An approach for Evaluating the Full Truck and Full Bucket Loading Strategies in Open-Pit Mining Using a Discrete Event Simulation and Machine Learning

by

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ABSTRACT

Material loading and hauling are crucial factors in the mining industry, comprising over 50% of the costs. Many studies covered optimization and improving the efficiency of truck-shovel operations. Decreasing operating costs is vital for mining companies to remain profitable and feasible. Truck-shovel operations efficiency affects the complete mining operation, from equipment performance through productivity to the final mill throughput. Autonomous trucks and shovels and the digitalization of mines are taking place now to reduce costs, increase safety and contribute to sustaining the environment. Operation uncertainties are a source of risk and pose a threat to the continuity of the operation. Enhancing mining and loading operation due to the high contribution in operating costs, which require mining projects to look for alternatives or real options when uncertainties are encountered; for example, equipment availability deteriorates with time or a queuing condition results in a change in mining operation. A proper decision should be involved in regarding the loading strategy.

This research evaluates the alternative options under uncertain conditions related to the shovel in mine. In addition, the research tries to answer the question of what will happen if a specific loading scenario in operation is run for a set of time, by developing and implementing a framework that considers the loading strategies and accounts for material properties and operator efficiency. Then a decision on a proper loading strategy based on these inputs in a short-term period will be recommended. Next, the machine learning model predicts the proper strategy and evaluates the feature importance based on the provided data. Through this study, a truck-shovel model was simulated using the Haulsim simulation software to create the production rates, cycle times and anticipated costs for each loading scenario in *order to investigate the sweet spots between these scenarios and the controlling key performance indicators in an open-pit mine.*

The proposed operation concepts of loading strategies are full truck and full bucket, which is a term called on shovel passes to the truck; full truck requires the highest passes to fill the truck, so the truck travels full and full bucket lower passes truck travel under full due to queueing conditions or production issues. Equipment selected in a mine with a different fleet size are run in a simulation to understand the full truck and full bucket.

The study results indicate a sweet point incorporated with changing the match factor between loading strategies; a huge decrease in haulage costs by ~ 25% and queueing trucks reduced by 50% in the simulation results. Moreover, the investigation of changing the capacity of the shovel, rolling resistance and haul roads is embedded as a sensitivity analysis in this work. Next, these outputs are trained and tested in a machine learning model in order to predict the loading strategy, whether full truck or full bucket. Moreover, signifying the most important feature affecting the prediction by using feature importance techniques, the feature was the cycle time in the case study. These conceptualized terms (full truck and full bucket) and the developed framework can integrate with autonomous trucks and shovels because decisions are easier to take than manually operated machines.

PREFACE

This thesis is an original work by Mohammad Al-Masri. Mohammad Al-Masri has been responsible for framework development, computer programming, configuring for running software, writing and editing. Dr. Yashar Pourrahimian is the supervisory author and was involved with the guidance of concept formation and manuscript compositions.

Parts from chapter 3 of this thesis have been presented in the CIM convention 2022, Vancouver as “M. Al-Masri, Y. Pourrahimian, A. Yaghini (2022). Simulation and Analysis of Loading Practices for Trucks and Shovels Under Production Variability”. I was responsible for the conceptualization, framework development, writing and editing. Dr. Yashar Pourrahimian is the supervisory author and was involved with the guidance of concept formation and manuscript compositions.

Parts from chapter 4 of this thesis have been presented in the CIM convention 2022, Vancouver as “M. Al-Masri, Y. Pourrahimian, A. Yaghini (2022). Simulation and Analysis of Loading Practices for Trucks and Shovels Under Production Variability”. I was responsible for the conceptualization, configuration of running software, computer programming, writing and editing. Dr. Yashar Pourrahimian is the supervisory author and was involved with the guidance of concept formation and manuscript compositions.

Chapters 1,2 and 5 were originally written and edited by Mohammad Al-Masri and reviewed by Dr. Yashar Pourrahimian.

This Thesis is Proudly Dedicated To:

My parents:

Rasem and Hala,

My brothers:

Waseem, Naseem and Nadeem

and

My lovely nieces:

Masa and Zaina

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LIST OF ABBREVIATIONS

Parameters

AI	Artificial Intelligence
AT	Available Time
BCM	Bankable Cubic Meter
BFF	Bucket Fill Factor
CART	Decision Tree Classifier
CT	Calendar Time
DES	Discrete Event Simulation
DL	Deep Learning
DT	Downtime
EDA	Exploratory Data Analysis
FB	Full Bucket
FT	Full Truck
KNN	K Neighbors Classifier
KPI	Key Performance Indicator
LDA	Linear Discriminant Analysis
LR	Logistic Regression
MF	Match Factor
ML	Machine Learning
NB	Gaussian Naïve Bayes
NP	Non-Productive Time
OD	Operating Delay
OT	Operating Time
OPMS	Open Pit Metal Solution software

PT	Productive Time
RF	Random Forest
RL	Reinforcement Learning
RR	Rolling Resistance
SB	Standby
SBE	External Standby
SBO	Operating Standby
Std	Standard Deviation
Shap	SHapley Additive exPlanations
SL	Supervised Learning
ST	Scheduled Time
SVM	Support Vector Machine
t	tonne
TKPH	Tonne Kilometres per Hour
UT	Unscheduled Time
WT	Working Time

CHAPTER 1

INTRODUCTION

This chapter discusses the background of the research topic and how it is developed in the literature. Starting from introducing the research's problem definition, then a summary of the related literature, followed by the general adapted methodology in addition to the scope and objectives of the study, which is also discussed. Finally, the scientific and industrial significance are elaborated, followed by a brief description of the thesis structure and contents.

1.1 Background

Mining and hauling are significant components of a mining project. Whether a mining project is based on surface or underground, loading and hauling still contribute to a significant proportion of the running operation costs ranging from 50-60% (Upadhyay et al., 2021). Reducing these costs is a significant factor in sustaining operation time and operating costs, whether through equipment technological enhancement, operator skill efficiency, complex dispatch systems, or even modern clouding systems and various loading strategies; operation enhancement is essential and valuable for any mining project in the upcoming time.

When considering loading strategies and practices in truck shovel system, investigating opportunities for enhancing and reducing these costs and productivity losses in the running operation is essential. This matter becomes more important when operations are run in unpredictable, uncertain conditions that cannot be determined or planned. This poses tremendous pressure and risk on the operation and the available optional alternatives for fleet configuration and loading strategies. For example, when shovel breaks down or its availability is reduced, and it is no longer serving the trucks for various operating reasons a decision should be made to enhance the operation.

Uncertainty is not related to the equipment and fleet level alone. It expands to almost everything in the mining life; because high uncertainties with different magnitudes characterize mining. For example, commodity prices fluctuate from time to time due to various reasons that are related to supply and demand or due to unexpected events like COVID-19 and it is consequences, other factors like human factors (operators to the high management) and skills that are not as planned to perform its role. Other significant uncertainties are related to the material in the mine (geological level), whether ore or waste and how it is extracted. This material has in place characteristics that differ when disturbed and dug up, inheriting the original characteristics with more voids (swelling) and less density per volume. In order to liberate this material from undisturbed to disturbed situations, blasting is a usual operation associated with extracting the material; uncertainties and efficiency of the conducted blasting are common things that change the final material fragment size, type, ore-waste mix, dilution, density, roundness and other factors. Consequently, when the shovel bucket encounters the material in the bench face, these uncertain parameters affects the final material filled in the bucket; hence the final payload that is passed from the shovel to the truck in a certain number of passes is also affected, especially the last pass.

This thesis focuses on simulating the loading strategies using a truck-shovel fleet and analyzing the resulting data in a meaningful framework to understand better the impact of the full truck (FT) and full bucket (FB) loading strategies in open-pit mining operations and identify the sweet spots that follow the adaptation and switch between loading strategies. With a specific potential for further improvements and opportunities in development in light of mining automation and digitalization at levels 4 and 5, fully autonomous trucks, and the potentially autonomous shovel, this will identify and bring these concepts of the FT and FB to the high importance level in short-term operational level in daily mining activities and possibly the long-term as policies, strategies and workflows.

1.2 Statement of the Problem

Truck shovel loading strategies have been a dilemma in loading payload and the number of passes; whether underloading or overloading the truck, each decision has its pros and cons and directly affects the efficiency. For instance, saturating a shovel to reach 100% efficiency or over results in queuing conditions, and undersaturation of the shovel below 100% results in higher costs.

Equipment matching is problematic as well; whether accounting for performance, production rate, operating costs, environmental impacts or operation constraints (grade, weather, accessibility, facilities matching), there will be a difference in the final results of the passes (decimal passes) and whether these passes will be rounded up or down, depending on the number of trucks and shovels, Figure 1-1 depicts this struggle and gives an example on the hydraulic shovel with various trucks configurations.

Payload is another essential concept; the final payload affects and contributes to payload policy, as in Figure 1-2, which determines whether the final truck’s load is good, under, over or even rejected. Some systems sometimes use conventional loading without any sensors monitoring the payload. Whether in shovel or truck, other systems are evolving. However, with a marginal payload accuracy of ~5%, new systems are now emerging to monitor the dig, payload, and material and send it to the clouding system for further monitoring and analysis. It is also important to mention that the final payload affects the cycle time and is affected by operator skill. Moreover, the higher payload values increases the maintenance costs of trucks and fuel consumption due to the high engine loading and mechanical fatigue frequency. At the time of loading, trucks' measurement accuracy can be reported after a few minutes of driving. This delay limits the shovel operator from quickly adapting to the loading practice.

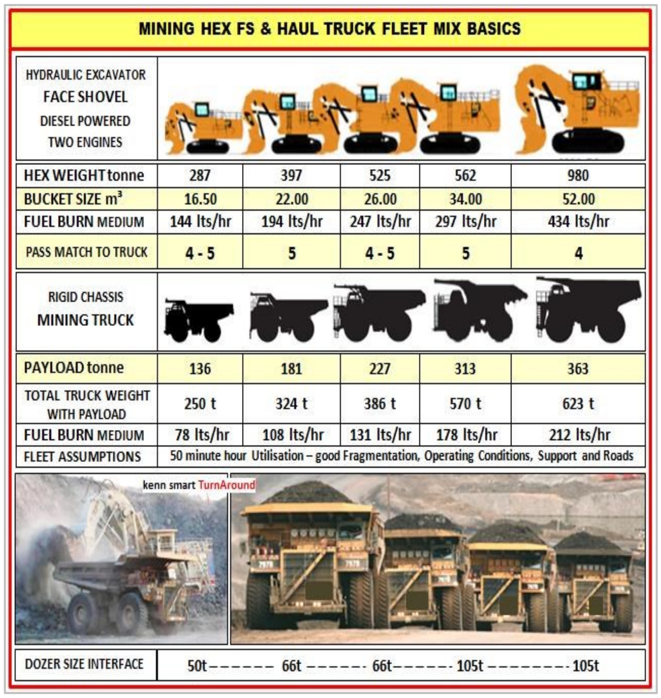


Figure 1-1 Equipment and pass matching in a hydraulic shovel (Kenn Smart, 2011)

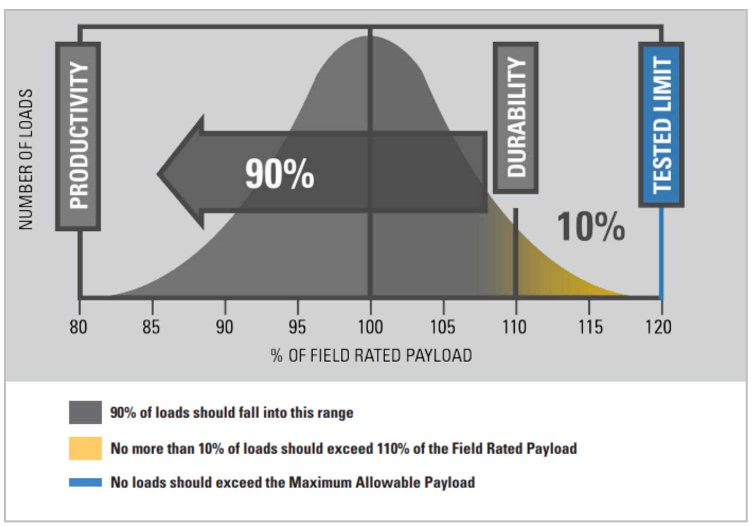


Figure 1-2 Payload policy based on Caterpillar guidelines (CAT, 2021)

Figure 1-3 illustrates the importance of loading practice in tire life, which is a major operating cost. These costs depend on the nature of the material loaded, i.e. fragmentation size, location of passes loaded in the truck's tray, number of passes and final payload in the truck.

Figure 1-4 illustrates the industrial and operational level point of view on truck-shovel passes. There is a debate in matching the passes that are required for loading the truck by shovel, the classical industrial point of view; which explains that when an increasing number of passes, there will be more than 30% loss in tph while if adapting the three passes the tph will be more than 30%, but it is unrealistic, sticking to the baseline with four passes will result in the proper tph (ideal and economic).

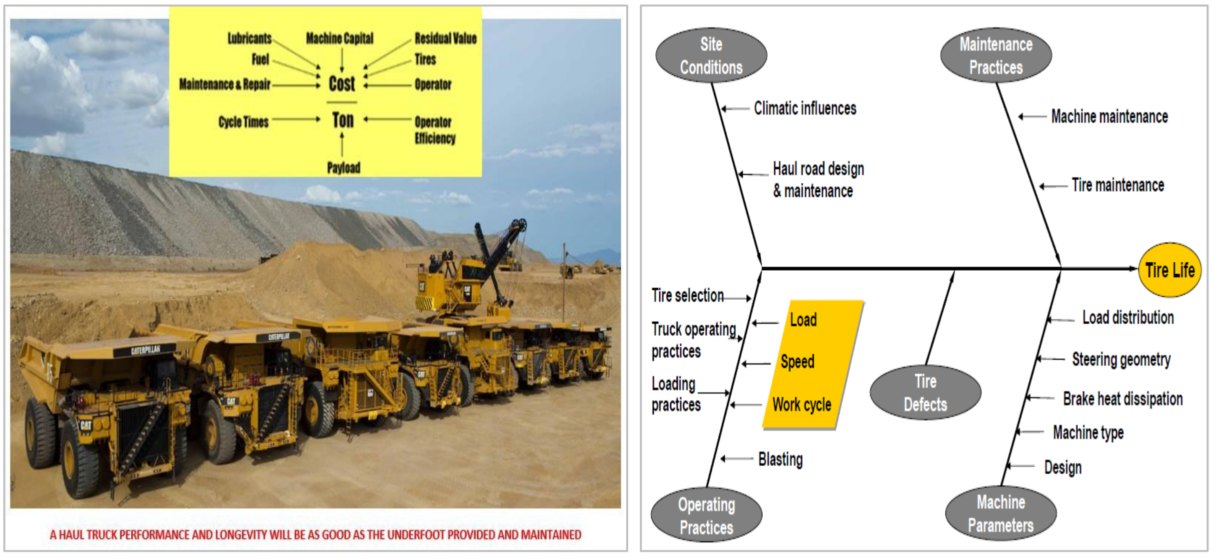


Figure 1-3 Payload, loading practice and load time effect tire life (Kenn Smart, 2011)

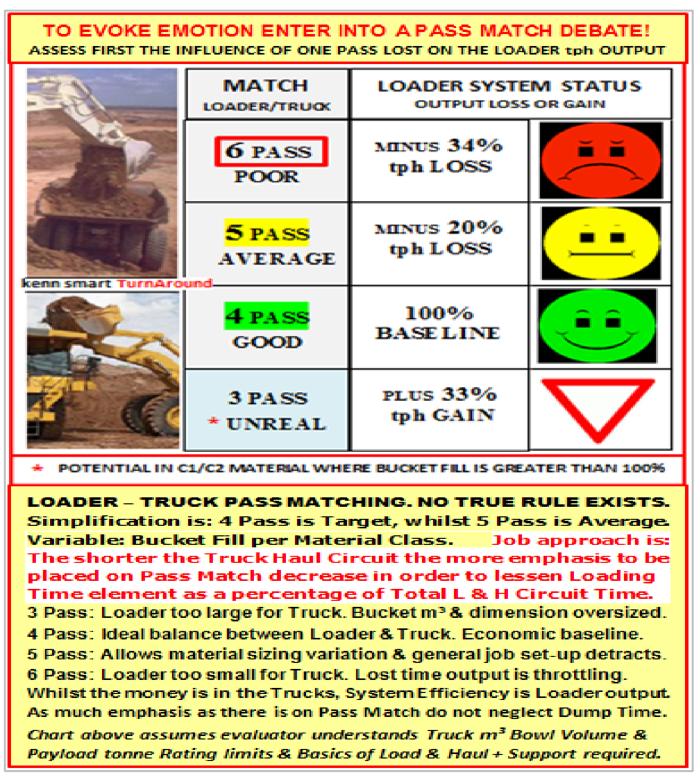


Figure 1-4 Example of pass matching and its effect on productivity (Kenn Smart, 2011)

Literature shows various ways of adapting loading strategies from many perspectives. However, no research included a discrete event simulation (DES) that uses the concepts of FT and FB in a straightforward framework that is applicable in an open-pit mine. Furthermore, most of the previous literature covered the small truck categories (earthmoving) instead of large mining trucks.

The following question will be investigated in the thesis:

Can a discrete event simulation framework be developed to model the full truck and full bucket in truck shovel loading strategies in open-pit mining operations and be used to further decide between these strategies based on the resulted KPIs to achieve operational improvements and determine any sweet spots under operation uncertainty?

1.3 Summary of Literature Review

The DES was introduced by Bauer and Calder (1973), followed by Sturgul and Harrison (1987), who discussed the use of simulation models using GPSS programming language. The literature reveals that there are many approaches in simulation techniques in mining operation's fleet and production analysis, including using the following techniques:

- Regression analysis: the way of mathematically sorting out which variables have an impact, as defined by Gallo (2015). This technique was implemented as found in (Smith, 1999; Chanda and Gardiner, 2010; Choudhary, 2015; Offei and Summers, 2010; Dindarloo and Siami-Irdemoosa, 2016).
- Expert systems: a computer program that uses artificial intelligence technologies to simulate the behaviour of something of interest that has knowledge in a particular field, as Lutkevich (2022) defined. This approach was found in (Alkass and Harris, 1988; Amirkhanian and Baker, 1992; and Kirmanli and Ercelebi, 2009).
- Using C programming language. This approach was adapted by Smith et al. (1995).
- Queuing models, approaches of literature are found in (Ringwald, 1987; Zeng et al., 2019).
- Quantitative formulas: uses simulation to derive quantitative formulas accounting for the effect of some parameters in operation using the available required resources and durations as Morley et al. (2013a) approach.

- Petri net or place transition net: a graph model (a mathematical technique) for controlling the behaviour of a system exhibiting concurrency in its operation, Dennis (2011). For example, Cheng et al. (2010) approach.
- Real-time GPS, Alshibani and Moselhi (2012) approach.
- Genetic algorithms, as adapted in (Marzouk et al., 2004;Shawki et al., 2009; and Hsiao et al., 2011).
- Neural network systems, approaches in (Shi 1999; Chao, 2001; Chanda and Gardiner, 2010; Soofastaei et al., 2016a).

The Specialized approaches using MATLAB and other platforms, Askari-Nasab et al. (2007) implemented DES to capture random field processes in open-pit and material simulations using MATLAB.

Kaboli and Carmichael (2016) covered underloading by examining truck parameters, including grade, payload and truck type. Their results indicated a small reduction in fuel consumption in overload trucks penalize trucks and mine roads maintenance, while it is important to strictly load trucks based on their capacity.

Operation costs were covered starting from Hardy (2007) in his studies about overloading and the resulting costs to Marinelli and Lambropoulos (2012) who examined cost comparisons between loading and hauling. They concluded that a loading procedure could result in a significant cost decrease depending on the hauling distance and the volume of the last pass. Additionally, Morley et al. (2013b), utilized Monte Carlo Simulation in their production and loader prioritization. They evaluated the costs of the four to six passes rule in different equipment configurations and concluded that it is not applicable in earthmoving applications. Carmichael and Mustaffa (2018) evaluated the loading policies, operation cost and environmental impacts.

In the literature that covers payload and passes, Schexnayder et al. (1999) emphasized matching the number of payloads to fill a truck as an integer number. Soofastaei et al. (2016a) thoroughly examined payload variance and mean. Kecojevic and Komljenovic (2010) related the payload with engine load factor and fuel consumption. Yaghini (2021) evaluated payload using operator behaviours and skills. In passes literature. Hays (1990) emphasized that the number of passes is a major in total loading time. Marinelli and Lambropoulos (2012) examined the passes per total loading time, partial passes, and the relations of last passes with hauling distance.

Summary of the related literature as found in Tapia et al. (2021) investigated loading methodologies in an open-pit mine. They used FT and FB scenarios by creating simulation models using Talpac software to understand cost and production analysis and how they relate to cycle and queuing time. Mustaffa (2021) investigated the impact of alternative loading practices on production and emission using Monte Carlo Simulation to compare these practices. The results showed that double-sided loading has the lowest effect on the environment.

Based on findings from the previous literature, a significant part of the research is covered by earthmoving trucks in simulation. However, there are some similarities between earthmoving trucks and mining trucks; a real mining equipment evaluation and simulation that consider open-pit data and operator efficiency will add more realistic value to the FT and FB approaches. Other literature was conducted using different and old simulation approaches, which could be time-consuming, hard to learn and not flexible.

The reviewed literature also reveals some discrepancies when dealing with the costs, utilization and production, which could be due to the adapted simulation method or operation properties. Which is still not fully understood, and there is no comprehensive framework available to understand the operation more thoroughly in open-pit mining loading practices. It is vital to note that no research used a machine learning (ML) system to understand and anticipate the data from an FT and FB analysis utilizing Haulsim software. Furthermore, no literature offered any guidance or suggestions for modifying loading techniques in developing autonomous trucks and shovels and future level 5 mining.

1.4 Objectives of the Study

The main objective of the research is to develop, apply and predict a theoretical simulation framework for short-term schedules in a mining operation. The framework aims to find a loading decision scenario that achieves improvement in the operation in various KPIs such as cycle time, lower material hauling costs and higher production based on the operation and input data in the simulation software.

In order to achieve these improvements, this research includes developing multiple frameworks that focus on:

- Develop a framework that helps to make the proper decision for loading strategies based on various sets of inputs in mining operations.
- Identify where the sweet spot in making the decisions to change loading strategy.

- Develop a methodology for ML and exploratory data analysis (EDA) application on the resulted data.
- Understand the operation in uncertainty under various match factors (MF).
- Predict in high accuracy the loading strategy based on the resulted simulated data.
- Understand and evaluate the most effective parameters in the prediction of the ML model to further evaluate and characterize the operation key performance indicators (KPI).
- Conceptualize the FT and FB in DES and ML frameworks.
- Estimate operations' KPIs based on different loading strategies.

1.5 Scope and Limitations of the Study

The scope of this study is limited to truck shovel simulation analysis in an operating mine hauling material from a specific source to a destination. In order to start simple and understand the operation clearly and to develop a policy, the following assumptions are considered:

- The dispatching system is simple and homogenous.
- The input schedule parameters are deterministic.
- There is a proposed change in MF that resulted in a changed fleet configuration.
- Hauled material characteristics are deterministic as an input in simulation (density, swell factor, Excavatability, BFF).
- Operator performance is deterministic.
- Auxiliary machines are not involved in simulation.
- Truck refuelling times are ignored.
- Equipment operating data are deterministic except for the variability times mentioned in the results.

1.6 Research Methodology

The primary motivation for this research is to understand when to select the proper loading strategy in an open-pit mining operation, either FT or FB, by considering the uncertainty in the operating shovel and the resulted excessive trucks. The impact of the selected loading strategy is then evaluated and compared with another loading strategy in terms of costs, production rates, cycle times and queued trucks. The framework initiates from the scheduling software and a short-term plan is imported into the Haulsim. Next, the operation is configured inside Haulsim to reflect the real mining operation equipment, material, and shifts. Then a framework for understanding the fleet size relation with loading strategies is developed by running multiple MF scenarios. The results are used in an ML for prediction and feature importance evaluation to further understand the data. Figure 1-5 summarizes the research methodology, and Figure 1-6 shows a detailed summary of DES.

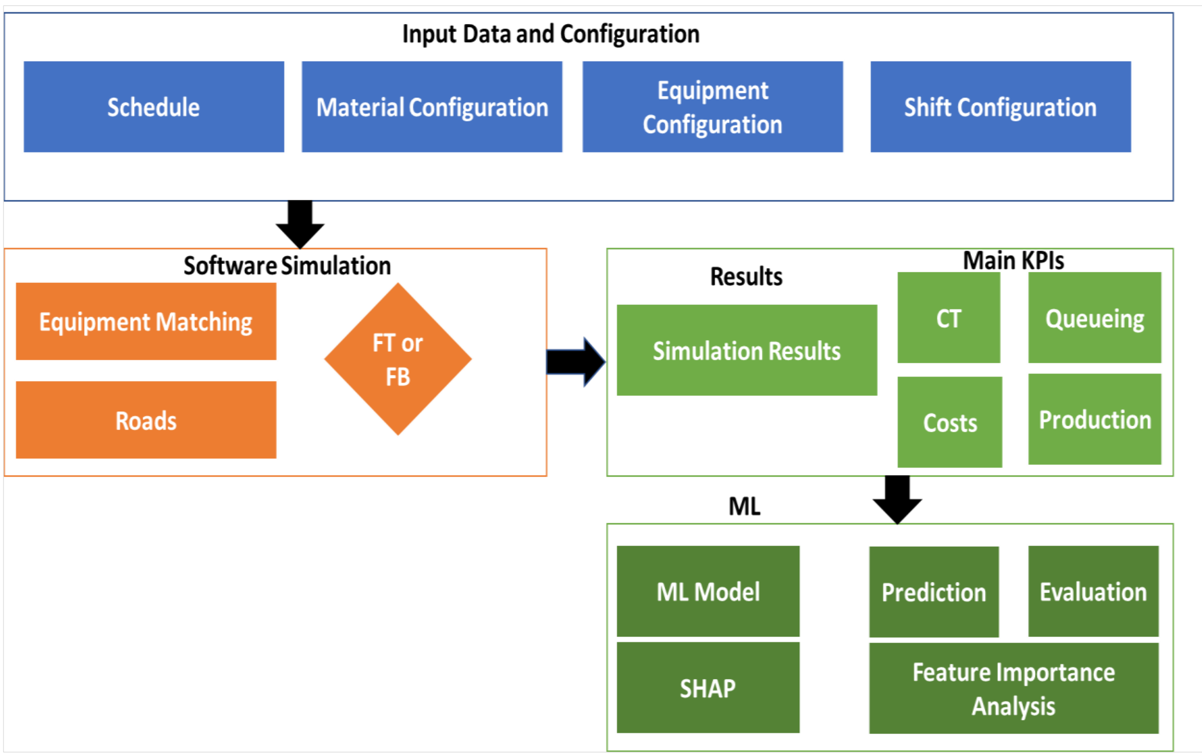


Figure 1-5 Summary of the proposed methodology

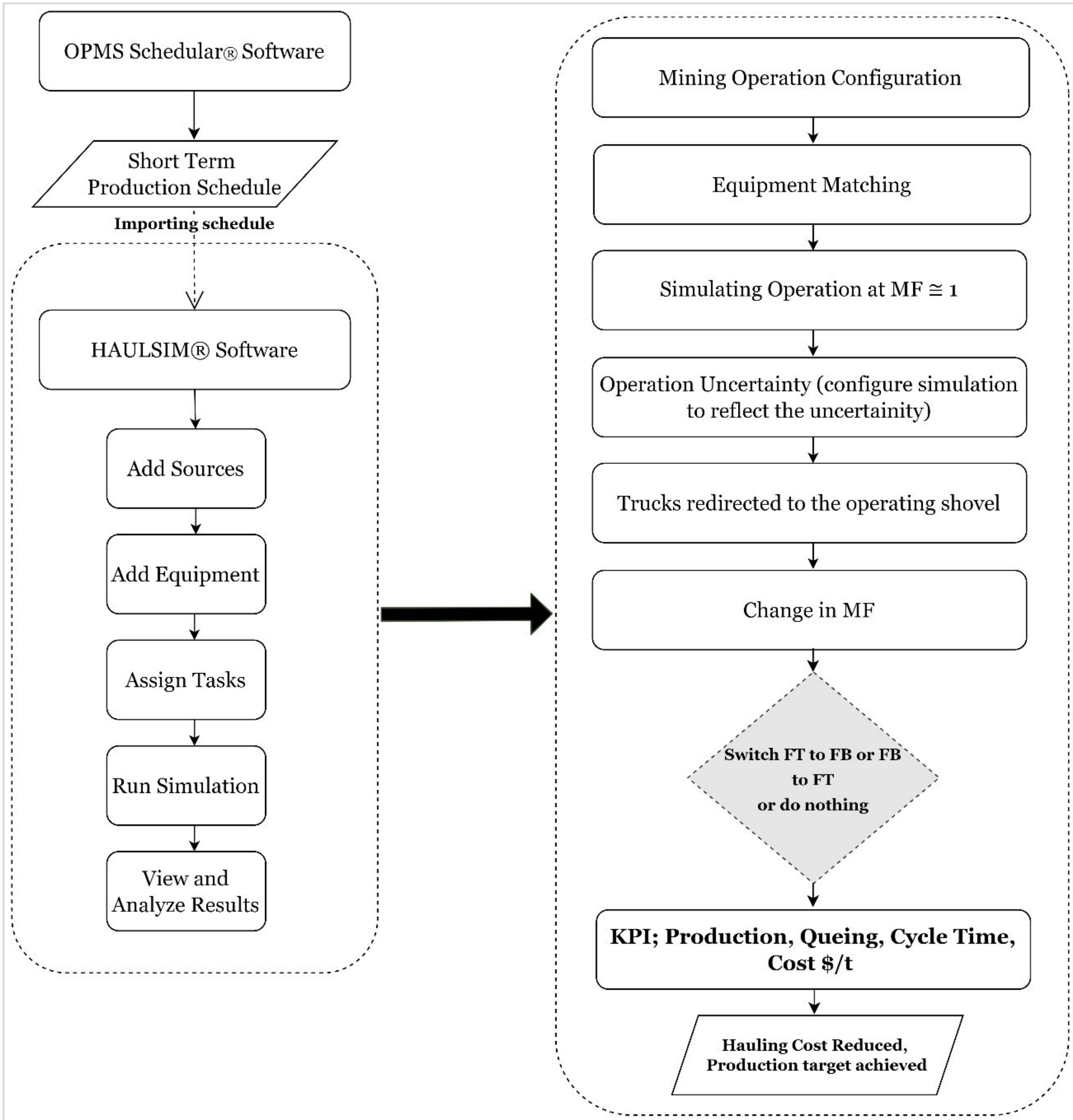


Figure 1-6 DES simulation methodology

The following summarizes the research tasks that are considered to model the FT and FB loading strategies:

- To understand when to select the optimal loading methodology (higher or lower passes or FT and FB will be discussed in the next chapters) based on mine changing operating conditions and the associated operation uncertainties.
- To understand what are the parameters that trigger this switch between loading strategies.

- To conceptualize the FT and FB as a concept in ML algorithms and the deep learning (DL) potential.
- Develop a framework or policy (guidelines) that honours the importance of loading trucks in full or partial full based on shovel availability and utilization, considering the uncertainties and normal running mining operation.
- To introduce this concept in the digital transformation in mining engineering, especially in the emerging Autonomous trucks and level 4 and level 5 of mining digitalization.
- To investigate the sweet spot between loading strategies and how or when to switch between these strategies in a basic form.
- To develop a framework for ML and data analysis that embeds the simulated data from loading strategies and evaluates the important factors affecting the switch between these factors.
- To create cycle time analysis, productivity curves and other operation KPIs for both loading strategies.

1.7 Scientific Contribution and Industrial Significance of the Research

This research is expected to contribute to research and industry with the following potential applications:

- Small mines that have no advanced dispatching system or complex dispatching system.
- Mines that predict and monitor the blasting properly, in a full integrable way.
- Introducing material uncertainty in all aspects, including geomechanical characteristics, density, excavatability and diggability, relating these conditions with changing loading strategies might result in lower operating costs.
- Carbon footprint and engine loading: where emissions rates are restricted, lowering the payloads might significantly reduce the total carbon emissions rate. (If old equipment emits carbon and other pollutants, this strategy might help).
- In mines with a lot of material variability (ore classified based on hardness), this might help select the passes required based on material hardness and density.
- Starting mines with a low cycle time requires hauling huge quantities, especially in the beginning when a lot of mine truck equipment and shovel has queuing conditions.

- Mines that adopt new facilities to reduce the cycle time of trucks and reduce trucks' travel times can be adapted to utilize more trucks and achieve the production target.
- If integrated into the system, mining that adapts the autonomous trucks and level 4 and the upcoming level 5 will yield a clear impact.
- Short cycle times and highly queuing situations, where many trucks are available and shovels are always queued.

1.8 Organization of the thesis

Chapter 1 is an introduction to the research topic. It explains the objectives behind this research and the scope of the research. Furthermore, a summary of the findings of the literature review and a summary of the proposed methodology is discussed in this chapter.

Chapter 2 presents the previous studies related to truck and shovel loading strategies, including earth working trucks and related literature review.

Chapter 3 explains the theoretical framework and steps followed for conducting this research, including software, followed steps, data analysis and machine learning.

Chapter 4 examines the results of the simulation, including the operation KPI and other important parameters.

Chapter 5 introduces the summary of the FT and FB research findings and discusses the results and ML analysis, then proposes a set of recommendations and future work.

CHAPTER 2

LITERATURE REVIEW

This chapter discusses the literature findings related to the research topic, including different papers and literature overviews which are examined to fully understand the existing problems in loading strategies, associated costs, simulation history and approaches, queuing effects, production, match factor, fuel consumption and finally a brief review on machine learning in this regard. Lastly, the most related literature is discussed and summarized.

2.1 Simulation Types and Techniques

This section discusses the concept of simulation that different researchers defined in addition to simulation purposes and the followed methodologies related to the mining fleet operation simulation. Banks and Nelson (2014) classified simulation models into static and dynamic models. A static simulation model represents a system at a particular point in time, while a dynamic simulation model represents a system that changes over time. It is further classified into the following:

- *Deterministic versus stochastic models*: a deterministic simulation model contains no random variables, e.g., a linear programming model, while a stochastic simulation model has one or more random variables as inputs and outputs, e.g., a queuing model.
- *Discrete versus continuous models*: a DES model represents a system in which the state variables change only at a discrete set of points in time. For example, a truck-shovel system is a typical discrete system. On the other hand, a continuous simulation model represents a system in which the state variables change continuously over time, such as a system associated with flowing fluids.

Bauer and Calder (1973) defined simulation as a concept. They defined simulation as a modelling technique that can predict the change in the performance of a system. They divided simulation into probabilistic Monte Carlo Simulation and standard using mathematical equations. Sturgul and Harrison (1987) approached earlier methods of simulation techniques. They discussed the use of simulation models using GPSS programming language to simulate various situations, including coal mine dispatching and mine fleet for uranium mine expansion. Ataeepour and Baafi (1999) implemented Arena software in simulation models, improving mine productivity. The status of mine simulations in Canada, including software and case studies, was addressed in an earlier study of the simulation literature by Vagenas (1999).

Then moving to robust and specialized approaches using MATLAB and other platforms, Askari-Nasab et al. (2007) implemented DES to capture random field processes in open-pit and material simulations using MATLAB. Shawki et al. (2015) implemented Arena software to improve excavator performance indices. Tabesh et al. (2016) implemented a simulation approach by incorporating truck shovel operations, road networks, stockpiles and other operations. They integrated the DES model into MATLAB, Excel and VBA to understand operation scenarios and uncertainties. Soofastaei et al. (2016) developed a DES model to investigate the payload variability on trucks in order to improve productivity and energy.

The literature reveals that there are many approaches in simulation techniques in mining operation's fleet and production analysis, including using the following:

- Regression analysis: the way of mathematically sorting out which variables have an impact (Gallo, 2015).
- Expert systems: a computer program that uses artificial intelligence technologies to simulate the behaviour of something of interest that has knowledge in a particular field (Lutkevich, 2022).
- Using C programming language.
- Queuing models.
- Quantitative formulas: uses simulation to derive quantitative formulas accounting for the effect of some parameters in operation using the available required resources and durations Morley et al. (2013a).
- Petri net or place transition net: a graph model (a mathematical technique) for controlling the behaviour of a system exhibiting concurrency in its operation (Dennis, 2011).
- Real-time GPS.
- Genetic algorithms.
- Neural network systems.

2.2 Different Approaches to Fleet Simulation

Earthmoving operation literature is considered due to the lack of related literature in mining engineering, especially in the early stages and the similarities between construction operation trucks, off-road trucks and mining trucks. Earthmoving productivity calculation was conducted by Smith (1999), who estimated the productivity by regression analyses; his findings showed a relationship between operating conditions and productivity. However, his analysis overestimated the operation's productivity when resources were not well known.

Several researchers have developed a system of earthmoving selection using an expert system technique (Alkass and Harris, 1988; Amirkhanian and Baker, 1992; and Kirmanli and Ercelebi, 2009). Chanda and Gardiner (2010) compared three methods of cycle time analysis productivity. These methods are simulation, artificial neural networks, and multiple regression. They benchmarked the results with a monitoring system in a mine and found that simulation underestimated and overestimated the results, and the other proposed methods showed better results. However, their data was case specific.

Smith et al. (1995) customized higher-level DES models using a programming language. They developed a DES model that was translated into a computer program written in the C programming language. Morley et al (2013b). utilized DES by developing quantitative formulas; they reached that a decrease in production does not directly correlate with an increase in cost. Cheng et al. (2010) implemented optimization and simulation using Perei net for equipment allocation, considering cost and other parameters in a dynamic constraint.

Alshibani and Moselhi (2012) integrated simulation with optimization using real-time GPS. Some researchers developed a framework using genetic algorithms for simulation-optimization of earthmoving operations (Marzouk et al., 2004;Shawki et al., 2009; and Hsiao et al., 2011). Neural network systems were developed by Shi (1999) and Chao (2001) for construction practitioners to forecast truck selection as well as earthmoving operations and performance.

Price (2017) defined DES as “a modelling technique that is widely used to model complex systems”. He also implied that fleet management systems' comprehensive data is rarely used to model fleets. The advantages include stochastic delays due to breakdowns and meal breaks, load and travel time, where some variables are random and dynamic, involving models that change with time. DES has been used extensively in different industries such as manufacturing, service providers, warehouse distribution, cashier checkout lanes market, department stores, airports, and mining. Price (2017) summarized the purposes of DES in mining as follows:

- Increase equipment utilization.
- Reduce waiting time and queuing.
- Study alternative investment ideas.
- Evaluate cost reduction ideas.
- Train operators in overall system operation.
- Support day-to-day decision-making.
- Minimize the effects of breakdowns.
- Understand the impact of mixed fleet interactions.

2.3 Simulation Software

There are several simulation software tools that one can use to model material loading and hauling in a mining operation. Some software programs involve learning the related programming language, while others have an interactive interface with pulldowns/command lines. Krause and Musingwini (2007) summarized the simulation software, programs and models for truck shovel analysis as follows:

- Iterative models that fit discrete empirical values to cycle variables, e.g.: machine repair model.
- Regressive models modify waiting time by using correction factors such as FPC ® by Caterpillar.
- Stochastic Monte Carlo models by fitting probability distributions to cycle variables, e.g.: Talpac ® and Haulsim ® by Runge Software.
- Stochastic graphic simulation following probability distributions within Monte Carlo simulation e.g.: Arena ® by Rockwell Software.
- General purpose simulation programming languages system (GPSS/H ®) by Wolverine Software and SIMAN.
- Simulation based on programming languages, C++ (C environments), Python and Java.

2.4 Cost, Production and Cycle Times

In payload and production analysis, the literature reveals many different claims, findings and disagreements in balancing the payload, production, cycle time and passes loaded. Smith et al. (1995) concluded that the additionally loaded bucket is an advantage provided the truck is not overloaded. Furthermore, they figured out that spotting and loading time similarly affect production; hence reducing operation cycle times is important for achieving maximum production. They also discussed the interactions of four factors in earthmoving operations: production, match factor, passes per load and load pass time. They concluded that adding trucks would not increase production. According to Schexnayder et al. (1999), payload weight affects incremental production; they emphasized matching the number of bucket loads to fill a truck as an integer number.

Hardy (2007) claimed that overloading trucks would increase productivity associated with increasing unit costs. Marinelli and Lambropoulos (2012) examined cost comparisons between loading and hauling. They came to a conclusion that, depending on the hauling distance and the volume of the last pass, a loading procedure could result in a significant cost decrease. Morley et al. (2013b)concluded that the four to six passes rule is not applicable when dealing with real earthmoving applications due to equipment combinations such as smaller excavators and larger trucks. They also concluded that considering trends, trucks and excavators must be analyzed separately. They also implemented that using a loader to satisfy production requirements and then selecting trucks after will result in a higher per unit cost; consequently, this may result in a high production cost to keep the loader always utilized.

Carmichael and Mustaffa (2018) examined the loading policies and environmental impacts, including loading in zero waiting time and double loading. They concluded that the former had the least impact on the environment and optimal cost advantage while the latter had the highest environmental impacts and non-favourable costs.

In the field of simulation and optimization in mining engineering, Moradi Afrapoli et al. (2019) developed a simulation-optimization framework that optimizes haul fleet size by implying heterogeneous and homogeneous fleets of various sizes and recommending that equipment failures and maintenance should be evaluated for the optimal fleet size. Moradi Afrapoli and Askari-Nasab (2019) explained in a review that connecting the strategic part of the mine plan to the operational part is difficult. However, the operation should achieve both the long-term and short-term goals. They also emphasized technical and geological uncertainty that are crucial components in fleet systems management, and the shovel relocation to new mining cut associated losses should be understood well. A multi-optimization model was created by Mohtasham et al. (2021) that determines the optimal production plan for the shovels and allocates the mine fleet in an optimal production target, head grade and fuel consumption. Upadhyay et al. (2021) developed a simulation-based algorithm that estimates the productivity under technical uncertainties, giving a solution with higher accuracy and lower dependency on haulage distance.

The number of passes required for loading and the shovel work cycle time determines the loading time, Hays (1990). Loading time has also attracted attention in the literature due to its impact on loading and material handling. Smith et al. (1995) found that the loader passing time has the greatest impact; by decreasing this time by three seconds, the cost per cubic metre will drop by almost nine percent, and production will rise by eleven percent. Kannan et al. (2003) created a statistical simulation model to account for payload and loading time variations.

As Hardy (2007) demonstrated, if working-face constraints are permissible, decreasing loader waiting time with this type of loading can be applied in double-sided loading fields. However, this application is only applied to mining in bulk operations, such as coal with a dragline and iron ore where selectivity is low. Mohtasham et al. (2021) classified cycle times in over trucking and under trucking circumstances. These concepts are demonstrated in Figure 2-1. In over trucking queueing time appears in operation, while in under trucking, shovel idling time is only incorporated. The remaining operational cycle times are found in both cases.

