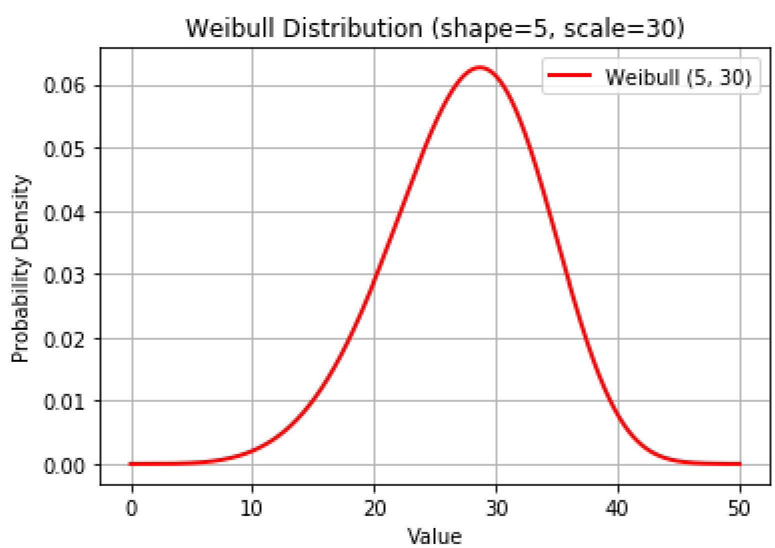

Figure 4.25. CAT 793C Down Time (Hours) Distribution

Table 4.34 shows the key performance indicators (KPIs) of the best scenarios considering trucks' failure. These scenarios were previously discussed without taking into account trucks' failure. Among them, scenario 6 with a homogeneous fleet of CAT 785C trucks emerges as the optimal choice when considering trucks' failure. It demonstrates superior performance in terms of tonnage transportation, and production rate. Similar to the previous observation, this scenario showcases higher average shovels' utilizations and average trucks' waiting times, which can be attributed to the larger number of trucks in the system compared to other scenarios. Although it does not have the lowest fuel consumption, it still maintains an acceptable fuel consumption rate per tonne of production.

Considering trucks' failure, a fleet with a higher number of smaller trucks proves to be more advantageous in meeting the hourly ore production rate. This is attributed to the increased flexibility offered by a larger quantity of smaller trucks, despite their lower average capacity per truck. Additionally, smaller trucks exhibit a lower average downtime compared to larger trucks, further contributing to their improved performance in the context of trucks' failure.

Table 4.34. KPIs of the Best Scenarios with the Trucks failure

Scenario	Util. Ore (%)	Util. Waste (%)	Average Qtime (Mins)	Total Qtime (Hrs)	FC (KL)	Ore Tonnage (KT)	Total Tonnage (KT)	Ore TPGOH (T)	SR
6(F)	78.09	53.50	3.41	527.40	360.76	530.53	1221.59	4421.10	1.30
13(F)	66.57	43.29	2.34	189.72	389.25	511.73	1180.48	4264.38	1.31
24(F)	71.76	50.05	2.91	378.45	343.44	501.73	1170.65	4181.08	1.33

Table 4.35 displays the percentage difference in KPIs resulting from the inclusion of the trucks' failure in the models.

Table 4.35. Differences' percentages in KPIs considering failure

Scenarios	Util. Ore (%)	Util. Waste (%)	Average Qtime (Mins)	Total Qtime (Hrs)	FC (KL)	Ore Tonnage (KT)	Total Tonnage (KT)	Ore TPGOH (T)	SR
6(F) and 6	-3.78	-4.84	-11.43	-15.25	-12.02	-3.96	-4.38	-3.96	-0.76
13(F) and 13	-7.03	-10.19	-11.03	-17.39	-14.36	-6.97	-8.86	-6.97	-2.96
24(F) and 24	-8.83	-7.13	-15.65	-21.80	-11.36	-9.03	-8.30	-9.03	1.53

Scenario 6 stands out with the least variation in KPIs compared to other scenarios. This suggests that incorporating a larger number of smaller trucks in the fleet can minimize production losses in the event of unplanned failures. However, when considering the presence of a stockpile or several stockpiles in the system and a slightly higher number of trucks in both types, a heterogenous fleet still outperforms homogenous fleets. Now, let's discuss three additional scenarios that consider a higher number of trucks to examine how the number of trucks can impact the KPIs when trucks' failure is considered. The selected scenarios include Scenario 9 with 36 CAT 785C trucks, Scenario 15 with 20 CAT 793C trucks, and Scenario 20 with 22 CAT 785C trucks and 4 CAT 793C trucks. Table C. 1 and Table C. 2 in APPENDIX C provide important KPIs for 6 scenarios including scenarios 6, 9, 13, 15, 20, and 24. Below are the outcomes from the results in the table:

Even with the addition of 6 more trucks to the fleet of 30 CAT 785C trucks in Scenario 9, the target production rate cannot be consistently met due to the requirement of around 30 trucks per hour based on the capacities of the plants. Despite having 36 trucks in this scenario, there are still instances where the available number of trucks falls below 30. Consequently, the higher number of trucks in the system results in a significant increase in waste tonnage transportation compared to ore tonnage transportation, leading to an increase in the stripping ratio. Although Scenario 9 exhibits higher productivity, it is not the most efficient option as it consumes more fuel and fails to meet the scheduled stripping ratio rate. The addition of a stockpile would greatly improve this scenario's performance in terms of ore tonnage production and enable it to meet the planned stripping ratio rate.

Increasing the number of trucks from 18 CAT 793C trucks (scenario 13) to 20 CAT 793C trucks (scenario 15) results in an increase in the production rate. However, it is evident that this increase is accompanied by a higher total fuel consumption. Comparing the fuel consumption per tonne of production, scenario 13 performs better than scenario 15, making it a more favorable option in terms of fuel efficiency. On the other hand, scenario 15 exhibits higher average tonnes per hour of operation (TPGOH) and total ore production, which may make it a more attractive choice. Ultimately, determining the optimal scenario requires a more comprehensive cost analysis, taking into account various factors and considering different operational scenarios. Depending on the specific circumstances, either scenario can be the preferred choice.