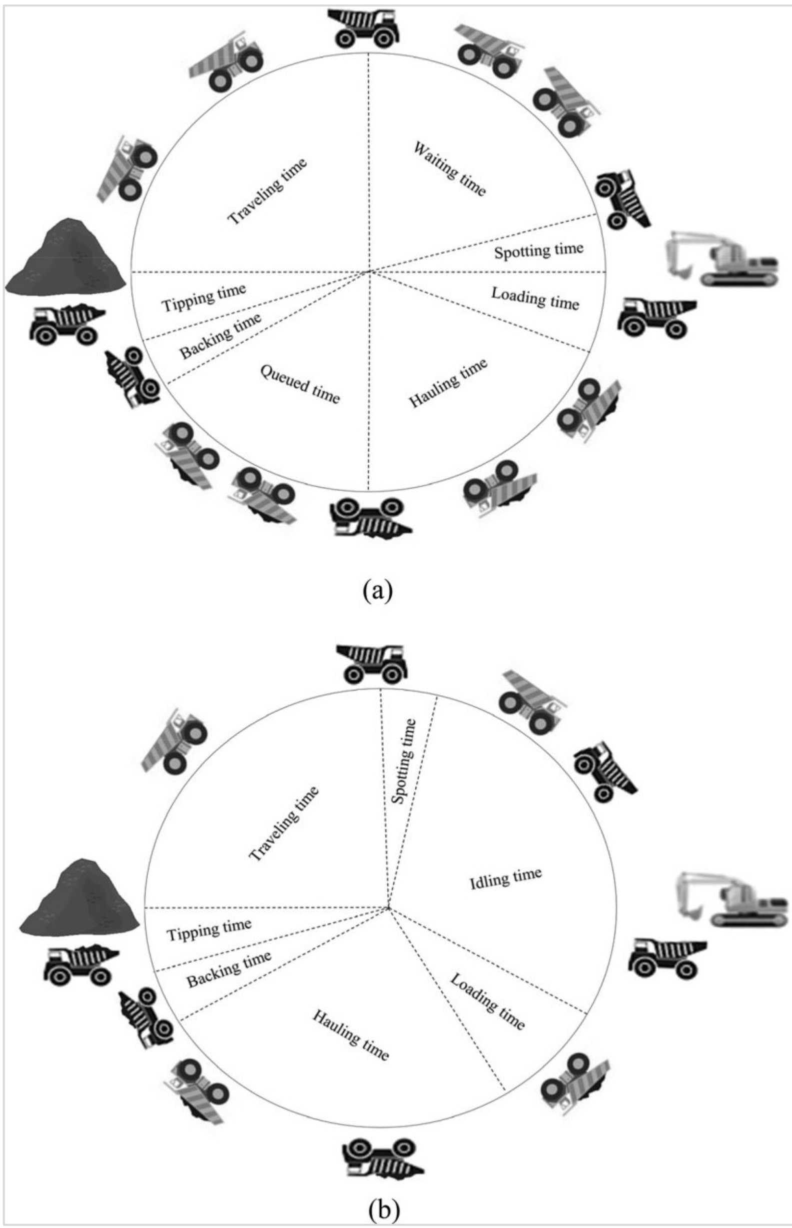


Figure 2-1 (a) Over-trucking and (b) under-trucking times in mining operation (Mohtasham et al., 2021)

2.5 Passes and Payloads

Smith et al. (1995) developed a simulation model to comprehend the load pass time and production relationship with a specific number of trucks in earthmoving operations. They further prepared six-factor experiments that include the number of trucks, passes loaded, loading time, travelling time and their relationship with production, match factor and production cost. They also came up to the conclusion that an extra bucket per load is advantageous for safety considerations and plant operation. One of his conclusions was that spotting and loading time affects the output equally. Additionally, they concluded that the travelling time would be the most important factor with increasing road distance. However, it is crucial to minimize these times to achieve the target production.

Marinelli and Lambropoulos (2012) investigated cost analysis for fleet loading practices and discovered different passes per total loading time. With their explanation that no reference considers the partially filled pass, their investigation assumed a MF equal to one and the same hauling distance. They finally concluded that partially and non-partially filled passes depend on the last pass percentage and hauling distance.

Soofastaei et al. (2016a) calculated the energy and cost savings directly related to payload and fuel consumption, emission and costs. They stressed that payload standard deviation should be minimized in order to reduce its variance; hence the high variance in payload values is not advised or recommended. Soofastaei et al. (2016b) proposed a simulation for truck bunching and payload variance in order to improve fleet productivity and energy efficiency. They found that the relationship between cycle time and payload variance is not linear.

The DRET energy model, which provides a trend for fuel consumption and road grade, distance, payload, and truck type, was used by Kaboli and Carmichael (2016); their results show that fuel consumption is decreased when overloading trucks up to a certain point. The amount of time it takes a truck to travel from its point of origin to its destination is referred to as its travel time. Factors like grades, truck power, GVW, speed, and the road's overall length all directly impact travel time.

In their operational efficiency proposal about production, Pasch and Uludag (2018) argued that decreasing the number of passes will shorten loading time and increase hourly production. However, due to ineffective loader utilization, it will not add additional production if there is under trucking and a reduction in the loader cycle time. Soofastaei et al. (2018) suggested that additional passes loaded over specific passes waste cycle time and energy, a term he called payload controlling. He argued that many attempts have to reduce payload variance, including technological and management systems and if payload variance persists, bunching phenomena will occur and the production will be reduced.

2.6 Queueing and Bunching

Queuing, over and under trucking conditions have also been examined in the literature, particularly at the operating loader or shovel, starting from Smith et al. (1995). This study focused on the idea that if trucks are waiting, then lower passes are required, which is reflected in a real situation when trucks are queued (over trucking situation). Instinctively, loader operators will naturally tend to underload the trucks to shorten the queue. According to Krzyzanowska (2007), increasing shovel passes will lengthen the time trucks must wait in queue at the shovel. And according to Hardy (2007), underloading a truck will extend the life of its tyres and truck components and reduce braking distance, bunching effect, and cycle time variability. He preferred underloading over overloading from a unit cost perspective.

Focusing on literature related to queuing theory, Ringwald (1987) referred to queuing theory as a bunching theory. Although the term developed into a different meaning, he constructed economic curves to select the optimum hauler number per loader number. Ta et al. (2013) proposed a linear model to reduce the number of trucks required to meet the target throughput under constraints based on finite queues. They calculated the shovel idle probability. According to Burt and Caccetta (2013), queuing theory, simulation, and artificial intelligence are unable to handle the sheer volume of decisions that must be made over various time frames.

Choudhary (2015) approached shovel and truck optimization by implementing overall equipment effectiveness and matching simultaneously, which minimizes the operating cost. He realized that the queue and waiting time were due to improper equipment matching. By creating a regression model, Kim and Bai (2015) identified the match factor, bucket loading cycle time, and the number of passes as important factors that affect earthmoving vehicle productivity. The bunching effect was also significantly influenced by these variables. Soofastaei et al. (2015) highlighted the importance of payload, its variability, and the ensuing travel time and bunching effect.

In order to predict activity times in mining operations, Ristovski et al. (2017) implemented machine learning for truck allocation by addressing stochastic approaches in travel time and queuing effect. Additionally, their analysis compared with dispatching software has improved equipment effectiveness. Fisonga and Mutambo (2017) developed a model that reduced queue length, achieved a good match factor, and determined the number of trucks. Zeng et al. (2019) investigated the bunching and queuing effect and its relationship to production. Using a multichannel queuing model, Elijah et al. (2021) determined that as the number of trucks is increased, the system's daily production will increase up to an optimal point with no further growth. However, it will be accompanied by a decrease in truck productivity and cost per tonne.

2.7 Match Factor

The match factor (MF) is an important indicator of a mining operation's efficiency. Burt and Caccetta (2018) defined the match factor as a measure of fleet productivity. It is a ratio that matches truck arrival rate to loader service rate. Their definition included over-trucking (MF>1) in which the loader is 100% efficient, and trucks are queued. In contrast, when loaders are waiting for trucks, the MF is less than one. There is no queueing at the loader when the match factor equals 1; this is the optimal situation but not achievable realistically due to bunching and maintenance.

Krause and Musingwini (2007) named terms over-equipped when trucks are more than required and under-equipped when there are few trucks. The consequences of an over-equipped situation will substantially increase the capital cost, while the under-equipped situation will not achieve the planned short-/long-term production. Dabbagh and Bagherpour (2019) examined the MF in their analysis using the ant colony algorithm; however, they state that it is not correct enough. They suggest using a detailed match factor which increased the production by ten percent.

Ozdemir and Kumral (2017) elaborated on some limitations of MF. Due to its simplicity and convenience, the match factor has significant limitations, which add uncertainty to fleet performance. These limitations are:

1. It assumes all the loaders and trucks are fully available. Frequent equipment failures are inevitable random phenomena and the fleet is hardly fully available. Furthermore, the number of available equipment is not independent of a given time. As such, it is a stochastic time series as a function of failure and repair rates of equipment. Given that time between failure and time to repair are outcomes of random functions, they are uncertain. Therefore, the match factor of the fleet is uncertain and dynamically changes over time.
2. Truck cycle times are also uncertain because of fluctuations in road conditions, equipment reliability, seasonal variations and driver habits, which are also affected by the outside environment Fang et al. (2016). Furthermore, the performances of loader and truck will mutually affect each other. For example, delay (e.g., due to the road

conditions) or quickness (e.g., due to the driver's habit) of a truck will result in waiting for loaders, or bunches/queues of trucks, respectively, such that cycle times vary.

3. Like truck cycle times, loader swing times also fluctuate with respect to operator habits, loader reliability and ground conditions.
4. Derivation of the match factor equation is basically based on the ratio of the maximum material quantity hauled by trucks to the maximum material quantity loaded by loaders. This assumes full utilization of loaders and their capacities. In addition to truck and loader availabilities associated with equipment failures, spaces within rock particles (fill factor) and carry-back (dead bed) in trucks may cause deviations from full fleet utilization.

According to Afrapoli (2018), the MF has some limitations, including that the MF does not account for any uncertainties in the input parameters and assumes a general rigid dispatching system, hence no consideration of the operation decision tool.

2.8 Energy and Fuel Consumption

The amount of fuel and energy consumed is another crucial operation KPI. Starting with Kecojevic and Komljenovic (2010) investigation of fuel consumption, power, and engine load factors as well as emission under various load conditions, and their findings that there is a direct relationship between fuel consumption and engine load factor as they illustrated the benefits of reducing truckload, they are affected by the amount of payload passed. As a result, engine load will be reduced, which will lower fuel consumption, carbon emissions, and associated operating costs.

By creating regressions of energy consumption and a stochastic simulation model, Awuah-Offei and Summers (2010) investigated operational strategies and produced high-impact energy-saving improvements in the coal mining industry. As a result, they developed strategies like shortening haul roads and increasing shovel and bucket capacity. Klanfar et al. (2016) studied load factors from various equipment for estimating fuel consumption. To predict truck fuel consumption in the mining industry, Soofastaei et al. (2016a) created an artificial neural network for predicting fuel consumption that considered gross vehicle weight, truck velocity, and total resistance. They discovered that total resistance, maximum speed, and gross vehicle weight affect fuel consumption. Further classification of fuel and energy consumption in the mining operation is shown in Figure 2-2.

All the previously found literature dealt with the truck's overloading point of view. However, Kaboli and Carmichael (2016) covered underloading by examining truck parameters, including grade, payload and truck type. Using the empirical model DRET/M, which gave trends for that parameter by comparing observed field data with data calculated from the model calculated. Their results indicated a small reduction in fuel consumption in overload trucks penalize trucks and mine roads maintenance, while it is important to strictly load trucks based on their capacity.

Dindarloo and Siami-Irdemoosa (2016) used regression methods to determine the most fuel-consumed elements. They found that truck empty idle time was an important factor in fuel consumption, resulting from queuing at loader. They added operator skills and driving styles too. Other factors showed a high correlation, including travelling empty-loaded times. In addition to road characteristics such as surface condition, grade and curvatures.

Peralta et al. (2016) investigated the relationship between equipment reliability and energy consumption. As a result, a maintenance policy based on the reliability of the equipment has been created. It reduces energy consumption and gas emission by developing multiple regression models to estimate the contributions of reliability on fuel consumption. It showed that truck reliability, distance and weight are the most important parameters affecting fuel consumption.

Topno et al. (2021) evaluated the energy of the electric shovel, and their results showed that the digging operation consumes the maximum power. They determined the specific power consumption by using the available operating time and actual power consumption; consequently, the potential for energy savings is evaluated.

In their profitability analysis of low-quality deposits (limestone), Krysa et al. (2021) proposed technical road terms divided into (weak, base, good and optimal). These roads should be optimally maintained so the fuel cost decreases when the roadside is maintained enough.

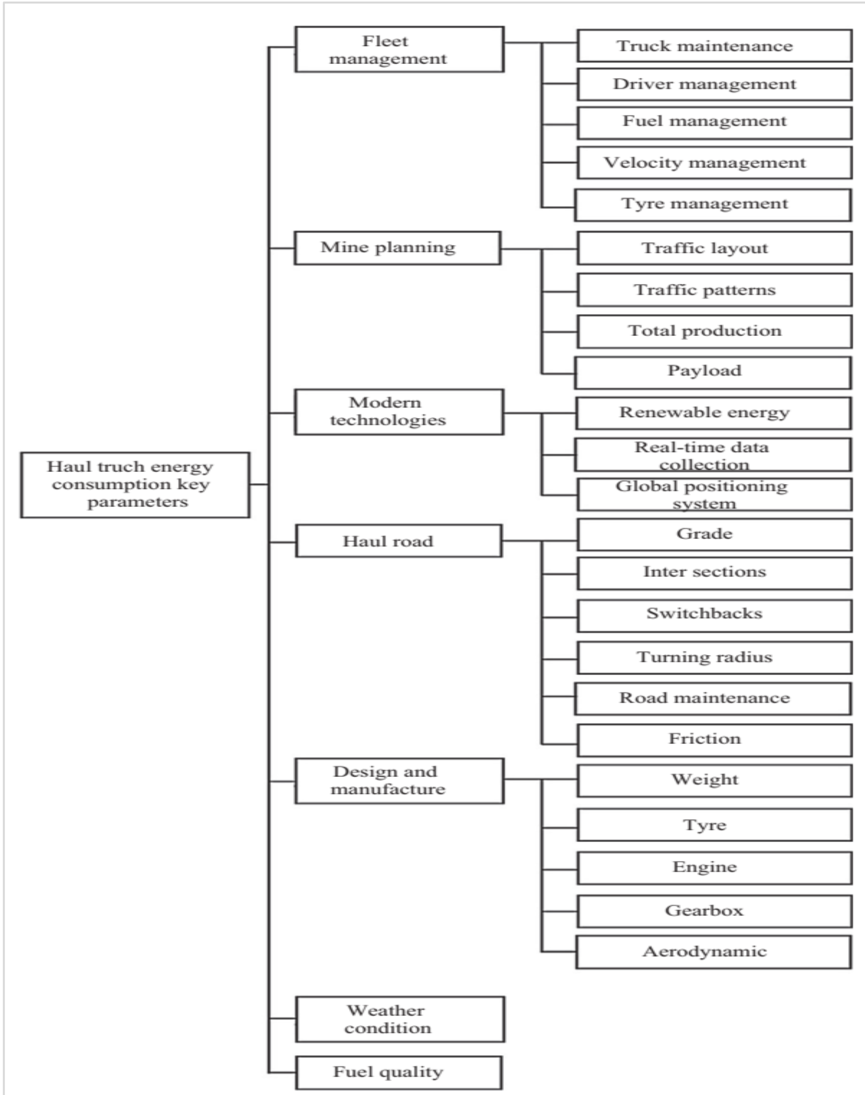


Figure 2-2 Energy consumption in haul trucks (Soofastaei et al., 2016)

2.9 Truck-Shovel Conventional Loading Types

Spotting is the process where the truck maneuvers into a position for loading. Loading is the process of placing mined material into a truck. The gathering of material into the bucket and then unloading the material into the truck is called a pass. A number of passes are usually required to load the truck. The spotting time of the truck is influenced by the selected loading method. There are typically four loading methods (Caterpillar, 2013):

1. Single-sided loading technique: the truck is spotted and loaded to one side of the shovel with a maximum swing of 90°. A second truck cannot be spotted and loaded until the first truck has pulled clear of the shovel. Therefore compared to double-sided loading, productivity is reduced, as shown in, Figure 2-3 (A).

2. Double-sided loading technique: the trucks are spotted and loaded alternately on both sides of the shovel. The shovel has a maximum swing of 90°. A sufficient working room at the rear and on both sides of the shovel should be ensured. Higher short-term productivity but higher risk of collisions. Requires well-trained operators, as shown in Figure 2-3 (B).

3. Drive-by loading technique: the shovel tracks are parallel with the face and the truck (tractor-trailer truck) drives onto one access ramp and stops adjacent to the shovel. After being loaded, the truck drives past the shovel. The shovel has a maximum swing of 90, as shown in Figure 2-3 (C).

4. Modified drive-by loading technique: the shovel tracks are parallel with the working face and when the truck drives under the shovel's swing path, the shovel dumps before the truck stops, then the truck is spotted by backing and stopping near the working face. The shovel has a maximum swing of 120°, as shown in Figure 2-3 (D).

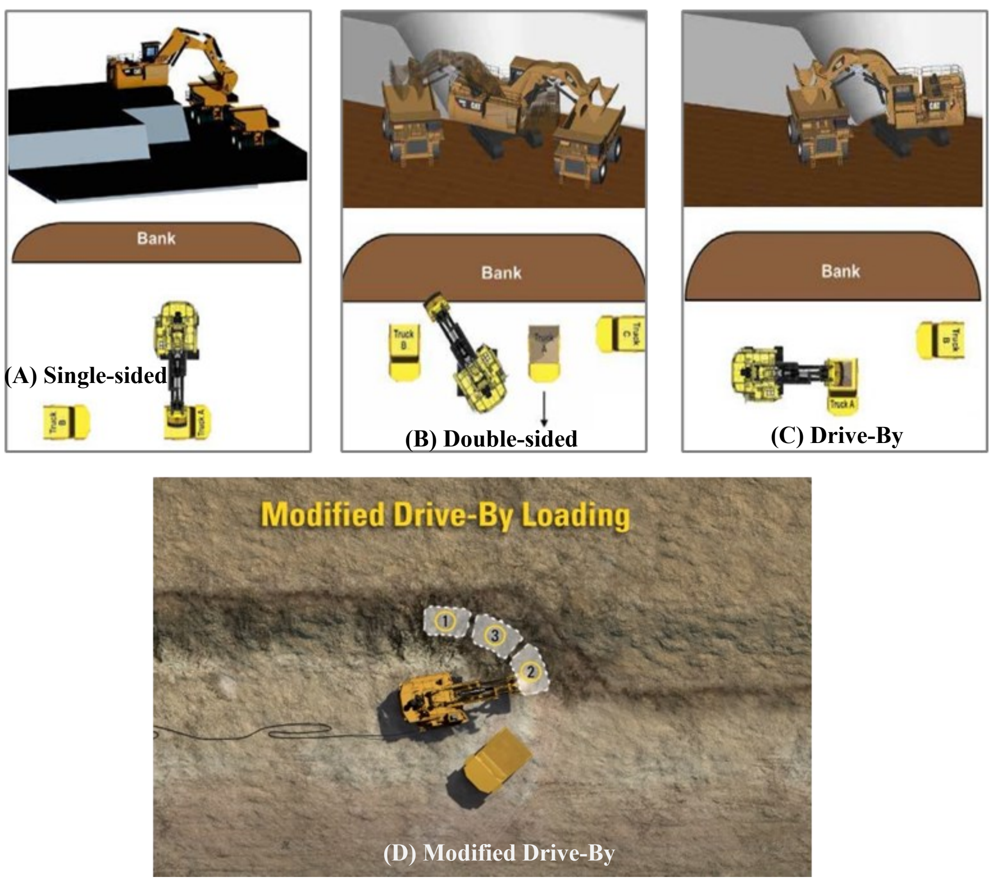


Figure 2-3 Loading types in a mining operation (CAT, 2013)

2.10 Other Approaches to Evaluate Payload

Operators' score was suggested by Yaghini (2021), who presented an approach to characterize and evaluate the payload using the operator ranking systems. The score is calculated based on the truck, shovel and mine productivity indices. He concluded that the operator with the highest score would typically load trucks to a higher capacity with less cycle time and load passes. Furthermore, he suggested a term called dynamic target loading (DTL), which modifies the conventional 10:10:20 rule by reducing term passes loading practices and giving the operator a flexible load range; consequently, the loading cycle and queue are reduced. This analogy, reducing trim passes, is comparable in concept to the FB analysis adopted in this research. Production is also covered as a project KPI that provides feedback about bucket payloads and cycle time enhancement opportunities.

2.11 Literature Related to Research

Recently, Tapia et al. (2021) investigated loading methodologies in an open-pit mine. They used FT and FB scenarios by creating simulation models using Talpac software to understand cost and production analysis and how they relate to cycle and queuing time. They further adapted Activity Based Costing (ABC) models, "which are built on the concept that resources usage is not a function of the amount of the final product, but rather, resources are consumed by the elementary tasks and processes required to produce a unit of the final product" as defined by Botín and Vergara (2015). In order to calculate production per cost, Tapia et al. (2021) concluded that a decision must be made when a situation requires a change. They argue that mining projects will favour the FT strategy over the FB till a specific transition point at which the operating cost of the FB is favoured.

Mustaffa (2021) investigated the impact of alternative loading practices on production and emission using Monte Carlo Simulation to compare these practices. The results showed that double-sided loading has the lowest effect on the environment. However, it is not always doable because it is limited to specific mining conditions and cannot be generalized. In addition, filling one bucket more than the full load can result in greater overall productivity, lower emissions, and reduced truck cycle time, which may lead to a production increase. Other similar loading terminologies in earthmoving are fractional loading as in Mustaffa (2021), known as fractional loading practice, which indicates that each truck gets loaded to a minimum of passes. However, it could be filled to higher passes if additional time is allowed, the arrival of the next truck and varies between trucks. A similar term called multiplier loading practice assumes minimum passes are used, but there could be an extra pass depending on the loader's available time. This will yield higher payloads and production rates associated with fuel consumption increases due to longer cycle time and loading time.

2.12 Artificial Intelligence (AI) and Machine learning (ML)

McCoy and Auret (2019) define ML as the development and application of mathematical and statistical models with an emphasis on using data rather than domain knowledge to determine the appropriate structure of the models. An ML model typically has a non-parametric structure in the sense that the number of model parameters is not defined on the basis of domain knowledge. They also emphasized that as machine learning techniques become more widely accessible as elements of software packages, applications of data-based modelling would probably increase in frequency and use more advanced techniques and analyses. Since most applications assume that observations are independent, modelling techniques for complex processes that consider time series data may be of particular interest.

Another ML definition, according to Jung and Choi (2021), is the process by which a computer learns through algorithms. The use of computer algorithms to simulate human learning and identify knowledge from the world to improve the performance of specific tasks based on that knowledge. They further classified ML techniques into 12 types, as in Figure 2-4. Their review on ML application in equipment management, fault diagnosis studies, haulage operation, and navigation. ML studies were conducted to optimize transportation means, such as trucks and loaders and to indicate the travelling status of the equipment. Additionally, predictive maintenance was performed to enhance the mine operation efficiency by predicting equipment failure.

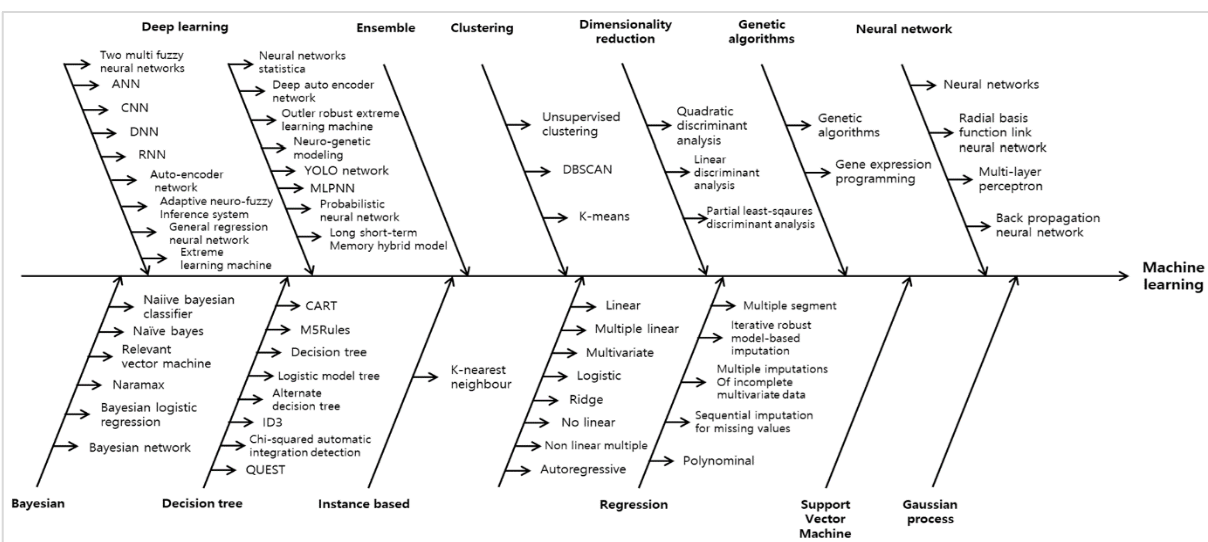


Figure 2-4 Classification of ML techniques (Jung and Choi, 2021)

In their review, Noriega and Pourrahimian (2022) defined ML methods as algorithms that can uncover complex patterns in data and use them to predict future outcomes. Additionally, they mentioned that ML had been used in process optimization. However, the mining industry is considered lower in adapting to AI and digital technologies. They emphasized that DES is common for more operation and short-term planning where equipment cycles are concerned. The supervised ML applies to these operations. They also investigated that supervised ML is the most adapted because it requires a large and labelled dataset, which is easily found in mining operations, while unsupervised ML is the least adapted. In their review, they mentioned that DES has a positive trend and has been successfully used for a long time in strategic mine planning. They further classified ML learning into:

- **Supervised Learning** (SL): function approximation from input vector data that accurately represents the issue to produce an output or specific prediction for the future.
- **Unsupervised Learning** (UL): this method uses datasets without labels and does not record the target's outcome.
- **Reinforcement Learning** (RL): this method uses interactions with the environment to teach computers how to map one situation to another.

In their conclusion, Noriega and Pourrahimian (2022) recommend focusing on guidelines and good practices for handling mining operations in the best way to build DES or the digital twin model further to support decision making. SL, which depends on labelled data, is popular in short-term planning, cost analysis, grade control, and equipment management. Using neural networks, SL has been used to forecast fuel consumption per operating cycle of mining trucks based on truck payload, loading time, and idle times.

Hyder et al. (2019) stated that ML started a decade ago. It provides many economic benefits for the mining industry, such as cost reduction, efficiency, high productivity, continuous production and improved safety. Nevertheless, they state that ML faces economic, financial, technological and social challenges. Mining sector growth can be through ML, which improves the industry's technological, economic and environmental perspective. They also imply that the rate of ML implementation is slow and faces many setbacks in the mining industry, and the biggest challenge is workers' and supervisors' resistance to different perspectives on ML technologies, from approving to disapproving realms.

The application field of ML in mining engineering is shown in Figure 2-5. It is subdivided into three categories, which are further divided into subcategories. Haulage operation under the equipment management category is one of the applications in the ML.

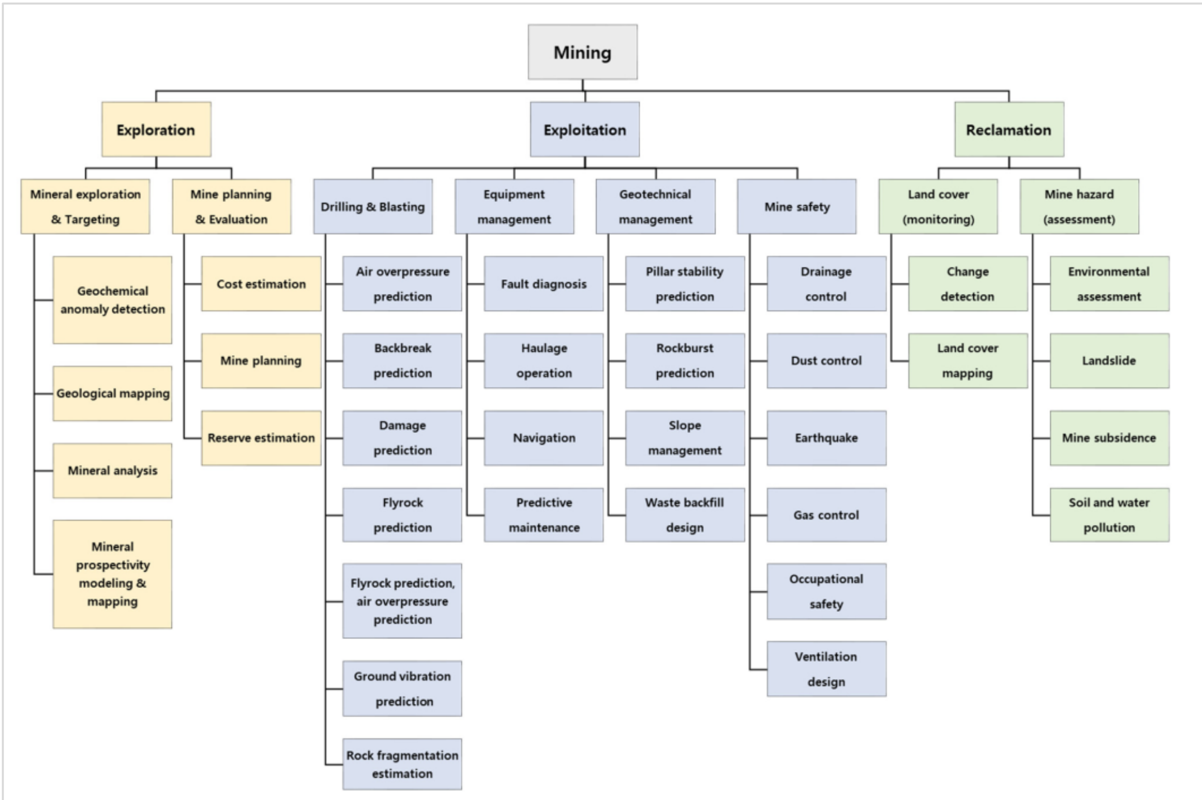


Figure 2-5 ML application fields in mining engineering (Jung and Choi, 2021)

GMG report (2019) defined terminologies of AI as follows:

- **AI**: a collection of techniques that allow for task automation by machines. These tasks are ones that humans typically perform, and their automation implies that machines mimic certain aspects of human intelligence, an alternative definition as a theoretical machine with general human cognitive abilities.
- **ML**: a subfield of AI that focuses on machines that take data related to a specific task and learn from that data in order to build a model.
- **DL**: consists of algorithms that can take vast quantities of data and recognize patterns.
- **Data Science:** analyze and extract insights from AI, ML and DL. It is a different activity from AI and ML.

Figure 2-6 illustrates these concepts and how they relate to one another.

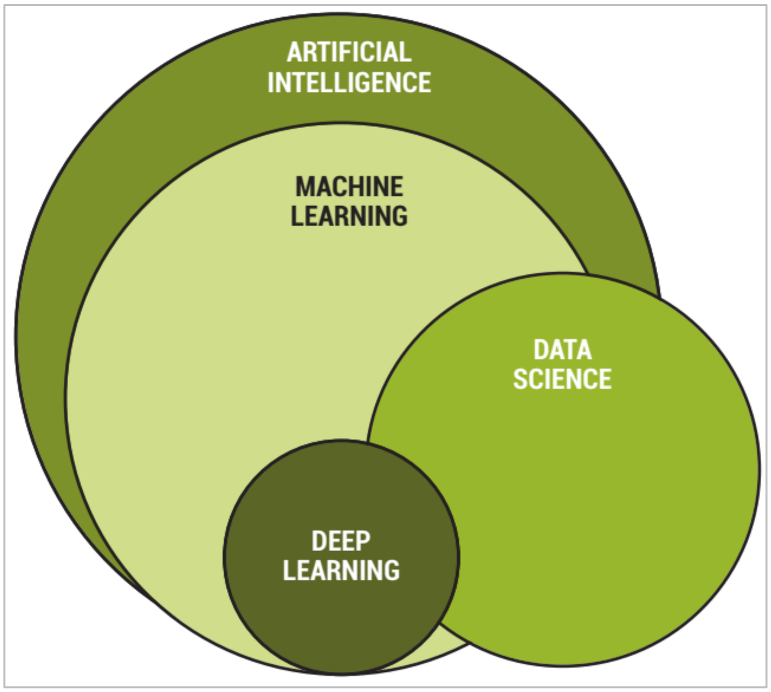


Figure 2-6 AI-related concepts (GMG, 2019)

GMG report (2019) mentions that in order for any AI concept or project to succeed, it should have:

- Coherent technological strategy: AI needs to be part of the organization's larger strategy for evaluating and implementing new technologies.
- Measuring and monitoring the quality of data: good data are the foundation of AI because poor data quality reduces the quality of project output. AI can also expose deficiencies in the data as the project progresses, so measuring and monitoring data and preparing plans to fill gaps are key to success. The data should be as complete as possible.
- Evaluate regularly the quality of communications among those responsible: those affected by the change should be engaged in discussions surrounding it, and they should feel confident that their opinions and concerns are being heard, understood, and considered.
- A return on investment: a clear understanding of its intended outcomes and the expected return on investment.

- Internal champion: ensuring that all relevant stakeholders are updated regularly and those developing and implementing the technology have the tools and resources they need to succeed.
- Agile: budgetary and organizational changes often affect huge, pre-planned projects that have long timelines. This in a way to deliver the highest-value aspects of a project as quickly as possible and to ensure that at least some parts of the project do in fact come to fruition.
- Focus on solving the problem for end users: whether target users are technicians taking notes on equipment or engineers making operational decisions, dashboards, key performance indicators (KPIs) and visualizations should be easy to use and understand. As a result, their use is more likely to become habitual, making daily decision-making more impactful.
- Covering long-term plans: the new technology company-wide and ingraining it in the organization's policies, procedures, tools, and habits. Additionally, these should include provisions for any of the following: support, maintenance, change management, retraining and tuning algorithms, scaling, installation and setup, and acquiring or implementing new hardware.

Further levels on AI maturity and levels as in Figure 2-7:

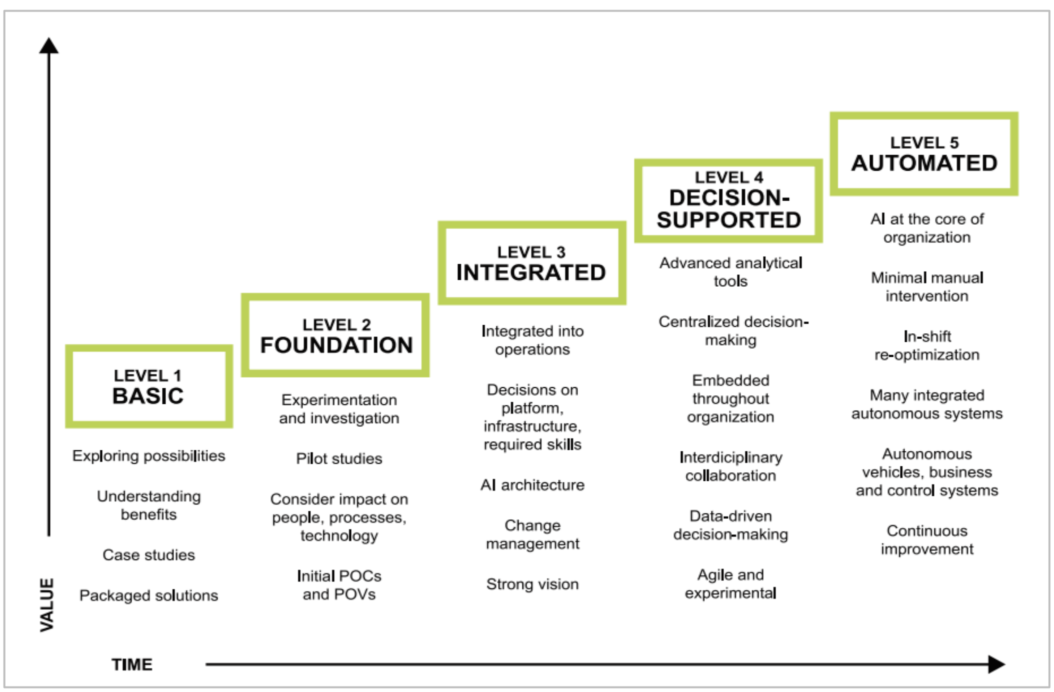


Figure 2-7 AI levels in Mining engineering (GMG, 2019)

These levels could be defined as:

- **Level 1**: organization is exploring what AI is, what it does, and how it can benefit them; examples: Facial feature recognition in driver safety systems. The use of cameras to determine particle size in digger and mill operations, automated planning and scheduling and autonomous vehicles.
- **Level 2**: there is a degree of experimentation and investigation into what the benefits of the technology are and what the organization requires in order to realize them. People; in terms of understanding the AI and ML concepts, process; effect on the way they are working and technology; how AI and ML fit inside an organization. These are important concepts that should be considered.
- **Level 3**: AI and ML are becoming integrated into business operations. AI and ML architecture is important at this level and investing in people and the right experts is also essential.
- **Level 4**: advanced analytical tools in order to provide centralized decision-making capabilities and further improve the operation by achieving interdisciplinary collaboration instead of siloed work, adapting data-driven decision making instead of experience-based, and adapting agile and experimental practices.
- **Level 5**: organization and most systems and processes are either fully automated or require minimal manual intervention. For example, the Automatic Haulage Systems (AHS) in Benjamin Miller (2019) article, these systems that are used by Caterpillar operating at Teck and Vale, while Komatsu operating at Codelco and Rio Tinto. Summing over 330 trucks worldwide. Caterpillar uses MineStar technology, accounting for more than 1 billion tons autonomously moved in less than a year and Komatsu uses FronRunner AHS.

In summary, according to the GMG report (2019), the mining industry is increasingly using AI as a tool to optimize processes and safety and enhance decision-making. AI is a collection of techniques that allow for task automation by machines. Success factors for implementing AI include coherent technology, good data management, effective communication, clear expectation, internal support agility and adaptability, end users consideration and long-term plans repeatability. Challenges that face AI and ML could be overcome through a robust foundation of planning, research and assessment and by establishing well-defined infrastructure and platforms, clear communication practices and effective management.

2.12.1 Logistic regression (LR)

Lee and Sambath (2006) and Yilmaz (2009) used the LR approach to create a landslide susceptibility map. Work injury predictions were studied by Paul (2009) to predict work injuries in underground mines using an LR model by identifying various factors responsible for work causing injuries in mines and risk estimation to the mine workers.

As stated by (Lee and Sambath, 2006), LR is useful for predicting the presence or outcome based on a set of values of predictor variables. They also stated that the advantage of logistic regression is that the variables might be either continuous or discrete or in any combination.

2.12.2 Random Forest (RF)

(Choi et al., 2021) defined RF as a robust ensemble learning approach that uses decisions from multiple trees to make a final decision. The number of trees should be sufficient to ensure the accuracy of the final decision or final objective. RF is applied for classification and regression ML problems. RF uses the bootstrap technique to sample data; the sub-samples are divided randomly into small datasets and each tree represents a full growth tree base on each sub-sample. Ohadi et al. (2020) determined the influential parameters in blasting designs using RF. They predicted the blast-induced outcomes based on rock mass conditions in the mine and blast design parameters.

2.12.3 Shap Weighing Technique

Shap (SHapley Additive exPlanations) is a game theoretic approach to explain the output of any machine learning model. It connects optimal credit allocation with local explanations using the classical Shapley values from game theory and their related extensions as defined by Lundberg (2020). It analyzes the importance of features by interpreting the results, plus it offers a powerful and insightful measure of the importance of a feature in a machine learning model. It has a python developed package that calculates Shap values.

Complicated models are often required to model natural settings, but they have low interpretability. Shapley values treat the model as a black box and use a data subset, known as background, with predictor features and model predictions to discover structures between each predictor feature and the model response, (Pyrcz, 2021).

Shapley values are adapted from game theory (Pyrcz, 2021), where the approach is used to calculate:

- Allocating resources between ‘players’ based on a summarization of marginal contributions to the game. Dividing up winnings between all players.
- The contribution of each predictor feature pushes the response prediction away from the mean value of the response over training.
- Shapley values are based completely on the model and do not access the accuracy of the model, so a poor model will potentially lead to an incorrect interpretation of Shapley values.

Feature ranking is a set of metrics that assign relative importance or value to each feature with respect to the information contained for inference and importance in predicting a response feature. There are a wide variety of possible methods to accomplish this. The general types of metrics that will consider for feature ranking:

1. Visual inspection of data distributions and scatter plots.
2. Statistical summaries.
3. Model-based.
4. Recursive feature elimination.

Also, it should not neglect expert knowledge. If additional information is known about physical processes, causation, reliability and availability of features, this should be integrated into assigning feature ranks.

2.13 Summary and Remarks

The literature review showed shortcomings and a few research covered the FT and FB concepts in detail, especially in open-pit mining using the DES. Based on these findings, a potential opportunity for future work that is related to these terms is possible. Partially loading trucks were found in the literature but not on a wide scale. Moreover, most of the literature covered the earth working equipment instead of mining equipment, so there is a size difference and operating costs and capital costs that are incomparable to each other.

There are no previous studies that focused on decision-making frameworks. Most of the literature focused on the theoretical side without answering the question of when a decision should be taken regards loading strategy under uncertainty.

AI and ML are now being adapted by research in the last decade, as literature revealed, but it is still not versed in the area of loading strategies. Bringing the capability of predicting the loading strategy and evaluating the feature importance is the beginning of the digital transformation in mining engineering and would be beneficial to understanding the loading strategies and making the operation decision more robust.

CHAPTER 3

THEORETICAL FRAMEWORK

The full truck and full bucket conceptual frameworks are covered in this chapter. From the framework's beginning at the shovel-bench interface, examining the material's general properties and the surrounding conditions. Followed by shovel-truck interaction as passes loaded, which is the main focus area of research when the higher and lower passes loading strategies are encountered. This is formulated in software concepts where equipment is matched and selected with a proper schedule and simulated. Moreover, the resulted simulated data with various scenarios are analyzed using exploratory data analysis and a machine learning model.

3.1 Introduction

This chapter covers the theoretical framework of the proposed FT and FB simulation approach in both a holistic way in mining operation and a detailed approach is discussed with a profound explanation, as well as further analysis of the simulation results, starting from the data which is imported as schedule data from an external software, Haulsim. Then the equipment configured in Haulsim and the final Discrete Event Simulation (DES) results are interpreted and analyzed. More analysis of the operation parameters and the results from simulated data are analyzed using Python programming language, where exploratory data analysis is conducted. Lastly, a machine learning classification model is created to predict the loading strategies based on the provided data that more understands the operation parameters and evaluates these parameters that trigger switching between loading strategies based on the provided simulation data.

Haulsim software is designed to have a set of options when dealing with loading strategies: a full bucket (FB) or full truck (FT). Prior to this software, the same commercial company released a similar previous software called Talpac that introduced this option in 1996, as mentioned by Ayres de Silva et al. (1996). But with fewer simulation options, operational configurations and equipment evaluation. Haulsim also allows for double loading strategies, but this is not discussed in this research because it is out of scope, and due to the nature of space constraints in the shovel-bench face area, exclusively the simulation is based on single-sided loading practices. Other new software like Micromine packages also involves the analysis of FT and FB.

3.2 Full Truck and Full Bucket Framework

Starting from the broad frameworks to understand where the FT and FB are placed in the frameworks allows understanding where the research topic is focused. Figure 3-1 illustrates the general view of FT and FB loading in mining operations. When a shovel with force applied to the working bench excavates to scoop (tuck, engage, dig, release, swing and pass); the required material that has recently been blasted with characteristics reflecting the nature of that material; loose density, fragment size and excavatability, affect the final bucket fill factor (BFF). This stage is performed by an operator with a scalable average efficiency and equipment; shovel with a known average utilization and availability. The following sections discuss the material characteristics.

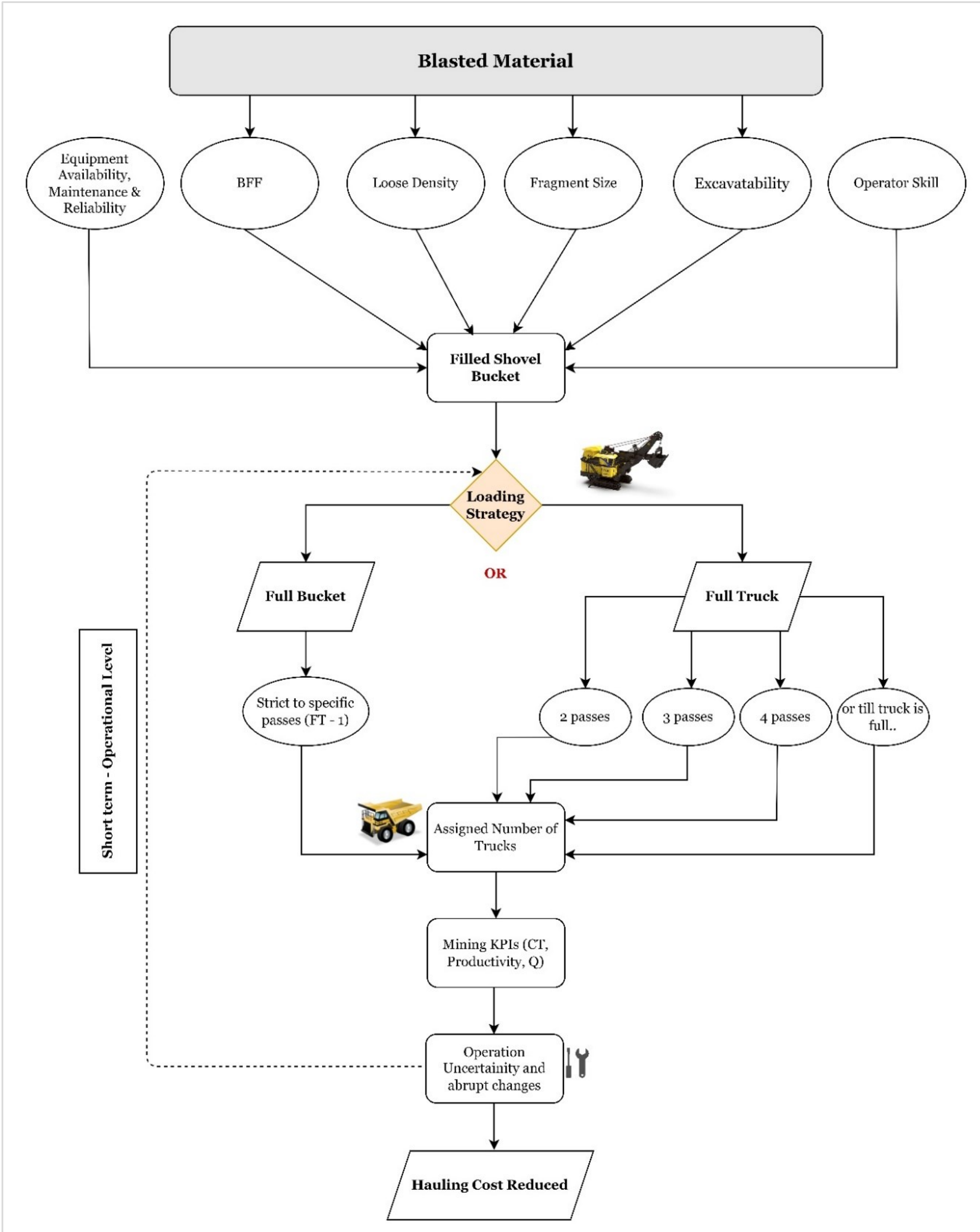


Figure 3-1 FT and FB flowchart in a mining operation

3.2.1 Shovel-Material Interaction

Because loading and hauling are the following processes after blasting, assessing post blasting of material in the mining operation is necessary when the distribution of fragmented material controls truck and shovel production rates resulting from blasting. As the blasting efficiency increases, the final production increases. Blasting efficiency is increased by optimizing blasting design when the objective fragmentation size is determined. Fragmentation is affected by uncontrollable parameters, including the physical and geomechanical properties of the material. Coarser material led to higher energy consumption, an increase in wear rates and a decrease in the loading and hauling productivity, final crusher and mills throughputs. In addition, fragmentation size affects fill factors and payloads. Dotto and Pourrahimian (2018) mentioned that poor fragmented material results in boulder sizes that are too big to handle and affect productivity negatively. Therefore, optimal fragmentation is essential for truck and shovel productivity. Good fragmentation results in a good heap in the bucket, while over fragmentation makes material flow more due to fines and no heaping is formed in the bucket. Diggability is a term used to describe how easily the material can be dug by the shovel, measured by specific dig energy. Loadsman et al. (2013) mentioned that as digging material gets harder, the payload decreases and the energy to fill increases.

BFF can be described as a measure of a particular material that fits in a bucket compared with the rated capacity of the bucket. Rated capacity is usually measured using struck or heaped ratings, while material has a particular angle of repose, as illustrated in the sketch in Figure 3-2, (Haulsim, 2022).

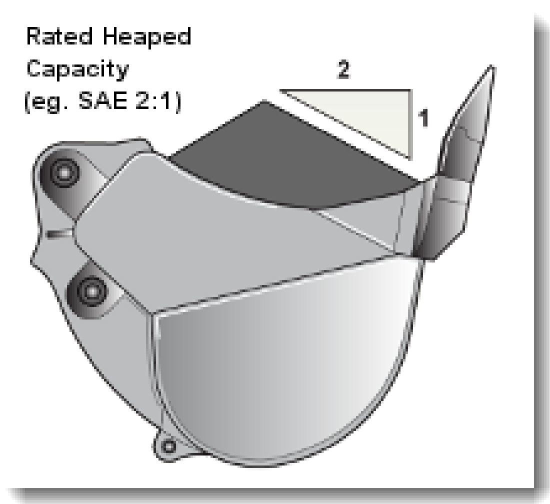


Figure 3-2 Concept of BFF (Haulsim, 2022)

The BFF is related to the material characteristics and geometry of the bucket loader, which could be calculated as the following equation (3.1):

$$Loader\ BFF = \frac{Actual\ Loose\ Volume\ of\ Material}{Volumetric\ Rated\ Capacity\ of\ Bucket} \tag{3.1}$$

The BFF usually ranges between 0.5 and 1.5 and is displayed on a heaped or struck basis. Excavatability effect BFF; it is a description of the material's ability to excavate. These values are illustrated in Table 3-1. Defining the swell factor, when the material is loaded from the ground, it swells, and the density of the material decreases due to swelling, which is called lose density. In-situ bank density is the material's density in the ground before it is disturbed (Haulsim, 2022).

Table 3-1 BFF and excavatability definitions (Haulsim, 2022)

Excavatability	**BFF Definition**
Very Hard	Poor + 0% * (Good - Poor)
Hard	Poor + 25% * (Good - Poor)
Medium to Hard	Poor + 50% * (Good - Poor)
Medium	Poor + 75% * (Good - Poor)
Easy	Poor + 100% * (Good - Poor)

Assessing the operational time in mining hauling and loading operation is important for measuring the operation's key performance indicator (KPI). Equipment mechanical availability is the time the machine is mechanically operational and physical availability is the time machine is physically operating. Figure 3-3 illustrates the time production model from the Global Mining Guidelines Group, (GMG, 2020). The figure honours the value productivity and production loss for equipment with actual work rate (tonne or BCM) relative to what was forecasted. Additionally, accounting for reduced productivity due to equipment functional, operational and setup deficiencies. Table 3-2 shows the definitions and some calculations of these time categories.

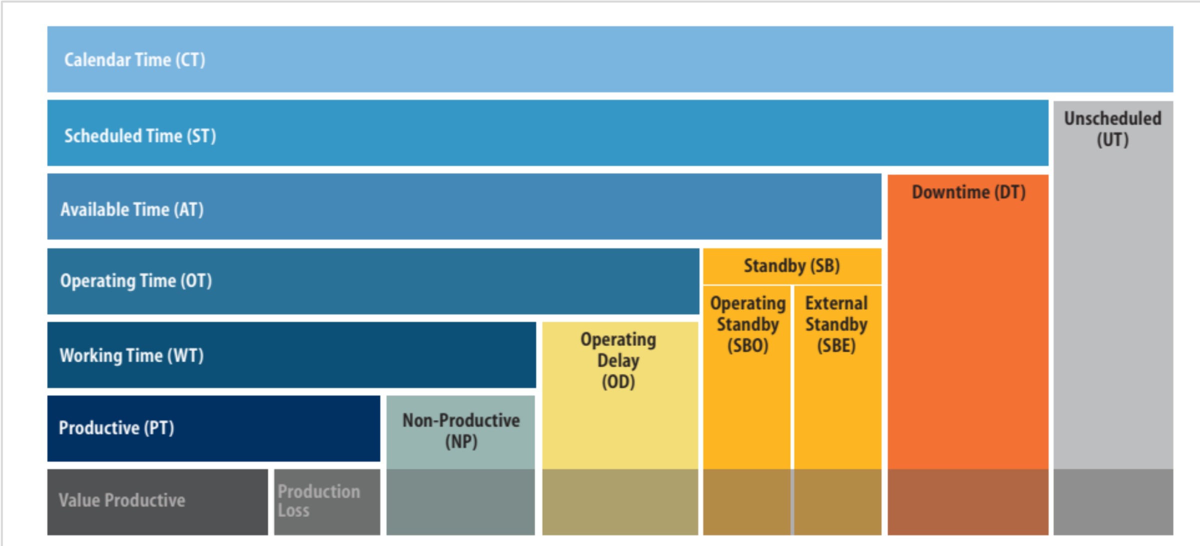


Figure 3-3 Time usage model (GMG - Time Usage Model, 2020)

3.2.2 Operator Skill and Efficiency

Khorzoughi and Hall (2016) studied the effect of operator skills and loading efficiency. They compared operators' KPIs in the loading and hauling operation, including passed payloads, productive cycle time, equivalent digging energy and loading rate. Yaghini (2021) emphasized that the operator's role in truck shovel loading is important and greatly influences the operation's productivity and efficacy. Through operator skills and loading habits, he quantified and proposed a scoring system for evaluating the operator skills in the operation, taking into consideration the operator's payload, shovel's cycle time and other KPIs to finalize the operator rank from best to worst. All the previous performance indicators affect the final payload in the shovel bucket, which has a specific capacity and range of filling material in the shovel bucket that varies from struck to heaped as a filling percentage of 90 to 110% of the bucket capacity, assuming average loading conditions.

3.2.3 Shovel Loading Truck (Digging and Filling)

After an operator fills the shovel's bucket, the payload is passed to the truck with a set number of passes, depending on the passes required to fill the truck and the pass and equipment matching configuration. It is common in mining operations that hauling trucks are at least 100% loaded or exceeding their final load capacities depending on whether companies strictly apply the loading policy or not and their actual compliance with these policies and skilled operators.

Table 3-2 Time usage definitions (GMG - Time Usage Model, 2020)

Term	Definition
Calendar Time (CT)	The total time available.
Scheduled Time (ST)	The equipment is required to meet business plan objectives and is assigned to an operation, project, or job. Scheduled Time = Calendar Time – Unscheduled Time
Unscheduled Time (UT)	The equipment is not scheduled or assigned in the system because it is not required due to external events.
Downtime (DT)	The equipment is required but is not in a condition to perform its intended function.
Available Time (AT)	The equipment is required and is in a condition to perform its intended function. Available Time = Scheduled Time – Downtime
Standby (SB)	The equipment is available but is not operating.
Operating Standby (SBO)	The equipment is available but not operating, and there is no immediate intent to operate due to a management decision or reasons within management control.
External Standby (SBE)	The equipment is available, required, and committed to a project or site, but it cannot be operated for reasons that are out of the immediate influence of operating management control. Standby = Operating Standby + External Standby
Operating Time (OT)	The equipment is available and under the control of a human or system. Operating Time = Available Time – (Operating Standby + External Standby)
Operating Delay (OD)	The equipment is operating but temporarily stopped or prevented from performing work due to delays that are inherent to the operation or the immediate physical and environmental conditions.
Working Time (WT)	The equipment is operating as assigned, performing its intended function, and carrying out activities that do and do not directly contribute to production. Working Time = Operating Time – Operating Delay
Non-Productive Time (NP)	The unavoidable activities that do not directly contribute to production but are required to enable continued safe and efficient operation.
Productive Time (PT)	The equipment is performing its intended function and is carrying out activities that directly contribute to production. Productive Time = Working Time – Non-Productive Time

In this step, the proposed loading strategies are involved and a proposed operational decision should be taken to proceed with the scenario of shovel's loading strategy as a FT or FB. Before proceeding with these terms, there should be a definition for these concepts, which could be defined as the following: shovel that loads in a FB; the truck requires less than a full shovel bucket load to reach its payload. Therefore, the truck will travel underloaded, and the additional pass time is not wasted (Haulsim, 2022). Another definition by Tapia et al. (2021) defines it as saving the additional pass of the loading equipment. While FT loading assumes the loader always tries to fill the truck, even if the last pass only requires a small portion of a bucket load. Therefore, this additional pass will consume more time in shovel loading and queuing conditions will occur (Haulsim, 2022).

3.2.4 Passes Loaded

Shovel load time depends on the number of passes to load the truck and Shovel cycle time. The number of passes N_p is calculated as the following equation (3.2) (Kennedy, 1990):

$$N_p = \frac{C_t}{C_l \times F_f \times F_s \times \rho} \tag{3.2}$$

Where C_t is the truck capacity (m3), C_l is loader capacity (m3), F_f is loader bucket fill factor, F_s is material swell factor, ρ is material bank bulk density (t/m3). As a general rule, the number of passes should be an integer number. Mine operators typically target to load the truck in three to five passes from a rope shovel.

3.2.5 Assigned Trucks

The assigned trucks are based on match factor (MF) as a reference; the usual value for MF in mining operation is 1, which means 100% efficiency. However, MF is uncertain and varies through short-term operations due to various uncertainties. Therefore, this research analyzes multiple trucks (1 to 30) to determine MF values with shovel configurations. Then FB and FT loading strategies are evaluated based on the selected fleet. The methodology for determining MF is covered in more detail in section **3.3.1**.

3.2.6 Operation Parameters

A set of operating configurations is usually prepared before running the simulation; this includes the hauled material, mining and hauling equipment data (capital costs, operating costs, operating data), shifts configuration as scheduled and unscheduled operating and non-operating time and rolling resistance (RR).

3.2.7 Operation Uncertainty

Generally, the mining operation is classified as considerably uncertain and unpredictable with time. In the mining equipment arena, the uncertainty and unpredictability of equipment are common, especially when equipment is getting older; this includes short and long delays, stoppages and breakdowns due to various reasons, whether related to the smallest scale mining operation or to the largest scale market situation that effect mining decision or any other reason. This research approach demonstrates shovel breakdown as an example of fleet uncertainty. Other reasons can be crusher reduced efficiency, stoppage, blasting efficiency, or variability in the material in mine. It is also known that any accident or unplanned incident affects the operation, and a feasible option is available when adapting a modified loading strategy; moreover, focusing on the scheduled and unscheduled delays that happen in the mining operation, the scheduled maintenance delay examples are as follows (Loadsman et al., 2013):

- Air systems
- Axle repairs
- Brake repairs
- Cab repairs
- Cleaning for maintenance
- Cleaning to repair
- Cooling system repairs
- Daily service
- Engine repairs
- Hydraulic repairs
- Inspection
- Light vehicle check
- Maintenance checks
- Major cab clean
- Major service
- Major shutdown
- Service break
- Suspension repairs
- Tyre inspection
- Tyres scheduled
- Tyres, tracks or frames
- Fire suppression
- Lube system repair
- Maintenance inspection
- Maintenance service
- Planned repairs
- Primary air system
- Primary brakes
- Primary cooling system
- Primary fire supply system
- Primary steering
- Primary wash-down
- Pre-Maintenance inspections
- Accidental equipment damage

Examples of the delays that result from unscheduled maintenance as the following (Loadsman et al., 2013):

- 2-Way radio
- Accident damage
- Accidental damage
- Air filters
- Air intake system
- Awaiting diagnosis
- Awaiting maintenance
- Backup alarm
- Battery
- Bearings
- Blade/bucket/bowl/ripper
- Blade/cutting edges
- Body/frame chassis
- Body/tray
- Fire suppression
- Frame/structure - front axle
- Front strut
- Fuel filters
- Fuel injectors
- Fuel pump
- Fuel system
- Fuel tank
- Gear shifting
- General electrical
- Hydraulic cylinders
- Hydraulic oil cooler
- Hydraulic oil level leaks
- Hydraulic pump – main
- Brake pump
- Brake test
- Brakes system
- Breakdown – electrical
- Breakdown – fleet management system
- Breakdown – mechanical
- Bucket
- Bucket general
- Bucket welding
- Cab/walkways
- Cab equipment
- Cabin
- Cabin controls
- Cabin/decks
- Chassis/body
- Control system
- Coolant system

- Dispatch system
- Drive brakes
- Drive cooling system radiator
- Lights/indicators
- Electrical emergency stop
- Main gearboxes
- Maintenance inspections
- Maintenance delay
- Park brake
- Power loss

- Electrical fail to start
- Electrical general
- Electrical fault - 24 volt
- Engine system
- Unplanned electrical
- Unplanned mechanical
- Filter system
- Filters
- Hydraulic valves
- Hydraulic filters
- Hydraulic pump
- Hydraulic cylinders
- Hydraulic general
- Lighting
- Lube system
- Lube system electrical
- Lube system mechanical
- Retarder
- Rock ejectors
- Rock/tyre management
- Starting system
- Structural damage
- Suspension
- Suspension cylinders
- Tray
- Truck box cleaning
- Tyre change
- Tyres unscheduled
- Undercarriage
- Unscheduled maintenance
- Wait electrician
- Wait fitter
- Wash-down equipment

And lastly, the examples of delays resulted from the standbys (Loadsman et al., 2013):

- Accident
- Blasting
- Blocked access
- Crib
- Dust/no water cart
- Electrical storm
- Environment/coal fires
- Environmental
- Environmental incident
- Equipment not required
- Blast misfire
- No available hopper
- No available shovel
- No heavy hauler
- No labour available
- No loading unit
- No operator - hot seating
- No operator
- No operator - other duties
- Off-shift due to roster structure

- Floor cleanup
- Fuel
- Holidays (shutdown)
- Idle
- Idle -Safety
- Illness
- Industrial action
- Loader delay
- Long-term standby
- No available crushers
- No available dumps
- No available shovels (auto)
- No available shovels call dispatching
- No available dump
- No available employee
- No available face
- Standby parked
- Stopped for an emergency
- Stop-work meeting
- Talk to a supervisor
- Toilet break
- Toolbox/safety talk
- Total operation shut down
- Operational/talk to the supervisor
- Operator travel
- Power down
- Power outage site
- Public holiday
- Return from maintenance
- Safety/meetings
- Safety shutdown
- Scheduled down
- Scheduled off shift
- Shift change
- Site emergency
- Smoke
- Snow
- Standby
- Standby no production
- Union meeting
- Special public holiday
- Wait on blast
- Wait on dust
- Weather
- Wet roads
- Work instructions

3.3 Detailed Framework Flowchart

This detailed flowchart focuses more on the methodology, and the approach followed in comparing FT and FB and generating the simulation results, as shown in Figure 3-4. At the beginning, a short-term production schedule created by Open Pit Metal Solution (OPMS) software is imported into Haulsim, which combines, adds data and runs the simulation. Moreover, integrating the shovel breakdown in the framework and comparing the simulation results under different calculated MFs. Additionally, conducting operational sensitivity analysis in selected input features from the operation. Next, the outcomes are assessed using Python programming and ML algorithms for predicting loading strategy and understanding the operation KPIs.

3.3.1 Match Factor (MF)

The MF provides a measure of the productivity of the fleet. It matches the truck arrival rate to the loader service rate by omitting the equipment capacities and productivity and including the loading and truck cycle times, (Burt and Caccetta, 2018). Equation (3.3) represents the most common formula for the MF calculation of a homogeneous fleet (Burt and Caccetta, 2018):

$$MF = \frac{t_{i,i'}\, X_i}{t_x\, X_{i'}} \tag{3.3}$$

Where X_i is the number of trucks of type i , $X_{i'}$ is the number of loaders of type i' , $t_{i,i'}$ is the time taken to load truck type i with loader type i' and t_x is the average cycle time for all trucks. This formula accounts for the actual productivity of the equipment. If the ratio exceeds 1.0, trucks arrive faster than the service rate (over trucking), and the loader is working 100% and queueing will occur. A ratio below 1.0 means that the service rate is higher than the arrival rate (under trucking), and fleet efficiency will be low, including the loader efficiency, because of the truck's waiting time (Burt and Caccetta, 2018). The approach in this thesis assumes that the fleet is homogeneous (one truck type) due to the nature of desirability and simplicity in the mine.

Mining operations tend to assume and stick to an MF equal one as a reference; however, this is not always possible due to the nature of the mining operation and the equipment, the fact that MF is stochastic and differs based on the operation KPIs, MF efficiency curve is shown in Figure 3-5.

In this thesis, the MF is calculated as a normal operation running assumption, with a set number of trucks assigned to a shovel to understand the effect of changing the number of trucks, which reflects on the final MF. However, when a shovel breaks down, MF surges to 1.5, accompanied by an increase in the number of trucks reassigned to the remaining working shovel, as shown in Figure 3-6.

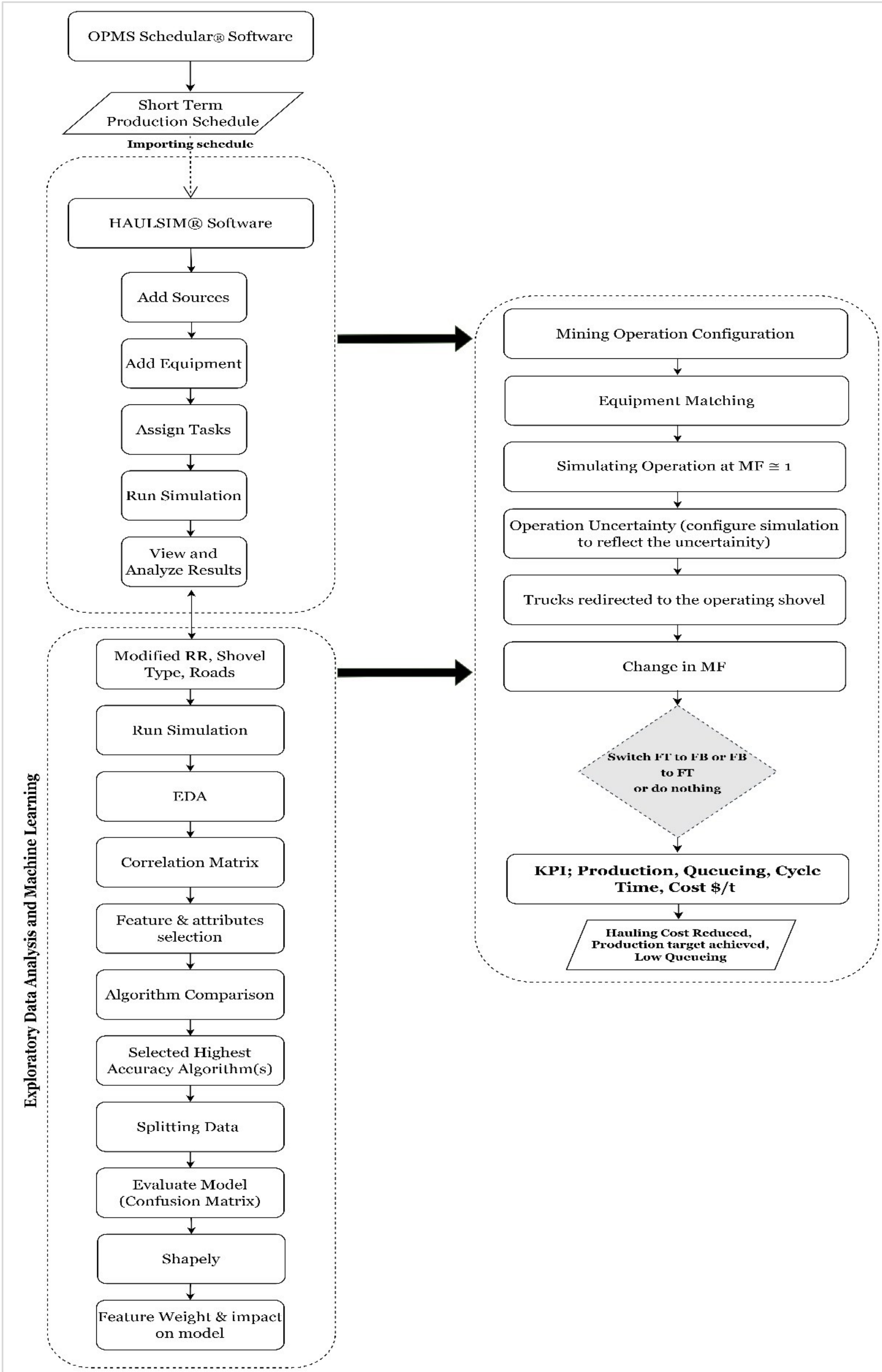


Figure 3-4 Detailed proposed framework for comparing FT and FB

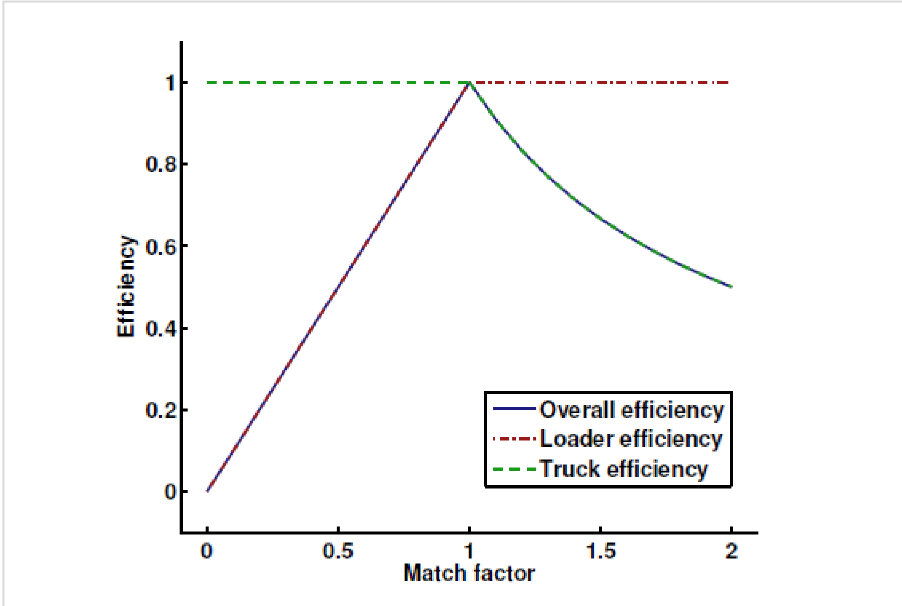


Figure 3-5 MF and truck-loader efficiency (C. N. Burt & Caccetta, 2018b)

After the equipment matching for operation is done, a short-term plan for a specific period is imported into Haulsim. The production schedule includes the material, equipment, and time selected to mimic the operation. This schedule includes the sources (shovels), destination, material quantities, and time steps. Next, the operation's simulation model is run at an MF of one. There are assigned trucks to each shovel that are homogeneous and dependent (same truck type and assigned to the same shovel) but with a similar destination target, the crusher.

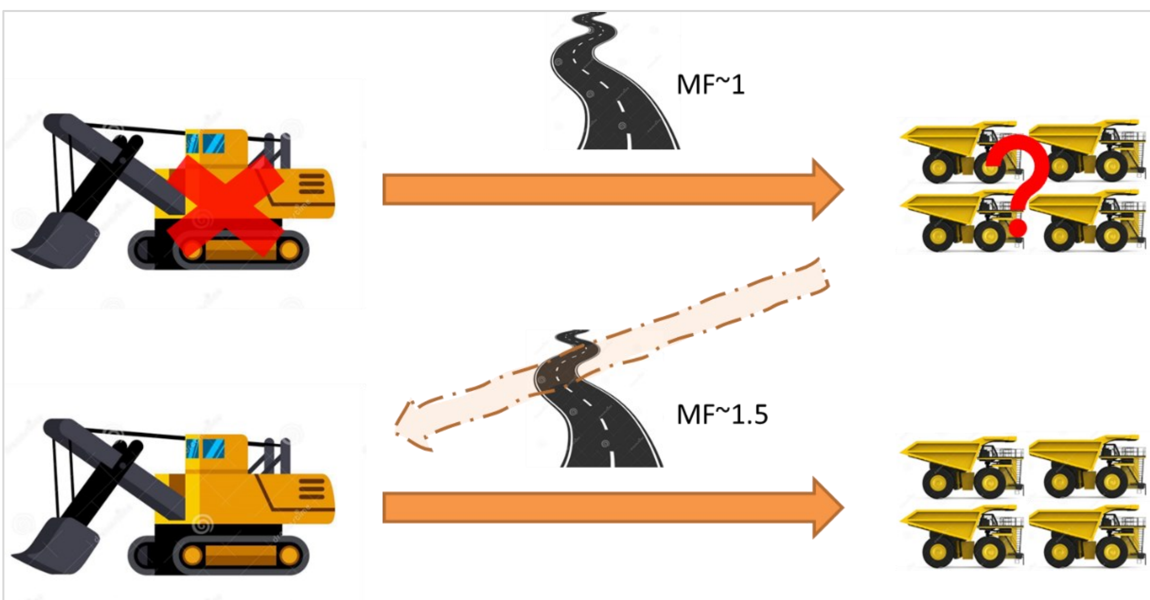


Figure 3-6 Reassigning trucks assumption in research methodology

The varying number of trucks to mimic the operation uncertainty and shovel stoppage changes the MF when operation uncertainty is encountered. For instance, if one of the shovels is no longer operating for a specific period of time due to major mechanical failure. As mentioned previously, other operation uncertainty can affect the fleet haulage. Therefore, unutilized trucks are redirected to the other shovel(s) (the working shovel) in a different mine road, and the MF increases. In this stage, a decision should be made to switch between the loading strategy from FT to the FB; the obtained operation KPIs control this switch.

3.3.2 Cornering Speed Algorithm

When a truck travels in a curve, the software uses a cornering speed algorithm to determine the final speed. Cornering speed is defined as the amount of force (centripetal force) needed to cause a vehicle to travel around a corner with a given radius. The maximum velocity of a vehicle can be calculated by calculating the force available to the vehicle through traction (friction between the vehicle and the road) and superelevation (banking of the road). The corner properties determine which road segments to include in a corner and the equivalent radius of the corner from that. The Road properties determine the speed limit for the equivalent radius. The cornering speed algorithm works in two phases; first, an equivalent radius is estimated for a corner, and second, the equivalent radius is used to calculate the speed limit for the corner (Haulsim, 2022).

3.3.3 Equivalent Radius

The road network in the 3D model consists of many straight road segments of various lengths and grades. Road segments that are grouped together to make a corner are used to calculate the equivalent radius by adding the total length of the road segments in the corner, in addition to the corner approach (in and out) and the total change in bearing of the road segments in the corner, (Haulsim, 2022). It is calculated as in equation (3.4):

$$\text{Equivalent Radius} = \frac{\text{Length}}{\text{Change in Bearing (Radians)}} \tag{3.4}$$

Limiting velocity by Lateral Traction Coefficient calculated as the equation (3.5):

$$\text{Max Velocity (m/s)} = \text{Radius} \times 9.81 \times \text{Lateral Coefficient of Traction} \tag{3.5}$$

Limiting velocity by Super Elevation calculated as in the equation (3.6):

$$\text{Max Velocity (m/s)} = \text{Radius} \times 9.81 \times \text{Tan(Super elevation)} \tag{3.6}$$

3.3.4 Equipment Selection Factors

One of the important criteria in surface mine equipment selection is determining the truck fleet size. There is a range of factors that must be taken into consideration pertaining to each piece of mobile equipment:

- Purpose and objective of each equipment.
- Different types of each equipment.
- Size and capacity.
- Operating cycle time.
- Turning radius/working radius.
- The number of equipment required for an operation.
- Health and safety considerations.

Bench height and passes per cycle also affect mine equipment matching, which is useful for operation productivity.

3.3.5 Cycle Time

Shovel cycle time can be defined as the time that includes truck spotting time, digging, swinging and loading time, as shown in Figure 3-7. While truck cycle time consists of travelling, waiting time, queuing, spotting, dumping and loading that starts from a specified point to the same point in the next cycle, as detailed in Figure 3-8.

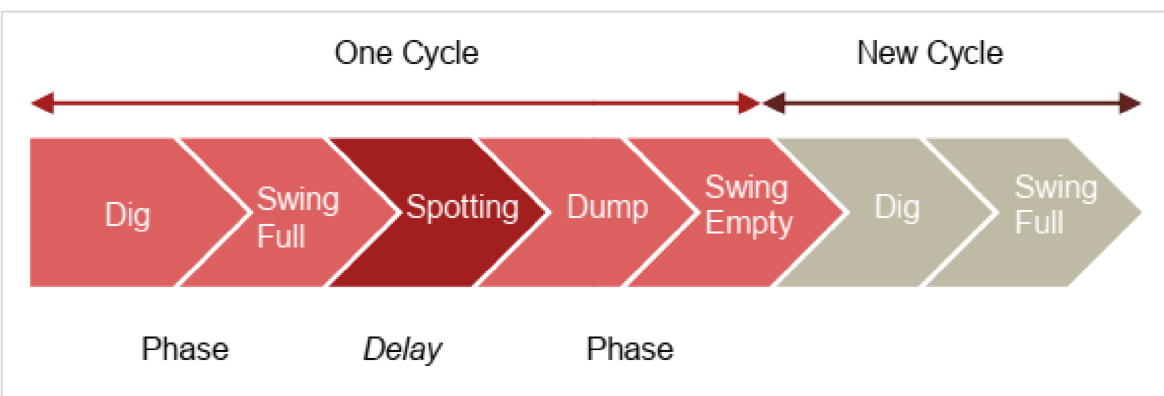


Figure 3-7 Shovel cycle time (Loadsman et al., 2013)

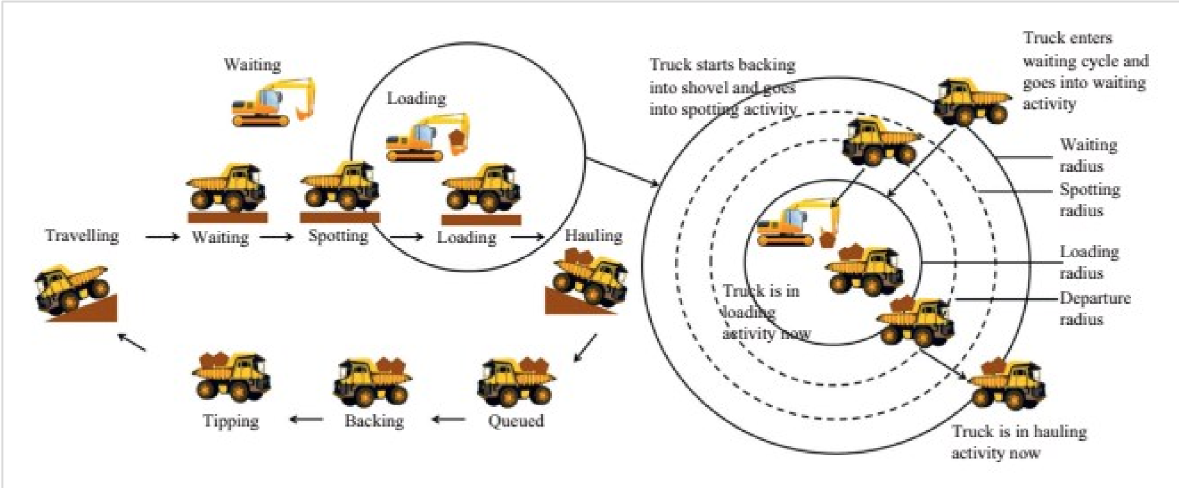


Figure 3-8 Truck cycle time concepts (Chaowasakoo et al., 2017)

The cycle time analysis in the running software assists in analyzing the mine hauling network on the road in the mine, which contains the following inputs:

Loader or shovel: the loading equipment type.

Truck: the hauler type.

Start location: the required starting location for the equipment.

End Location: the required ending location for the equipment.

3.3.6 Que and Truck Arrival Rate

Queuing system is defined as customers' arrival for service, waiting for their turn and moving to the next server. In mining operations, queuing is observed in the hauling cycle of trucks. When the trucks arrive at the shovel, wait for their turn in the queue until the truck ahead is finished. Also, it can happen on dumping sites and any other location that requires service (May et al., 2012). The queuing model and analysis that is incorporated in the simulation results use equation (3.7):

$$r = \frac{\lambda}{\mu} \qquad 3.7$$

Where r is the expected number of trucks in service, λ is the average arrival rate of new trucks, μ is the average service rate per loader.

The average number of trucks in a queueing system, L and the average time a truck spends waiting in line for the shovel W, can be expressed as in equation (3.8):

$$L = \lambda W \qquad 3.8$$

Equations (3.7) and (3.8) are applied to the simulation data to calculate the number of trucks queued at the shovel in both loading strategies: FT and FB.

3.3.7 Software Concepts

Software terms should be defined in order to understand the operation and analyze the simulation data; as the following explains these concepts (Haulsim, 2022) :

Road networks: the road network provides a path for the equipment to move around in the model. Properties of the road network are used to determine the speed that the equipment moves across the network.

Road properties: the road contains the following information for each segment:

- Distance: the segment distance is the distance the truck travels within the segment. The sum of the segment distances should be the total length of the haul network. When a segment is on a grade, the distance should be the actual distance over which the truck travels, that is, the distance along the grade.
- Grade: the grade of the haul segment is expressed as a percentage. The percentage represents the vertical rise divided by the horizontal distance. For example, a grade of 10% represents a rise of 10 metres over a horizontal distance of 100 metres. An ascent has a positive grade, while a descent has a negative grade. Typical ramp grades range from 6% to 12% or -6% to -12%.
- Bearing (degrees): the bearing defines the direction in which the road segment is heading. A bearing of 0° will be due north.
- Bearing change (degrees): changing the bearing from one segment to the next.
- Rolling resistance (RR): RR results from the frictional force between the truck tyres and the ground surface. This frictional force is directed at a tangent to the truck tyres, parallel to the ground surface, and acts in the opposite direction to the truck's motion. The greater the gross vehicle weight of the truck, the greater the rolling resistance. The rolling resistance is expressed as a percentage of the component of the gross vehicle weight that is normal (perpendicular) to the ground surface. The normal component of the gross vehicle weight changes within the haul profile as grade and truck payload change. The percentage rolling resistance also changes as the surface changes from

smooth to rocky and rough. Therefore, the force due to the rolling resistance changes along the haul profile.

- Maximum speed full.
- Maximum speed empty.
- Delay: the delay time, in seconds, that the truck will wait in the middle of the segment before continuing the trip.
- Final speed limited by corner: the maximum final speed a truck can reach in a segment due to an approaching corner.
- Max speed limited by corner: the maximum speed a truck can travel through a segment due to cornering properties.
- Equivalent radius (discussed previously in section **3.3.3**).

Other software concepts are defined as the following:

Locations: At least one source, destination and ancillary location is required for a simulation to be completed. The locations define where the network material moves from and to. **Ancillary:** Locations are places where equipment goes when it is not productive.

Sources: The place where the shovel (loader) is located and the hauling equipment are loaded. **Destinations**: Places where the material is dumped to waste or discarded in crusher or conveyor by hauling units.

Equipment: The defined equipment used for hauling material in the mine. The loading unit works at a load and haul source location, where it loads payload and haul units. The load and haul units then take the material from the source location to a destination.

Material: Properties of moving materials, such as density and swell factor, are essential to calculating load times.

Tasks: Tasks represent a material movement from the source location to a destination. Tasks are a combination of equipment, source, destination and material type. Depending on the task type, it may also have other attributes.

The software uses simple dispatching logic; the aim of the dispatcher is to allocate trucks to loading units. When the system is balanced, the loading units should achieve the dispatcher target rates with minimal queueing of trucks. The first allocation of trucks is based on the order that they appear in the load and haul list.

3.4 Data Analysis and Machine Learning

The data analysis is conducted using Python programming language using Anaconda navigator, a GUI tool that installs and launches Jupiter notebooks. The navigator is used for creating documents that contain live codes, visualization and text using Python, in our case. The version that runs in the simulation is 3.9.7, and the libraries imported include pandas, NumPy, seaborn, matplotlib, SHAP and sklearn. The approach starts with cleaning and preparing the data for the exploratory data analysis, cleaning any outliers, if available and any wrong data.

3.4.1 Exploratory Data Analysis (EDA)

The EDA is an important step in the proposed methodology. An EDA is conducted to understand the simulated data and to generate a statistical summary for the simulated data. It helps identify issues with the data and manage them before running and further analyzing and understanding the behaviour of the proposed input features used to predict loading strategies. In this stage, summary statistics, scatter plots, histograms and correlation matrices are generated. Correlation matrices are important in identifying relationships in the data set. There are two common correlation matrices; Pearson measures the strength of the linear relationship between variables and Spearman measures the monotonic, never decreases nor increases variables; the association between two variables in terms of ranks.

3.4.2 Machine Learning (ML)

ML is a method of data analysis that automates analytical model building. ML algorithms that iteratively learn from data allow computers to find hidden insights without explicitly being programmed where to look. The general ML approach is illustrated in Figure 3-9. The definition of terminologies used in the process is as follows:

Dataset: A set of data that contain features important for solving the problem.

Feature: Important pieces of data that help understand a problem. Features are fed into the ML algorithm to help in learning the process.

Model: the representation of a phenomenon that the ML algorithm learned during the training process. The model is developed after training an algorithm.

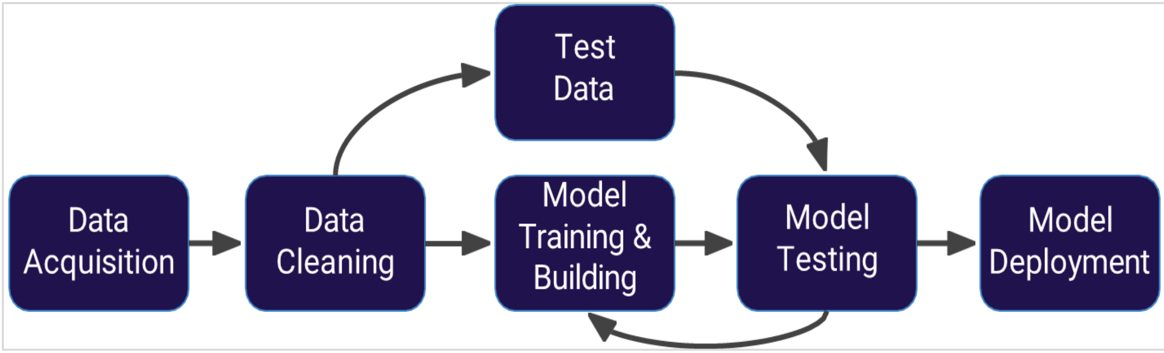


Figure 3-9 Machine learning process

For simulation data, the logistic regression analysis is used to model and predict the data and RF is used to prepare for the Shapley library, which is used to evaluate the importance of the operation's features.