Both scenario 20 and scenario 24 feature a heterogeneous fleet, with scenario 20 having two additional CAT 785C trucks and one fewer CAT 973C truck compared to scenario 24. Scenario 20 exhibits a slightly higher production rate and fuel consumption compared to scenario 24. Both scenarios demonstrate high productivity and have similar KPIs. When considering failure scenarios, introducing a greater number of small trucks to the optimal heterogeneous scenario can lead to increased efficiency. Smaller trucks are more flexible and better suited to meet the desired ore production rate, particularly due to the capacity of the hourly hoppers. Their agility allows for better adaptation to the operational demands and helps optimize the overall efficiency of the fleet.

According to the provided failure time statistics, it can be inferred that the CAT 785C truck type has a lower average downtime compared to other truck type. However, scenarios involving this truck type have a higher total downtime. This is primarily due to the larger number of trucks present in the system for these scenarios.

When considering fuel consumption per tonne production rate as the key factor, scenario 6 with a homogeneous fleet of small trucks, as well as scenarios 20 and 24 with heterogeneous fleets, emerge as the most reliable and efficient options. However, scenario 6 stands out with a higher production rate and its flexibility in truck dispatching, making it the optimal choice when accounting for unforeseen failures in the model.

The failure effects are discussed in detail for 3 of these scenarios. Table C. 3, Table C. 4, Table C. 5, and Table C. 6 are about failure time of each truck in each replication, trucks' total and average failure times, and daily average TPGOH and trucks availability in the system respectively for the fleet with 30 CAT 785C trucks. Table C. 7, Table C. 8, and Table C. 9 provide same information data for the fleet with 20 CAT 793C trucks. Lastly, Table C. 10, Table C. 11, and Table C. 12 present the similar information data for the fleet consisting of 20 CAT 785C trucks and 5 CAT 793C.

The results indicate that the daily average number of available trucks in the system has a significant impact on the daily average TPGOH, highlighting how a decrease in the number of available trucks can lead to a reduction in the TPGOH (Figure 4.26, Figure 4.27).

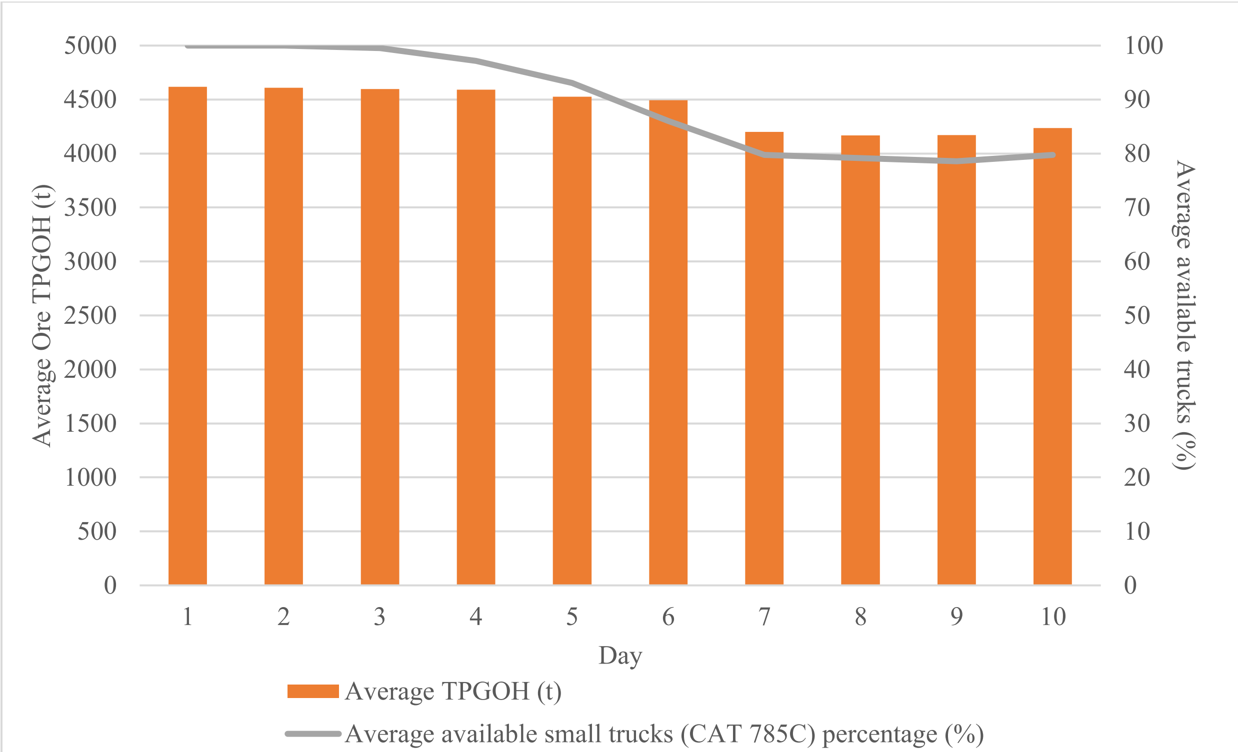

Figure 4.26. Truck failure effect on average TPGOH Whitin Scenario 6: (Homogenous fleet - 30 small trucks)

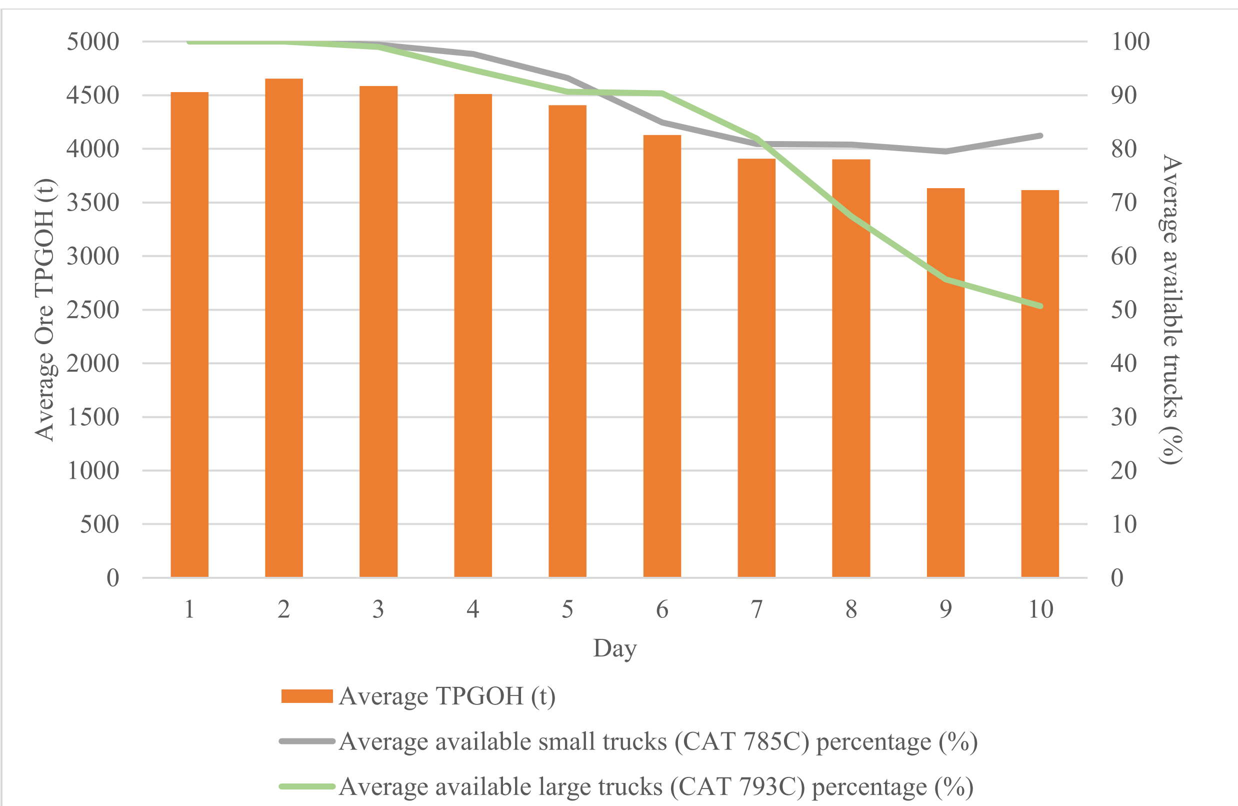

Figure 4.27. Truck failure effect on average TPGOH Whitin Scenario 24: (Heterogenous fleet - 25 Small and 5 large trucks)

5 CONCLUSION AND RECOMMENDATION

There are several methods to decrease fuel consumption and GHG emission in open-pit mining operations, including better dispatching system and proper allocation, applying fuel-efficient hauling trucks, decreasing human mistakes by automating the trucks, improving road network, and so on.

The main emphasis of this study was on truck dispatching optimization and determining the optimal number of trucks required in the system. The presented model aimed to minimize the deviation from the flow rates of the paths, shovel idle time, truck wait time, and truck fuel consumption. A significant contribution of this study was the inclusion of fuel consumption minimization as an objective to the truck dispatching model, which had both economic and environmental benefits. Another major contribution of this work was to consider truck uptime and downtime, and subsequently enhancing its reliability and practicality.

To capture the uncertainty associated with open-pit mining operations, a discrete event simulation model using Arena simulation software (Rockwell Automation, 2019) was developed. Various scenarios were examined, taking into account objective weights, the number of trucks, and their types. The effectiveness of the developed model was illustrated through its application in the Gol-E-Gohar iron ore mine in Iran, which served as a case study. In the scenario with 30 CAT 785C trucks and no failure assumption, fuel consumption was reduced by 4.88% per tonne of production compared to the Tri-Obj. benchmark model, leading to a total fuel savings of over 12,000 liters. Giving priority to fuel consumption minimization objective, the implementation of the new model resulted in a potential reduction of up to 6% in fuel consumption per tonne of production, which led to a noticeable overall decrease of up to 20,000 liters in fuel consumption. Additionally, the model successfully maintained the scheduled production rate while achieving a 3.74% increase in waste material extraction, equivalent to approximately 26.2 kilotonnes over the ten days of the simulated operation. The number and types of trucks in a mining fleet significantly impacted operational efficiency, productivity, and cost-effectiveness. In addition to an efficient dispatching system, optimizing the size and selection of available trucks played a crucial role in establishing a productive and energy-efficient haulage system in open-pit mines. Among the explored scenarios, scenario 24, which involved a combination of 20 CAT 785C trucks and 5 CAT 793C trucks in a heterogeneous fleet, exhibited the most favorable performance in meeting production targets and minimizing fuel consumption. This configuration effectively balanced the need for high productivity with the imperative to minimize fuel consumption and environmental impact, aligning with the GHG mitigation objective of the study. Scenario 6, consisting of 30 CAT 785C trucks, had a 5.83% higher fuel consumption ratio and 5.45% higher fuel consumption per tonne of production. Each CAT 793C truck transported greater quantities of waste compared to each CAT 785C truck, attributed to its higher capacity. It is worth noting that while there was no hourly capacity limitation for dumping in the waste disposal area, the plants had specific hourly hopper capacities. Trucks with lower capacities offered more flexibility in transferring ore materials within the system and were a more appropriate choice for assignment to ore shovels.