3.4.3 Multiple ML Algorithms

In order to observe the best results of what could be simulated in operation, a set of models is prepared to examine the best recall results for various ML algorithms using specific code APPENDIX B. Each model enters into train and test data. These models are selected from the supervised ML under classification and regression models because the data set is labelled and training is possible for further prediction. The selected models are:

- *LDA: Linear Discriminant Analysis*; a linear model for classification and dimensionality reduction that is used for feature extraction in pattern classification problems (Sunil Kumar Dash, 2021).
- *KNN: K Neighbors Classifier*; non-parametric, supervised learning classifier which uses proximity to make classifications or predictions of data (IBM, 2022)
- CART: Decision Tree Classifier; predictive model, which explains how an outcome variable's values can be predicted based on other values (Q Software, 2022).
- *NB: Gaussian NB*; a type of Naïve Bayes classifier algorithm, used when the features have continuous values assuming all features have a gaussian (normal) distribution (Rahul Saxena, 2017).
- *SVM*: Support Vector Machine; a supervised machine learning model that uses classification algorithms for two classification problems (Bruno Stecanella, 2017).

3.4.4 Random Forest (RF)

The RF is a supervised ML algorithm that is used widely in classification and regression problems. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and improve the performance of the model. As the name suggests, RF is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. Instead of relying on one decision tree, the RF takes the prediction from each tree based on the majority of predictions' votes and predicts the final output. The RF works in two-phase first is to create the RF by combining N decision tree, and second is to make predictions for each tree created in the first phase.

3.4.5 Logistic Regression (LR)

The LR allows predicting a categorical label based on historical feature data. Usually, two discrete class labels, by converting a LR into a classification model through the logistic function as shown in Figure 3-10. The zero values are assigned to the FB category and one value is assigned to the FT category.

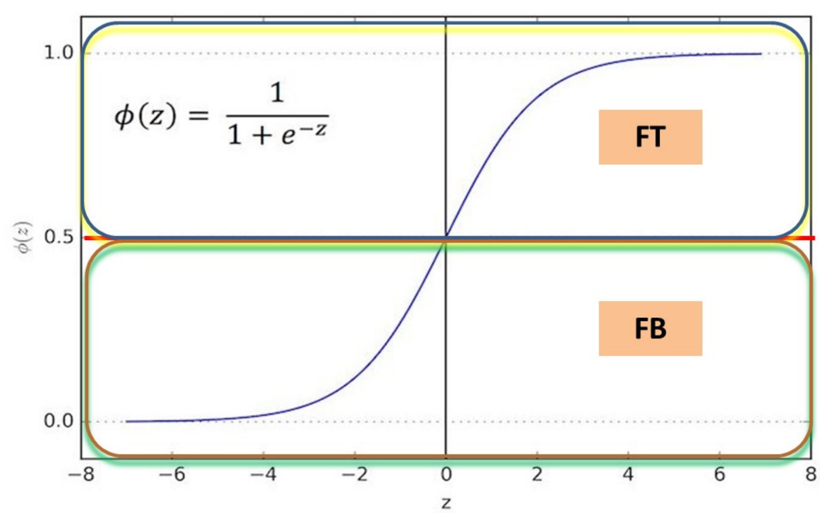


Figure 3-10 Logistic regression function

3.4.6 Classification Metrics

To calculate the accuracy of the resulted LR model, the following classification metrics are used:

- *Precision:* is the ratio of the number of all true positive over true positive plus false positive.
- *Recall:* is the ratio of the number of all true positive over true positive plus false negative.
- *Accuracy:* divides total true values over all values.

Figure 3-11 illustrates these concepts of ML evaluations.

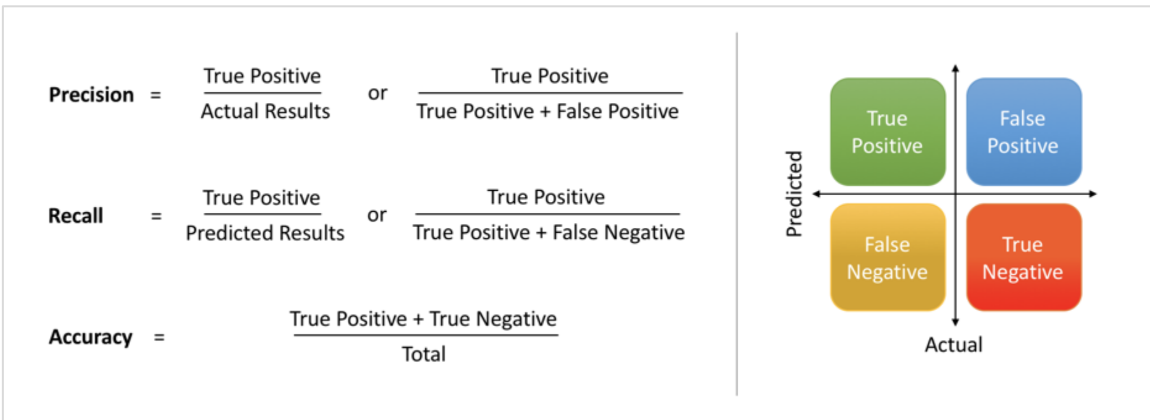


Figure 3-11 Machine learning model evaluations (Saxena, 2018)

3.4.7 Model Parameters

A classification model is trained to predict loading strategy, which can then be added to SHAP to understand the parameters. Therefore, identifying parameters that predict in the models is critical for fully understanding the operation.

3.4.8 Interpreting Model-SHAP Weighing Technique

Features importance aims to assign a score for each input feature in the predictive model. Based on its importance in predicting the loading strategies by using SHAP values to rank the importance of features in predicting the outputs building on game theory concepts. Figure 3-12 illustrates the SHAP as the explainer model for explaining these predictions. By indicating the relationships that combine to create the model's output. Plotting the SHAP values of each feature for each sample enables users to quickly determine which features are most crucial for a given model.

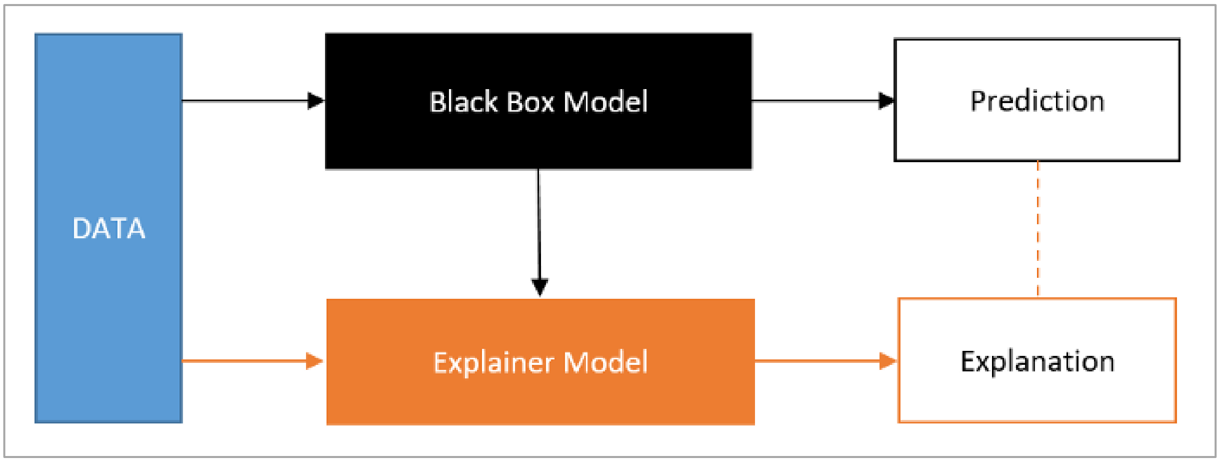


Figure 3-12 Interpreting machine learning models using SHAP

3.4.9 Gini map

GINI importance (or mean decrease impurity) is a method computed from the RF structure. In any random forest, a set of Decision Trees is constructed. Each decision tree is a set of internal nodes and leaves. In the internal node, the selected feature is used to make a decision on how to divide the data set into two separate sets with similar responses within. The features for internal nodes are selected with some criterion, which for classification tasks can be Gini impurity or information gain, and for regression is variance reduction. It can be measured how each feature decreased the impurity of the split (the feature with the highest decrease is selected for the internal node). For each feature, collect how on average, it decreases the impurity. The average over all trees in the forest is the measure of the feature importance.

3.5 Summary and Conclusion

In summary, the chapter focuses on multiple frameworks developed to understand the loading strategies in open-pit mining operations, using DES techniques to mimic the real mining operation and generate results under the FT and FB loading scenarios.

The approach begins with understanding the material characteristics and associated operator efficiency, configuring these data and defining the material type. The resulting passes matching between truck-shovel under both loading strategies is evaluated further with a different number of trucks to highlight the sweet spots and opportunities of switching under operational and short-term levels. Based on the previous approach, all associated hauling costs, cycle times, production rates and queueing conditions are compared as well. The approach assumes reassignments of trucks from another shovel due to lower efficiency and/or availability.

In the expanded methodological approach, queuing model and truck arrival rate are important in calculating the number of queued trucks. The MF formula is useful for identifying the number of trucks in various operating efficiencies.

In the higher level approach, EDA and ML model, a set of data is generated to better understand the sensitivity of the operation, adding the rolling resistance effect, different shovel types and hauling roads. This is followed to yield meaningful data that is used in the ML prediction model. Furthermore, analysis of feature importance is reached by using the Shapley approach. Feature importance is critical in evaluating the most important parameter in predicting loading strategy for operation open-pit mining KPIs.

CHAPTER 4

CASE STUDY AND DISCUSSION OF RESULTS

This chapter discusses the simulation results of the FT and FB loading strategies in a selected mine after applying the proposed broad and detailed frameworks discussed in the previous chapter and following the software framework to generate the accurate simulation results. Next, interprets the results to get a more understanding. Finally, all results and operation KPIs are compared, presented, evaluated and discussed. Furthermore, the data is brought in Python programming language to apply in a ML model that predicts the loading strategy based on selected parameters and understands the most important parameters triggering that switch.

4.1 Introduction

This chapter analyzes the FT and FB study results, implementing the proposed simulation methodology for FT and FB at proper levels. First, beginning from the broader simulation, which comprises the assumptions and the general understanding at the beginning of the problem, then going through the methodology that requires the software application and the methodology that evaluates and interprets the data.

The related software used in the simulation is Haulsim which connects the fleet assessment mining operation plans to build a digital twin of mining operation delivering an accurate representation of the haulage operations, in addition to fundamental data analysis for the resulted outputs using Python programming language under Anaconda data science platform. Moreover, a ML model is run for traversing the operation parameters to understand the most influential parameters that trigger switching from FB to FT loading strategies. Section **4.2**, deals with importing the schedule data to Haulsim software. Then section **4.3** presents the simulation environment configuration and sections **4.4** through **4.11** discuss various simulation results. Then data analysis using Python and ML is discussed in section **4.12** and section **4.13** concludes this chapter.

4.2 Scheduling Data

Scheduling data for a gold mine was exported from a scheduling software OPMS and imported into the Haulsim software. By using the software ability to import schedules, the schedular button in the get external toolbar, which gives the ability to build a model from any schedule data using external software source for various schedule configurations, including sources and destinations, resource (equipment) and mine layouts that vary throughout the schedule time. The data exported covered a specific interval for the sake of loading strategies evaluations and comparing; the total number of steps was seven and the total tonnage to be mined was 2,023,945 tonnes from pushback 5 level 880m in in the eastern pit. Table 4-1 shows the details of steps Ids and quantities, the crusher was the final destination for all trucks.

Figure 4-1 illustrates the general mine layout and the location of pushback 5. The original gold mine included two types of materials; waste material: non-acid forming material and potential acid forming material. Ore material: high-grade sulphide, low-grade sulphide and low-grade oxide. The mine has two pits; east and west pit. The eastern pit has four pushbacks, while the western pit has one pushback.

Table 4-1 Selected schedule used in running simulation

Step Id	Resource (shovel)	Source	Destinations	Quantity (tonne)
106,668	2802	EAST\PBack5\880\P48_54	CRUSHER	111,243.69
106,693	2804	EAST\PBack5\880\P48_55	CRUSHER	113,467.23
106,704	2804	EAST\PBack5\880\P47_58	CRUSHER	185,245.53
106,737	2802	EAST\PBack5\880\P48_57	CRUSHER	384,398.62
106,751	2802	EAST\PBack5\880\P49_57	CRUSHER	529,305.00
106,762	2804	EAST\PBack5\880\P48_58	CRUSHER	614,780.46
106,783	2804	EAST\PBack5\880\P48_58	CRUSHER	85,504.54

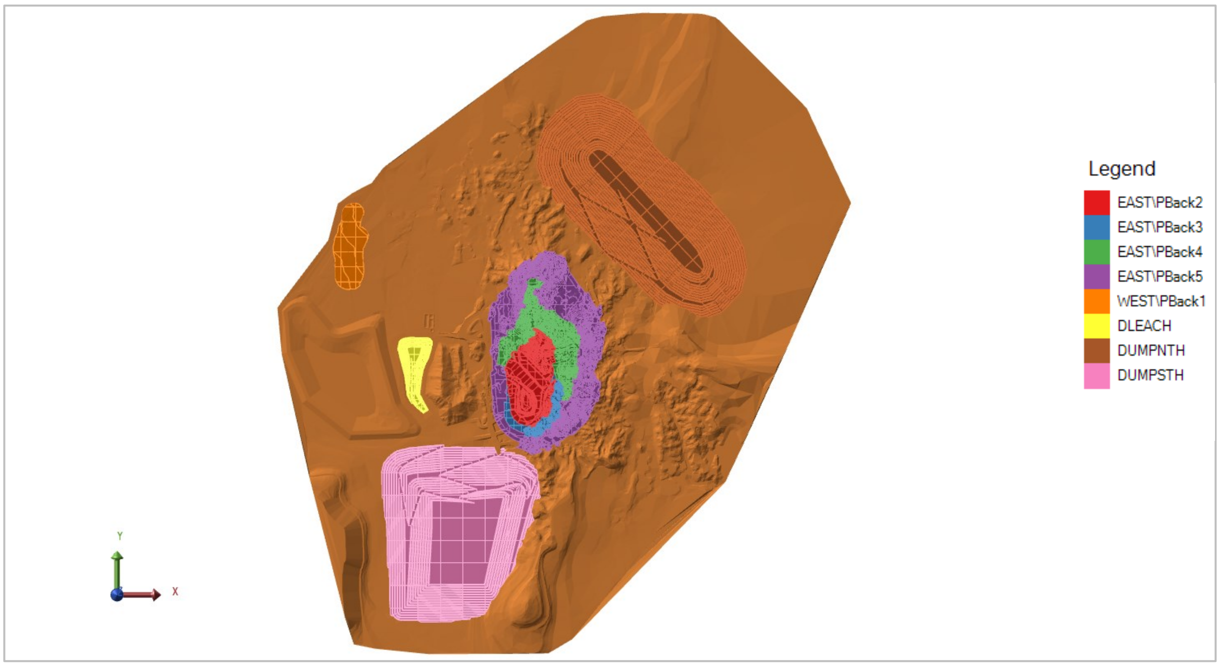


Figure 4-1 Mine layout including pushback 5 coloured in purple

4.3 Setting Up the Simulation Environment

Before starting the simulation, a set of definitions and configurations are needed to run the simulation properly. These include mine hauling roads, equipment (truck and shovel) configuration (operating data and cost data), and hauled material characteristics (loose density and BFF).

4.3.1 Material Characteristics

The selected material in the simulation is high-grade sulphide (HGSx). Table 4-2 summarizes the material's characteristics.

Table 4-2 Hauled material characteristics

Material Characteristics		Unit
In-situ Bank Density	2.4	t/m^3
Swell Factor	1.25	-
Loose Density	1.92	t/m^3
BFF-Heaped	97.5	%
BFF-Struck	97.5	%

4.3.2 Equipment Data

Operating and costing data for the mining fleet are included in the simulation for both shovels and trucks. The shovels used in the simulation are P&H 2800 XPC and the trucks are CAT 793F. Table 4-3 presents shovel configuration data. Table 4-4 presents the configuration of the truck CAT 793 F.

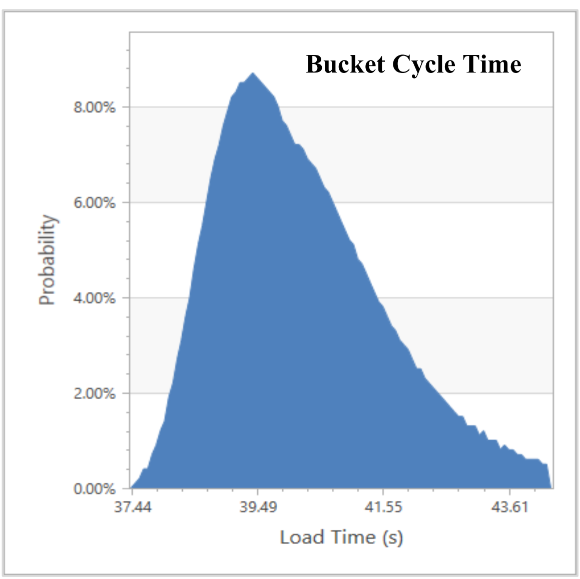
Table 4-3 P&H 2800 XPC shovel data in the simulation

Shovel P&H 2800 XPC			
Operating Data	Capacity	32.78	m^3
	Bucket Cycle Time	40	sec
	Filled Capacity	31.96	lcm
	Filled Payload	61.49	t
	Maximum Production Rate	5533.95	t/h
Costing Data	Purchase price	19,714,300	$
	Life	20	years
	Owning Cost	101.27	$/hour
	Operating Cost	129.95	$/hour

Table 4-4 CAT 793F truck data used in the simulation

Truck Cat 793 F			
Operating Data	Capacity	175	m^3
	Actual Capacity	117.89	lcm
	Payload	226.8	t
	Dump Time	60	sec
	Spot Time @ Loading	24	sec
	Spot Time @ Dump	18	sec
Costing Data	Purchase price	3,568,900	$
	Life	15	years
	Owning Cost	24.44	$/hour
	Operating Cost	435.28	$/hour

Figure 4-2 illustrates the distributions used for the shovel's loading time and bucket payload. For shovel loading time, the mean value is 40 seconds, and the distribution is skewed to the right. At the same time, the payload factor is one and skewed to the left. Figure 4-3 illustrates the distributions used for trucks. For truck dump time, the mean value is 30 seconds. Moreover, for the truck's load and carry time, the estimated mean of the value of which there is a 50% probability of occurrence is 40 seconds.



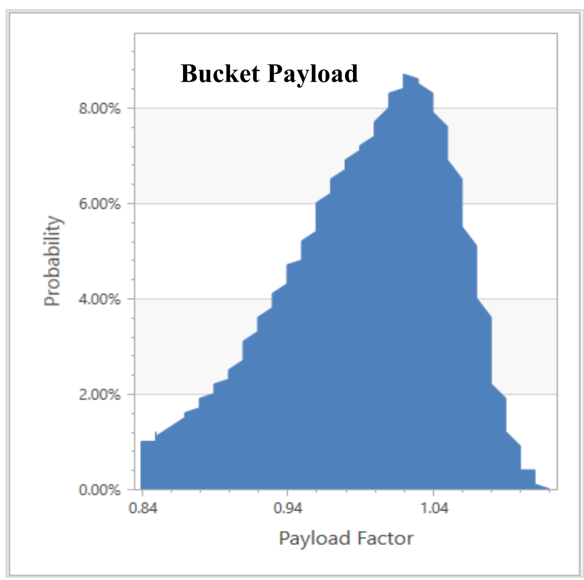


Figure 4-2 Distribution data for P&H 2800 XPC

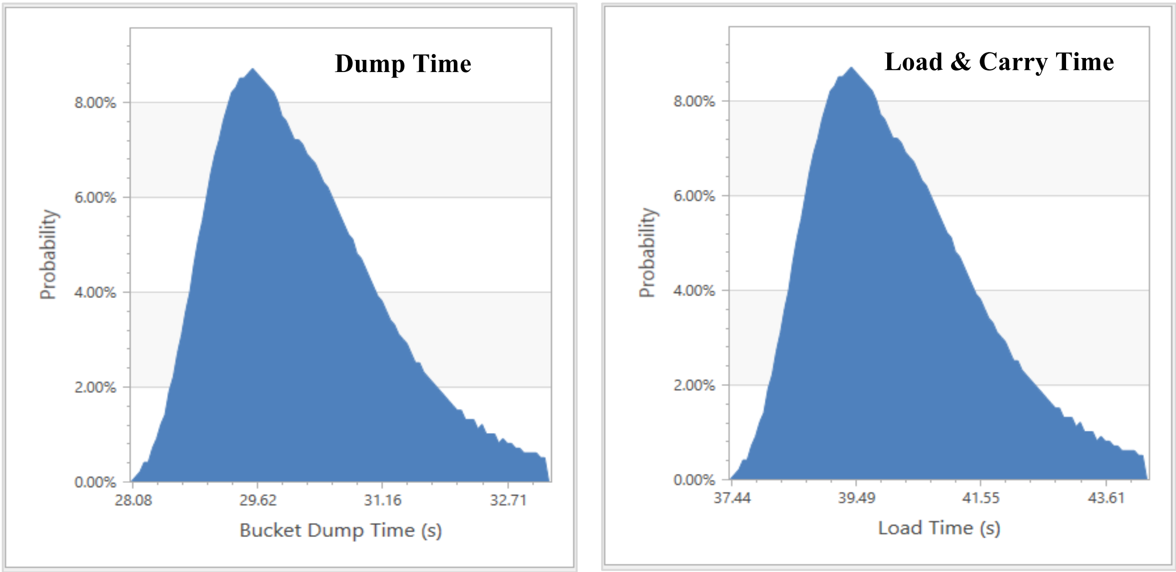


Figure 4-3 Distribution data for CAT 793 F

4.3.3 Shifts and Working Times

Table 4-5 represents the time data for the simulation model. The non-operating shift delays and the operating delays are estimated to be 30 and 60 min in each shift, respectively. Therefore, the actual working time in a shift is 6.5 hours, and shovel and truck availability is assumed to be 85%.

Table 4-5 Shifts data and effective working times

Working Time		
Mon-Fri	5	days/week
Shift Duration	8	hours
Non-Operating Shift Delays	0.5	hour
Shift Operating Time	7.5	hours
Operating Shift Delays	1	hour
Shift Working Time	6.5	hours
Shovel Availability	85	%
Truck Availability	85	%

4.3.4 Simulation Model

The material hauling operation in the mine is modelled using Haulsim software. Examples of the simulation animation in the software for loading trucks CAT 793F by P&H 2800 shovels at the ore source location and crusher destination are shown in the images in Figure 4-4 for single truck-shovel loading and Figure 4-5 representing the queueing conditions, Figure 4-6 for dumping at the destination which is the crusher and Figure 4-7 shows the trucks reducing speed at corner.

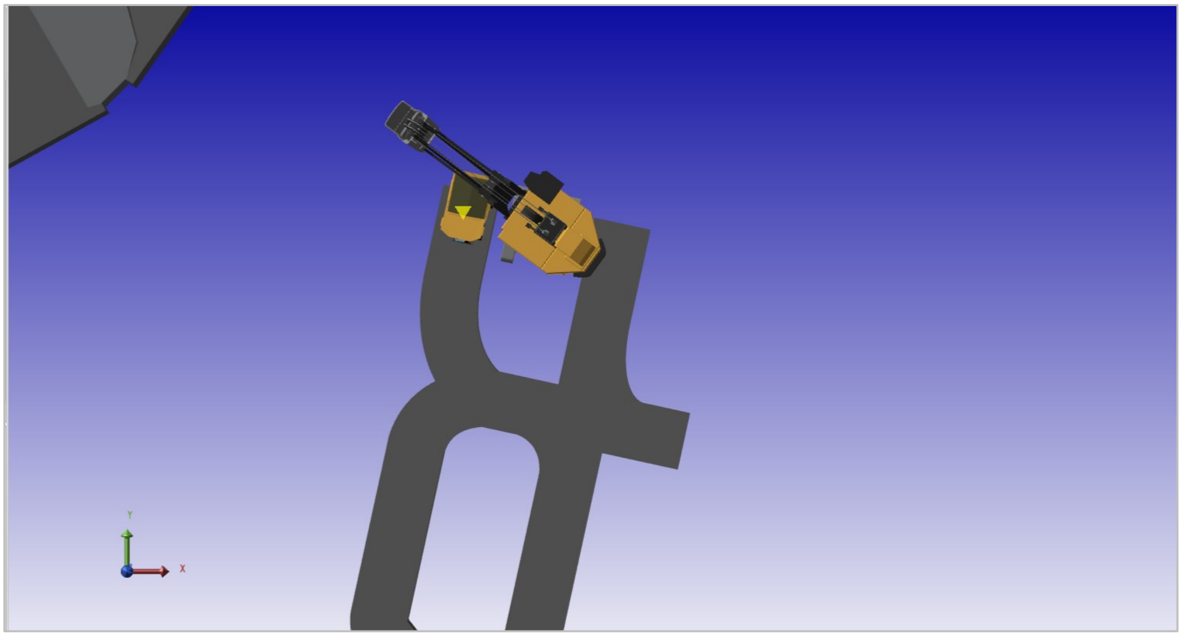


Figure 4-4 CAT 793F trucks being loaded by 2800 rope shovel

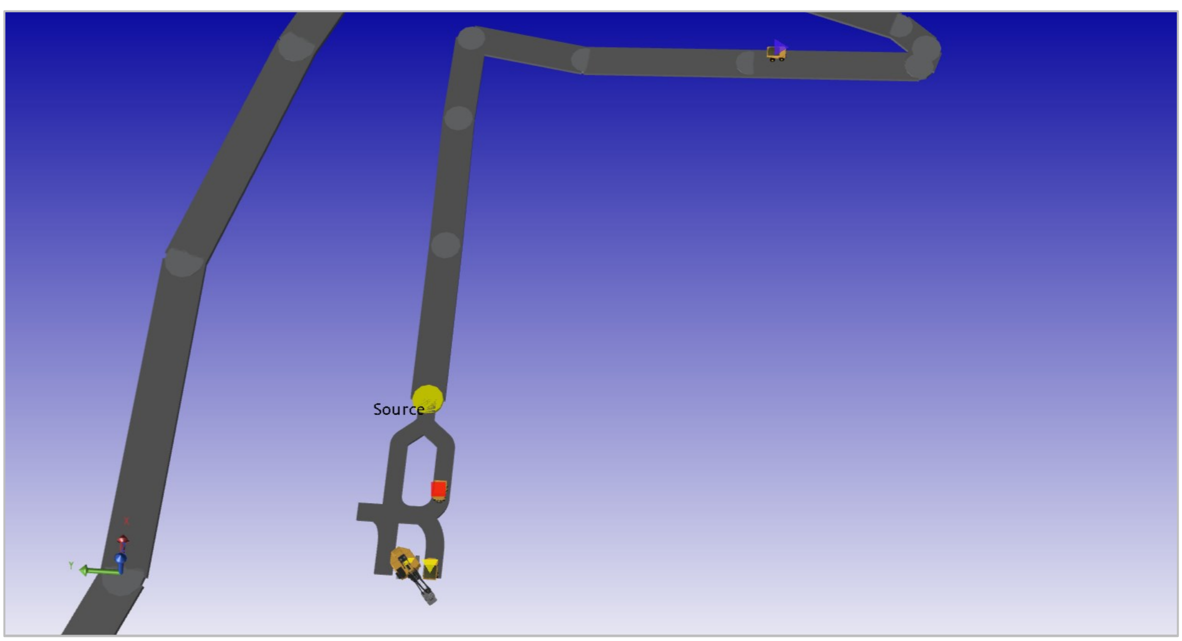


Figure 4-5 CAT 793F queued at shovel

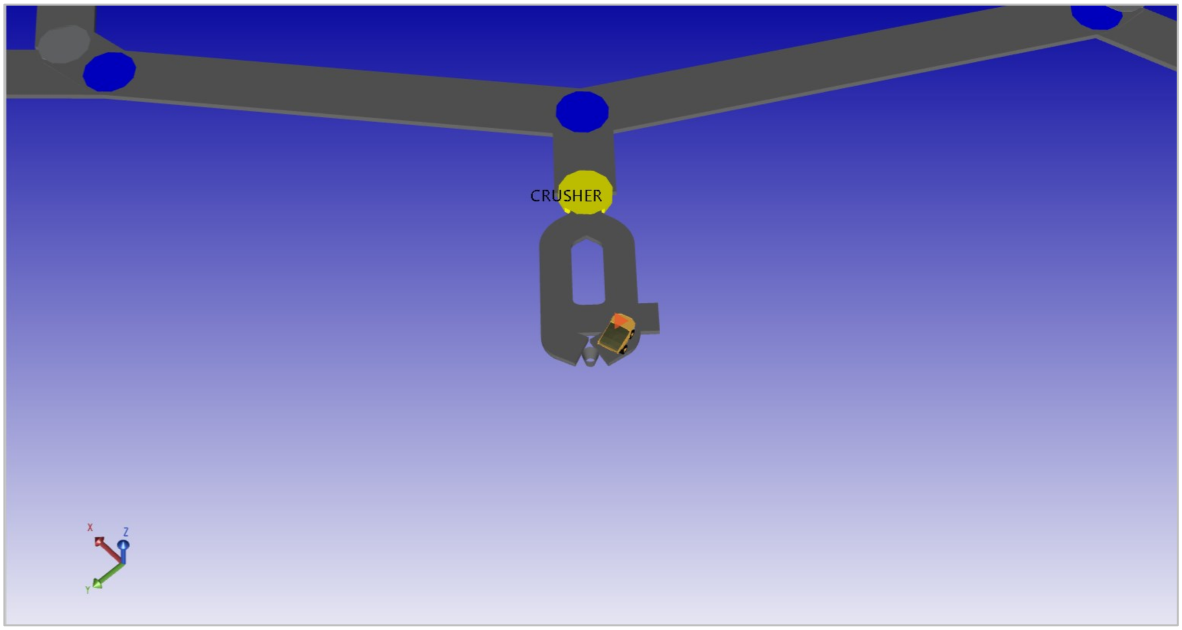


Figure 4-6 CAT 793F dumping at crusher

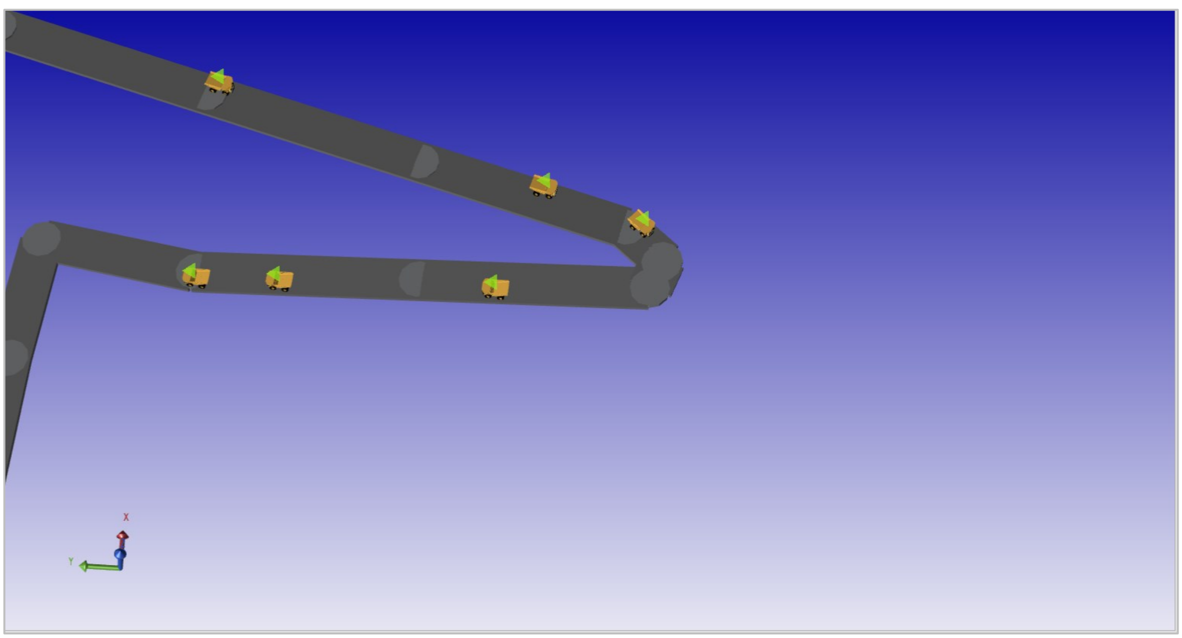


Figure 4-7 CAT 793F trucks travelling empty at road corner

4.4 Roads and Cycle Time Analysis

Two mining haul roads were implemented for simulation (denoted as R1 and R2) as in Figure 4-8. Each road begins in a bench face and ends in the crusher. Both working benches have high-grade sulphide (HGSx). The lengths of R1 and R2 are 3.46 km and 2.65 km, respectively. The maximum grade in R1 is 10.6 %, and in R2, 8.76 %. Both roads have a rolling resistance (RR) of 2%. Each haul road segment's final cycle time is different due to varying distances and the accompanied cornering speeds. (more details on road segments and intersegment details are available in APPENDIX C).

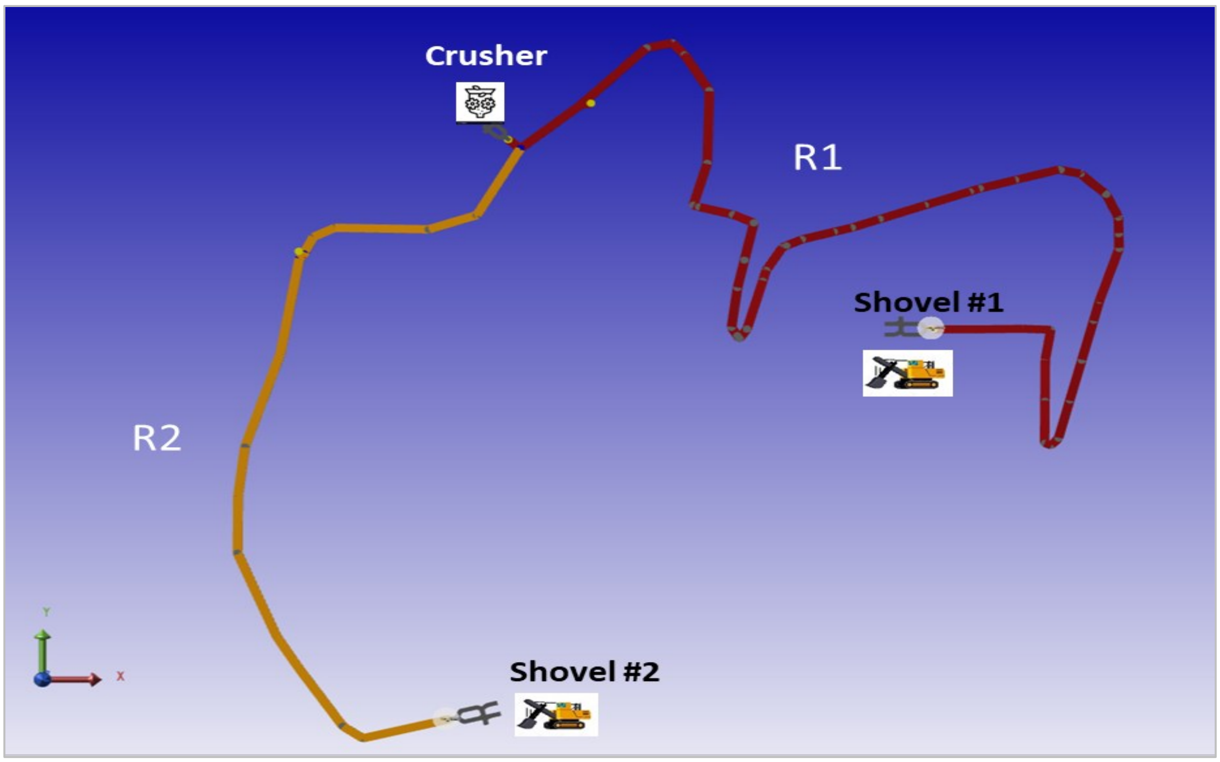


Figure 4-8 Layout of haul roads in the simulation model

Rise and run are a visual display of the implemented roads that change in height across their length. The term rise means how many units move up or down from point to point on the graph that would change the y values. While run means how far left or right moves from point to point. For the two hauling roads, rise and run profiles are significantly different, as shown in Figure 4-9 and Figure 4-10. It is clear that R1 has higher slope values over 0 to 175 m rise, which requires more cycle time due to reduced truck speed when loaded and travelling uphill. However, in R2 the slope changed within small segments (average downslope to 20m then upslope to 20m), accompanied by the segments total length that is less in road 2. Therefore, the total cycle time is much less over the road distance.

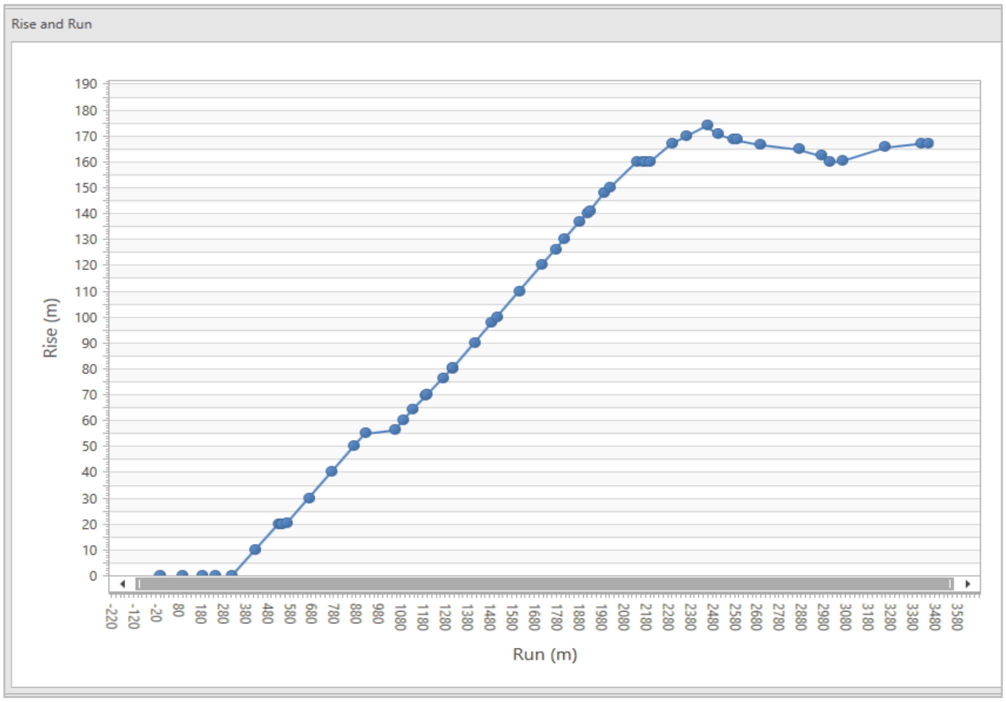


Figure 4-9 Rise and run profile for haul road 1 (R1)

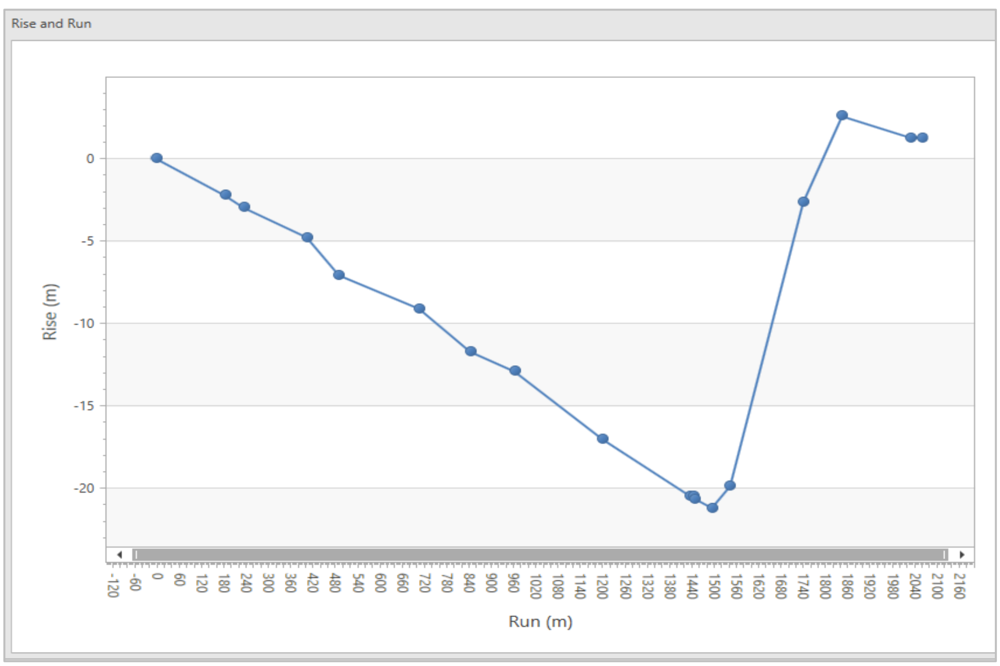


Figure 4-10 Rise and run profile for haul road 2 (R2)

The cycle time analysis was done for one truck and one shovel to understand and analyze the differences between the haul roads. Table 4-6 presents the results for both the FT and FB scenarios in R1 and R2.

Table 4-6 Cycle time analysis for haul roads within loading strategies

	Haul Road 1 (R1)		Haul Road 2 (R2)		
	Shovel	**Truck**	**Shovel**	**Truck**	**Unit**
	P&H 2800 XPC	Cat 793 F	P&H 2800 XPC	Cat 793 F	HGSx
FT Loading	Distance	3463.57	Distance	2064.89	m
	Travel Time	0:12:16	Travel Time	0:04:17	hh:mm:ss
	Reverse Travel Time	0:07:17	Reverse Travel Time	0:03:44	hh:mm:ss
	Total Distance	6927.13	Total Distance	4129.79	m
	Total Travel Time	0:19:33	Total Travel Time	0:08:01	hh:mm:ss
	Total Cycle Time	0:23:25	Total Cycle Time	0:11:53	hh:mm:ss
	Payload	226.80	Payload	226.80	tonne
FB Loading	Distance	3463.57	Distance	2064.89	m
	Travel Time	0:11:12	Travel Time	0:04:11	hh:mm:ss
	Reverse Travel Time	0:07:17	Reverse Travel Time	0:03:44	hh:mm:ss
	Total Distance	6927.13	Total Distance	4129.79	m
	Total Travel Time	0:18:29	Total Travel Time	0:07:55	hh:mm:ss
	Total Cycle Time	0:21:41	Total Cycle Time	0:11:07	hh:mm:ss
	Payload	184.17	Payload	184.17	tonne

Results show that cycle time with a FB loading strategy (including truck travel times) is less than FT. This is due to the fact that the trucks have less payload in the FB scenario and consequently, they travel uphill faster.

In R1, the cycle time in FT loading strategy is 23.42 min, while in FB loading strategy is 21.68 min. There is a 7.4% difference between the two loading strategies. FT travelling time also has an 8.7% difference because of the same reason explained for the cycle time. The reverse time has no differences between the loading strategies because the trucks are empty and travel on the same road in both scenarios. Analyzing R2 cycle time shows a 6.83% difference between FT and FB loading strategies. Travelling time has the same case as R1 with a difference of 1.25%. The lesser difference can be interpreted as R2 has less distance, almost 40%, than R1. Another reason for the difference is the rise and run and grades that are higher in R1 over frequent segments; this affects the cycle time and travel time.