In scenarios where truck failures were considered, a fleet with a higher number of smaller trucks proved advantageous in meeting the hourly ore production rate due to increased flexibility, despite the lower average capacity per truck. Smaller trucks also exhibited lower average downtime compared to larger trucks, further contributing to their improved performance in the context of truck failures. When considering fuel consumption per tonne of production rate as the key factor, scenario 6 with a homogeneous fleet of 30 number of small trucks, as well as scenarios 20 (with 22 small trucks and 4 large trucks) and 24 (with 20 small trucks and 5 large trucks) with heterogeneous fleets, emerged as the most reliable and efficient options. However, scenario 6 stood out with a higher production rate and flexibility in truck dispatching, making it the optimal choice when accounting for unforeseen failures in the model.

In conclusion, considering factors such as truck failures, fuel consumption, and production rates, scenario 6 with a homogeneous fleet of 30 number of CAT 785C trucks demonstrated favorable performance. However, incorporating one or more stockpiles into the system and having a slightly higher number of trucks of both types available would likely lead to a heterogeneous fleet outperforming homogeneous fleets, it is important to note that stockpiling was not considered in the framework of this study. These considerations ensured a steady flow of materials, mitigated the effects of truck failures, and optimized overall production efficiency in the mining operation.

The effectiveness of the thesis model in reducing fuel consumption can be better demonstrated in a larger mine with a more intricate road network, comprising a higher number of shovels and diverse unloading points, including stockpiles that can be considered as loading points as well.

Considering the age of trucks in simulation and optimization modeling is an important aspect to explore in future studies. Age can significantly impact a truck's performance, including factors such as failure rates, fuel consumption, and carbon emissions. By incorporating the age factor into the model, researchers can gain a more accurate understanding of how aging trucks affect overall system efficiency, operational costs, and environmental impact. This analysis can provide insights into optimal truck maintenance schedules, replacement strategies, and the potential benefits of utilizing newer and more fuel-efficient truck types.

Another area for future study can involve in incorporating shovel failure into the simulation modeling. Shovels play a critical role in the mining operation, and their reliability and downtime can have a substantial impact on overall productivity. By considering shovel failures in the simulation model, researchers can assess the effects on production schedules, equipment utilization, and operational costs. This inclusion would result in a more reliable and realistic model, allowing for a comprehensive evaluation of the system's performance and potential areas for improvement.

Furthermore, the current model's lack of stockpile consideration presents an opportunity for future research. Stockpiles are essential components in mining operations, serving as buffers to accommodate fluctuations in demand and supply. By incorporating stockpiles into the model, researchers can analyze their impact on system performance, equipment utilization, and material handling efficiency. This enhanced model would provide a more comprehensive understanding of the overall mining process, leading to improved decision-making regarding stockpile management, equipment requirements, and production planning.

It is recommended that future studies include consideration of the age of trucks, shovel failure analysis, and consideration of stockpiles to improve the reliability, realism, and comprehensiveness of the modeling approach. By considering these additional factors, more accurate predictions can be made, better optimization strategies can be devised, and ultimately, mining operations can become more efficient. In addition, future studies can focus on applying In-pit crushing and conveying (IPCC) in the mine haulage system. IPCC is a system used in mining that involves crushing ore or waste material in the pit and then conveying it to the processing plant or waste dump using conveyor belts. This approach reduces operating costs, energy consumption, and the need for truck transportation.

In-pit crushing and conveying systems (IPCC) are gaining attention due to their lower operating costs, continuous operation regime, reduced labor, and lower energy consumption. However, they require high capital costs and have reduced flexibility. The combination of IPCC and truck shovel hauling systems in open-pit mining offers advantages such as improved productivity, operational flexibility, enhanced safety, and energy efficiency. It allows for efficient material handling, reduces congestion, and optimizes resource allocation. Additionally, it helps in reducing GHG emissions and overall carbon footprint. Therefore, exploring the application of the combined IPCC and truck shovel hauling systems in mining as a future study would be advantageous.

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APPENDIX A

Table A. 1. Shovel 1 Utilization Statistics

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	73.25	0.11	73.28	0.05	0.14
Tri-Obj.	81.11	0.23	81.0	0.1	0.29
Quad-Obj.	81.22	0.28	81.3	0.13	0.35
Diff. 2 to 1 (%)	10.72	110.58	10.53	110.58	110.58
Diff. 3 to 1 (%)	10.88	155.29	10.94	155.29	155.29
Diff. 3 to 2 (%)	0.14	21.23	0.37	21.23	21.23

Table A. 2. Shovel 1 Total Queue Statistics (Hours)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	75.22	2.07	75.44	0.93	2.57
Tri-Obj.	155.5	4.92	157.12	2.2	6.11
Quad-Obj.	165.9	8.21	164.73	3.67	10.2
Diff. 2 to 1 (%)	106.72	137.46	108.27	137.46	137.46
Diff. 3 to 1 (%)	120.54	296.22	118.36	296.22	296.22
Diff. 3 to 2 (%)	6.68	66.85	4.84	66.85	66.85

Table A. 3. Shovel 1 Average Queue Statistics (mins)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	2.56	2.35	2.32	0.03	0.07
Tri-Obj.	4.79	3.2	4.51	0.03	0.09
Quad-Obj.	5.1	3.26	4.87	0.03	0.09
Diff. 2 to 1 (%)	87.11	36.17	94.4	0.0	28.57
Diff. 3 to 1 (%)	99.22	38.72	109.91	0.0	28.57
Diff. 3 to 2 (%)	6.47	1.87	7.98	0.0	0.0

Table A. 4. Shovel 1 Hauled Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	248.89	0.65	248.74	0.29	0.81
Tri-Obj.	275.72	0.68	276.04	0.3	0.85
Quad-Obj.	276.49	0.72	276.5	0.32	0.89
Diff. 2 to 1 (%)	10.78	4.22	10.97	4.22	4.22
Diff. 3 to 1 (%)	11.09	10.16	11.16	10.16	10.16
Diff. 3 to 2 (%)	0.28	5.7	0.17	5.7	5.7

Table A. 5. Shovel 2 Utilization Statistics

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	69.88	0.43	69.83	0.19	0.53
Tri-Obj.	81.28	0.25	81.26	0.11	0.32
Quad-Obj.	81.1	0.39	81.2	0.17	0.48
Diff. 2 to 1 (%)	16.32	-41.0	16.37	-41.0	-41.0
Diff. 3 to 1 (%)	16.06	-10.52	16.28	-10.52	-10.52
Diff. 3 to 2 (%)	-0.22	51.66	-0.07	51.66	51.66

Table A. 6. Shovel 2 Total Queue Statistics (Hours)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	61.98	2.86	61.3	1.28	3.55
Tri-Obj.	160.69	2.78	161.33	1.24	3.45
Quad-Obj.	166.72	3.42	166.92	1.53	4.24
Diff. 2 to 1 (%)	159.24	-2.57	163.18	-2.57	-2.57
Diff. 3 to 1 (%)	168.97	19.65	172.3	19.65	19.65
Diff. 3 to 2 (%)	3.75	22.81	3.46	22.81	22.81

Table A. 7. Shovel 2 Average Queue Statistics (mins)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	2.21	2.22	1.85	0.02	0.07
Tri-Obj.	4.95	3.26	4.68	0.03	0.09
Quad-Obj.	5.14	3.34	4.85	0.03	0.09
Diff. 2 to 1 (%)	123.98	46.85	152.97	50.0	28.57
Diff. 3 to 1 (%)	132.58	50.45	162.16	50.0	28.57
Diff. 3 to 2 (%)	3.84	2.45	3.63	0.0	0.0

Table A. 8. Shovel 2 Hauled Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	237.55	1.72	237.09	0.77	2.14
Tri-Obj.	276.68	0.66	276.36	0.3	0.82
Quad-Obj.	275.9	0.69	275.93	0.31	0.86
Diff. 2 to 1 (%)	16.47	-61.69	16.56	-61.69	-61.69
Diff. 3 to 1 (%)	16.15	-60.0	16.38	-60.0	-60.0
Diff. 3 to 2 (%)	-0.28	4.4	-0.16	4.4	4.4

Table A. 9. Shovel 3 Utilization Statistics

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	57.26	0.4	57.31	0.18	0.5
Tri-Obj.	44.59	0.3	44.49	0.14	0.38
Quad-Obj.	44.93	0.26	44.87	0.12	0.33
Diff. 2 to 1 (%)	-22.13	-24.12	-22.37	-24.12	-24.12
Diff. 3 to 1 (%)	-21.52	-34.32	-21.71	-34.32	-34.32
Diff. 3 to 2 (%)	0.78	-13.44	0.85	-13.44	-13.44

Table A. 10. Shovel 3 Total Queue Statistics (Hours)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	163.2	6.35	162.81	2.84	7.88
Tri-Obj.	71.39	5.14	70.07	2.3	6.39
Quad-Obj.	68.96	5.36	69.6	2.4	6.65
Diff. 2 to 1 (%)	-56.26	-18.95	-56.96	-18.95	-18.95
Diff. 3 to 1 (%)	-57.75	-15.56	-57.25	-15.56	-15.56
Diff. 3 to 2 (%)	-3.41	4.18	-0.67	4.18	4.18

Table A. 11. Shovel 3 Average Queue Statistics (mins)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	4.04	3.69	3.29	0.03	0.09
Tri-Obj.	2.27	3.07	1.3	0.03	0.09
Quad-Obj.	2.18	2.86	1.25	0.03	0.08
Diff. 2 to 1 (%)	-43.81	-16.8	-60.49	0.0	0.0
Diff. 3 to 1 (%)	-46.04	-22.49	-62.01	0.0	-11.11
Diff. 3 to 2 (%)	-3.96	-6.84	-3.85	0.0	-11.11

Table A. 12. Shovel 3 Hauled Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	286.45	2.24	286.6	1.0	2.79
Tri-Obj.	222.45	1.72	222.23	0.77	2.13
Quad-Obj.	224.4	1.43	223.89	0.64	1.77
Diff. 2 to 1 (%)	-22.34	-23.54	-22.46	-23.54	-23.54
Diff. 3 to 1 (%)	-21.66	-36.36	-21.88	-36.36	-36.36
Diff. 3 to 2 (%)	0.88	-16.78	0.75	-16.78	-16.78

Table A. 13. Shovel 4 Utilization Statistics

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	56.82	0.39	56.75	0.18	0.49
Tri-Obj.	44.94	0.37	44.92	0.17	0.46
Quad-Obj.	49.89	0.27	49.94	0.12	0.34
Diff. 2 to 1 (%)	-20.91	-6.0	-20.85	-6.0	-6.0
Diff. 3 to 1 (%)	-12.19	-31.03	-12.0	-31.03	-31.03
Diff. 3 to 2 (%)	11.02	-26.63	11.18	-26.63	-26.63

Table A. 14. Shovel 4 Total Queue Statistics (Hours)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	141.25	4.36	143.6	1.95	5.41
Tri-Obj.	79.56	4.09	80.25	1.83	5.08
Quad-Obj.	130.03	13.56	124.99	6.07	16.84
Diff. 2 to 1 (%)	-43.67	-6.03	-44.12	-6.03	-6.03
Diff. 3 to 1 (%)	-7.94	211.46	-12.96	211.46	211.46
Diff. 3 to 2 (%)	63.43	231.47	55.75	231.47	231.47

Table A. 15. Shovel 4 Average Queue Statistics (mins)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	3.52	3.41	2.8	0.03	0.09
Tri-Obj.	2.51	4.44	1.34	0.05	0.13
Quad-Obj.	3.69	4.28	2.32	0.04	0.12
Diff. 2 to 1 (%)	-28.69	30.21	-52.14	66.67	44.44
Diff. 3 to 1 (%)	4.83	25.51	-17.14	33.33	33.33
Diff. 3 to 2 (%)	47.01	-3.6	73.13	-20.0	-7.69