One of the important results in cycle time analysis is the average payload for both FT and FB. Due to the higher loaded pass tendency in the FT, the calculated average payload in cycle time analysis was 226.8 tonnes. In contrast, in FB, the average payload was 184.1 tonnes. The difference in final payload between loading strategies was 18%. Considering the payloads, the productivity per truck in R1 was higher for the FT at a rate of 581.15 t/h, while for FB, it was 12.32% less (509.55 t/h) than FT.

Other parameters, such as the basic site Tonne Kilometres per Hour (TKPH); which is an essential expression of the working capacity of a tire representing the load capacity in relation to heat generation, were lower in the FT with a value of 947.35, while in the FB, the value is 978.57. Loading truck full affects the TKPH negatively and reduces the tires life and equipment reliability with time, with the general understanding that lower TKPH means lower heat resistance which is not recommended for truck hauling, and higher TKPH means higher heat resistance which means better truck hauling conditions. However, the lower TKPH has a higher cut and wear resistance.

Additionally, the total fuel consumed was higher by 8% in FT (36.23 litre/trip) than in FB (33.47 litre/trip). The reason is the higher payload, which requires more engine power to move the truck hence more fuel consumption.

4.5 MF Analysis

To understand the operation correctly, MF criteria were selected as 1 and 1.5; the latter was selected because of increasing trucks and the availability of only one shovel in operation. These basic analyses are illustrated in Figure 4-11.

The normal hauling in mining operation usually runs at MF equals 1. The case study resulted in 10 trucks when the loading strategy was FT. With changing the loading strategy to FB, the proper number of trucks (at MF=1) was 12. This difference in the number of trucks is due to lower passes affecting the MF formula.

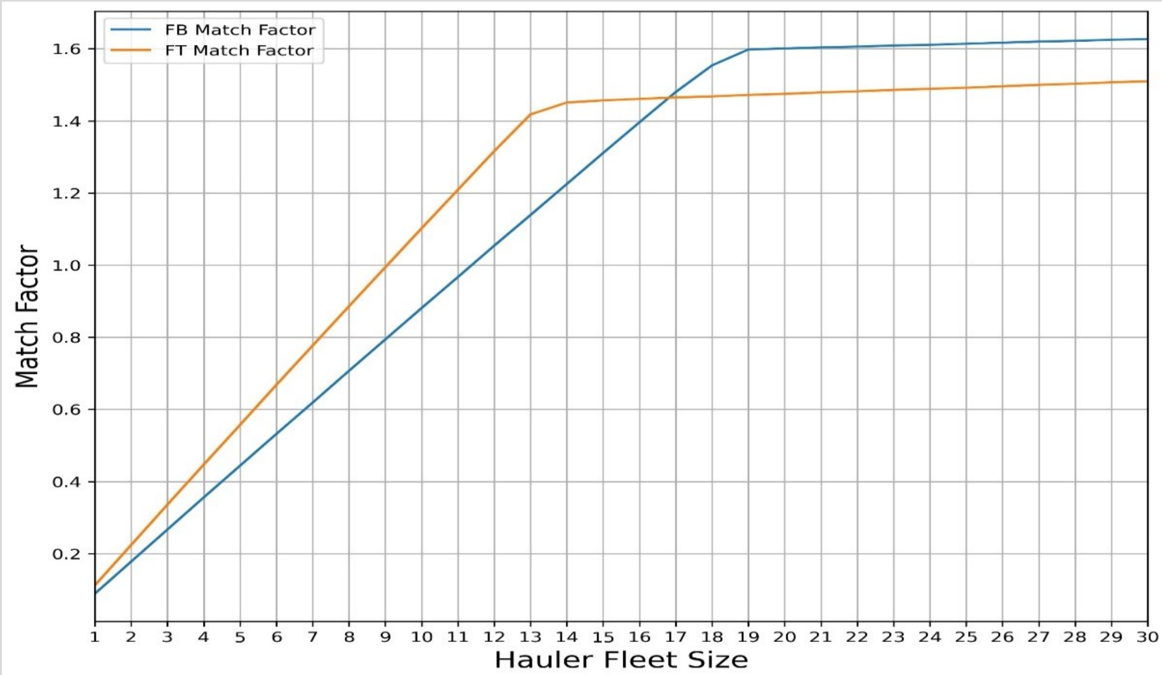


Figure 4-11 MF analysis for FB and FT

Detailed MF analysis and differences are available in Table 4-7. It can be seen that the difference between FT and FB becomes negative after the number of fleet equals 16. The highest MF difference between loading strategies was in fleet size 13. With the assumption that 2 shovels were working at MF equal 1, and one of the shovels broken down and trucks were redirected to another shovel. Adding 10 trucks to the operating shovel, the MF surged to 1.475 on an FT basis and 1.601 on an FB basis. Based on this sudden change, a decision should be made.

4.6 Cycle Time Simulation Results

Running the simulation with the correct configuration produces a range of cycle time results, as shown in Figure 4-12, where the FT loading strategy with a variable number of trucks on the x-axis always has a longer cycle time than the FB loading strategy. This is because, as previously mentioned, a loaded truck is heavier and requires more time to travel and load.

When fleet sizes are between 1 and 15, the cycle times difference is less than 5 minutes between the FT and FB. The normal conditions based on MF equals 1, the number of trucks equals 10, and with FB scenarios, the number of trucks should be 12; after that, the gap between the two loading strategies increases after the number of fleet equals 15, inducing the privilege of the FB loading strategy over the FT.

Table 4-7 MF values for the different fleet in loading scenarios

Hauler Fleet Size	MF (FT)	MF (FB)	Difference
1	0.112	0.089	0.023
2	0.224	0.178	0.046
3	0.336	0.267	0.069
4	0.447	0.356	0.091
5	0.557	0.444	0.113
6	0.668	0.532	0.136
7	0.777	0.619	0.158
8	0.886	0.707	0.179
9	0.994	0.794	0.2
10	1.102	0.881	0.221
11	1.209	0.967	0.242
12	1.316	1.054	0.262
13	1.418	1.139	0.279
14	1.451	1.225	0.226
15	1.457	1.311	0.146
16	1.461	1.396	**0.065**
17	1.465	1.48	**-0.015**
18	1.468	1.554	-0.086
19	1.472	1.598	-0.126
20	1.475	1.601	-0.126
21	1.479	1.604	-0.125
22	1.482	1.606	-0.124
23	1.486	1.609	-0.123
24	1.489	1.611	-0.122
25	1.492	1.614	-0.122
26	1.496	1.617	-0.121
27	1.5	1.62	-0.12
28	1.503	1.622	-0.119
29	1.507	1.625	-0.118
30	1.51	1.627	-0.117

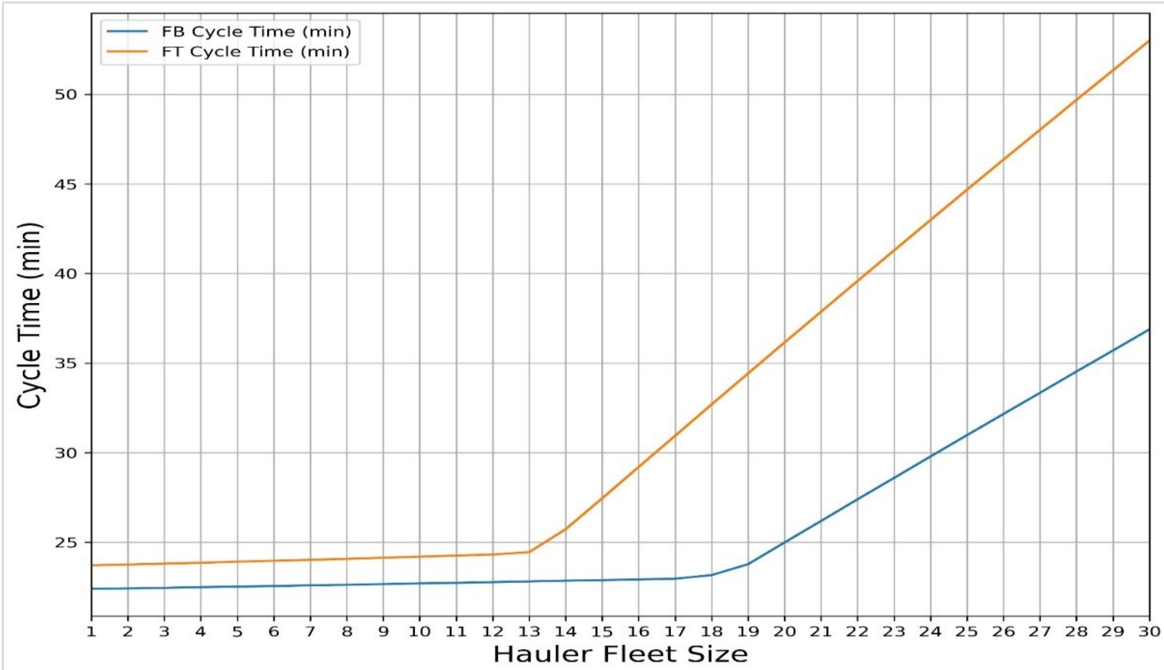


Figure 4-12 Simulated cycle time for loading strategies

4.7 Production-Cost-Fleet Curves

The simulation model was run for a different number of trucks to capture the effect of MF change from 1 to 1.5 in FB and FT loading strategies. Figure 4-13 and Figure 4-14 show the cost-production fleet curves for the FT and FB, respectively.

In the FT loading strategy (Figure 4-13), with increasing the number of trucks in the fleet, the production increases until the number of the truck is equal to 13; after this point, the production slightly increases until the number of trucks in the fleet reaches to 24. In the FB loading strategy (Figure 4-14), the fleet production has a similar trend to the FT strategy, but the production still increases till the fleet size is equal to 19.

Moving to the cost curve (total cost of unit ownership is the cost to buy the trucks and shovels plus their operating costs), in Figure 4-13, the cost decreases with the increased number of trucks until number 13; then it increases steadily until the last truck. The cost of the FB loading strategy decreases until the number of trucks equals 18, increasing afterwards. The increase in cost occurs earlier in the FT loading strategy. Finally, a comparison of the number of trucks in queue shows that at the beginning, there is a slight increase in both loading strategies. In the FT strategy, the number of trucks in the queue is insignificant until the fleet size is equal to 13; after this point, the number of trucks in the queue increases steadily until the fleet size is equal to 24. The FB strategy has the same behaviour, but the prominent increase in the number of trucks in the queue is stated after fleet size 18.

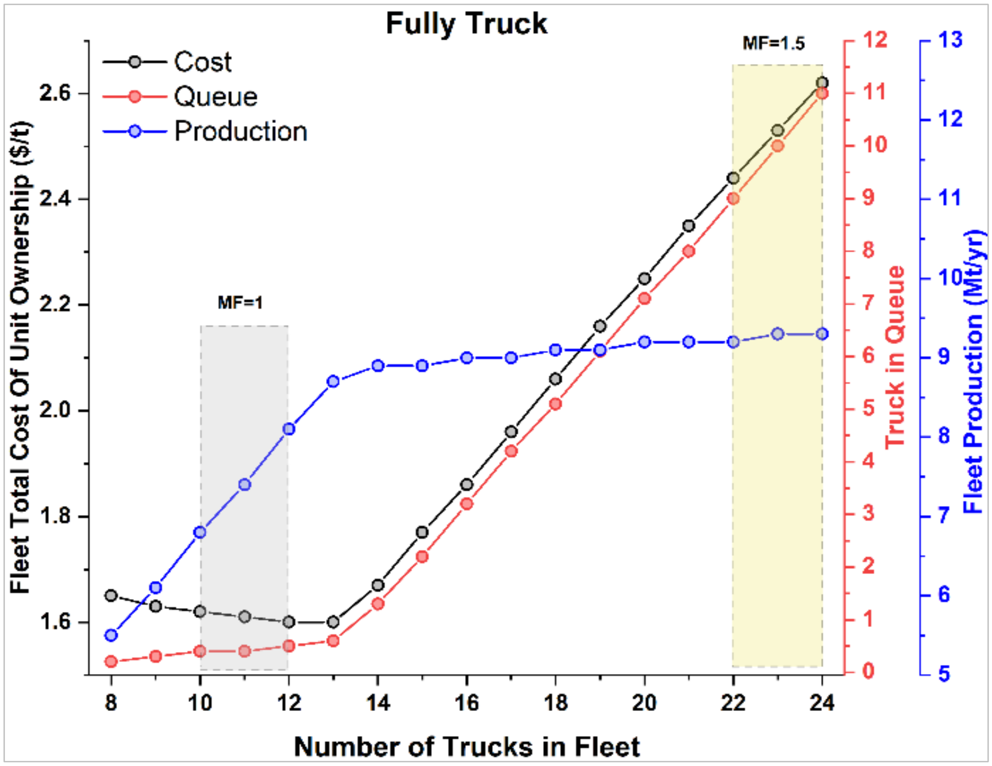


Figure 4-13 Cost-Production-Fleet curves for FT loading strategy

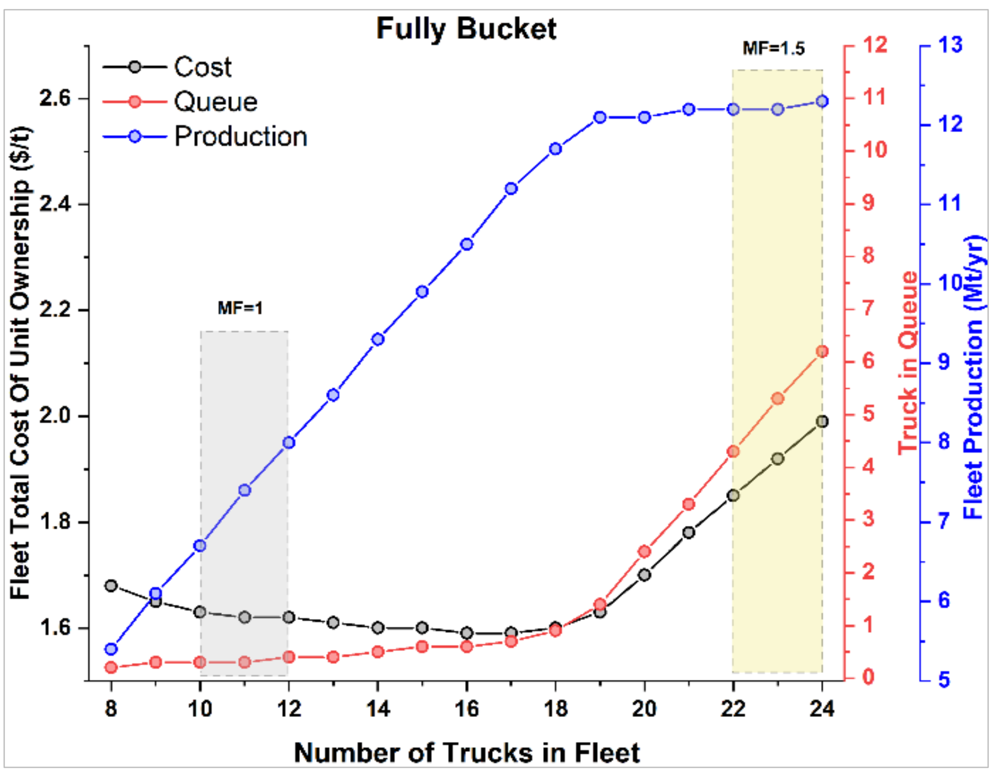


Figure 4-14 Cost-Production-Fleet curves for FB loading strategy

In Figure 4-13 and Figure 4-14, areas with average MF of 1 and 1.5 has been highlighted. For MF of 1, the sufficient number of trucks is between 10 and 12. For this area, in the FT strategy, the total cost for hauling is between 1.60 and 1.62 $/t, while in the FB strategy, it is between 1.62 and 1.63 $/t, which is a small difference. Fleet production is the same case, 6.8 to 8.1 Mt/yr in FT and 6.7 to 8.0 Mt/yr in FB. Also, there is a negligible difference in queuing conditions between FT and FB strategies. Therefore, considering the cost, production, and number of trucks in the queue, the FT loading strategy is suitable when the MF is 1.

In contrast, when the MF increases to 1.5, the FB strategy works much better. This increase in the MF happens because of the uncertainty and unplanned equipment breakdowns or any operation stoppage or unplanned queueing that significantly affects the operation. This research assumed that one of the shovels broke down for a time, and the trucks are sent to the other available shovel. When the MF is in 1.5, the shovel controls the operation. In this situation, the cost of FB strategy is much lesser than FT, ranging from 1.85 to 2.0 $/t, while in FT strategy, it varies between 2.45 and 2.65 $/t with a difference equal % 25. In addition, the production of FB strategy (12.25 Mt/yr) is much higher than the FT strategy. Another advantage for the FB when the MF is 1.5 is the number of trucks waiting for the shovel. The number of trucks in the queue for the FT strategy is double that for the FB strategy.

Figure 4-15 and Figure 4-16 show the detailed operating costs for FT and FB loading strategies, including the fuel costs. The major difference is that in the FT scenario, the maintenance, fuel and other operating costs spike within a fleet size of more than 13, while in FB, theses costs spike when the fleet size is more than 18. Other important features of these curves are that they start similar in costs with fleet size 1 and end with higher costs in the FT scenario. Fuel costs in FT start to increase more than FB after fleet size 13. The difference reaches 25.6% in fleet fuel costs ($/t) when the fleet size reaches 30.

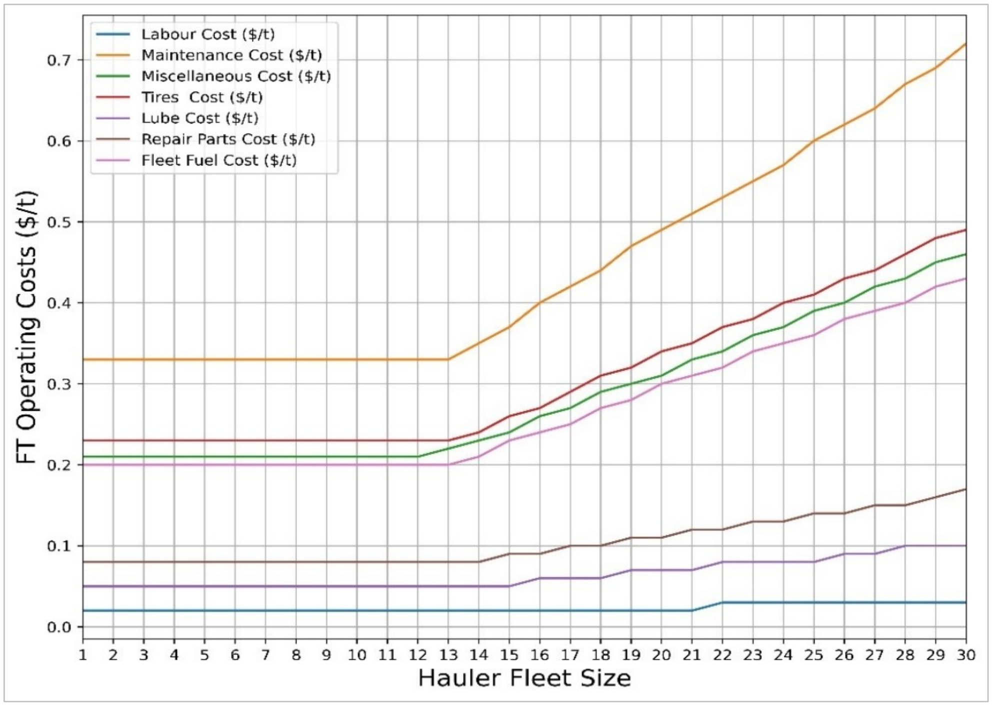


Figure 4-15 Operating Costs in FT Strategy

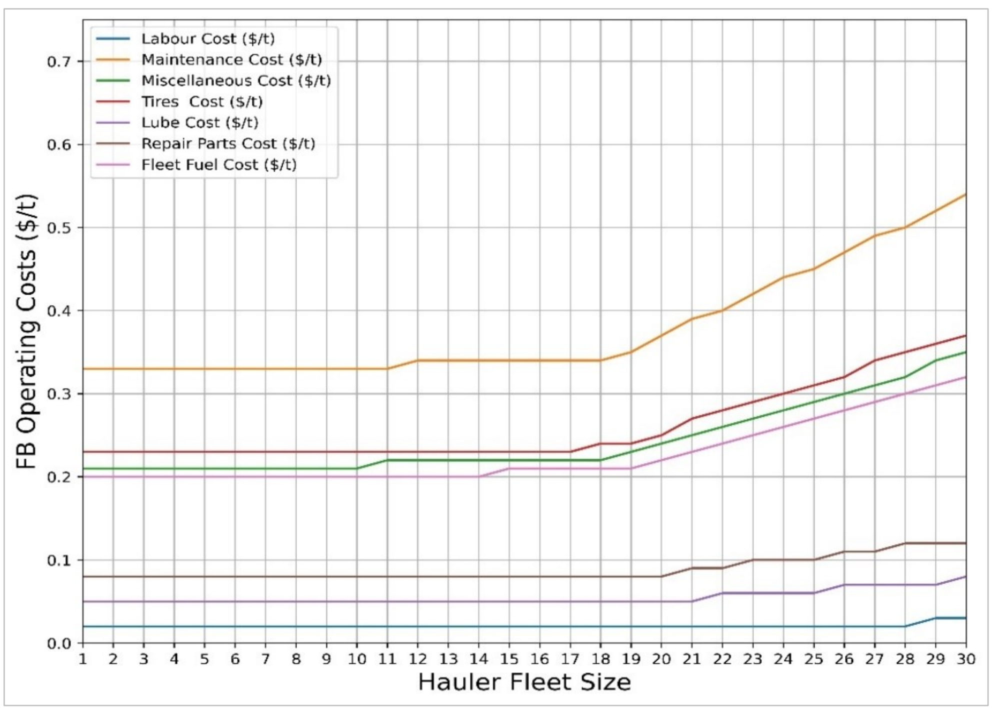


Figure 4-16 Operating Costs in FB Strategy

Figure 4-17 and Figure 4-18 shows the owning cost for FT and FB strategies. Both cost curves are similar in behaviour with slight differences, but the minimum owning cost for FB is at fleet size 18, while in FT, the minimum owning cost is at fleet size 13. The owning costs in FT increase after fleet size 13 and reach more than 0.6 $/t after fleet size 21, while in FB, the owning cost doesn't exceed 0.6 $/t after fleet size 18. And there is no difference in owning costs between the loading strategies when fleets size in a range of 10-13 trucks.

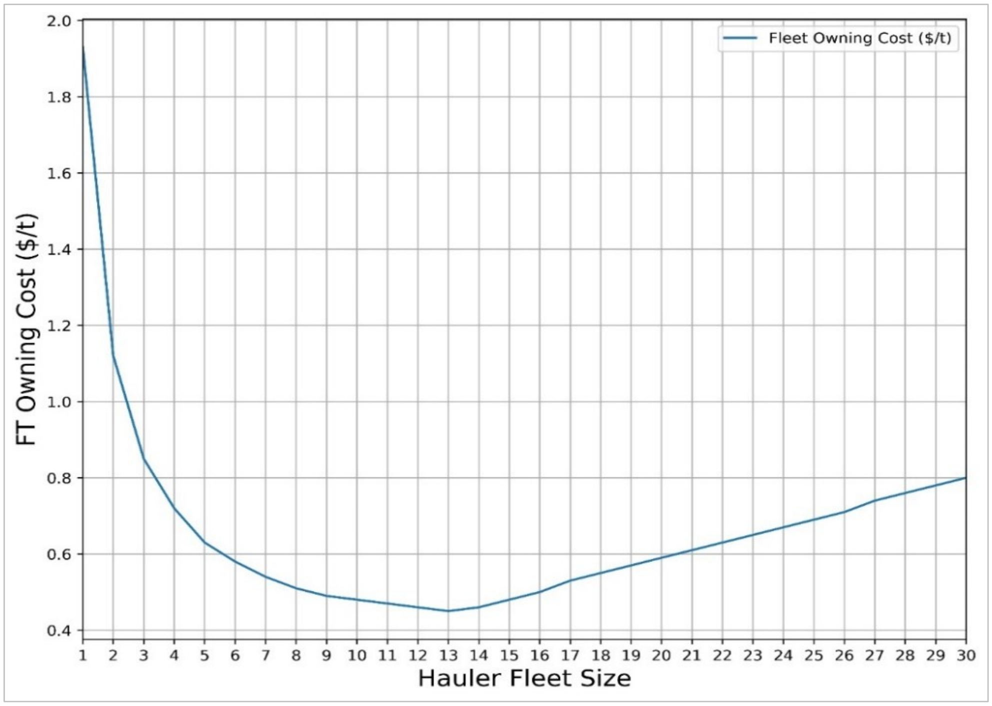


Figure 4-17 Owning Cost in FT Strategy

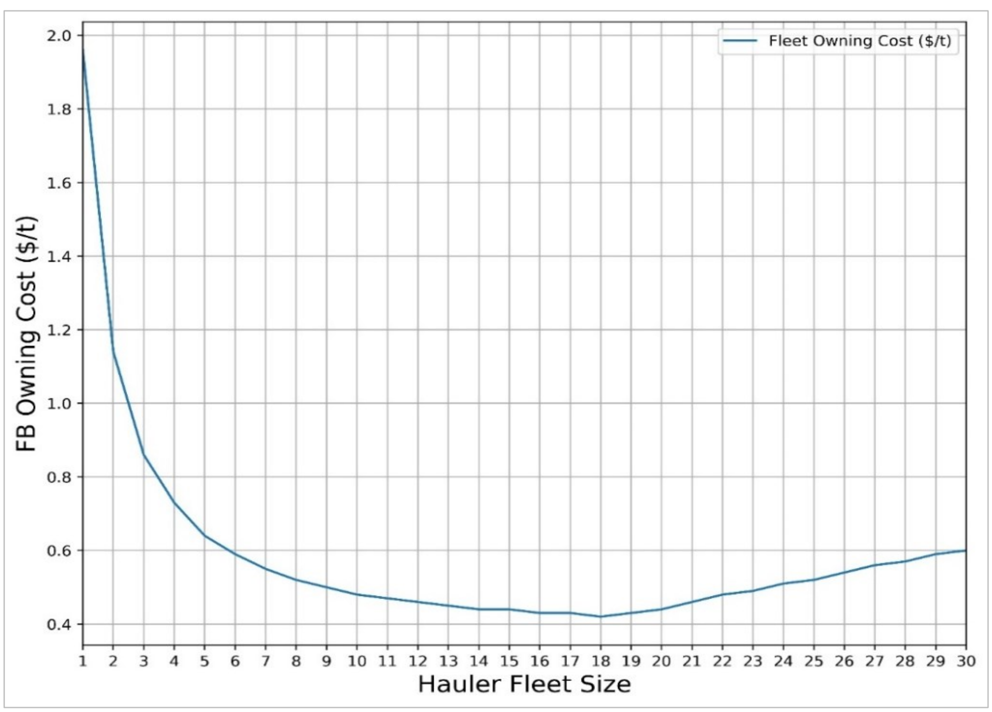


Figure 4-18 Owning Cost in FB Strategy

4.8 Hourly production Curves

The production rate difference between FT and FB and the truck production rate in both scenarios are shown in Figure 4-19. Changing fleet size from 1 to 30 on the x-axis and production rate for each truck on the y-axis, at the beginning till fleet size equals 13, the difference between loading strategies is less than 25 t/h, and the difference decreases from 9 to fleet size 13, then the gap increases in the same amount between loading strategies, exactly at fleet size 17 and beyond. A flipping point appears when the number of trucks exceeds 13, resulting in higher truck production in FB strategy and decreasing hourly production rate with an increasing number of trucks. This is due to lost time in queueing and bunching effect, but when the number of trucks is less than 12, the production rate is much higher in FT, which supports that in real operation, the FT strategy is more favoured. Conservatively, FT has the higher hand, accompanied by MF equal 1 and operation efficiency of 100%.

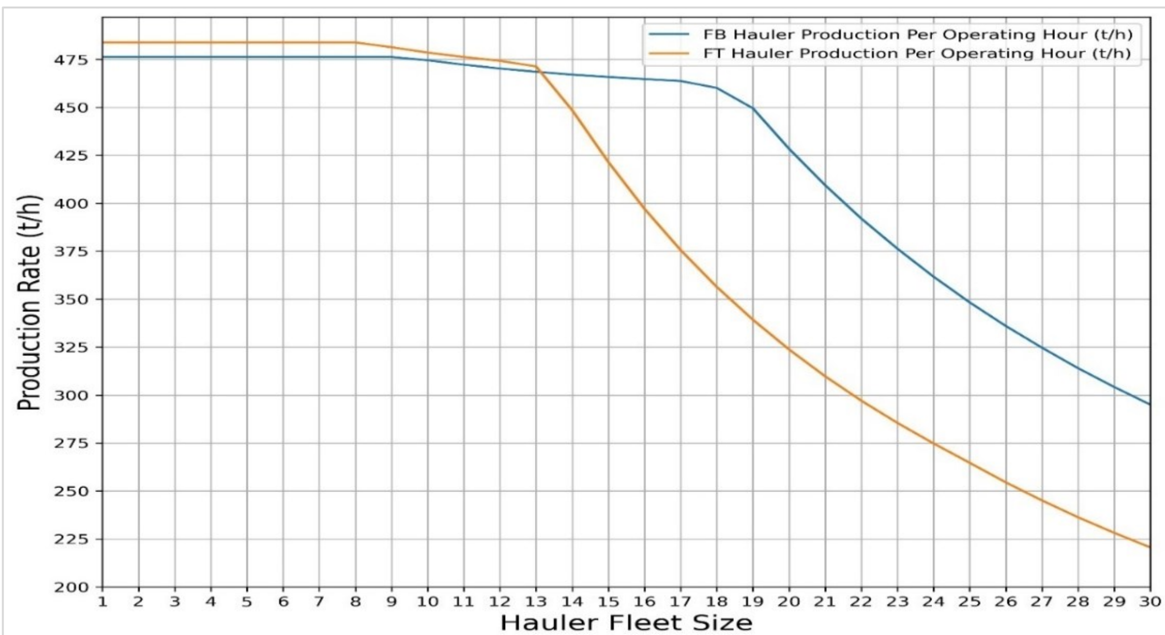


Figure 4-19 Trucks production rate results

Figure 4-20 shows that the switching point was the same for the shovel hourly production rate case, but the curve had been inverted. From the case in trucks point of view, when MF approximated 1, the FT had higher hourly production than FB; the difference was 260 t/h, but when the number of trucks exceeded 13, FB strategy had a higher production when MF approximated 1.5; the difference between the strategies was 250 t/h. After the fleet size reached 13, the difference between loading strategies started to widen steadily until the fleet size reached 19, and the difference almost continued past this point, favouring the FB strategy over the FT.

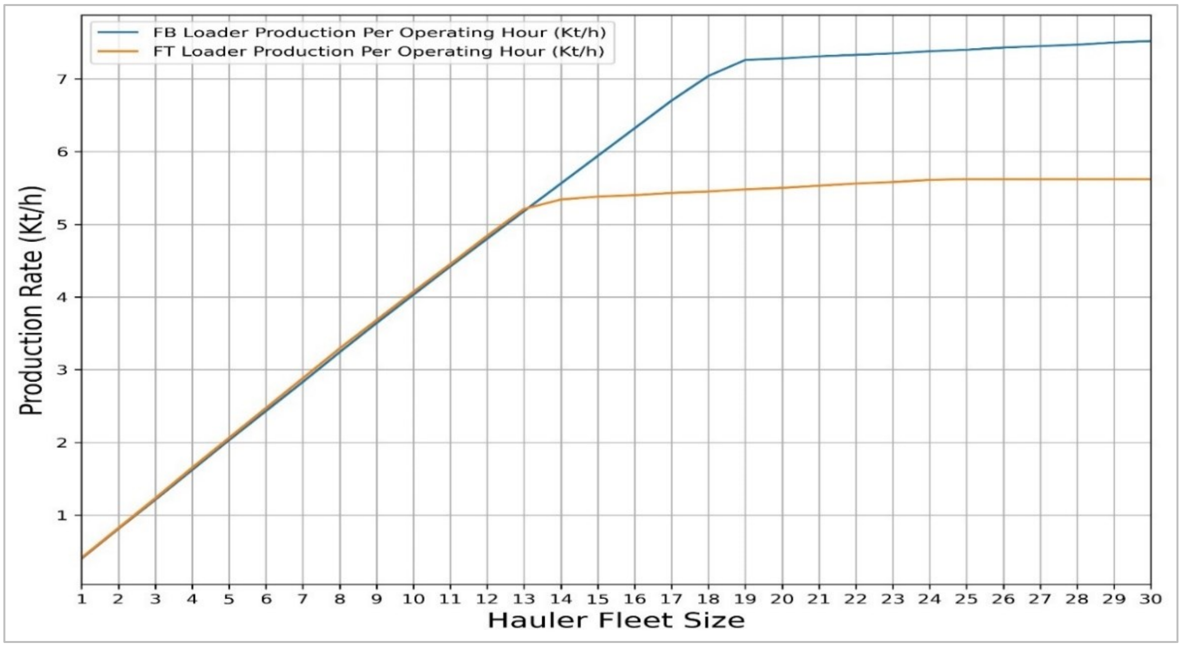


Figure 4-20 Shovel production rate results

4.9 Tonne-Kilometers Per Hour (TKPH)

To comprehend the impact of payload differences resulting from FT and FB loading strategies on tyres and tyre reliability. One of the common truck KPIs in operation, the TKPH (Tonne-Kilometers Per Hour), was created. Both the simulated data for axle 1, the front axle, and axle 2, the rear axle, were recorded. As shown in Figure 4-21, the TKPH analysis for axle 1 revealed that the FB strategy consistently had a higher TKPH than the FT strategy. This was because the trucks' lower payloads resulted in a lower load on the trucks' tyres. The difference between loading strategies is balanced till fleet size equals 13. The gap increases after trucks number exceed 13 steadily till fleet size equals 30. This poses a potential need and adds additional benefit to considering FB loading strategy when match factor change is encountered, and the fleet number increases significantly or when tire life is important at a specific time in the year.

Axle 2 exhibits nearly identical behaviour for both strategies for TKPH. Axle 1 typically carries more dead weight loads than other rear axles (loads from the engine, mechanical drive, and chassis), with almost a 50 percent difference in TKPH values between axle 1 and axle 2 when taking into account both loading strategy scenarios.

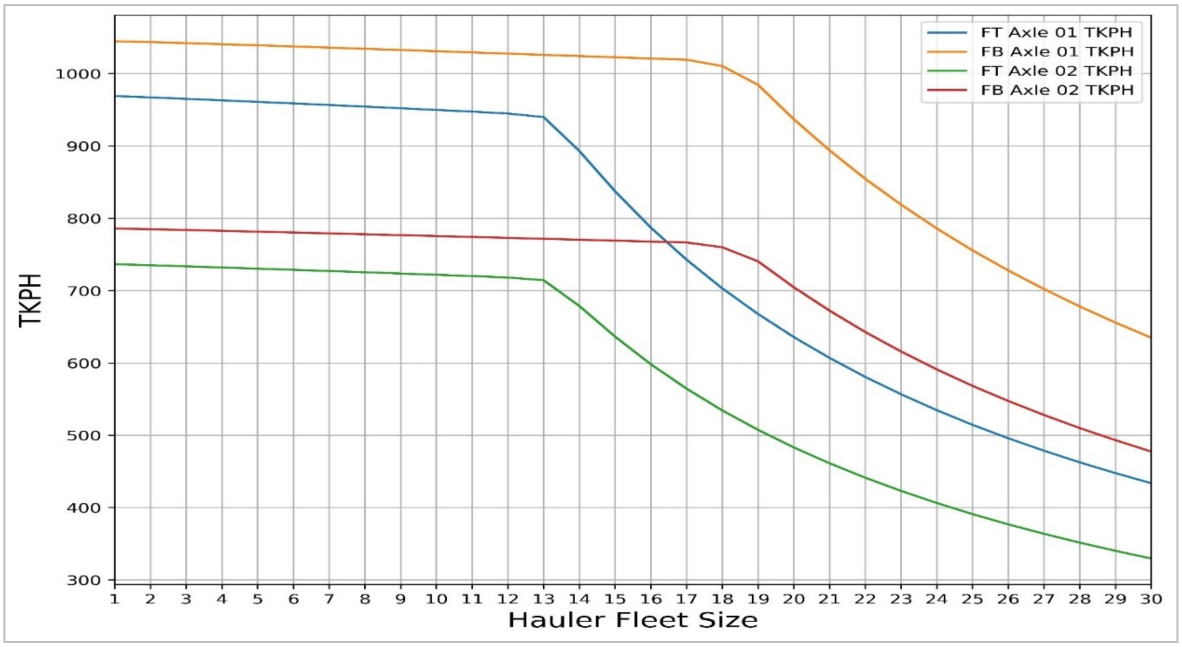


Figure 4-21 Basic site TKPH for axle 1 and axle 2

4.10 Fuel Consumption

Another mining truck performance indicator is fuel consumption. Figure 4-22 illustrates how fleet size is represented using an x-axis for fleet size and y-axis for production in tonnes per fuel consumption. After fleet size 19, the production per fuel difference in the FB scenario was 25% higher. From fleet equal 1 to 13, there is a difference of less than 2% before FB flips and consumes more fuel.

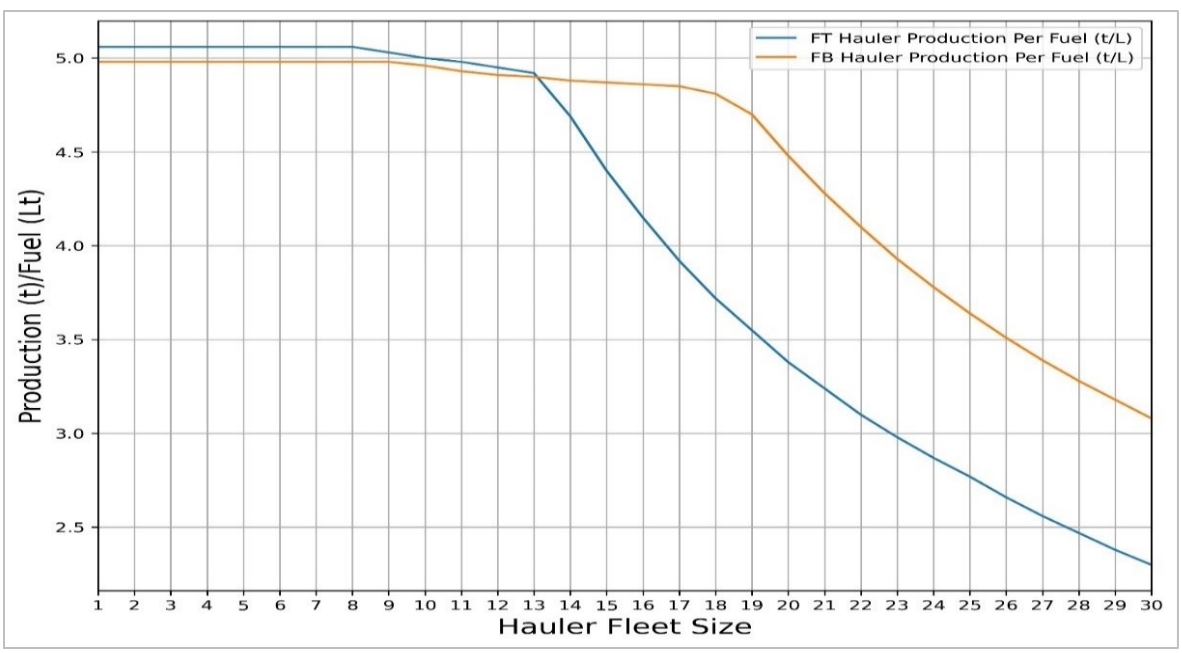


Figure 4-22 Truck production per fuel liter

4.11 Shovel Efficiency analysis

In the shovel production per consumed electricity t/kWh analysis, the varying fleet size on the x-axis and the consumed energy KWh in shovel production are plotted against each other in Figure 4-23. The shovel electricity consumption in the FT strategy was higher until trucks number 13, where flipping occurs, and FB consumption increased. The gap widened once the number of trucks reached 18. This mean that in the case of FT shovel loading, the trucks needing 4 buckets to be fully loaded result in lower shovel level production and higher electricity consumption. However, once the FB strategy was adjusted, the productivity of the shovel increased because it is now operating at its highest efficiency and requires fewer passes to fill the trucks.

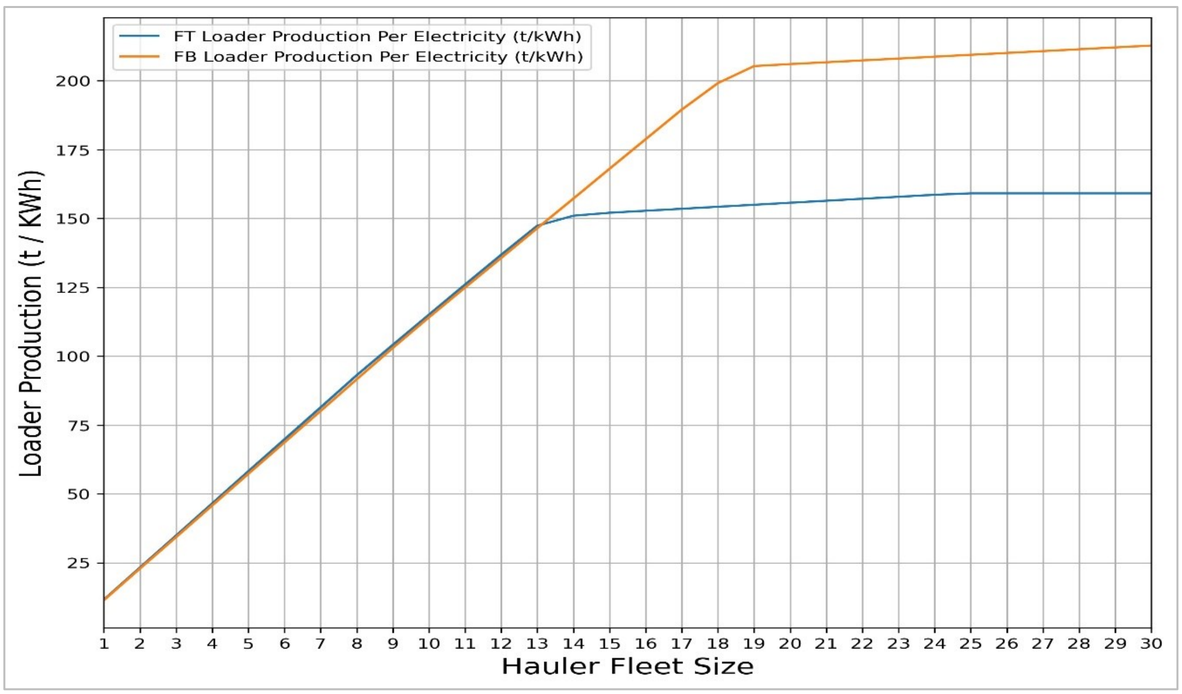


Figure 4-23 Loader production per consumed electricity

4.12 Machine Learning - Controlling Parameters in Loading Strategies

The following topics discuss the implementation of ML algorithms using Python programming language in predicting and understanding the key features that affect the loading strategies. Starting with data preparation in a detailed explanation, moving on to exploratory data analysis, selecting the appropriate machine learning algorithms for predicting model and accuracy evaluation, and finally weighing the important factors that influence the choice of loading strategy.

4.12.1 Data preparation

In order to run ML properly and evaluate the model, the data should be cleaned and reflect the real situation of hauling operations in a mine. For this purpose, the raw data obtained from simulation for MF of 0.75 and greater were selected. The data for MF<1 was selected to understand the behaviour of operation parameters even with lower efficiency (MF<1) in the hauling operation, as shown in Figure 4-24.