Table A. 16. Shovel 4 Hauled Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	283.51	2.03	283.38	0.91	2.52
Tri-Obj.	224.28	1.63	224.3	0.73	2.02
Quad-Obj.	249.3	1.57	249.1	0.7	1.95
Diff. 2 to 1 (%)	-20.89	-19.8	-20.85	-19.8	-19.8
Diff. 3 to 1 (%)	-12.07	-22.59	-12.1	-22.59	-22.59
Diff. 3 to 2 (%)	11.16	-3.48	11.05	-3.48	-3.48

Table A. 17. Shovel 5 Utilization Statistics

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	84.56	0.25	84.48	0.11	0.31
Tri-Obj.	74.19	0.42	74.25	0.19	0.52
Quad-Obj.	73.84	0.36	73.92	0.16	0.44
Diff. 2 to 1 (%)	-12.26	69.72	-12.11	69.72	69.72
Diff. 3 to 1 (%)	-12.67	44.17	-12.5	44.17	44.17
Diff. 3 to 2 (%)	-0.47	-15.06	-0.44	-15.06	-15.06

Table A. 18. Shovel 5 Total Queue Statistics (Hours)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	410.08	3.28	408.5	1.47	4.07
Tri-Obj.	96.53	1.87	96.16	0.84	2.32
Quad-Obj.	90.69	1.84	90.17	0.82	2.28
Diff. 2 to 1 (%)	-76.46	-42.89	-76.46	-42.89	-42.89
Diff. 3 to 1 (%)	-77.88	-43.96	-77.93	-43.96	-43.96
Diff. 3 to 2 (%)	-6.05	-1.88	-6.23	-1.88	-1.88

Table A. 19. Shovel 5 Average Queue Statistics (mins)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	12.11	3.14	12.07	0.03	0.09
Tri-Obj.	3.25	2.78	3.02	0.03	0.08
Quad-Obj.	3.07	2.65	2.87	0.03	0.08
Diff. 2 to 1 (%)	-73.16	-11.46	-74.98	0.0	-11.11
Diff. 3 to 1 (%)	-74.65	-15.61	-76.22	0.0	-11.11
Diff. 3 to 2 (%)	-5.54	-4.68	-4.97	0.0	0.0

Table A. 20. Shovel 5 Hauled Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	287.6	1.25	288.03	0.56	1.55
Tri-Obj.	252.22	1.15	252.01	0.51	1.42
Quad-Obj.	251.42	1.56	251.63	0.7	1.94
Diff. 2 to 1 (%)	-12.3	-8.43	-12.51	-8.43	-8.43
Diff. 3 to 1 (%)	-12.58	24.83	-12.64	24.83	24.83
Diff. 3 to 2 (%)	-0.32	36.32	-0.15	36.32	36.32

Table A. 21. Plant 1 Total Queue Statistics (Hours)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	0.0	0.0	0.0	0.0	0.0
Tri-Obj.	47.0	8.39	47.32	3.75	10.42
Quad-Obj.	27.6	9.0	24.94	4.03	11.18
Diff. 3 to 2 (%)	-41.27	7.29	-47.3	7.29	7.29

Table A. 22. Plant 1 Average Queue Statistics (mins)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	0.0	0.0	0.0	0.0	0.0
Tri-Obj.	1.45	2.59	0.0	0.03	0.07
Quad-Obj.	0.85	2.01	0.0	0.02	0.06
Diff. 3 to 2 (%)	-41.24	-22.52	0.0	-22.5	-22.5

Table A. 23. Plant 1 Hauled Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	237.64	1.73	237.47	0.77	2.15
Tri-Obj.	276.19	0.03	276.18	0.02	0.04
Quad-Obj.	276.22	0.03	276.24	0.01	0.03
Diff. 2 to 1 (%)	16.22	-98.06	16.3	-98.06	-98.06
Diff. 3 to 1 (%)	16.23	-98.4	16.33	-98.4	-98.4
Diff. 3 to 2 (%)	0.01	-17.62	0.02	-17.62	-17.62

Table A. 24. Plant 2 Total Queue Statistics (Hours)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	0.0	0.0	0.0	0.0	0.0
Tri-Obj.	67.46	6.49	66.04	2.9	8.06
Quad-Obj.	41.43	2.89	41.51	1.29	3.59
Diff. 3 to 2 (%)	-38.58	-55.42	-37.14	-55.42	-55.42

Table A. 25. Plant 2 Average Queue Statistics (mins)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	0.0	0.0	0.0	0.0	0.0
Tri-Obj.	2.08	3.07	0.0	0.03	0.09
Quad-Obj.	1.27	2.42	0.0	0.02	0.07
Diff. 3 to 2 (%)	-38.59	-21.21	0.0	-35.76	-21.22

Table A. 26. Plant 2 Hauled Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	248.79	0.49	248.77	0.22	0.61
Tri-Obj.	276.21	0.04	276.23	0.02	0.05
Quad-Obj.	276.17	0.05	276.17	0.02	0.06
Diff. 2 to 1 (%)	11.02	-91.55	11.04	-91.55	-91.55
Diff. 3 to 1 (%)	11.0	-90.74	11.02	-90.74	-90.74
Diff. 3 to 2 (%)	-0.02	9.61	-0.02	9.61	9.61

Table A. 27. WasteDump Hauled Tonnages Statistics (kt)

Model	Mean	Stdev	Median	StdErr	ConLev
Dispatch	857.56	3.68	858.08	1.65	4.57
Tri-Obj.	698.95	3.8	697.89	1.7	4.72
Quad-Obj.	725.12	1.23	725.32	0.55	1.53
Diff. 2 to 1 (%)	-18.5	3.36	-18.67	3.36	3.36
Diff. 3 to 1 (%)	-15.44	-66.6	-15.47	-66.6	-66.6
Diff. 3 to 2 (%)	3.74	-67.68	3.93	-67.68	-67.68

APPENDIX B

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

Scenario	Number of trucks 785C	Number of trucks 793C	Utilization Ore (%)	Utilization Waste (%)	Average Qtime (Mins)	Total Qtime (Hrs)	FC (KL)	Ore Tonnage (KT)	Total Tonnage (KT)	Ore TPGOH (T)	SR
1	22	0	67.84	47.55	2.72	373.29	298.31	461.50	1080.23	3845.87	1.34
2	24	0	74.92	50.84	2.82	416.18	324.12	508.44	1166.06	4237.02	1.29
3	26	0	79.40	54.31	3.12	488.36	346.97	541.50	1241.02	4512.54	1.29
4	28	0	80.20	54.98	3.51	555.85	378.91	545.41	1253.44	4545.11	1.30
5	29	0	80.60	56.15	3.67	591.81	392.78	548.64	1272.59	4572.02	1.32
6*	30	0	81.16	56.22	3.85	622.29	410.04	552.39	1277.51	4603.23	1.31
7	32	0	81.29	58.40	4.16	686.96	440.67	552.36	1304.78	4603.02	1.36
8	34	0	81.18	59.44	4.61	770.65	470.49	552.26	1317.77	4602.15	1.39
9*	36	0	81.19	60.14	4.92	825.31	506.12	552.32	1324.50	4602.65	1.40
10	0	15	68.85	43.14	2.13	175.38	369.04	529.10	1196.37	4409.20	1.26
11	0	16	70.85	45.66	2.28	195.68	393.42	544.77	1248.65	4539.73	1.29
12	0	17	70.96	46.96	2.40	213.87	421.65	545.57	1270.10	4546.44	1.33
13*	0	18	71.60	48.20	2.63	229.66	454.54	550.06	1295.28	4583.85	1.35
14	0	19	71.73	49.06	2.66	239.92	485.36	551.08	1312.29	4592.29	1.38
15*	0	20	71.95	48.64	2.84	254.45	517.51	552.31	1305.70	4602.59	1.36
16	0	21	71.94	50.61	3.00	274.56	545.11	552.14	1333.44	4601.17	1.42
17	0	22	72.07	52.89	3.18	299.42	572.12	552.27	1372.42	4602.28	1.49
18	25	3	80.05	53.94	3.75	552.06	418.24	552.21	1263.46	4601.73	1.29
19	26	3	80.15	55.59	3.83	577.76	433.62	552.23	1285.20	4601.89	1.33
20*	22	4	79.39	54.70	3.59	521.00	388.72	551.17	1277.53	4593.06	1.32
21	23	4	79.55	54.89	3.70	543.67	405.79	551.29	1281.59	4594.05	1.32
22	24	4	79.70	55.45	3.77	549.45	429.54	551.96	1289.60	4599.71	1.34
23	19	5	76.77	53.48	3.14	432.65	376.35	538.51	1258.84	4487.59	1.34
24*	20	5	78.71	53.89	3.45	483.93	387.44	551.52	1276.65	4596.02	1.31
25	21	5	79.12	55.32	3.67	522.96	400.03	551.37	1292.61	4594.76	1.34

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

APPENDIX C

Table C. 1. KPIs considering trucks' failure for selected scenarios

Scenario	Number of trucks 785C	Number of trucks 793C	Utilization Ore (%)	Utilization Waste (%)	Average Qtime (Mins)	Total Qtime (Hrs)	FC (KL)	Ore Tonnage (KT)	Total Tonnage (KT)	Ore TPGOH (T)	SR
6(F)	30	0	78.09	53.50	3.41	527.40	360.76	530.53	1221.59	4421.10	1.30
9(F)	36	0	80.78	58.33	4.41	725.99	435.97	548.19	1298.40	4568.29	1.37
13(F)	0	18	66.57	43.29	2.34	189.72	389.25	511.73	1180.48	4264.38	1.31
15(F)	0	20	70.06	45.12	2.51	213.17	440.18	537.50	1235.80	4479.19	1.30
20(F)	22	4	73.77	50.49	3.04	409.93	345.31	511.46	1179.22	4262.17	1.31
24(F)	20	5	71.76	50.05	2.91	378.45	343.44	501.73	1170.65	4181.08	1.33

Table C. 2. Production tonnage, Fuel consumption, and Failure time KPIs for selected scenarios

Scenario	Number of trucks 785C	Number of trucks 793C	FC (KL)	Ore Tonnage (KT)	Total Tonnage (KT)	FC per Ton Total Production (L)	FC per Ton Ore Production (L)	Total Failure Time (Hrs)	Average Failure Time (Hrs)
6(F)	30	0	360.76	530.53	1221.59	0.30	0.68	332.04	11.07
9(F)	36	0	435.97	548.19	1298.40	0.34	0.80	424.85	11.80
13(F)	0	18	389.25	511.73	1180.48	0.33	0.76	239.33	13.30
15(F)	0	20	440.18	537.50	1235.80	0.36	0.82	244.30	12.21
20(F)	22	4	345.31	511.46	1179.22	0.29	0.68	298.73	11.49
24(F)	20	5	343.44	501.73	1170.65	0.29	0.68	279.09	11.16

Table C. 3. Homogeneous CAT 785C Failure Time of each truck (Hours) part 1

Rep\Truck#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	14	19	0	0	16	14	0	0	16	18	0	0	0	15	20
2	0	0	0	15	16	16	11	0	16	14	15	17	13	17	0
3	16	15	16	0	12	18	19	10	0	0	17	18	17	16	0
4	0	0	17	14	18	15	19	0	17	0	15	0	17	13	14
5	0	12	15	17	0	12	13	12	0	10	14	11	13	20	0
Avg	6	9.2	9.6	9.2	12.4	15	12.4	4.4	9.8	8.4	12.2	9.2	12	16.2	6.8

Table C. 4. Homogeneous CAT 785C Failure Time of each truck (Hours) part 2

Rep\Truck#	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	17	15	0	15	19	19	15	17	15	16	19	20	14	0	17
2	0	15	12	19	12	18	17	18	17	0	15	18	15	16	0
3	0	20	15	13	16	18	0	16	16	18	18	0	0	0	15
4	14	0	19	14	0	18	14	18	0	0	0	11	0	0	20
5	13	14	19	15	0	19	16	20	17	14	0	0	19	9	16
Avg	8.8	12.8	13	15.2	9.4	18.4	12.4	17.8	13	9.6	10.4	9.8	9.6	5	13.6