4.12.2 Categorical Data

FB data is less than FT in the implemented data amount because it is related to the MF that considers the number of passes affecting the loading times and shovel efficiency. In our reference to MF=0.75. This does not affect the ML model results because the difference in counted data between FT and FB is less than 15%, and the usual difference affecting the ML model is more than 40%. If this is the case, further data processing for the imbalanced classification is required to overcome this issue.

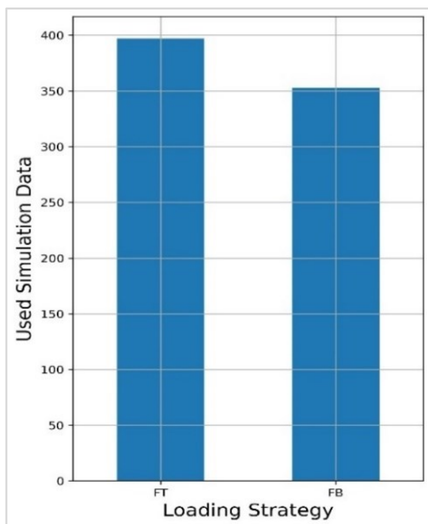


Figure 4-24 Used simulation data categories

4.12.3 Rolling Resistance (RR) Data

Figure 4-25 shows the implemented data for RR. This data was included in the ML model in order to analyze the effect of increased RR (2%, 4% and 6%) in the loading strategy and understand more how the other operating parameters are affected, such as costs and cycle times, and how RR triggers the loading strategy.

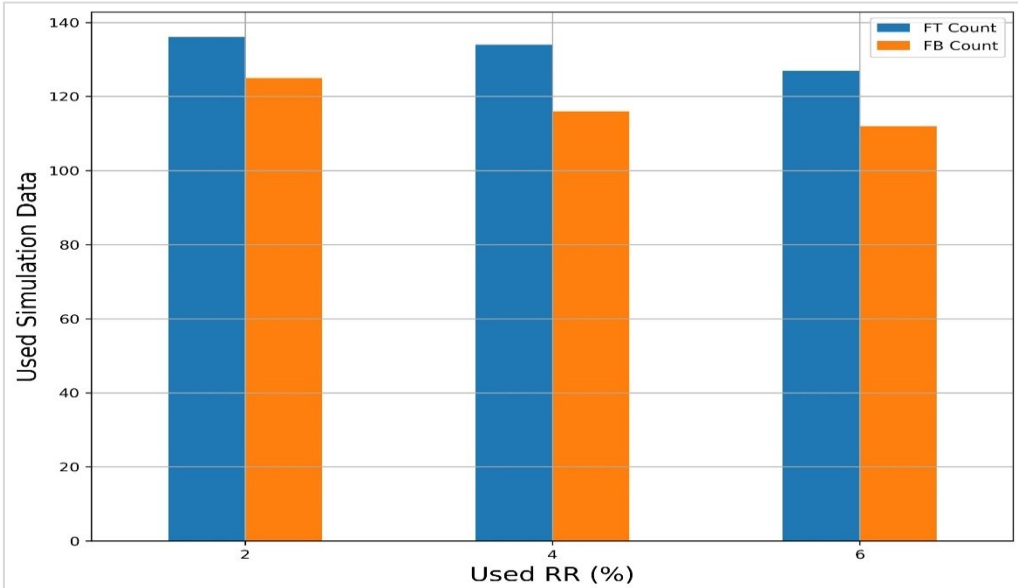


Figure 4-25 Considered RRs in the simulation model

4.12.4 Different Shovels Data

Shovel types (different bucket capacities) were included in the simulation data, as shown in Figure 4-26. Changing the shovel types, including CAT 7395, CAT7495 and the original P&H2800, these shovels are included to honour the varying operating shovel parameters, mainly the bucket capacity, which was 32.1 m^3 for CAT 7395, and 56 m^3 for CAT7495 and 32.78 m^3 for P&H2800 and other shovel characteristics.

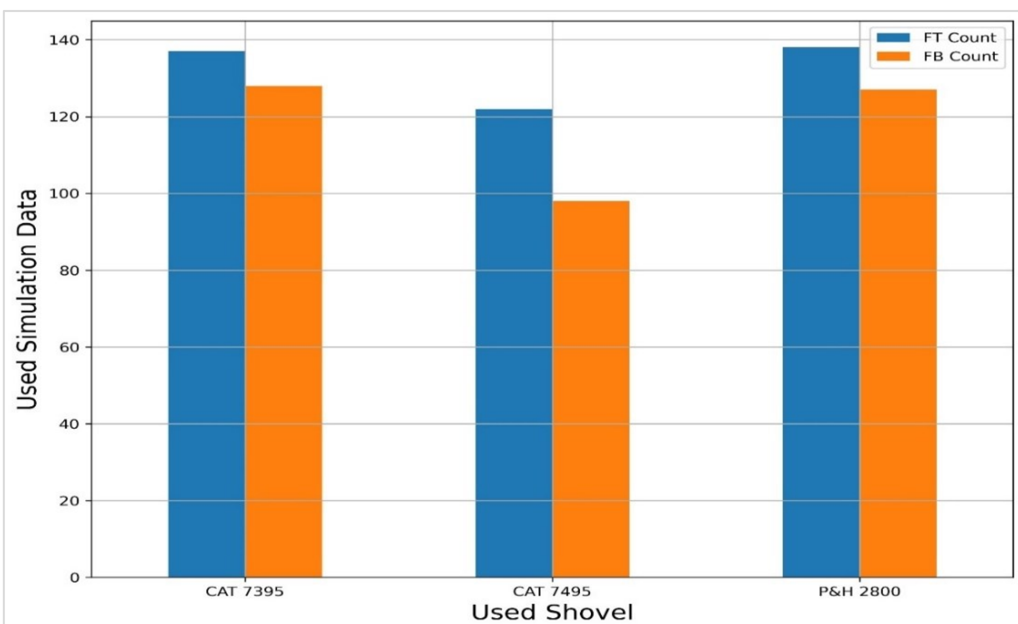


Figure 4-26 Used simulation data for shovel type

4.12.5 Different Roads Data

Additional mine road is added to understand the effect of different grades, lengths and geometries on the loading strategies, as shown in Figure 4-27. Combining the previous variabilities in the simulated data for loading strategies gives broader interpretable results of the machine learning model, including a simulation variety of grades, rolling resistance, roads and shovels.

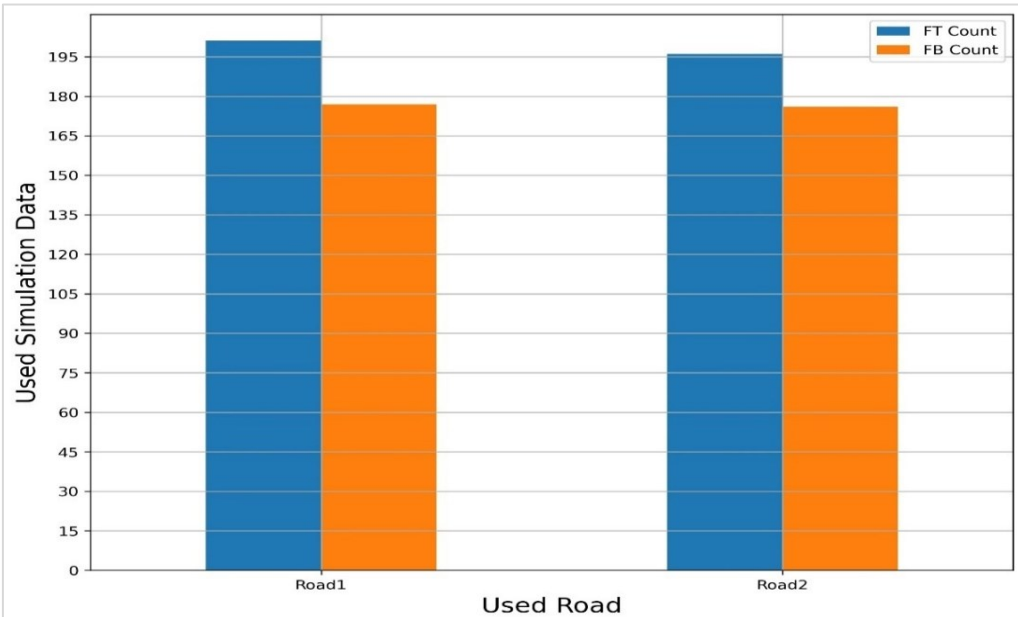


Figure 4-27 Used Simulation data with roads

4.12.6 Exploratory Data Analysis (EDA)

An EDA using Python programming language was conducted to understand and illustrate the resulting simulation data. Plus, the relationships between the input parameters in the hauling and loading operation and the parameters that control the switch between FT and FB strategies in the simulated loading and hauling operation.

Starting from the original dataset containing 750 records with 22 attributes that resulted from Haulsim simulation and filtered out based on MF of 0.75 and above, each entry represents the adapted loading strategy and the associated input data from simulation in the EDA. Table 4-8 summarizes the statistics of these values.

A correlation matrix was generated to examine these relationships between operation loading strategies and selected parameters for the correlation approach, as in Figure 4-28. Some input parameters are linearly correlated, such as cycle time and fleet size, the number of trucks queued, cost and fleet size.

Table 4-8 Statistical summaries of the used simulation data

Parameter	Count	Mean	Std	Min	25%	50%	75%	Max
Hauler Fleet Size	750	19.95	6.22	7.00	15.00	20.00	25.00	30.00
Hauler Average Travel Time (min)	750	22.56	1.78	19.36	21.27	22.21	23.79	25.97
Hauler Average Load Queue Time (min)	750	13.86	11.73	0.73	2.49	11.52	22.85	44.31
Hauler Average Cycle Time (min)	750	39.11	12.09	22.65	28.66	36.30	48.00	69.26
Fleet Production / Year (Mt)	750	7.81	1.73	4.36	6.98	7.21	8.75	12.52
Trucks in Q	750	6.96	5.53	0.20	1.30	6.30	11.60	19.50
Loading Strat (1 FT 0 FB)	750	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Loader Hourly Utilization	750	2.79	6.28	0.00	0.00	0.00	0.00	30.60
Match Factor	750	1.07	0.09	0.75	1.07	1.11	1.13	1.17
Hauler Production Per Operating Hour (t/h)	750	297.80	83.83	167.21	224.93	291.55	367.54	478.50
Fleet Operating Unit Cost ($/t)	750	1.61	0.46	0.94	1.20	1.51	1.95	2.63
Fleet Total Cost of Unit Ownership ($/t)	750	2.59	0.72	1.47	1.96	2.43	3.13	4.24
Fleet Owning Unit Cost ($/t)	750	0.63	0.16	0.33	0.51	0.60	0.75	1.03
Fleet Fuel Unit Cost ($/t)	750	0.35	0.10	0.20	0.26	0.33	0.43	0.58
Hauler Operating Unit Cost ($/t)	750	1.59	0.46	0.91	1.18	1.49	1.94	2.60
Hauler Total Cost of Unit Ownership ($/t)	750	2.49	0.73	1.43	1.86	2.34	3.03	4.08
Hauler Owning Unit Cost ($/t)	750	0.55	0.16	0.32	0.41	0.52	0.67	0.90
Hauler Fuel Unit Cost ($/t)	750	0.35	0.10	0.20	0.26	0.33	0.43	0.57
Loader Operating Unit Cost ($/t)	750	0.02	0.01	0.00	0.00	0.02	0.03	0.05
Loader Total Cost of Unit Ownership ($/t)	750	0.10	0.08	0.00	0.00	0.15	0.16	0.26
Loader Owning Unit Cost ($/t)	750	0.08	0.06	0.00	0.00	0.12	0.12	0.20
Rolling Resistance	750	3.94	1.63	2.00	2.00	4.00	6.00	6.00

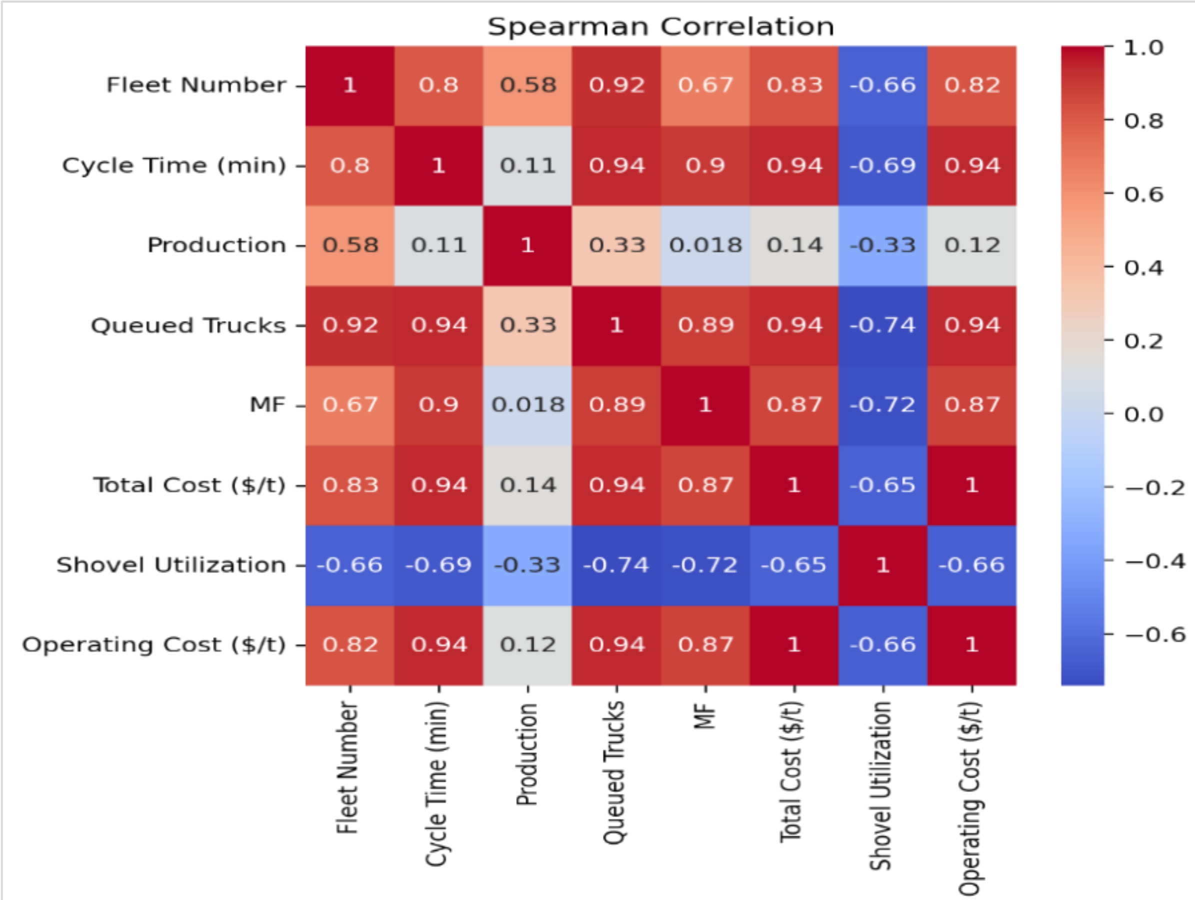


Figure 4-28 Spearman correlation matrix for simulated data

In contrast, other parameters, such as shovel utilization, is reversely correlated with the other selected features especially when queuing condition occurs. It is reversely correlated but less strong with other operating parameters. Pearson correlation matrix has quite similar correlation values between the operating parameters, as illustrated in Figure 4-29.

However, features such as trucks queued and fleet production have a big difference value between two correlation approaches equal to 0.27 in Queued truck and Fleet production, and a 0.22 match factor has much difference between queued trucks and loader utilization, more of these differences summarized in Table 4-9. This difference is because Spearman correlation considers the monotonic relationships while Pearson evaluates the linear relationship between two continuous variables.

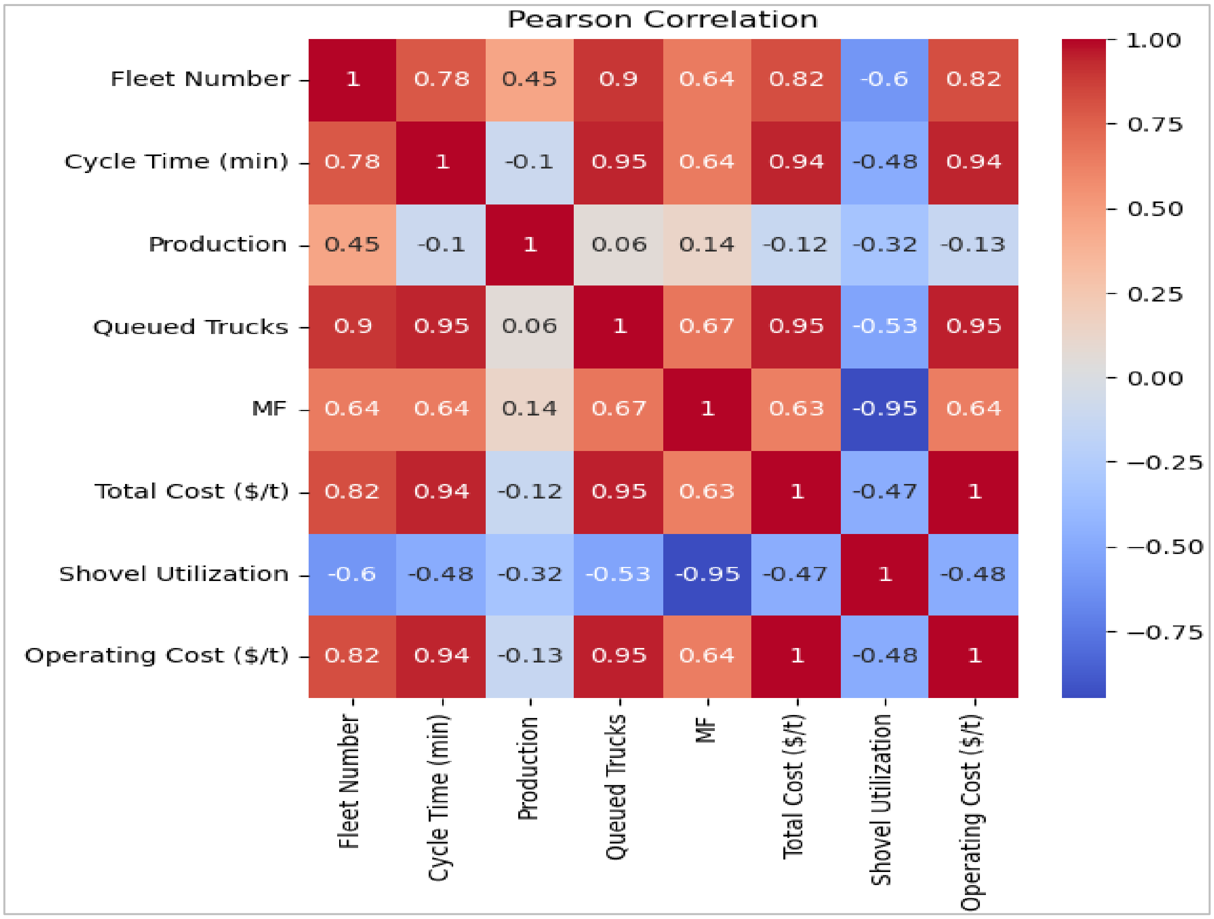


Figure 4-29 Pearson correlation matrix for simulated data

Table 4-9 Correlation matrices result differences

	Truck Fleet Size	**Truck Cycle Time (min)**	**Fleet Production / Year (Mt)**	**Trucks in Q**	**Match Factor**	**Fleet Cost of Unit Ownership ($/t)**	**Shovel Hourly Utilization**	**Fleet Operating Unit Cost ($/t)**
Truck Fleet Size	0.00	0.02	0.13	0.02	0.03	0.00	-0.05	0.00
Truck Average Cycle Time (min)	0.02	0.00	0.21	0.00	0.26	0.00	-0.21	0.00
Fleet Production / Year (Mt)	0.13	0.21	0.00	0.27	-0.12	0.26	-0.02	0.25
Trucks in Q	0.02	0.00	0.27	0.00	0.22	-0.01	-0.22	-0.01
Match Factor	0.03	0.26	-0.12	0.22	0.00	0.24	0.22	0.24
Fleet Total Cost of Unit Ownership ($/t)	0.00	0.00	0.26	-0.01	0.24	0.00	-0.18	0.00
Shovel Hourly Utilization	-0.05	-0.21	-0.02	-0.22	0.22	-0.18	0.00	-0.19
Fleet Operating Unit Cost ($/t)	0.00	0.00	0.25	-0.01	0.24	0.00	-0.19	0.00

4.12.7 Multiple ML Algorithms

Figure 4-30 illustrates the comparison of the algorithms generated. Most algorithms showed a high accuracy median value except for the Gaussian NB algorithm, valued at 0.57. The LR showed the highest recall value at 0.9, followed by CART and the RF with accuracy values of 0.83 and 0.795, respectively. Therefore, ML implementation was done based on the LR method due to its higher accuracy and the tendency of dual categorical values. The final decision would be a FT or FB based on certain parameters. Additional RF analysis was used to weight the parameters based on their significance in the loading strategy.

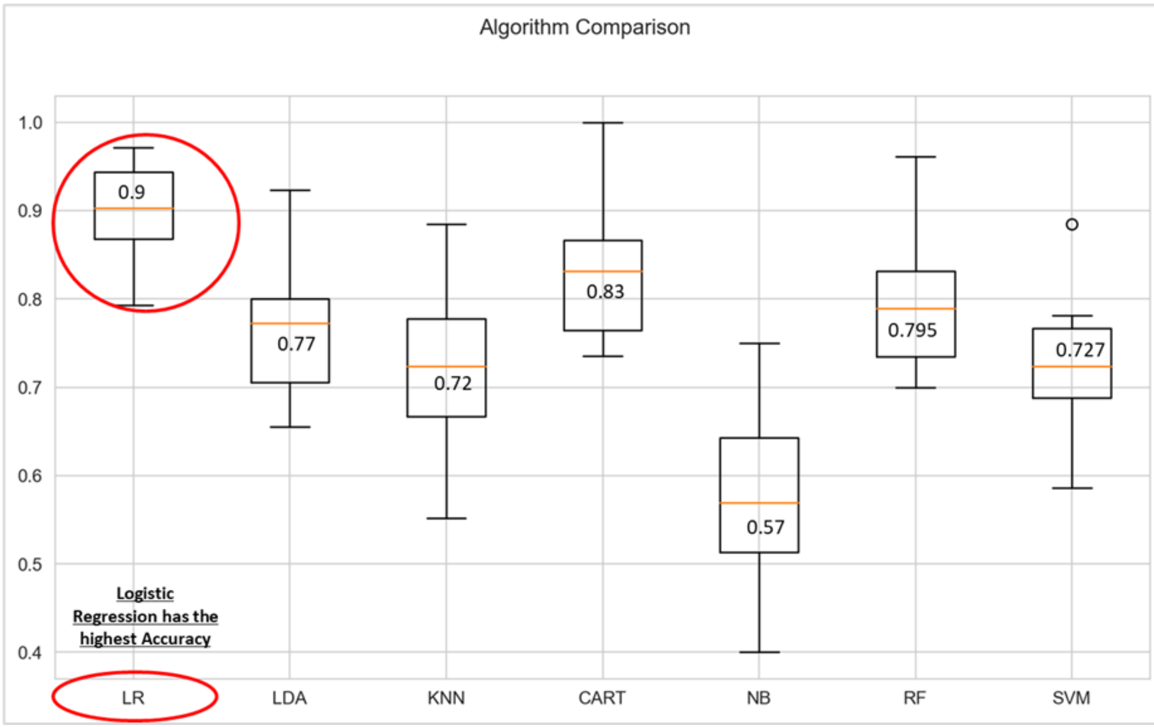


Figure 4-30 Analysis and comparison of multiple algorithms

4.12.8 Logistic Regression (LR)

The simulated data from various scenarios were implemented into the LR model to understand the effecting factors in the operation and to predict the loading strategy based on the selected data features. The training data feature included hauler fleet size, cycle time, trucks in the queue, MF and RR. The testing was based on 20% of the simulated data in 750 records. The confusion matrix illustrated in Figure 4-31 shows more than 90% accuracy in predicting the loading strategies.

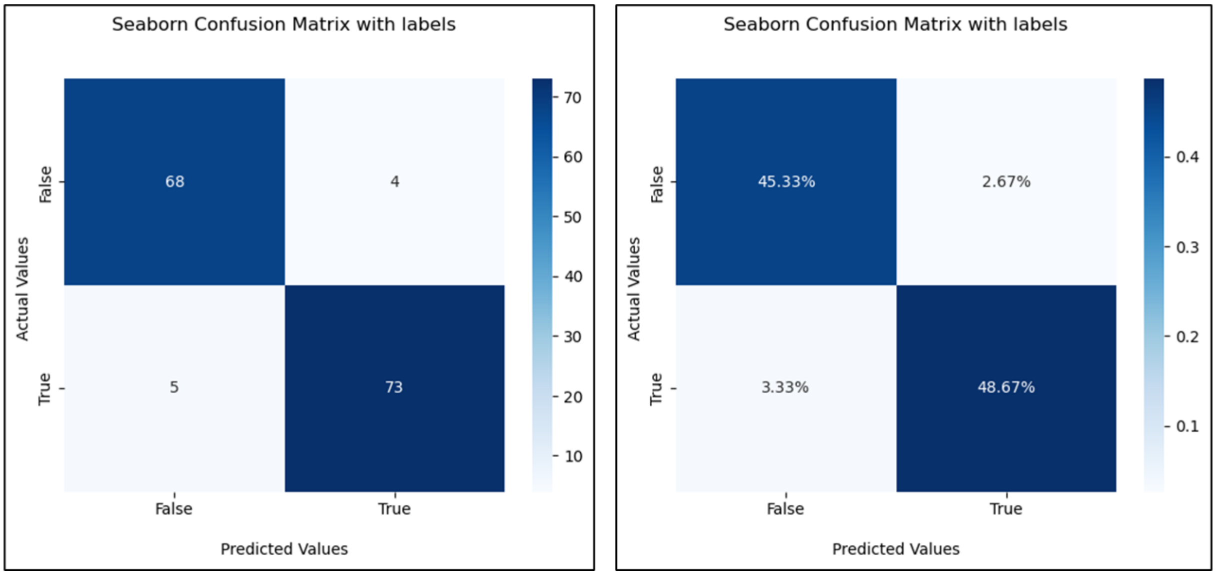


Figure 4-31 confusion matrix for the logistic regression model

In order to interpret the resulting logistic regression ML model, after training the data, parameter weights are evaluated, as shown in Figure 4-32. It is clear that the cycle time is the major effecting factor in predicting the loading strategies followed by MF, while the trucks in queue feature have the lowest feature importance.

variable	coefficient
Hauler Average Cycle Time (min)	2.590000
Match Factor	0.300000
Hauler Fleet Size	-0.200000
Rolling Resistance	-2.280000
Trucks in Q	-4.320000

Figure 4-32 Logistic regression feature importance results

4.12.9 Shap Values

Shap values (SHapley Additive exPlanations) is a cooperative game theory method used to increase the transparency and interpretability of ML methods. In Figure 4-33, the order of columns represents the amount of information accountable for in ML prediction, colour reflects the real data, and the x-axis represents the shap value impact on the model categorical decision (FT or FB). Each dot corresponds to an individual loading strategy in the simulation. The dot's position on the x-axis shows the feature's impact on the model's prediction for that strategy. When multiple dots land at the same x position, they pile up to show density. To get an overview of which features are most important for a model, the SHAP values of every feature for every sample can be plotted. The figure examines these values by sorting the sum of SHAP value magnitudes over all samples and uses SHAP values to show the distribution of each feature's impacts on the model. The colour represents the feature value; red for high values and blue for low values. Similar to logistic regression cycle time has the highest impact on model output and the queued trucks has the lowest impact.

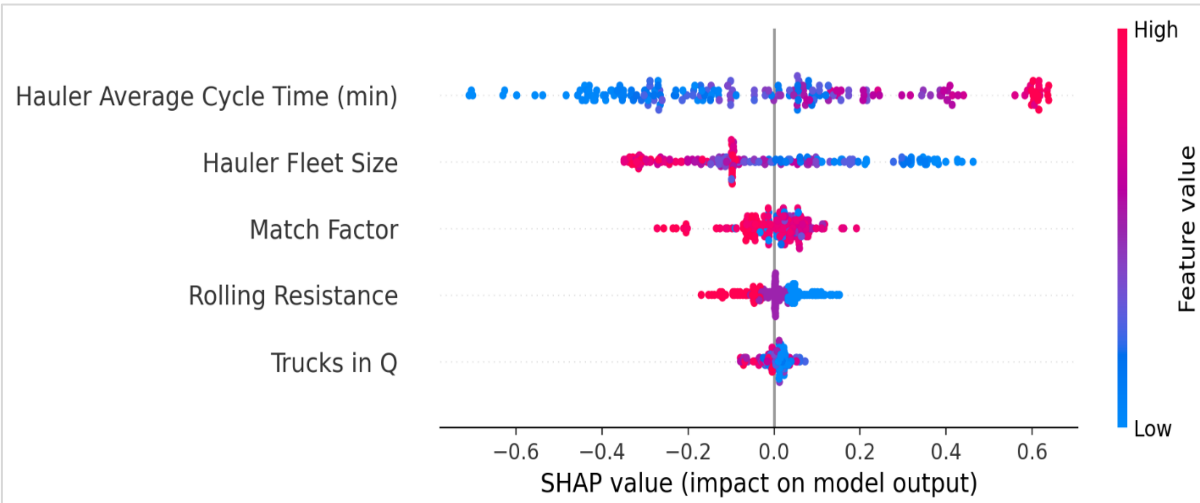


Figure 4-33 A set of bee swarm plots for the machine learning model

Similarly, plotting the data in a different method, as shown in Figure 4-34 the cycle time contributes the most to the model prediction, followed by fleet size. Results of Gini map are in APPENDIX A.

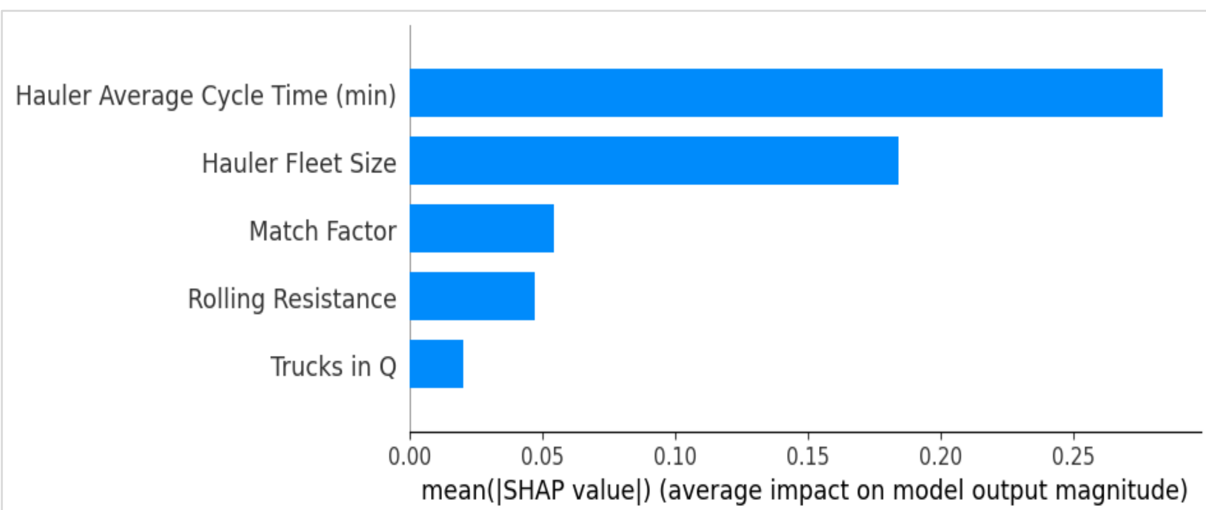


Figure 4-34 Bar plot Shapley feature importance in predicting model

4.13 Summary and conclusion

This chapter demonstrated the case study in the application of loading strategies frameworks. By using DES at different levels for understanding and comparing the results in each case scenario under the assumption of uncertainty. Starting with material, equipment and shift configuration in the software and importing a schedule for examining the loading strategies. Next, selecting different fleet sizes based on referenced MF and running the simulation.

In the results stage, simulation data showed that cycle time under the FT loading strategy is always higher than the FB strategy. FT strategy also showed that queueing conditions are always higher than FB using queueing theory and truck arrival rate formula in calculating the number of trucks queued at the shovel. In contrast, the production rates were higher in the FB scenario than in FT when the number of trucks increased; this might be useful in achieving higher production in a certain period of the mine plan.

Simulation data showed that Production-Cost-Fleet curves were meaningful in reflecting the operation KPIs and determining the sweet spots. The cost difference between loading strategies might reach 25% if MF surged to 1.5 and the fleet was reassigned to a different shovel. Furthermore, queued trucks were almost half the number in FB. Based on these analyses, an opportunity that advantaged the FB over FT based on increasing the MF in hauling and loading operations, which were directly related to the impact of equipment availability, utilization, and operator skills.

The results showed that it is possible to provide a recommended loading decision when planned and unplanned operation uncertainties occur. Furthermore, it is possible now to predict the proper loading strategy using ML algorithms with higher accuracy and evaluate the most valuable KPI in operation, which induce this change in loading strategy. The results confirmed that it is possible to provide a recommended decision when planned and unplanned operation stoppages resulting in queuing or shovel breakdown for a short time.

CHAPTER 5

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

This chapter covers the contribution and importance of the research. The conclusions of this research are emphasized, as well as recommendations for future work.

5.1 Summary of Research

This research presents a simulation framework for adapting the full truck (FT) and full bucket (FB) loading strategies in an open-pit mine using the discrete event simulation (DES) approach and taking into consideration the equipment uncertainty in operation.

The simulation framework starts by configuring the mining operation data from the shovel operator and shovel material perspectives. A set of assumptions is considered to conceptualize the simulation's loading strategies. Then embedding the decision of the loading strategies, whether FT or FB in operation. Next, generating the operational key performance indicators (KPIs) related to the fleet, such as cycle time, fleet production rate, number of queued trucks and material costs; and based on the final results, the preferred loading strategy is adopted.

This research aimed to evaluate the advantages of considering FT or FB in the mining operation using DES under uncertain conditions. Moreover, the queueing conditions of the truck at the shovel were calculated based on queuing theory approach. The match factor (MF) was also introduced in this operation and was directly related between shovels and various trucks.

The final results were brought in a machine learning (ML) model in order to predict the loading strategy based on a set of features. Features data was created from additional scenarios to adapt the real mine operation more. So it included various rolling resistance (RR), mine haul roads, and different shovel sizes. Feature data was also evaluated and ranked based on prediction importance; this would be useful in understanding the triggering element that induces the switch more. Based on the selected element, more potential studies on the selected element could be built to enhance the operation.

5.2 Conclusions

The main conclusions of this research are the following:

- At match factor ≅ 1, the default loading strategy is the FT in normal circumstances. The reality in truck-shovel operation is that most operators try to fill the truck even if it takes longer loading times to achieve the production rate. Usually, the operation runs at MF equal to 1, which means 100% efficiency.
- Shovel availability signifies the importance of switching between a FT and FB loading strategies. Therefore, shovel uncertainty is a significant factor that should be considered in loading strategies.

- When shifting from FT to FB, hauling costs can be reduced up to 25% in operation. The resulted difference in costs is based on a high service rate from the shovel point and more utilization of the trucks, i.e., no queueing, plus the trucks' lower fuel consumption rate because they are underloaded.
- Switching from FT to FB increases the production to a point where production stabilizes. However, it is wise to control to what extent the number of trucks will be reassigned to the shovel. The number of trucks should not exceed the saturation point of production.
- Queuing conditions at shovel are reduced when switching from FT to FB. Due to the high service rate from adapting the FB strategy, the number of trucks queued at shovels is reduced and no time is wasted at the shovel. This can be beneficial for mining operations with high queueing conditions or constraints at the shovel.
- Shovel production and utilization increase when the FB strategy is adapted due to lower passes (faster loading); hence, the loading time will be low. If a mining operation requires more production rates without changing the fleet size, then a FB strategy may help in achieving this target.
- ML algorithms are useful and crucial in predicting and understanding how the operation is running. The implemented logistic regression was capable of predicting the loading strategy with higher accuracy based on a set of simulated data. The ML methodology handles any data at any stage in the life of mine, opening the area for different short-term analyses and potentially the long-term by understanding the operation as all; material changing characteristics, anticipated blasting, equipment availability and utilization, production rate requirements. All previous information could be utilized and used in prediction. This goes as well with feature importance and will evaluate the most contributing feature in ML prediction.
- Cycle time is the primary factor affecting the adapted loading strategy based on the simulated data. The importance of cycle time makes it the controlling parameter in operation. Generally, shorter cycle times, queueing conditions and high production requirements will favour the FB loading strategy more.

5.3 Contributions of the Research

The main contribution of this research is in evaluating the FT and FB loading strategies in mining operations and providing the knowledge gained through each selected strategy as a result of multiple operation KPIs. Developing a framework that places the loading strategies shows how the loading strategy influences the operation. Also, a DES model was created to understand the effect of the loading strategy where results indicated the sweet spots of each loading strategy in different circumstances. The contribution of the ML is that it can now predict the proper loading strategy with higher accuracy. The methodological approach could be integrated into more complicated dispatching logic and advanced autonomous trucks.

5.4 Recommendations for Future Research

The following suggestion is a set of recommendations for future research, taking into consideration the research limitations which can be improved more in future:

- Incorporating the effect of fragmentation size of blasted material and geological uncertainty. Fragmentation size is a crucial element affecting the loaded bucket, which affects the final payload and the adapted loading strategy. It is also important to consider the optimization field in blasting outcomes that depend on blast design and the nature of the material.
- Integrating with Autonomous trucks data will give valuable results and more understanding due to a reduction in uncertainties.
- Investigate in reducing greenhouse gas (GHG) emissions by increasing production; with the new consideration of carbon footprints resulting from mining activities, reducing fuel consumption resulting from lower truck loading will reduce the emissions rate.
- Investigate integrating with In-Pit Extraction Process IPEP in oil sands (ore hauling is shortened will affect cycle time) outcome would be reducing GHG.
- Investigating the deep learning (DL) and reinforcement learning analysis can be done to optimize loading strategies, especially when huge data is available.
- Integrating with autonomous trucks (level 4 and potentially level 5) data will give valuable results and more understanding due to a reduction in uncertainties (human factor, breaks, time losses) (involving sense, thinking and act).
- Investigate the effect of shovel allocation plan on loading strategies.

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APPENDIX A

Gini Map

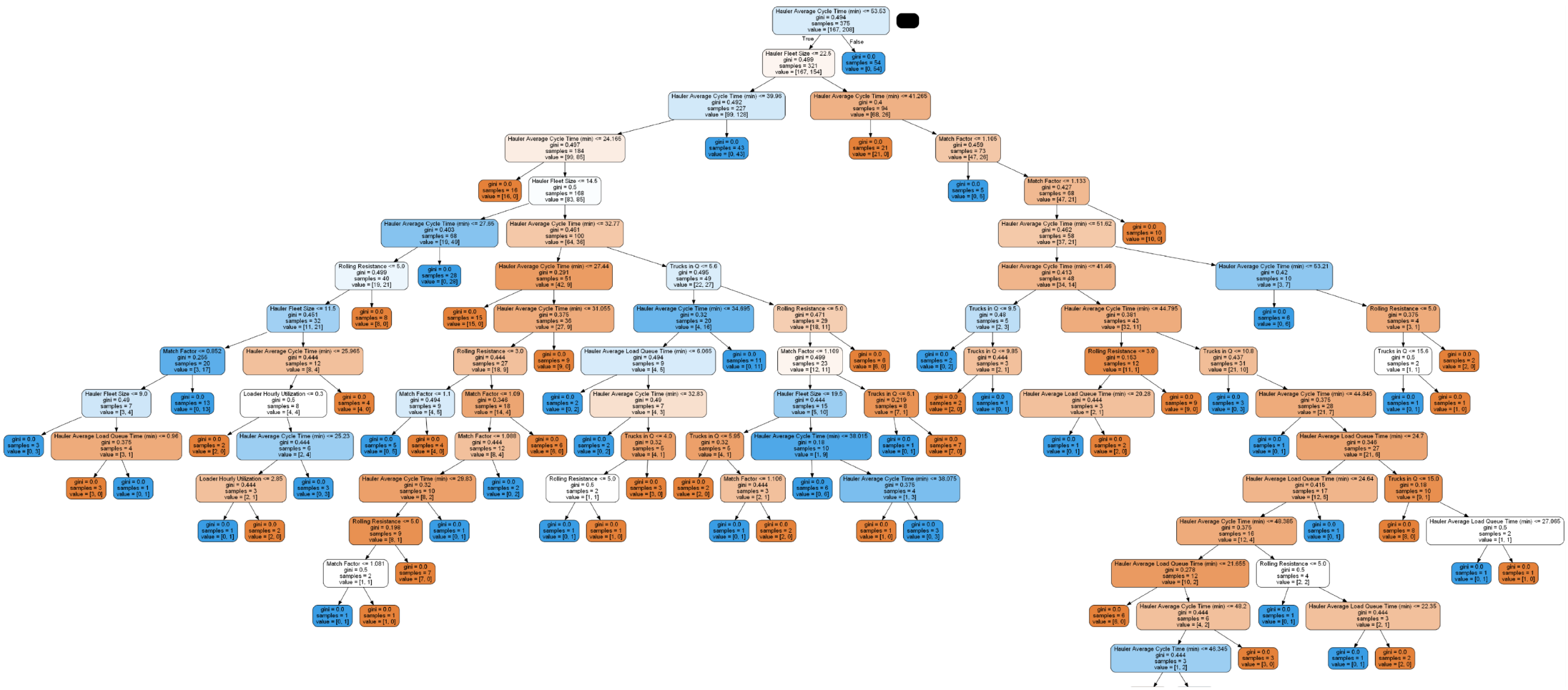

Figure 0-1 Gini map

APPENDIX B

Python Codes

```
##Importing Libraries##
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib as mpl
import numpy as np

## Reading and editing Dataframes##
df = pd.read_csv('RR2_19022022_All__orig_filt_Drop_2.csv')

df.columns.tolist()

df.dtypes.tolist()

df.describe().T

df1 = df[['Hauler Fleet Size', 'Hauler Average Travel Time (min)', 'Hauler
Average Load Queue Time (min)',
          'Hauler Average Cycle Time (min)', 'Fleet Production / Year
(Mt)', 'Trucks in Q', 'Match Factor',
          'Rolling Resistance', 'Fleet Total Cost Of Unit Ownership ($/t)',
'Loader Hourly Utilization',
          'Fleet Owning Unit Cost ($/t)', 'Hauler Production Per Operating
Hour (t/h)',
          'Loader Production Per Operating Hour (t/h)','Fleet Operating
Unit Cost ($/t)',
          'Loader Total Cost Of Unit Ownership ($/t)','Loader Operating
Unit Cost ($/t)',
          'Hauler Operating Unit Cost ($/t)', 'Hauler Total Cost Of Unit
Ownership ($/t)',
          'Loading Strat (1 FT 0 FB)','Road','Shovel_type']].copy()

df1b = df[['Hauler Fleet Size','Hauler Average Cycle Time (min)', 'Fleet
Production / Year (Mt)', 'Trucks in Q', 'Match Factor',
          'Fleet Total Cost Of Unit Ownership ($/t)', 'Loader Hourly
Utilization',
          'Fleet Operating Unit Cost ($/t)' ]].copy()

##Exploratory Data Analysis##
corrMatrix = df1b.corr('pearson')

corrMatrix

corrMatrix_spearman.to_excel('Pearson.xlsx')
```

```
plt.figure(figsize=(6, 6))

corrMatrix = df1b.corr('pearson')
sns.heatmap(corrMatrix, annot=True,cmap='coolwarm',xticklabels=1)
plt.title("Pearson Correlation")

corrMatrix_spearman = df1b.corr('spearman')

corrMatrix_spearman

corrMatrix_spearman.to_excel('spearman.xlsx')

plt.figure(figsize=(6, 6))

corrMatrix = df1b.corr('spearman')
sns.heatmap(corrMatrix, annot=True,cmap='coolwarm',xticklabels=1)
plt.title("Spearman Correlation")

plt.figure(figsize=(15, 12))
corrMatrix = df1b.corr('spearman')
sns.heatmap(corrMatrix, annot=True,cmap='coolwarm')
plt.title("Spearman Correlation")
ax.set_xticklabels(df1b,rotation=45)
plt.savefig('Spearman_corr.png', bbox_inches='tight')

plt.figure(figsize=(15, 15))
corrMatrix = df.corr('spearman')
sns.heatmap(corrMatrix, annot=True,cmap='coolwarm')
plt.title("Spearman Correlation")
plt.savefig('Spearman_corr.png', bbox_inches='tight')

plt.figure(figsize=(15, 15))
corrMatrix = df1.corr('spearman')
sns.heatmap(corrMatrix, annot=True,cmap='coolwarm')
plt.title("Spearman Correlation")


plt.figure(figsize=(15, 15))
corrMatrix = df1.corr()
sns.heatmap(corrMatrix, annot=True,cmap='coolwarm',vmin=-1, vmax=1,
center=0,square=True)
plt.title("Pearson Correlation")
#ax.set_xticklabels(
#    ax.get_xticklabels(),
 #   rotation=45,
 #   horizontalalignment='right'
#)
plt.savefig('Pearson_corr.png', bbox_inches='tight')

df1.corr()

def f(df1):
    if df1['Loading Strat (1 FT 0 FB)'] == 1:
        val = 'Full Truck'
    else:
        val = 'Full Bucket'
```

```
    return val

df1['Loading Cat'] = df1.apply(f, axis=1)

pd.set_option("display.max_rows", None)

pd.set_option("display.max_columns", None)

df_FT = df1[df1['Loading Cat']=='Full Truck']

df_FB = df1[df1['Loading Cat']=='Full Bucket']

##EDA Plotting##
sns.countplot(x='Loading Cat',data=df1)

sns.countplot(x='Loading Cat',data=df1,hue='Rolling Resistance')

df1.info()

sns.countplot(x='Loading Cat',data=df1,hue='Shovel_type')

sns.countplot(x='Loading Cat',data=df1,hue='Road')

df2 = df1

df3 = pd.concat([df2,Load_strat],axis=1)

df3.rename(columns={1: "Full Truck"}, inplace=True)

df3.drop(['Loading Cat','Road','Shovel_type'],axis=1,inplace=True)

df4 = df3

df4.drop(['Full Truck','Loading Strat (1 FT 0 FB)','Loader Production Per
Operating Hour (t/h)'],axis=1,inplace=True)

##Machine Learning##
df_train = df4[['Hauler Fleet Size','Hauler Average Cycle Time
(min)','Trucks in Q'
               ,'Match Factor','Rolling Resistance']]

X = df_train

y = df3['Loading Strat (1 FT 0 FB)']

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=101)

from sklearn.linear_model import LogisticRegression

logmodel = LogisticRegression()

logmodel.fit(X_train,y_train)
```

```
predictions = logmodel.predict(X_test)

from sklearn.metrics import classification_report

print(classification_report(y_test,predictions))

from sklearn.metrics import confusion_matrix

confusion_matrix(y_test,predictions)

cf_matrix = confusion_matrix(y_test,predictions)

ax = sns.heatmap(cf_matrix, annot=True, cmap='Blues')

ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');

## Ticket labels - List must be in alphabetical order
ax.xaxis.set_ticklabels(['False','True'])
ax.yaxis.set_ticklabels(['False','True'])

## Display the visualization of the Confusion Matrix.

plt.savefig('LR_Confusion_matrix.png', bbox_inches='tight')

ax = sns.heatmap(cf_matrix/np.sum(cf_matrix), annot=True,
            fmt='.2%', cmap='Blues')

ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');

## Ticket labels - List must be in alphabetical order
ax.xaxis.set_ticklabels(['False','True'])
ax.yaxis.set_ticklabels(['False','True'])

## Display the visualization of the Confusion Matrix.

plt.savefig('LR_Confusion_matrix_perc.png', bbox_inches='tight')

from sklearn.datasets import make_classification
from sklearn.metrics import plot_confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC

ax = sns.heatmap(cf_matrix, annot=True, cmap='Blues')

ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');

## Ticket labels - List must be in alphabetical order
ax.xaxis.set_ticklabels(['False','True'])
ax.yaxis.set_ticklabels(['False','True'])
```

```
## Display the visualization of the Confusion Matrix.
plt.show()

ax = sns.heatmap(cf_matrix/np.sum(cf_matrix), annot=True,
            fmt='.2%', cmap='Blues')

ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');

## Ticket labels - List must be in alphabetical order
ax.xaxis.set_ticklabels(['False','True'])
ax.yaxis.set_ticklabels(['False','True'])

## Display the visualization of the Confusion Matrix.
plt.show()

from sklearn.model_selection import train_test_split, KFold,
cross_val_score # to split the data
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, fbeta_score #To evaluate our model

from sklearn.model_selection import GridSearchCV

# Algorithmns models to be compared
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
random_state=101)



# prepare models
models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('RF', RandomForestClassifier()))
models.append(('SVM', SVC(gamma='auto')))



# evaluate each model in turn
results = []
names = []
scoring = 'recall'
```

```
for name, model in models:
        kfold = KFold(n_splits=10)
        cv_results = cross_val_score(model, X_train, y_train, cv=kfold,
scoring=scoring)
        results.append(cv_results)
        names.append(name)
        msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
        print(msg)

# boxplot algorithm comparison
fig = plt.figure(figsize=(11,6))
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()

#Seting the Hyper Parameters
param_grid = {"max_depth": [3,5, 7, 10,None],
              "n_estimators":[3,5,10,25,50,150],
              "max_features": [4,7,15,20]}

#Creating the classifier
model = RandomForestClassifier(random_state=2)

grid_search = GridSearchCV(model, param_grid=param_grid, cv=5,
scoring='recall', verbose=4)
grid_search.fit(X_train, y_train)

print(grid_search.best_score_)
print(grid_search.best_params_)

rf = RandomForestClassifier(max_depth=None, n_estimators=15,
random_state=2)

#trainning with the best params
rf.fit(X_train, y_train)

#Testing the model on
#Predicting using our  model
y_pred = rf.predict(X_test)

# Verificaar os resultados obtidos
print(accuracy_score(y_test,y_pred))
print("\n")
print(confusion_matrix(y_test, y_pred))
print("\n")
print(fbeta_score(y_test, y_pred, beta=2))

pip install shap

from sklearn.datasets import load_boston
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.inspection import permutation_importance
import shap
```

```
logmodel_rf = LogisticRegression()

#random forest
rf = RandomForestRegressor(n_estimators=100)
rf.fit(X_train, y_train)

rf.feature_importances_

mpl.rcParams.update(mpl.rcParamsDefault)

shap.summary_plot(shap_values, X_test, plot_type="bar",show=False)

plt.savefig('outputbar.png' ,bbox_inches='tight', dpi=200)

shap.summary_plot(shap_values, X_test,show=False)

plt.savefig('outputbar_shap.png' ,bbox_inches='tight', dpi=200)
```

APPENDIX C

Rimpull data

R1 FB					
Index	From	To	Distance (m)	Grade (%)	Load
1	(10,560.00, 10,837.50, 920.00)	(10,660.00, 10,837.50, 920.00)	100	0	Full
2	(10,660.00, 10,837.50, 920.00)	(10,749.55, 10,838.64, 920.00)	89.56	0	Full
3	(10,749.55, 10,838.64, 920.00)	(10,809.95, 10,836.44, 920.00)	60.44	0	Full
4	(10,809.95, 10,836.44, 920.00)	(10,798.13, 10,762.40, 920.00)	74.98	0	Full
5	(10,798.13, 10,762.40, 920.00)	(10,795.87, 10,657.86, 930.00)	105.04	9.56	Full
6	(10,795.87, 10,657.86, 930.00)	(10,793.62, 10,553.31, 940.00)	105.04	9.56	Full
7	(10,793.62, 10,553.31, 940.00)	(10,805.99, 10,548.86, 940.00)	13.16	0	Full
8	(10,805.99, 10,548.86, 940.00)	(10,807.72, 10,548.24, 940.00)	1.83	0	Full
9	(10,807.72, 10,548.24, 940.00)	(10,822.95, 10,565.72, 940.37)	23.19	1.58	Full
10	(10,822.95, 10,565.72, 940.37)	(10,845.50, 10,660.87, 950.00)	98.26	9.85	Full
11	(10,845.50, 10,660.87, 950.00)	(10,868.92, 10,759.64, 960.00)	102	9.85	Full
12	(10,868.92, 10,759.64, 960.00)	(10,892.33, 10,858.41, 970.00)	102	9.85	Full
13	(10,892.33, 10,858.41, 970.00)	(10,904.04, 10,907.80, 975.00)	51	9.85	Full
14	(10,904.04, 10,907.80, 975.00)	(10,944.63, 11,035.54, 976.38)	134.05	1.03	Full
15	(10,944.63, 11,035.54, 976.38)	(10,943.26, 11,071.79, 980.00)	36.45	9.98	Full
16	(10,943.26, 11,071.79, 980.00)	(10,941.74, 11,112.31, 984.05)	40.75	9.98	Full
17	(10,941.74, 11,112.31, 984.05)	(10,914.97, 11,168.16, 989.48)	62.17	8.77	Full
18	(10,914.97, 11,168.16, 989.48)	(10,910.71, 11,172.03, 990.00)	5.77	9.04	Full
19	(10,910.71, 11,172.03, 990.00)	(10,859.82, 11,218.30, 996.22)	69.07	9.04	Full
20	(10,859.82, 11,218.30, 996.22)	(10,817.79, 11,227.05, 1,000.00)	43.09	8.81	Full
21	(10,817.79, 11,227.05, 1,000.00)	(10,813.87, 11,227.87, 1,000.35)	4.02	8.81	Full
22	(10,813.87, 11,227.87, 1,000.35)	(10,721.02, 11,201.05, 1,010.00)	97.13	9.98	Full
23	(10,721.02, 11,201.05, 1,010.00)	(10,646.56, 11,179.54, 1,017.74)	77.89	9.98	Full
24	(10,646.56, 11,179.54, 1,017.74)	(10,625.15, 11,171.72, 1,020.00)	22.91	9.93	Full
25	(10,625.15, 11,171.72, 1,020.00)	(10,530.55, 11,137.15, 1,030.00)	101.21	9.93	Full
26	(10,530.55, 11,137.15, 1,030.00)	(10,435.95, 11,102.58, 1,040.00)	101.21	9.93	Full

27	(10,435.95, 11,102.58, 1,040.00)	(10,377.99, 11,081.40, 1,046.13)	62.02	9.93	Full
28	(10,377.99, 11,081.40, 1,046.13)	(10,340.13, 11,070.68, 1,050.00)	39.53	9.84	Full
29	(10,340.13, 11,070.68, 1,050.00)	(10,273.95, 11,051.94, 1,056.77)	69.12	9.84	Full
30	(10,273.95, 11,051.94, 1,056.77)	(10,241.55, 11,036.10, 1,060.00)	36.21	8.95	Full
31	(10,241.55, 11,036.10, 1,060.00)	(10,233.60, 11,032.21, 1,060.79)	8.89	8.95	Full
32	(10,233.60, 11,032.21, 1,060.79)	(10,199.98, 10,976.11, 1,067.73)	65.77	10.6	Full
33	(10,199.98, 10,976.11, 1,067.73)	(10,192.62, 10,949.74, 1,070.00)	27.47	8.3	Full
34	(10,192.62, 10,949.74, 1,070.00)	(10,160.24, 10,833.73, 1,080.00)	120.87	8.3	Full
35	(10,160.24, 10,833.73, 1,080.00)	(10,144.66, 10,810.58, 1,080.00)	27.9	0	Full
36	(10,144.66, 10,810.58, 1,080.00)	(10,140.35, 10,817.77, 1,080.00)	8.39	0	Full
37	(10,140.35, 10,817.77, 1,080.00)	(10,128.33, 10,837.81, 1,080.00)	23.37	0	Full
38	(10,128.33, 10,837.81, 1,080.00)	(10,140.68, 10,933.84, 1,087.03)	97.07	7.26	Full
39	(10,140.68, 10,933.84, 1,087.03)	(10,154.87, 10,999.78, 1,090.00)	67.51	4.41	Full
40	(10,154.87, 10,999.78, 1,090.00)	(10,174.10, 11,089.14, 1,094.03)	91.5	4.41	Full
41	(10,174.10, 11,089.14, 1,094.03)	(10,130.99, 11,109.32, 1,090.91)	47.7	-6.55	Full
42	(10,130.99, 11,109.32, 1,090.91)	(10,061.96, 11,127.76, 1,088.82)	71.48	-2.92	Full
43	(10,061.96, 11,127.76, 1,088.82)	(10,049.84, 11,132.15, 1,088.47)	12.89	-2.78	Full
44	(10,049.84, 11,132.15, 1,088.47)	(10,078.39, 11,232.96, 1,086.74)	104.78	-1.65	Full
45	(10,078.39, 11,232.96, 1,086.74)	(10,082.83, 11,408.66, 1,084.89)	175.77	-1.05	Full
46	(10,082.83, 11,408.66, 1,084.89)	(10,032.15, 11,495.34, 1,082.45)	100.44	-2.43	Full
47	(10,032.15, 11,495.34, 1,082.45)	(10,006.53, 11,524.93, 1,079.89)	39.23	-6.53	Full
48	(10,006.53, 11,524.93, 1,079.89)	(9,953.18, 11,512.28, 1,080.33)	54.83	0.81	Full
49	(9,953.18, 11,512.28, 1,080.33)	(9,818.04, 11,374.01, 1,085.58)	193.41	2.71	Full
50	(9,818.04, 11,374.01, 1,085.58)	(9,694.87, 11,268.84, 1,087.16)	161.96	0.98	Full
51	(9,694.87, 11,268.84, 1,087.16)	(9,669.77, 11,290.64, 1,087.15)	33.24	-0.04	Full

52	(9,669.77, 11,290.64, 1,087.15)	(9,694.87, 11,268.84, 1,087.16)	33.24	0.04	Empty
53	(9,694.87, 11,268.84, 1,087.16)	(9,818.04, 11,374.01, 1,085.58)	161.96	-0.98	Empty
54	(9,818.04, 11,374.01, 1,085.58)	(9,953.18, 11,512.28, 1,080.33)	193.41	-2.71	Empty
55	(9,953.18, 11,512.28, 1,080.33)	(10,006.53, 11,524.93, 1,079.89)	54.83	-0.81	Empty
56	(10,006.53, 11,524.93, 1,079.89)	(10,032.15, 11,495.34, 1,082.45)	39.23	6.53	Empty
57	(10,032.15, 11,495.34, 1,082.45)	(10,082.83, 11,408.66, 1,084.89)	100.44	2.43	Empty
58	(10,082.83, 11,408.66, 1,084.89)	(10,078.39, 11,232.96, 1,086.74)	175.77	1.05	Empty
59	(10,078.39, 11,232.96, 1,086.74)	(10,049.84, 11,132.15, 1,088.47)	104.78	1.65	Empty
60	(10,049.84, 11,132.15, 1,088.47)	(10,061.96, 11,127.76, 1,088.82)	12.89	2.78	Empty
61	(10,061.96, 11,127.76, 1,088.82)	(10,130.99, 11,109.32, 1,090.91)	71.48	2.92	Empty
62	(10,130.99, 11,109.32, 1,090.91)	(10,174.10, 11,089.14, 1,094.03)	47.7	6.55	Empty
63	(10,174.10, 11,089.14, 1,094.03)	(10,154.87, 10,999.78, 1,090.00)	91.5	-4.41	Empty
64	(10,154.87, 10,999.78, 1,090.00)	(10,140.68, 10,933.84, 1,087.03)	67.51	-4.41	Empty
65	(10,140.68, 10,933.84, 1,087.03)	(10,128.33, 10,837.81, 1,080.00)	97.07	-7.26	Empty
66	(10,128.33, 10,837.81, 1,080.00)	(10,140.35, 10,817.77, 1,080.00)	23.37	0	Empty
67	(10,140.35, 10,817.77, 1,080.00)	(10,144.66, 10,810.58, 1,080.00)	8.39	0	Empty
68	(10,144.66, 10,810.58, 1,080.00)	(10,160.24, 10,833.73, 1,080.00)	27.9	0	Empty
69	(10,160.24, 10,833.73, 1,080.00)	(10,192.62, 10,949.74, 1,070.00)	120.87	-8.3	Empty
70	(10,192.62, 10,949.74, 1,070.00)	(10,199.98, 10,976.11, 1,067.73)	27.47	-8.3	Empty
71	(10,199.98, 10,976.11, 1,067.73)	(10,233.60, 11,032.21, 1,060.79)	65.77	-10.6	Empty
72	(10,233.60, 11,032.21, 1,060.79)	(10,241.55, 11,036.10, 1,060.00)	8.89	-8.95	Empty
73	(10,241.55, 11,036.10, 1,060.00)	(10,273.95, 11,051.94, 1,056.77)	36.21	-8.95	Empty
74	(10,273.95, 11,051.94, 1,056.77)	(10,340.13, 11,070.68, 1,050.00)	69.12	-9.84	Empty
75	(10,340.13, 11,070.68, 1,050.00)	(10,377.99, 11,081.40, 1,046.13)	39.53	-9.84	Empty
76	(10,377.99, 11,081.40, 1,046.13)	(10,435.95, 11,102.58, 1,040.00)	62.02	-9.93	Empty

77	(10,435.95, 11,102.58, 1,040.00)	(10,530.55, 11,137.15, 1,030.00)	101.21	-9.93	Empty
78	(10,530.55, 11,137.15, 1,030.00)	(10,625.15, 11,171.72, 1,020.00)	101.21	-9.93	Empty
79	(10,625.15, 11,171.72, 1,020.00)	(10,646.56, 11,179.54, 1,017.74)	22.91	-9.93	Empty
80	(10,646.56, 11,179.54, 1,017.74)	(10,721.02, 11,201.05, 1,010.00)	77.89	-9.98	Empty
81	(10,721.02, 11,201.05, 1,010.00)	(10,813.87, 11,227.87, 1,000.35)	97.13	-9.98	Empty
82	(10,813.87, 11,227.87, 1,000.35)	(10,817.79, 11,227.05, 1,000.00)	4.02	-8.81	Empty
83	(10,817.79, 11,227.05, 1,000.00)	(10,859.82, 11,218.30, 996.22)	43.09	-8.81	Empty
84	(10,859.82, 11,218.30, 996.22)	(10,910.71, 11,172.03, 990.00)	69.07	-9.04	Empty
85	(10,910.71, 11,172.03, 990.00)	(10,914.97, 11,168.16, 989.48)	5.77	-9.04	Empty
86	(10,914.97, 11,168.16, 989.48)	(10,941.74, 11,112.31, 984.05)	62.17	-8.77	Empty
87	(10,941.74, 11,112.31, 984.05)	(10,943.26, 11,071.79, 980.00)	40.75	-9.98	Empty
88	(10,943.26, 11,071.79, 980.00)	(10,944.63, 11,035.54, 976.38)	36.45	-9.98	Empty
89	(10,944.63, 11,035.54, 976.38)	(10,904.04, 10,907.80, 975.00)	134.05	-1.03	Empty
90	(10,904.04, 10,907.80, 975.00)	(10,892.33, 10,858.41, 970.00)	51	-9.85	Empty
91	(10,892.33, 10,858.41, 970.00)	(10,868.92, 10,759.64, 960.00)	102	-9.85	Empty
92	(10,868.92, 10,759.64, 960.00)	(10,845.50, 10,660.87, 950.00)	102	-9.85	Empty
93	(10,845.50, 10,660.87, 950.00)	(10,822.95, 10,565.72, 940.37)	98.26	-9.85	Empty
94	(10,822.95, 10,565.72, 940.37)	(10,807.72, 10,548.24, 940.00)	23.19	-1.58	Empty
95	(10,807.72, 10,548.24, 940.00)	(10,805.99, 10,548.86, 940.00)	1.83	0	Empty
96	(10,805.99, 10,548.86, 940.00)	(10,793.62, 10,553.31, 940.00)	13.16	0	Empty
97	(10,793.62, 10,553.31, 940.00)	(10,795.87, 10,657.86, 930.00)	105.04	-9.56	Empty
98	(10,795.87, 10,657.86, 930.00)	(10,798.13, 10,762.40, 920.00)	105.04	-9.56	Empty
99	(10,798.13, 10,762.40, 920.00)	(10,809.95, 10,836.44, 920.00)	74.98	0	Empty
100	(10,809.95, 10,836.44, 920.00)	(10,749.55, 10,838.64, 920.00)	60.44	0	Empty
101	(10,749.55, 10,838.64, 920.00)	(10,660.00, 10,837.50, 920.00)	89.56	0	Empty
102	(10,660.00, 10,837.50, 920.00)	(10,560.00, 10,837.50, 920.00)	100	0	Empty

Index	Time (hh:mm:ss)	Minimum Speed (km/h)	Maximum Speed (km/h)	Actual Initial Speed (km/h)	Final Speed (km/h)
1	0:00:25	0	20.02	0	20
2	0:00:16	20	20.02	20	20
3	0:00:11	14.04	20.02	20	14.04
4	0:00:14	14.04	20.02	14.04	20
5	0:00:24	15.2	20	20	15.2
6	0:00:25	15.2	15.2	15.2	15.2
7	0:00:03	15.2	18.11	15.2	16.81

8	0:00:00	16.22	16.81	16.81	16.22
9	0:00:05	16.22	16.23	16.22	16.22
10	0:00:24	14.84	16.22	16.22	14.84
11	0:00:25	14.84	14.84	14.84	14.84
12	0:00:25	14.84	14.84	14.84	14.84
13	0:00:12	14.84	14.84	14.84	14.84
14	0:00:18	14.84	33.8	14.84	30.49
15	0:00:05	21.01	30.49	30.49	21.01
16	0:00:09	15.15	21.01	21.01	15.15
17	0:00:14	15.15	15.69	15.15	15.69
18	0:00:01	15.6	15.69	15.69	15.6
19	0:00:16	15.6	15.6	15.6	15.6
20	0:00:10	15.6	15.68	15.6	15.68
21	0:00:01	15.67	15.68	15.68	15.67
22	0:00:24	14.68	15.67	15.67	14.68
23	0:00:19	14.68	14.68	14.68	14.68
24	0:00:06	14.68	14.73	14.68	14.73
25	0:00:25	14.73	14.74	14.73	14.74
26	0:00:25	14.74	14.74	14.74	14.74
27	0:00:15	14.74	14.74	14.74	14.74
28	0:00:10	14.74	14.85	14.74	14.85
29	0:00:17	14.85	14.85	14.85	14.85
30	0:00:08	14.85	15.63	14.85	15.63
31	0:00:02	15.63	15.63	15.63	15.63
32	0:00:17	13.82	15.63	15.63	13.82
33	0:00:06	13.82	15.85	13.82	15.85
34	0:00:27	15.62	15.85	15.85	15.62
35	0:00:06	15.62	15.63	15.62	15.62
36	0:00:02	15.62	18.29	15.62	18.29
37	0:00:04	18.29	23.28	18.29	22.3
38	0:00:17	19.06	22.3	22.3	19.06
39	0:00:11	19.06	23.97	19.06	23.97
40	0:00:13	23.72	25.98	23.97	23.72
41	0:00:07	23.72	23.74	23.72	23.72
42	0:00:10	18.61	28.99	23.72	18.61
43	0:00:03	14.39	18.61	18.61	14.39
44	0:00:15	14.39	36.51	14.39	36.43
45	0:00:18	24.52	42.9	36.43	24.52
46	0:00:12	24.45	33.79	24.52	24.45
47	0:00:06	24.45	24.47	24.45	24.45

48	0:00:07	24.31	29.42	24.45	24.31
49	0:00:23	24.31	32.73	24.31	32.73
50	0:00:20	15.32	36.93	32.73	15.32
51	0:00:13	0	17.23	15.32	0
52	0:00:13	0	17.23	0	15.32
53	0:00:19	15.32	44.54	15.32	44.54
54	0:00:18	24.31	48.29	44.54	24.31
55	0:00:07	24.31	29.84	24.31	24.45
56	0:00:06	24.45	24.47	24.45	24.45
57	0:00:12	24.45	33.79	24.45	24.52
58	0:00:18	24.52	43.74	24.52	36.43
59	0:00:15	14.39	36.51	36.43	14.39
60	0:00:03	14.39	18.61	14.39	18.61
61	0:00:10	18.61	28.99	18.61	23.72
62	0:00:07	23.72	23.74	23.72	23.72
63	0:00:10	23.72	39.38	23.72	39.38
64	0:00:06	39.31	43.73	39.38	39.31
65	0:00:11	22.3	39.31	39.31	22.3
66	0:00:04	18.29	23.28	22.3	18.29
67	0:00:02	15.62	18.29	18.29	15.62
68	0:00:06	15.62	15.63	15.62	15.62
69	0:00:16	15.62	38.49	15.62	37.6
70	0:00:03	33.43	37.6	37.6	33.43
71	0:00:09	21.21	33.75	33.43	21.21
72	0:00:01	21.21	23.37	21.21	23.37
73	0:00:05	23.37	30.61	23.37	30.61
74	0:00:07	30.61	41.03	30.61	41.03
75	0:00:03	41.03	43.51	41.03	43.48
76	0:00:05	43.48	43.51	43.48	43.48
77	0:00:08	43.48	43.51	43.48	43.48
78	0:00:08	43.48	43.51	43.48	43.48
79	0:00:02	43.48	43.51	43.48	43.48
80	0:00:07	38.34	43.51	43.48	38.34
81	0:00:12	20.51	38.34	38.34	20.51
82	0:00:01	20.51	21.55	20.51	21.55
83	0:00:06	21.55	27.76	21.55	24.72
84	0:00:09	24.72	31.55	24.72	25.16
85	0:00:01	23.89	25.16	25.16	23.89
86	0:00:08	23.89	31.78	23.89	27.89
87	0:00:05	27.89	34.9	27.89	34.9

88	0:00:04	30.49	35.65	34.9	30.49
89	0:00:12	30.49	46.19	30.49	43.48
90	0:00:04	43.48	43.51	43.48	43.48
91	0:00:08	43.48	43.51	43.48	43.48
92	0:00:09	36.39	43.51	43.48	36.39
93	0:00:13	16.22	36.39	36.39	16.22
94	0:00:05	16.22	16.23	16.22	16.22
95	0:00:00	16.22	16.81	16.22	16.81
96	0:00:03	15.84	18.38	16.81	15.84
97	0:00:14	15.84	37.22	15.84	37.22
98	0:00:13	20	38.21	37.22	20
99	0:00:14	14.04	20.02	20	14.04
100	0:00:11	14.04	20.02	14.04	20
101	0:00:16	20	20.02	20	20
102	0:00:25	0	20.02	20	0
Index	Average Speed (km/h)	Elevation Change (m)	Fuel Consumed (L)	Fuel Burn Rate (L/h)	Duty Cycle (%)
1	14.6	0	0.66	95.7	32.96
2	20.02	0	0.43	95.7	22.75
3	18.98	0	0.3	95.7	14.86
4	19.17	0	0.37	95.7	33.87
5	15.88	10	0.63	95.7	100
6	15.19	10	0.66	95.7	100
7	16.9	0	0.07	95.71	43.01
8	16.52	0	0.01	95.76	0
9	16.23	0.37	0.14	95.7	35.65
10	14.99	9.63	0.63	95.7	100
11	14.84	10	0.66	95.7	100
12	14.84	10	0.66	95.7	100
13	14.84	5	0.33	95.7	100
14	26.45	1.38	0.48	95.7	82.23
15	25.39	3.62	0.14	95.69	100
16	17.25	4.05	0.23	95.7	100
17	15.64	5.43	0.38	95.7	100
18	15.64	0.52	0.04	95.7	100
19	15.6	6.22	0.42	95.7	100
20	15.67	3.78	0.26	95.7	100
21	15.67	0.35	0.02	95.68	100
22	14.8	9.65	0.63	95.7	100
23	14.67	7.74	0.51	95.7	100

24	14.7	2.26	0.15	95.7	100
25	14.74	10	0.66	95.7	100
26	14.74	10	0.66	95.7	100
27	14.74	6.13	0.4	95.7	100
28	14.82	3.87	0.26	95.7	100
29	14.85	6.77	0.45	95.7	100
30	15.46	3.23	0.22	95.7	100
31	15.62	0.79	0.05	95.72	100
32	14.21	6.93	0.44	95.7	100
33	15.31	2.27	0.17	95.7	100
34	15.85	10	0.73	95.7	99.66
35	15.63	0	0.17	95.7	18.24
36	16.95	0	0.05	95.68	63.46
37	21.11	0	0.11	95.7	63.54
38	19.98	7.03	0.46	95.7	100
39	22.13	2.97	0.29	95.7	100
40	25.07	4.03	0.35	95.7	90.89
41	23.74	3.12	0.19	95.7	0
42	24.66	2.08	0.28	95.7	13.77
43	16.5	0.36	0.07	95.68	0
44	25.49	1.73	0.39	95.7	68.21
45	35.61	1.85	0.47	95.7	31.07
46	29.14	2.44	0.33	95.7	25.14
47	24.47	2.55	0.15	95.7	0
48	26.99	0.44	0.19	95.71	53.43
49	29.73	5.25	0.62	95.7	100
50	28.68	1.59	0.54	95.7	29.12
51	9.38	0.01	0.34	95.7	6.07
52	9.38	0.01	0.34	95.7	15.95
53	29.93	1.59	0.52	95.7	43.53
54	37.67	5.25	0.49	95.7	4.98
55	27.11	0.44	0.19	95.7	20.36
56	24.47	2.55	0.15	95.7	57.08
57	29.14	2.44	0.33	95.7	35.47
58	35.77	1.85	0.47	95.7	49.78
59	25.49	1.73	0.39	95.7	0.27
60	16.5	0.36	0.07	95.68	41.28
61	24.66	2.08	0.28	95.7	40.46
62	23.74	3.12	0.19	95.7	56.37
63	31.55	4.03	0.28	95.7	12.54

64	41.54	2.97	0.16	95.69	7.55
65	30.8	7.03	0.3	95.7	0
66	21.11	0	0.11	95.7	6.6
67	16.95	0	0.05	95.68	0
68	15.63	0	0.17	95.7	8.57
69	27.46	10	0.42	95.7	0
70	35.51	2.27	0.07	95.68	0
71	27.63	6.93	0.23	95.7	0
72	22.29	0.79	0.04	95.69	0
73	26.99	3.23	0.13	95.69	0
74	35.82	6.77	0.18	95.7	0
75	42.89	3.87	0.09	95.69	0
76	43.51	6.13	0.14	95.7	0
77	43.51	10	0.22	95.7	0
78	43.51	10	0.22	95.7	0
79	43.51	2.26	0.05	95.7	0
80	42.17	7.74	0.18	95.69	0
81	29.43	9.65	0.32	95.7	0
82	21.03	0.35	0.02	95.67	0
83	25.17	3.78	0.16	95.7	0
84	28.24	6.22	0.23	95.7	0
85	24.53	0.52	0.02	95.65	0
86	28.5	5.43	0.21	95.7	0
87	31.4	4.05	0.12	95.7	0
88	33.34	3.62	0.1	95.69	0
89	39.3	1.38	0.33	95.7	47.05
90	43.51	5	0.11	95.71	0
91	43.51	10	0.22	95.7	0
92	41.6	10	0.23	95.69	0
93	26.3	9.63	0.36	95.7	0
94	16.23	0.37	0.14	95.7	1.97
95	16.52	0	0.01	95.76	29.45
96	17.3	0	0.07	95.71	11.63
97	26.53	10	0.38	95.7	0
98	29.55	10	0.34	95.7	0
99	19.17	0	0.37	95.7	7.67
100	18.98	0	0.3	95.7	17.11
101	20.02	0	0.43	95.7	10.69
102	14.6	0	0.66	95.7	4.91

Index	Velocity Limit	Performance Limit	Corner Speed (km/h)	Equivalent Corner Radius (m)	Actual Power Curve
1	TopSpeed	Rimpull	0	0	Rimpull
2	TopSpeed	FinalSpeed	0	0	Rimpull
3	TopSpeed	FinalSpeed	14.04	17.72	Rimpull
4	TopSpeed	Rimpull	0	0	Rimpull
5	TopSpeed	Rimpull	0	0	Rimpull
6	TopSpeed	Rimpull	15.84	22.55	Rimpull
7	TopSpeed	Retard	0	0	Rimpull
8	TopSpeed	FinalSpeed	16.22	23.64	Rimpull
9	TopSpeed	Retard	16.22	23.64	Rimpull
10	TopSpeed	Rimpull	0	0	Rimpull
11	TopSpeed	Rimpull	0	0	Rimpull
12	TopSpeed	Rimpull	0	0	Rimpull
13	TopSpeed	Retard	0	0	Rimpull
14	TopSpeed	FinalSpeed	30.49	83.56	Rimpull
15	TopSpeed	Retard	0	0	Rimpull
16	TopSpeed	Retard	27.89	69.94	Rimpull
17	TopSpeed	Rimpull	23.89	51.31	Rimpull
18	TopSpeed	Retard	0	0	Rimpull
19	TopSpeed	Rimpull	24.72	54.94	Rimpull
20	TopSpeed	Rimpull	0	0	Rimpull
21	TopSpeed	Retard	20.51	37.83	Rimpull
22	TopSpeed	Retard	0	0	Rimpull
23	TopSpeed	Rimpull	0	0	Rimpull
24	TopSpeed	Rimpull	0	0	Rimpull
25	TopSpeed	Rimpull	0	0	Rimpull
26	TopSpeed	Rimpull	0	0	Rimpull
27	TopSpeed	Rimpull	0	0	Rimpull
28	TopSpeed	Rimpull	0	0	Rimpull
29	TopSpeed	Rimpull	38.74	134.96	Rimpull
30	TopSpeed	Retard	0	0	Rimpull
31	TopSpeed	Rimpull	21.21	40.45	Rimpull
32	TopSpeed	Retard	33.43	100.44	Rimpull
33	TopSpeed	Rimpull	0	0	Rimpull
34	TopSpeed	FinalSpeed	15.62	21.92	Rimpull
35	TopSpeed	Retard	15.62	21.92	Rimpull
36	TopSpeed	MaximumAcceleration	0	0	Rimpull
37	TopSpeed	FinalSpeed	22.3	44.69	Rimpull

38	TopSpeed	Retard	0	0	Rimpull
39	TopSpeed	Rimpull	0	0	Rimpull
40	TopSpeed	FinalSpeed	23.72	50.57	Rimpull
41	TopSpeed	Retard	23.72	50.57	Rimpull
42	TopSpeed	Retard	0	0	Rimpull
43	TopSpeed	Retard	14.39	18.61	Rimpull
44	TopSpeed	FinalSpeed	36.43	119.33	Rimpull
45	TopSpeed	FinalSpeed	24.52	54.07	Rimpull
46	TopSpeed	Retard	24.45	53.74	Rimpull
47	TopSpeed	Retard	24.45	53.74	Rimpull
48	TopSpeed	FinalSpeed	24.31	53.15	Rimpull
49	TopSpeed	Rimpull	0	0	Rimpull
50	TopSpeed	FinalSpeed	15.32	21.1	Rimpull
51	TopSpeed	FinalSpeed	0	0	Rimpull
52	TopSpeed	Retard	15.32	21.1	Rimpull
53	TopSpeed	MaximumAcceleration	0	0	Rimpull
54	TopSpeed	Retard	24.31	53.15	Rimpull
55	TopSpeed	FinalSpeed	24.45	53.74	Rimpull
56	TopSpeed	Retard	24.45	53.74	Rimpull
57	TopSpeed	Retard	24.52	54.07	Rimpull
58	TopSpeed	FinalSpeed	36.43	119.33	Rimpull
59	TopSpeed	Retard	14.39	18.61	Rimpull
60	TopSpeed	MaximumAcceleration	0	0	Rimpull
61	TopSpeed	Retard	23.72	50.57	Rimpull
62	TopSpeed	Retard	23.72	50.57	Rimpull
63	TopSpeed	MaximumAcceleration	0	0	Rimpull
64	TopSpeed	Retard	0	0	Rimpull
65	TopSpeed	FinalSpeed	22.3	44.69	Rimpull
66	TopSpeed	Retard	0	0	Rimpull
67	TopSpeed	FinalSpeed	15.62	21.92	Rimpull
68	TopSpeed	Retard	15.62	21.92	Rimpull
69	TopSpeed	Retard	0	0	Rimpull
70	TopSpeed	FinalSpeed	33.43	100.44	Rimpull
71	TopSpeed	FinalSpeed	21.21	40.45	Rimpull
72	TopSpeed	MaximumAcceleration	0	0	Rimpull
73	TopSpeed	MaximumAcceleration	38.74	134.96	Rimpull
74	TopSpeed	MaximumAcceleration	0	0	Rimpull
75	TopSpeed	Retard	0	0	Rimpull
76	TopSpeed	Retard	0	0	Rimpull
77	TopSpeed	Retard	0	0	Rimpull

78	TopSpeed	Retard	0	0	Rimpull
79	TopSpeed	Retard	0	0	Rimpull
80	TopSpeed	Retard	0	0	Rimpull
81	TopSpeed	FinalSpeed	20.51	37.83	Rimpull
82	TopSpeed	MaximumAcceleration	0	0	Rimpull
83	TopSpeed	FinalSpeed	24.72	54.94	Rimpull
84	TopSpeed	Retard	0	0	Rimpull
85	TopSpeed	FinalSpeed	23.89	51.31	Rimpull
86	TopSpeed	Retard	27.89	69.94	Rimpull
87	TopSpeed	MaximumAcceleration	0	0	Rimpull
88	TopSpeed	Retard	30.49	83.56	Rimpull
89	TopSpeed	Retard	0	0	Rimpull
90	TopSpeed	Retard	0	0	Rimpull
91	TopSpeed	Retard	0	0	Rimpull
92	TopSpeed	Retard	0	0	Rimpull
93	TopSpeed	FinalSpeed	16.22	23.64	Rimpull
94	TopSpeed	Retard	16.22	23.64	Rimpull
95	TopSpeed	MaximumAcceleration	0	0	Rimpull
96	TopSpeed	FinalSpeed	15.84	22.55	Rimpull
97	TopSpeed	MaximumAcceleration	0	0	Rimpull
98	TopSpeed	Retard	0	0	Rimpull
99	TopSpeed	FinalSpeed	14.04	17.72	Rimpull
100	TopSpeed	Rimpull	0	0	Rimpull
101	TopSpeed	FinalSpeed	0	0	Rimpull
102	TopSpeed	FinalSpeed	0	0	Rimpull

R1 FT					
Index	From	To	Distance (m)	Grade (%)	Load
1	(10,560.00, 10,837.50, 920.00)	(10,660.00, 10,837.50, 920.00)	100	0	Full
2	(10,660.00, 10,837.50, 920.00)	(10,749.55, 10,838.64, 920.00)	89.56	0	Full
3	(10,749.55, 10,838.64, 920.00)	(10,809.95, 10,836.44, 920.00)	60.44	0	Full
4	(10,809.95, 10,836.44, 920.00)	(10,798.13, 10,762.40, 920.00)	74.98	0	Full
5	(10,798.13, 10,762.40, 920.00)	(10,795.87, 10,657.86, 930.00)	105.04	9.56	Full
6	(10,795.87, 10,657.86, 930.00)	(10,793.62, 10,553.31, 940.00)	105.04	9.56	Full
7	(10,793.62, 10,553.31, 940.00)	(10,805.99, 10,548.86, 940.00)	13.16	0	Full
8	(10,805.99, 10,548.86, 940.00)	(10,807.72, 10,548.24, 940.00)	1.83	0	Full
9	(10,807.72, 10,548.24, 940.00)	(10,822.95, 10,565.72, 940.37)	23.19	1.58	Full
10	(10,822.95, 10,565.72, 940.37)	(10,845.50, 10,660.87, 950.00)	98.26	9.85	Full
11	(10,845.50, 10,660.87, 950.00)	(10,868.92, 10,759.64, 960.00)	102	9.85	Full
12	(10,868.92, 10,759.64, 960.00)	(10,892.33, 10,858.41, 970.00)	102	9.85	Full
13	(10,892.33, 10,858.41, 970.00)	(10,904.04, 10,907.80, 975.00)	51	9.85	Full

14	(10,904.04, 10,907.80, 975.00)	(10,944.63, 11,035.54, 976.38)	134.05	1.03	Full
15	(10,944.63, 11,035.54, 976.38)	(10,943.26, 11,071.79, 980.00)	36.45	9.98	Full
16	(10,943.26, 11,071.79, 980.00)	(10,941.74, 11,112.31, 984.05)	40.75	9.98	Full
17	(10,941.74, 11,112.31, 984.05)	(10,914.97, 11,168.16, 989.48)	62.17	8.77	Full
18	(10,914.97, 11,168.16, 989.48)	(10,910.71, 11,172.03, 990.00)	5.77	9.04	Full
19	(10,910.71, 11,172.03, 990.00)	(10,859.82, 11,218.30, 996.22)	69.07	9.04	Full
20	(10,859.82, 11,218.30, 996.22)	(10,817.79, 11,227.05, 1,000.00)	43.09	8.81	Full
21	(10,817.79, 11,227.05, 1,000.00)	(10,813.87, 11,227.87, 1,000.35)	4.02	8.81	Full
22	(10,813.87, 11,227.87, 1,000.35)	(10,721.02, 11,201.05, 1,010.00)	97.13	9.98	Full
23	(10,721.02, 11,201.05, 1,010.00)	(10,646.56, 11,179.54, 1,017.74)	77.89	9.98	Full
24	(10,646.56, 11,179.54, 1,017.74)	(10,625.15, 11,171.72, 1,020.00)	22.91	9.93	Full
25	(10,625.15, 11,171.72, 1,020.00)	(10,530.55, 11,137.15, 1,030.00)	101.21	9.93	Full
26	(10,530.55, 11,137.15, 1,030.00)	(10,435.95, 11,102.58, 1,040.00)	101.21	9.93	Full
27	(10,435.95, 11,102.58, 1,040.00)	(10,377.99, 11,081.40, 1,046.13)	62.02	9.93	Full
28	(10,377.99, 11,081.40, 1,046.13)	(10,340.13, 11,070.68, 1,050.00)	39.53	9.84	Full
29	(10,340.13, 11,070.68, 1,050.00)	(10,273.95, 11,051.94, 1,056.77)	69.12	9.84	Full
30	(10,273.95, 11,051.94, 1,056.77)	(10,241.55, 11,036.10, 1,060.00)	36.21	8.95	Full
31	(10,241.55, 11,036.10, 1,060.00)	(10,233.60, 11,032.21, 1,060.79)	8.89	8.95	Full
32	(10,233.60, 11,032.21, 1,060.79)	(10,199.98, 10,976.11, 1,067.73)	65.77	10.6	Full
33	(10,199.98, 10,976.11, 1,067.73)	(10,192.62, 10,949.74, 1,070.00)	27.47	8.3	Full
34	(10,192.62, 10,949.74, 1,070.00)	(10,160.24, 10,833.73, 1,080.00)	120.87	8.3	Full
35	(10,160.24, 10,833.73, 1,080.00)	(10,144.66, 10,810.58, 1,080.00)	27.9	0	Full
36	(10,144.66, 10,810.58, 1,080.00)	(10,140.35, 10,817.77, 1,080.00)	8.39	0	Full
37	(10,140.35, 10,817.77, 1,080.00)	(10,128.33, 10,837.81, 1,080.00)	23.37	0	Full
38	(10,128.33, 10,837.81, 1,080.00)	(10,140.68, 10,933.84, 1,087.03)	97.07	7.26	Full
39	(10,140.68, 10,933.84, 1,087.03)	(10,154.87, 10,999.78, 1,090.00)	67.51	4.41	Full
40	(10,154.87, 10,999.78, 1,090.00)	(10,174.10, 11,089.14, 1,094.03)	91.5	4.41	Full
41	(10,174.10, 11,089.14, 1,094.03)	(10,130.99, 11,109.32, 1,090.91)	47.7	-6.55	Full