Table C. 5. Homogeneous CAT 785C Total and Average Failure Times (Hours)

Truck type	Total failure time (Hrs)	Average failure time (Hrs)
785C	331.6	11.05

Table C. 6. Homogeneous CAT 785C TPGOH Based on Available Number of Trucks in the System

Day	TPGOH (T)	Average available trucks percentage (%)	Average number of failed trucks	Maximum number of failed trucks	Average number of available trucks	Minimum number of available trucks
1	4618.85	100.00	0	0	30	30
2	4609.8	100.00	0	0	30	30
3	4597.2	99.53	0.14	1	30	29
4	4590.73	97.17	0.85	2	29	28
5	4527.71	93.10	2.07	5	28	25
6	4493.05	86.03	4.19	8	26	22
7	4199.62	79.77	6.07	10	24	20
8	4168.29	79.17	6.25	10	24	20
9	4171.35	78.57	6.43	11	24	19
10	4235.24	79.73	6.08	11	24	19

Table C. 7. Homogeneous CAT 793C Failure Time of each truck (Hours)

Rep\Truck#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	23	37	0	0	28	22	0	0	27	32	0	0	0	25	38	29	24	0	25	0
2	0	0	0	26	28	0	15	0	27	0	24	31	0	0	0	0	25	17	0	0
3	27	0	28	0	0	0	35	12	0	0	31	32	0	27	0	0	38	26	0	0
4	0	0	29	22	34	25	35	0	31	0	0	0	31	0	0	22	0	35	0	0
5	0	0	24	30	0	0	19	17	0	13	0	0	19	0	0	20	23	35	0	0
Avg	10	7.4	16.2	15.6	18	9.4	20.8	5.8	17	9	11	12.6	10	10.4	7.6	14.2	22	22.6	5	0

Table C. 8. Homogeneous CAT 793C Total and Average Failure Times (Hours)

Truck type	Total failure time (Hrs)	Average failure time (Hrs)
793C	244.6	12.23

Table C. 9. Homogeneous CAT 793C TPGOH Based on Available Number of Trucks in the System

Day	TPGOH (T)	Average available trucks percentage (%)	Average number of failed trucks	Maximum number of failed trucks	Average number of available trucks	Minimum number of available trucks
1	4623.23	100.00	0.00	0.00	20.00	20.00
2	4593.99	100.00	0.00	0.00	20.00	20.00
3	4599.53	98.86	0.23	1.00	20.00	19.00
4	4600.00	97.07	0.59	2.00	19.00	18.00
5	4536.32	91.42	1.72	4.00	18.00	16.00
6	4499.83	84.31	3.14	6.00	17.00	14.00
7	4409.89	76.21	4.76	7.00	15.00	13.00
8	4266.55	74.07	5.19	10.00	15.00	10.00
9	4293.28	74.10	5.18	9.00	15.00	11.00
10	4360.72	73.41	5.32	8.00	15.00	12.00

Table C. 10. Heterogenous Fleet's Failure Time of each truck (Hours)

Truck Type	785C																				793C				
Rep\Truck#	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
1	14	19	0	0	16	14	0	0	16	18	0	0	0	15	20	17	15	0	15	19	0	24	0	25	27
2	0	0	0	15	16	16	11	0	16	14	15	17	13	17	0	0	15	12	19	12	0	0	0	0	0
3	16	15	16	0	12	18	19	10	0	19	17	18	17	16	0	0	20	15	13	16	33	0	27	0	0
4	0	0	17	14	18	15	19	0	17	0	15	0	17	13	14	14	0	19	14	0	0	0	33	0	0
5	0	12	15	17	0	12	13	12	0	10	14	11	13	20	0	13	14	19	15	0	36	28	0	31	21
Avg	6	9.2	9.6	9.2	12.4	15	12.4	4.4	9.8	12.2	12.2	9.2	12	16.2	6.8	8.8	12.8	13	15.2	9.4	13.8	10.4	12	11.2	9.6

Table C. 11. Heterogenous Fleet's Total and Average Failure Times (Hours)

Truck type	Total failure time (Hrs)	Average failure time (Hrs)
785C	215.8	10.79
793C	57	11.4

Table C. 12. Heterogenous Fleet's TPGOH Based on Available Number of Trucks in the System

Day	TPGOH (T)	Average available trucks percentage (%)		Average number of failed trucks		Maximum number of failed trucks		Average number of available trucks		Minimum number of available trucks	
		785C	793C	785C	793C	785C	793C	785C	793C	785C	793C
1	4529.79	100.00	100.00	0.00	0.00	0.00	0.00	20.00	5.00	20.00	5.00
2	4654.67	100.00	100.00	0.00	0.00	0.00	0.00	20.00	5.00	20.00	5.00
3	4585.53	99.42	99.00	0.12	0.05	1.00	1.00	20.00	5.00	19.00	4.00
4	4511.60	97.66	94.67	0.47	0.27	1.00	1.00	20.00	5.00	19.00	4.00
5	4407.13	93.18	90.64	1.36	0.47	4.00	2.00	19.00	5.00	16.00	3.00
6	4129.28	84.89	90.33	3.02	0.48	5.00	2.00	17.00	5.00	15.00	3.00
7	3906.56	80.87	81.94	3.83	0.90	7.00	2.00	16.00	4.00	13.00	3.00
8	3901.58	80.75	67.39	3.85	1.63	8.00	3.00	16.00	3.00	12.00	2.00
9	3634.35	79.49	55.64	4.10	2.22	6.00	3.00	16.00	3.00	14.00	2.00
10	3614.84	82.47	50.67	3.51	2.47	6.00	5.00	16.00	3.00	14.00	0.00