42	(10,130.99, 11,109.32, 1,090.91)	(10,061.96, 11,127.76, 1,088.82)	71.48	-2.92	Full
43	(10,061.96, 11,127.76, 1,088.82)	(10,049.84, 11,132.15, 1,088.47)	12.89	-2.78	Full
44	(10,049.84, 11,132.15, 1,088.47)	(10,078.39, 11,232.96, 1,086.74)	104.78	-1.65	Full
45	(10,078.39, 11,232.96, 1,086.74)	(10,082.83, 11,408.66, 1,084.89)	175.77	-1.05	Full
46	(10,082.83, 11,408.66, 1,084.89)	(10,032.15, 11,495.34, 1,082.45)	100.44	-2.43	Full
47	(10,032.15, 11,495.34, 1,082.45)	(10,006.53, 11,524.93, 1,079.89)	39.23	-6.53	Full
48	(10,006.53, 11,524.93, 1,079.89)	(9,953.18, 11,512.28, 1,080.33)	54.83	0.81	Full
49	(9,953.18, 11,512.28, 1,080.33)	(9,818.04, 11,374.01, 1,085.58)	193.41	2.71	Full
50	(9,818.04, 11,374.01, 1,085.58)	(9,694.87, 11,268.84, 1,087.16)	161.96	0.98	Full
51	(9,694.87, 11,268.84, 1,087.16)	(9,669.77, 11,290.64, 1,087.15)	33.24	-0.04	Full
52	(9,669.77, 11,290.64, 1,087.15)	(9,694.87, 11,268.84, 1,087.16)	33.24	0.04	Empty
53	(9,694.87, 11,268.84, 1,087.16)	(9,818.04, 11,374.01, 1,085.58)	161.96	-0.98	Empty
54	(9,818.04, 11,374.01, 1,085.58)	(9,953.18, 11,512.28, 1,080.33)	193.41	-2.71	Empty
55	(9,953.18, 11,512.28, 1,080.33)	(10,006.53, 11,524.93, 1,079.89)	54.83	-0.81	Empty
56	(10,006.53, 11,524.93, 1,079.89)	(10,032.15, 11,495.34, 1,082.45)	39.23	6.53	Empty
57	(10,032.15, 11,495.34, 1,082.45)	(10,082.83, 11,408.66, 1,084.89)	100.44	2.43	Empty
58	(10,082.83, 11,408.66, 1,084.89)	(10,078.39, 11,232.96, 1,086.74)	175.77	1.05	Empty
59	(10,078.39, 11,232.96, 1,086.74)	(10,049.84, 11,132.15, 1,088.47)	104.78	1.65	Empty
60	(10,049.84, 11,132.15, 1,088.47)	(10,061.96, 11,127.76, 1,088.82)	12.89	2.78	Empty
61	(10,061.96, 11,127.76, 1,088.82)	(10,130.99, 11,109.32, 1,090.91)	71.48	2.92	Empty
62	(10,130.99, 11,109.32, 1,090.91)	(10,174.10, 11,089.14, 1,094.03)	47.7	6.55	Empty
63	(10,174.10, 11,089.14, 1,094.03)	(10,154.87, 10,999.78, 1,090.00)	91.5	-4.41	Empty
64	(10,154.87, 10,999.78, 1,090.00)	(10,140.68, 10,933.84, 1,087.03)	67.51	-4.41	Empty
65	(10,140.68, 10,933.84, 1,087.03)	(10,128.33, 10,837.81, 1,080.00)	97.07	-7.26	Empty
66	(10,128.33, 10,837.81, 1,080.00)	(10,140.35, 10,817.77, 1,080.00)	23.37	0	Empty

67	(10,140.35, 10,817.77, 1,080.00)	(10,144.66, 10,810.58, 1,080.00)	8.39	0	Empty
68	(10,144.66, 10,810.58, 1,080.00)	(10,160.24, 10,833.73, 1,080.00)	27.9	0	Empty
69	(10,160.24, 10,833.73, 1,080.00)	(10,192.62, 10,949.74, 1,070.00)	120.87	-8.3	Empty
70	(10,192.62, 10,949.74, 1,070.00)	(10,199.98, 10,976.11, 1,067.73)	27.47	-8.3	Empty
71	(10,199.98, 10,976.11, 1,067.73)	(10,233.60, 11,032.21, 1,060.79)	65.77	-10.6	Empty
72	(10,233.60, 11,032.21, 1,060.79)	(10,241.55, 11,036.10, 1,060.00)	8.89	-8.95	Empty
73	(10,241.55, 11,036.10, 1,060.00)	(10,273.95, 11,051.94, 1,056.77)	36.21	-8.95	Empty
74	(10,273.95, 11,051.94, 1,056.77)	(10,340.13, 11,070.68, 1,050.00)	69.12	-9.84	Empty
75	(10,340.13, 11,070.68, 1,050.00)	(10,377.99, 11,081.40, 1,046.13)	39.53	-9.84	Empty
76	(10,377.99, 11,081.40, 1,046.13)	(10,435.95, 11,102.58, 1,040.00)	62.02	-9.93	Empty
77	(10,435.95, 11,102.58, 1,040.00)	(10,530.55, 11,137.15, 1,030.00)	101.21	-9.93	Empty
78	(10,530.55, 11,137.15, 1,030.00)	(10,625.15, 11,171.72, 1,020.00)	101.21	-9.93	Empty
79	(10,625.15, 11,171.72, 1,020.00)	(10,646.56, 11,179.54, 1,017.74)	22.91	-9.93	Empty
80	(10,646.56, 11,179.54, 1,017.74)	(10,721.02, 11,201.05, 1,010.00)	77.89	-9.98	Empty
81	(10,721.02, 11,201.05, 1,010.00)	(10,813.87, 11,227.87, 1,000.35)	97.13	-9.98	Empty
82	(10,813.87, 11,227.87, 1,000.35)	(10,817.79, 11,227.05, 1,000.00)	4.02	-8.81	Empty
83	(10,817.79, 11,227.05, 1,000.00)	(10,859.82, 11,218.30, 996.22)	43.09	-8.81	Empty
84	(10,859.82, 11,218.30, 996.22)	(10,910.71, 11,172.03, 990.00)	69.07	-9.04	Empty
85	(10,910.71, 11,172.03, 990.00)	(10,914.97, 11,168.16, 989.48)	5.77	-9.04	Empty
86	(10,914.97, 11,168.16, 989.48)	(10,941.74, 11,112.31, 984.05)	62.17	-8.77	Empty
87	(10,941.74, 11,112.31, 984.05)	(10,943.26, 11,071.79, 980.00)	40.75	-9.98	Empty
88	(10,943.26, 11,071.79, 980.00)	(10,944.63, 11,035.54, 976.38)	36.45	-9.98	Empty
89	(10,944.63, 11,035.54, 976.38)	(10,904.04, 10,907.80, 975.00)	134.05	-1.03	Empty
90	(10,904.04, 10,907.80, 975.00)	(10,892.33, 10,858.41, 970.00)	51	-9.85	Empty
91	(10,892.33, 10,858.41, 970.00)	(10,868.92, 10,759.64, 960.00)	102	-9.85	Empty
92	(10,868.92, 10,759.64, 960.00)	(10,845.50, 10,660.87, 950.00)	102	-9.85	Empty
93	(10,845.50, 10,660.87, 950.00)	(10,822.95, 10,565.72, 940.37)	98.26	-9.85	Empty
94	(10,822.95, 10,565.72, 940.37)	(10,807.72, 10,548.24, 940.00)	23.19	-1.58	Empty
95	(10,807.72, 10,548.24, 940.00)	(10,805.99, 10,548.86, 940.00)	1.83	0	Empty
96	(10,805.99, 10,548.86, 940.00)	(10,793.62, 10,553.31, 940.00)	13.16	0	Empty
97	(10,793.62, 10,553.31, 940.00)	(10,795.87, 10,657.86, 930.00)	105.04	-9.56	Empty
98	(10,795.87, 10,657.86, 930.00)	(10,798.13, 10,762.40, 920.00)	105.04	-9.56	Empty

99	(10,798.13, 10,762.40, 920.00)	(10,809.95, 10,836.44, 920.00)	74.98	0	Empty
100	(10,809.95, 10,836.44, 920.00)	(10,749.55, 10,838.64, 920.00)	60.44	0	Empty
101	(10,749.55, 10,838.64, 920.00)	(10,660.00, 10,837.50, 920.00)	89.56	0	Empty
102	(10,660.00, 10,837.50, 920.00)	(10,560.00, 10,837.50, 920.00)	100	0	Empty

Index	Time (hh:mm:ss)	Minimum Speed (km/h)	Maximum Speed (km/h)	Actual Initial Speed (km/h)	Final Speed (km/h)
1	0:00:25	0	20.02	0	20
2	0:00:16	20	20.02	20	20
3	0:00:11	14.04	20.02	20	14.04
4	0:00:14	14.04	20.02	14.04	20
5	0:00:26	13.21	20	20	13.21
6	0:00:29	13.18	13.21	13.21	13.18
7	0:00:03	13.18	17.3	13.18	16.81
8	0:00:00	16.22	16.81	16.81	16.22
9	0:00:05	16.22	16.23	16.22	16.22
10	0:00:27	12.67	16.22	16.22	12.67
11	0:00:29	12.67	12.67	12.67	12.67
12	0:00:29	12.67	12.67	12.67	12.67
13	0:00:14	12.67	12.67	12.67	12.67
14	0:00:19	12.67	32.34	12.67	30.49
15	0:00:05	19.79	30.49	30.49	19.79
16	0:00:09	13.38	19.79	19.79	13.38
17	0:00:16	13.38	14.53	13.38	14.53
18	0:00:01	14.41	14.53	14.53	14.41
19	0:00:18	14.11	14.41	14.41	14.11
20	0:00:11	14.11	14.47	14.11	14.47
21	0:00:01	14.47	14.47	14.47	14.47
22	0:00:27	12.49	14.47	14.47	12.49
23	0:00:22	12.49	12.49	12.49	12.49
24	0:00:07	12.49	12.55	12.49	12.55
25	0:00:29	12.55	12.56	12.55	12.56
26	0:00:29	12.56	12.56	12.56	12.56
27	0:00:18	12.56	12.56	12.56	12.56
28	0:00:11	12.56	12.68	12.56	12.68
29	0:00:20	12.68	12.68	12.68	12.68
30	0:00:10	12.68	14.04	12.68	14.04
31	0:00:02	14.04	14.12	14.04	14.12
32	0:00:20	11.7	14.12	14.12	11.7
33	0:00:07	11.7	14.54	11.7	14.54
34	0:00:29	14.54	15.19	14.54	15.19
35	0:00:06	15.19	15.63	15.19	15.62
36	0:00:02	15.62	18.29	15.62	18.29
37	0:00:04	18.29	23.28	18.29	22.3
38	0:00:19	16.17	22.3	22.3	16.17
39	0:00:12	16.17	21.78	16.17	21.78
40	0:00:15	21.78	22.71	21.78	22.71

41	0:00:07	22.71	23.74	22.71	23.72
42	0:00:10	18.61	28.99	23.72	18.61
43	0:00:03	14.39	18.61	18.61	14.39
44	0:00:15	14.39	36.45	14.39	36.43
45	0:00:18	24.52	42.42	36.43	24.52
46	0:00:12	24.45	33.79	24.52	24.45
47	0:00:06	24.45	24.47	24.45	24.45
48	0:00:07	24.31	28.97	24.45	24.31
49	0:00:25	24.31	29.84	24.31	29.84
50	0:00:21	15.32	34.67	29.84	15.32
51	0:00:13	0	17.23	15.32	0
52	0:00:13	0	17.23	0	15.32
53	0:00:19	15.32	44.54	15.32	44.54
54	0:00:18	24.31	48.29	44.54	24.31
55	0:00:07	24.31	29.84	24.31	24.45
56	0:00:06	24.45	24.47	24.45	24.45
57	0:00:12	24.45	33.79	24.45	24.52
58	0:00:18	24.52	43.74	24.52	36.43
59	0:00:15	14.39	36.51	36.43	14.39
60	0:00:03	14.39	18.61	14.39	18.61
61	0:00:10	18.61	28.99	18.61	23.72
62	0:00:07	23.72	23.74	23.72	23.72
63	0:00:10	23.72	39.38	23.72	39.38
64	0:00:06	39.31	43.73	39.38	39.31
65	0:00:11	22.3	39.31	39.31	22.3
66	0:00:04	18.29	23.28	22.3	18.29
67	0:00:02	15.62	18.29	18.29	15.62
68	0:00:06	15.62	15.63	15.62	15.62
69	0:00:16	15.62	38.49	15.62	37.6
70	0:00:03	33.43	37.6	37.6	33.43
71	0:00:09	21.21	33.75	33.43	21.21
72	0:00:01	21.21	23.37	21.21	23.37
73	0:00:05	23.37	30.61	23.37	30.61
74	0:00:07	30.61	41.03	30.61	41.03
75	0:00:03	41.03	43.51	41.03	43.48
76	0:00:05	43.48	43.51	43.48	43.48
77	0:00:08	43.48	43.51	43.48	43.48
78	0:00:08	43.48	43.51	43.48	43.48
79	0:00:02	43.48	43.51	43.48	43.48
80	0:00:07	38.34	43.51	43.48	38.34
81	0:00:12	20.51	38.34	38.34	20.51
82	0:00:01	20.51	21.55	20.51	21.55
83	0:00:06	21.55	27.76	21.55	24.72
84	0:00:09	24.72	31.55	24.72	25.16
85	0:00:01	23.89	25.16	25.16	23.89
86	0:00:08	23.89	31.78	23.89	27.89
87	0:00:05	27.89	34.9	27.89	34.9

88	0:00:04	30.49	35.65	34.9	30.49
89	0:00:12	30.49	46.19	30.49	43.48
90	0:00:04	43.48	43.51	43.48	43.48
91	0:00:08	43.48	43.51	43.48	43.48
92	0:00:09	36.39	43.51	43.48	36.39
93	0:00:13	16.22	36.39	36.39	16.22
94	0:00:05	16.22	16.23	16.22	16.22
95	0:00:00	16.22	16.81	16.22	16.81
96	0:00:03	15.84	18.38	16.81	15.84
97	0:00:14	15.84	37.22	15.84	37.22
98	0:00:13	20	38.21	37.22	20
99	0:00:14	14.04	20.02	20	14.04
100	0:00:11	14.04	20.02	14.04	20
101	0:00:16	20	20.02	20	20
102	0:00:25	0	20.02	20	0

Index	Average Speed (km/h)	Elevation Change (m)	Fuel Consumed (L)	Fuel Burn Rate (L/h)	Duty Cycle (%)
1	14.6	0	0.66	95.7	37
2	20.02	0	0.43	95.7	25.54
3	18.98	0	0.3	95.7	16.68
4	19.17	0	0.37	95.7	38.02
5	14.33	10	0.7	95.7	100
6	13.18	10	0.76	95.7	100
7	15.43	0	0.08	95.69	56.23
8	16.52	0	0.01	95.76	0
9	16.23	0.37	0.14	95.7	40.02
10	13.26	9.63	0.71	95.7	100
11	12.67	10	0.77	95.7	100
12	12.67	10	0.77	95.7	100
13	12.66	5	0.39	95.7	100
14	24.76	1.38	0.52	95.7	87.98
15	24.7	3.62	0.14	95.69	100
16	15.47	4.05	0.25	95.7	100
17	14.22	5.43	0.42	95.7	100
18	14.46	0.52	0.04	95.71	100
19	14.17	6.22	0.47	95.7	100
20	14.35	3.78	0.29	95.7	100
21	14.47	0.35	0.03	95.74	100
22	12.81	9.65	0.73	95.7	100
23	12.48	7.74	0.6	95.7	100
24	12.52	2.26	0.18	95.7	100
25	12.56	10	0.77	95.7	100
26	12.56	10	0.77	95.7	100
27	12.56	6.13	0.47	95.7	100
28	12.64	3.87	0.3	95.7	100
29	12.67	6.77	0.52	95.7	100
30	13.56	3.23	0.26	95.7	100

31	14.09	0.79	0.06	95.7	100
32	12.13	6.93	0.52	95.7	100
33	13.45	2.27	0.2	95.7	100
34	15.11	10	0.77	95.7	100
35	15.62	0	0.17	95.7	22.29
36	16.95	0	0.05	95.68	71.24
37	21.11	0	0.11	95.7	71.34
38	18.18	7.03	0.51	95.7	100
39	19.86	2.97	0.33	95.7	100
40	22.28	4.03	0.39	95.7	100
41	23.69	3.12	0.19	95.7	0
42	24.66	2.08	0.28	95.7	15.46
43	16.5	0.36	0.07	95.68	0
44	25.48	1.73	0.39	95.7	76.33
45	35.49	1.85	0.47	95.7	33.08
46	29.14	2.44	0.33	95.7	28.22
47	24.47	2.55	0.15	95.7	0
48	26.75	0.44	0.2	95.7	57.93
49	28.22	5.25	0.66	95.7	100
50	27.82	1.59	0.56	95.7	38.45
51	9.38	0.01	0.34	95.7	6.82
52	9.38	0.01	0.34	95.7	15.95
53	29.93	1.59	0.52	95.7	43.53
54	37.67	5.25	0.49	95.7	4.98
55	27.11	0.44	0.19	95.7	20.36
56	24.47	2.55	0.15	95.7	57.08
57	29.14	2.44	0.33	95.7	35.47
58	35.77	1.85	0.47	95.7	49.78
59	25.49	1.73	0.39	95.7	0.27
60	16.5	0.36	0.07	95.68	41.28
61	24.66	2.08	0.28	95.7	40.46
62	23.74	3.12	0.19	95.7	56.37
63	31.55	4.03	0.28	95.7	12.54
64	41.54	2.97	0.16	95.69	7.55
65	30.8	7.03	0.3	95.7	0
66	21.11	0	0.11	95.7	6.6
67	16.95	0	0.05	95.68	0
68	15.63	0	0.17	95.7	8.57
69	27.46	10	0.42	95.7	0
70	35.51	2.27	0.07	95.68	0
71	27.63	6.93	0.23	95.7	0
72	22.29	0.79	0.04	95.69	0
73	26.99	3.23	0.13	95.69	0
74	35.82	6.77	0.18	95.7	0
75	42.89	3.87	0.09	95.69	0
76	43.51	6.13	0.14	95.7	0
77	43.51	10	0.22	95.7	0

78	43.51	10	0.22	95.7	0
79	43.51	2.26	0.05	95.7	0
80	42.17	7.74	0.18	95.69	0
81	29.43	9.65	0.32	95.7	0
82	21.03	0.35	0.02	95.67	0
83	25.17	3.78	0.16	95.7	0
84	28.24	6.22	0.23	95.7	0
85	24.53	0.52	0.02	95.65	0
86	28.5	5.43	0.21	95.7	0
87	31.4	4.05	0.12	95.7	0
88	33.34	3.62	0.1	95.69	0
89	39.3	1.38	0.33	95.7	47.05
90	43.51	5	0.11	95.71	0
91	43.51	10	0.22	95.7	0
92	41.6	10	0.23	95.69	0
93	26.3	9.63	0.36	95.7	0
94	16.23	0.37	0.14	95.7	1.97
95	16.52	0	0.01	95.76	29.45
96	17.3	0	0.07	95.71	11.63
97	26.53	10	0.38	95.7	0
98	29.55	10	0.34	95.7	0
99	19.17	0	0.37	95.7	7.67
100	18.98	0	0.3	95.7	17.11
101	20.02	0	0.43	95.7	10.69
102	14.6	0	0.66	95.7	4.91

Index	Velocity Limit	Performance Limit	Corner Speed (km/h)	Equivalent Corner Radius (m)	Actual Power Curve
1	TopSpeed	Rimpull	0	0	Rimpull
2	TopSpeed	FinalSpeed	0	0	Rimpull
3	TopSpeed	FinalSpeed	14.04	17.72	Rimpull
4	TopSpeed	Rimpull	0	0	Rimpull
5	TopSpeed	Retard	0	0	Rimpull
6	TopSpeed	Rimpull	15.84	22.55	Rimpull
7	TopSpeed	Retard	0	0	Rimpull
8	TopSpeed	FinalSpeed	16.22	23.64	Rimpull
9	TopSpeed	Retard	16.22	23.64	Rimpull
10	TopSpeed	Rimpull	0	0	Rimpull
11	TopSpeed	Rimpull	0	0	Rimpull
12	TopSpeed	Retard	0	0	Rimpull
13	TopSpeed	Rimpull	0	0	Rimpull
14	TopSpeed	FinalSpeed	30.49	83.56	Rimpull
15	TopSpeed	Retard	0	0	Rimpull
16	TopSpeed	Retard	27.89	69.94	Rimpull
17	TopSpeed	Rimpull	23.89	51.31	Rimpull
18	TopSpeed	Retard	0	0	Rimpull
19	TopSpeed	Retard	24.72	54.94	Rimpull

20	TopSpeed	Rimpull	0	0	Rimpull
21	TopSpeed	Retard	20.51	37.83	Rimpull
22	TopSpeed	Rimpull	0	0	Rimpull
23	TopSpeed	Retard	0	0	Rimpull
24	TopSpeed	Rimpull	0	0	Rimpull
25	TopSpeed	Rimpull	0	0	Rimpull
26	TopSpeed	Rimpull	0	0	Rimpull
27	TopSpeed	Retard	0	0	Rimpull
28	TopSpeed	Rimpull	0	0	Rimpull
29	TopSpeed	Retard	38.74	134.96	Rimpull
30	TopSpeed	Rimpull	0	0	Rimpull
31	TopSpeed	Rimpull	21.21	40.45	Rimpull
32	TopSpeed	Retard	33.43	100.44	Rimpull
33	TopSpeed	Rimpull	0	0	Rimpull
34	TopSpeed	Retard	15.62	21.92	Rimpull
35	TopSpeed	Rimpull	15.62	21.92	Rimpull
36	TopSpeed	MaximumAcceleration	0	0	Rimpull
37	TopSpeed	FinalSpeed	22.3	44.69	Rimpull
38	TopSpeed	Retard	0	0	Rimpull
39	TopSpeed	Rimpull	0	0	Rimpull
40	TopSpeed	Rimpull	23.72	50.57	Rimpull
41	TopSpeed	Rimpull	23.72	50.57	Rimpull
42	TopSpeed	Retard	0	0	Rimpull
43	TopSpeed	Retard	14.39	18.61	Rimpull
44	TopSpeed	FinalSpeed	36.43	119.33	Rimpull
45	TopSpeed	FinalSpeed	24.52	54.07	Rimpull
46	TopSpeed	Retard	24.45	53.74	Rimpull
47	TopSpeed	Retard	24.45	53.74	Rimpull
48	TopSpeed	FinalSpeed	24.31	53.15	Rimpull
49	TopSpeed	Rimpull	0	0	Rimpull
50	TopSpeed	FinalSpeed	15.32	21.1	Rimpull
51	TopSpeed	FinalSpeed	0	0	Rimpull
52	TopSpeed	Retard	15.32	21.1	Rimpull
53	TopSpeed	MaximumAcceleration	0	0	Rimpull
54	TopSpeed	Retard	24.31	53.15	Rimpull
55	TopSpeed	FinalSpeed	24.45	53.74	Rimpull
56	TopSpeed	Retard	24.45	53.74	Rimpull
57	TopSpeed	Retard	24.52	54.07	Rimpull
58	TopSpeed	FinalSpeed	36.43	119.33	Rimpull
59	TopSpeed	Retard	14.39	18.61	Rimpull
60	TopSpeed	MaximumAcceleration	0	0	Rimpull
61	TopSpeed	Retard	23.72	50.57	Rimpull
62	TopSpeed	Retard	23.72	50.57	Rimpull
63	TopSpeed	MaximumAcceleration	0	0	Rimpull
64	TopSpeed	Retard	0	0	Rimpull
65	TopSpeed	FinalSpeed	22.3	44.69	Rimpull
66	TopSpeed	Retard	0	0	Rimpull

67	TopSpeed	FinalSpeed	15.62	21.92	Rimpull
68	TopSpeed	Retard	15.62	21.92	Rimpull
69	TopSpeed	Retard	0	0	Rimpull
70	TopSpeed	FinalSpeed	33.43	100.44	Rimpull
71	TopSpeed	FinalSpeed	21.21	40.45	Rimpull
72	TopSpeed	MaximumAcceleration	0	0	Rimpull
73	TopSpeed	MaximumAcceleration	38.74	134.96	Rimpull
74	TopSpeed	MaximumAcceleration	0	0	Rimpull
75	TopSpeed	Retard	0	0	Rimpull
76	TopSpeed	Retard	0	0	Rimpull
77	TopSpeed	Retard	0	0	Rimpull
78	TopSpeed	Retard	0	0	Rimpull
79	TopSpeed	Retard	0	0	Rimpull
80	TopSpeed	Retard	0	0	Rimpull
81	TopSpeed	FinalSpeed	20.51	37.83	Rimpull
82	TopSpeed	MaximumAcceleration	0	0	Rimpull
83	TopSpeed	FinalSpeed	24.72	54.94	Rimpull
84	TopSpeed	Retard	0	0	Rimpull
85	TopSpeed	FinalSpeed	23.89	51.31	Rimpull
86	TopSpeed	Retard	27.89	69.94	Rimpull
87	TopSpeed	MaximumAcceleration	0	0	Rimpull
88	TopSpeed	Retard	30.49	83.56	Rimpull
89	TopSpeed	Retard	0	0	Rimpull
90	TopSpeed	Retard	0	0	Rimpull
91	TopSpeed	Retard	0	0	Rimpull
92	TopSpeed	Retard	0	0	Rimpull
93	TopSpeed	FinalSpeed	16.22	23.64	Rimpull
94	TopSpeed	Retard	16.22	23.64	Rimpull
95	TopSpeed	MaximumAcceleration	0	0	Rimpull
96	TopSpeed	FinalSpeed	15.84	22.55	Rimpull
97	TopSpeed	MaximumAcceleration	0	0	Rimpull
98	TopSpeed	Retard	0	0	Rimpull
99	TopSpeed	FinalSpeed	14.04	17.72	Rimpull
100	TopSpeed	Rimpull	0	0	Rimpull
101	TopSpeed	FinalSpeed	0	0	Rimpull
102	TopSpeed	FinalSpeed	0	0	Rimpull

R2 FB					
Index	**From**	**To**	**Distance (m)**	**Grade (%)**	**Load**
1	(9,549.81, 9,892.64, 1,085.88)	(9,370.73, 9,846.02, 1,083.65)	185.06	-1.21	Full
2	(9,370.73, 9,846.02, 1,083.65)	(9,329.64, 9,875.03, 1,082.91)	50.31	-1.47	Full
3	(9,329.64, 9,875.03, 1,082.91)	(9,237.07, 10,017.58, 1,081.11)	169.98	-1.06	Full

4	(9,237.07, 10,017.58, 1,081.11)	(9,192.41, 10,091.88, 1,078.81)	86.72	-2.66	Full
5	(9,192.41, 10,091.88, 1,078.81)	(9,111.98, 10,292.13, 1,076.78)	215.81	-0.94	Full
6	(9,111.98, 10,292.13, 1,076.78)	(9,112.26, 10,429.70, 1,074.17)	137.6	-1.89	Full
7	(9,112.26, 10,429.70, 1,074.17)	(9,126.26, 10,548.51, 1,072.97)	119.63	-1	Full
8	(9,126.26, 10,548.51, 1,072.97)	(9,198.46, 10,774.38, 1,068.85)	237.17	-1.74	Full
9	(9,198.46, 10,774.38, 1,068.85)	(9,237.18, 11,005.34, 1,065.43)	234.2	-1.46	Full
10	(9,237.18, 11,005.34, 1,065.43)	(9,243.54, 11,011.75, 1,065.41)	9.04	-0.3	Full
11	(9,243.54, 11,011.75, 1,065.41)	(9,245.95, 11,016.34, 1,065.24)	5.18	-3.16	Full
12	(9,245.95, 11,016.34, 1,065.24)	(9,265.94, 11,057.53, 1,064.69)	45.8	-1.2	Full
13	(9,265.94, 11,057.53, 1,064.69)	(9,310.15, 11,079.41, 1,066.02)	49.35	2.69	Full
14	(9,310.15, 11,079.41, 1,066.02)	(9,506.48, 11,074.35, 1,083.22)	197.14	8.76	Full
15	(9,506.48, 11,074.35, 1,083.22)	(9,605.70, 11,108.26, 1,088.46)	104.99	4.99	Full
16	(9,605.70, 11,108.26, 1,088.46)	(9,694.87, 11,268.84, 1,087.16)	183.69	-0.7	Full
17	(9,694.87, 11,268.84, 1,087.16)	(9,669.77, 11,290.64, 1,087.15)	33.24	-0.04	Full
18	(9,669.77, 11,290.64, 1,087.15)	(9,694.87, 11,268.84, 1,087.16)	33.24	0.04	Empty
19	(9,694.87, 11,268.84, 1,087.16)	(9,605.70, 11,108.26, 1,088.46)	183.69	0.7	Empty
20	(9,605.70, 11,108.26, 1,088.46)	(9,506.48, 11,074.35, 1,083.22)	104.99	-4.99	Empty
21	(9,506.48, 11,074.35, 1,083.22)	(9,310.15, 11,079.41, 1,066.02)	197.14	-8.76	Empty
22	(9,310.15, 11,079.41, 1,066.02)	(9,265.94, 11,057.53, 1,064.69)	49.35	-2.69	Empty
23	(9,265.94, 11,057.53, 1,064.69)	(9,245.95, 11,016.34, 1,065.24)	45.8	1.2	Empty
24	(9,245.95, 11,016.34, 1,065.24)	(9,243.54, 11,011.75, 1,065.41)	5.18	3.16	Empty
25	(9,243.54, 11,011.75, 1,065.41)	(9,237.18, 11,005.34, 1,065.43)	9.04	0.3	Empty
26	(9,237.18, 11,005.34, 1,065.43)	(9,198.46, 10,774.38, 1,068.85)	234.2	1.46	Empty
27	(9,198.46, 10,774.38, 1,068.85)	(9,126.26, 10,548.51, 1,072.97)	237.17	1.74	Empty
28	(9,126.26, 10,548.51, 1,072.97)	(9,112.26, 10,429.70, 1,074.17)	119.63	1	Empty

29	(9,112.26, 10,429.70, 1,074.17)	(9,111.98, 10,292.13, 1,076.78)	137.6	1.89	Empty
30	(9,111.98, 10,292.13, 1,076.78)	(9,192.41, 10,091.88, 1,078.81)	215.81	0.94	Empty
31	(9,192.41, 10,091.88, 1,078.81)	(9,237.07, 10,017.58, 1,081.11)	86.72	2.66	Empty
32	(9,237.07, 10,017.58, 1,081.11)	(9,329.64, 9,875.03, 1,082.91)	169.98	1.06	Empty
33	(9,329.64, 9,875.03, 1,082.91)	(9,370.73, 9,846.02, 1,083.65)	50.31	1.47	Empty
34	(9,370.73, 9,846.02, 1,083.65)	(9,549.81, 9,892.64, 1,085.88)	185.06	1.21	Empty

Index	Time (hh:mm:ss)	Minimum Speed (km/h)	Maximum Speed (km/h)	Actual Initial Speed (km/h)	Final Speed (km/h)
1	0:00:33	0	34.51	0	19.59
2	0:00:07	19.59	30.03	19.59	29.61
3	0:00:15	29.61	48.14	29.61	48.14
4	0:00:06	48.14	56.18	48.14	56.18
5	0:00:18	29.46	56.27	56.18	29.46
6	0:00:13	29.46	47.58	29.46	47.58
7	0:00:09	41.58	50.5	47.58	41.58
8	0:00:17	41.58	57.38	41.58	54.44
9	0:00:22	20.84	54.44	54.44	20.84
10	0:00:01	20.84	23.03	20.84	22.99
11	0:00:01	22.99	24.17	22.99	24.17
12	0:00:06	24.17	30.37	24.17	27.67
13	0:00:06	27.67	27.69	27.67	27.67
14	0:00:41	15.69	27.67	27.67	15.69
15	0:00:18	15.69	22.84	15.69	21.29
16	0:00:24	15.65	36.32	21.29	15.65
17	0:00:13	0	17.38	15.65	0
18	0:00:13	0	17.38	0	15.65
19	0:00:24	15.65	36.62	15.65	21.29
20	0:00:13	21.29	35.31	21.29	30.1
21	0:00:20	27.67	43.59	30.1	27.67
22	0:00:06	27.67	27.69	27.67	27.67
23	0:00:06	24.17	30.37	27.67	24.17
24	0:00:01	22.99	24.17	24.17	22.99
25	0:00:01	20.84	23.03	22.99	20.84
26	0:00:22	20.84	53.75	20.84	53.75
27	0:00:16	41.58	57.22	53.75	41.58
28	0:00:09	41.58	51.84	41.58	48.52
29	0:00:13	29.46	48.52	48.52	29.46
30	0:00:18	29.46	55.59	29.46	55.59
31	0:00:06	52.08	56.23	55.59	52.08

32	0:00:15	29.61	52.08	52.08	29.61
33	0:00:07	19.59	30.03	29.61	19.59
34	0:00:33	0	34.51	19.59	0
Index	Average Speed (km/h)	Elevation Change (m)	Fuel Consumed (L)	Fuel Burn Rate (L/h)	Duty Cycle (%)
1	20.21	2.23	0.88	95.7	37.28
2	25.01	0.74	0.19	95.69	66.73
3	39.73	1.8	0.41	95.7	99.58
4	52.38	2.31	0.16	95.7	81.76
5	43.01	2.03	0.48	95.7	1.05
6	38.82	2.6	0.34	95.7	93.4
7	47.09	1.2	0.24	95.7	34.97
8	50.95	4.12	0.45	95.7	88.3
9	37.64	3.42	0.6	95.7	0
10	21.95	0.03	0.04	95.69	76.61
11	23.58	0.16	0.02	95.7	32.19
12	27.8	0.55	0.16	95.71	55.92
13	27.69	1.32	0.17	95.7	73.59
14	17.39	17.21	1.08	95.7	100
15	20.85	5.23	0.48	95.7	95.76
16	27.29	1.29	0.64	95.7	39.15
17	9.4	0.01	0.34	95.7	5.62
18	9.4	0.01	0.34	95.7	16.22
19	27.33	1.29	0.64	95.7	28.86
20	29.49	5.23	0.34	95.7	5.56
21	36.19	17.21	0.52	95.7	0
22	27.69	1.32	0.17	95.7	0
23	27.8	0.55	0.16	95.71	18.33
24	23.58	0.16	0.02	95.7	4.06
25	21.95	0.03	0.04	95.69	0.76
26	37.61	3.42	0.6	95.7	78.21
27	51.75	4.12	0.44	95.7	36.78
28	47.56	1.2	0.24	95.7	69.56
29	38.99	2.6	0.34	95.7	0
30	42.96	2.03	0.48	95.7	83.52
31	55.07	2.31	0.15	95.69	53.42
32	40.85	1.8	0.4	95.7	0
33	25.01	0.74	0.19	95.69	2.57
34	20.21	2.23	0.88	95.7	16.78
Index	Velocity Limit	Performance Limit	Corner Speed (km/h)	Equivalent Corner Radius (m)	Actual Power Curve
1	TopSpeed	FinalSpeed	19.59	34.5	Rimpull

2	TopSpeed	Retard	29.61	78.82	Rimpull
3	TopSpeed	Rimpull	0	0	Rimpull
4	TopSpeed	Rimpull	0	0	Rimpull
5	TopSpeed	FinalSpeed	29.46	78.02	Rimpull
6	TopSpeed	Rimpull	0	0	Rimpull
7	TopSpeed	FinalSpeed	41.58	155.4	Rimpull
8	TopSpeed	Retard	0	0	Rimpull
9	TopSpeed	FinalSpeed	20.84	39.06	Rimpull
10	TopSpeed	FinalSpeed	22.99	47.5	Rimpull
11	TopSpeed	MaximumAcceleration	0	0	Rimpull
12	TopSpeed	FinalSpeed	27.67	68.81	Rimpull
13	TopSpeed	Retard	27.67	68.81	Rimpull
14	TopSpeed	Retard	30.1	81.43	Rimpull
15	TopSpeed	FinalSpeed	21.29	40.76	Rimpull
16	TopSpeed	FinalSpeed	15.65	22.02	Rimpull
17	TopSpeed	FinalSpeed	0	0	Rimpull
18	TopSpeed	FinalSpeed	15.65	22.02	Rimpull
19	TopSpeed	Retard	21.29	40.76	Rimpull
20	TopSpeed	Retard	30.1	81.43	Rimpull
21	TopSpeed	FinalSpeed	27.67	68.81	Rimpull
22	TopSpeed	Retard	27.67	68.81	Rimpull
23	TopSpeed	Retard	0	0	Rimpull
24	TopSpeed	FinalSpeed	22.99	47.5	Rimpull
25	TopSpeed	Retard	20.84	39.06	Rimpull
26	TopSpeed	Rimpull	0	0	Rimpull
27	TopSpeed	FinalSpeed	41.58	155.4	Rimpull
28	TopSpeed	Retard	0	0	Rimpull
29	TopSpeed	FinalSpeed	29.46	78.02	Rimpull
30	TopSpeed	Rimpull	0	0	Rimpull
31	TopSpeed	Retard	0	0	Rimpull
32	TopSpeed	FinalSpeed	29.61	78.82	Rimpull
33	TopSpeed	Retard	19.59	34.5	Rimpull
34	TopSpeed	FinalSpeed	0	0	Rimpull

R2 FT					
Index	From	To	Distance (m)	Grade (%)	Load
1	(9,549.81, 9,892.64, 1,085.88)	(9,370.73, 9,846.02, 1,083.65)	185.06	-1.21	Full
2	(9,370.73, 9,846.02, 1,083.65)	(9,329.64, 9,875.03, 1,082.91)	50.31	-1.47	Full
3	(9,329.64, 9,875.03, 1,082.91)	(9,237.07, 10,017.58, 1,081.11)	169.98	-1.06	Full
4	(9,237.07, 10,017.58, 1,081.11)	(9,192.41, 10,091.88, 1,078.81)	86.72	-2.66	Full
5	(9,192.41, 10,091.88, 1,078.81)	(9,111.98, 10,292.13, 1,076.78)	215.81	-0.94	Full
6	(9,111.98, 10,292.13, 1,076.78)	(9,112.26, 10,429.70, 1,074.17)	137.6	-1.89	Full

7	(9,112.26, 10,429.70, 1,074.17)	(9,126.26, 10,548.51, 1,072.97)	119.63	-1	Full
8	(9,126.26, 10,548.51, 1,072.97)	(9,198.46, 10,774.38, 1,068.85)	237.17	-1.74	Full
9	(9,198.46, 10,774.38, 1,068.85)	(9,237.18, 11,005.34, 1,065.43)	234.2	-1.46	Full
10	(9,237.18, 11,005.34, 1,065.43)	(9,243.54, 11,011.75, 1,065.41)	9.04	-0.3	Full
11	(9,243.54, 11,011.75, 1,065.41)	(9,245.95, 11,016.34, 1,065.24)	5.18	-3.16	Full
12	(9,245.95, 11,016.34, 1,065.24)	(9,265.94, 11,057.53, 1,064.69)	45.8	-1.2	Full
13	(9,265.94, 11,057.53, 1,064.69)	(9,310.15, 11,079.41, 1,066.02)	49.35	2.69	Full
14	(9,310.15, 11,079.41, 1,066.02)	(9,506.48, 11,074.35, 1,083.22)	197.14	8.76	Full
15	(9,506.48, 11,074.35, 1,083.22)	(9,605.70, 11,108.26, 1,088.46)	104.99	4.99	Full
16	(9,605.70, 11,108.26, 1,088.46)	(9,694.87, 11,268.84, 1,087.16)	183.69	-0.7	Full
17	(9,694.87, 11,268.84, 1,087.16)	(9,669.77, 11,290.64, 1,087.15)	33.24	-0.04	Full
18	(9,669.77, 11,290.64, 1,087.15)	(9,694.87, 11,268.84, 1,087.16)	33.24	0.04	Empty
19	(9,694.87, 11,268.84, 1,087.16)	(9,605.70, 11,108.26, 1,088.46)	183.69	0.7	Empty
20	(9,605.70, 11,108.26, 1,088.46)	(9,506.48, 11,074.35, 1,083.22)	104.99	-4.99	Empty
21	(9,506.48, 11,074.35, 1,083.22)	(9,310.15, 11,079.41, 1,066.02)	197.14	-8.76	Empty
22	(9,310.15, 11,079.41, 1,066.02)	(9,265.94, 11,057.53, 1,064.69)	49.35	-2.69	Empty
23	(9,265.94, 11,057.53, 1,064.69)	(9,245.95, 11,016.34, 1,065.24)	45.8	1.2	Empty
24	(9,245.95, 11,016.34, 1,065.24)	(9,243.54, 11,011.75, 1,065.41)	5.18	3.16	Empty
25	(9,243.54, 11,011.75, 1,065.41)	(9,237.18, 11,005.34, 1,065.43)	9.04	0.3	Empty
26	(9,237.18, 11,005.34, 1,065.43)	(9,198.46, 10,774.38, 1,068.85)	234.2	1.46	Empty
27	(9,198.46, 10,774.38, 1,068.85)	(9,126.26, 10,548.51, 1,072.97)	237.17	1.74	Empty
28	(9,126.26, 10,548.51, 1,072.97)	(9,112.26, 10,429.70, 1,074.17)	119.63	1	Empty
29	(9,112.26, 10,429.70, 1,074.17)	(9,111.98, 10,292.13, 1,076.78)	137.6	1.89	Empty
30	(9,111.98, 10,292.13, 1,076.78)	(9,192.41, 10,091.88, 1,078.81)	215.81	0.94	Empty
31	(9,192.41, 10,091.88, 1,078.81)	(9,237.07, 10,017.58, 1,081.11)	86.72	2.66	Empty

32	(9,237.07, 10,017.58, 1,081.11)	(9,329.64, 9,875.03, 1,082.91)	169.98	1.06	Empty
33	(9,329.64, 9,875.03, 1,082.91)	(9,370.73, 9,846.02, 1,083.65)	50.31	1.47	Empty
34	(9,370.73, 9,846.02, 1,083.65)	(9,549.81, 9,892.64, 1,085.88)	185.06	1.21	Empty
Index	Time (hh:mm:ss)	Minimum Speed (km/h)	Maximum Speed (km/h)	Actual Initial Speed (km/h)	Final Speed (km/h)
1	0:00:33	0	34.31	0	19.59
2	0:00:07	19.59	30.03	19.59	29.61
3	0:00:16	29.61	46.44	29.61	46.44
4	0:00:06	46.44	54.49	46.44	54.49
5	0:00:18	29.46	55.01	54.49	29.46
6	0:00:13	29.46	46.66	29.46	46.66
7	0:00:09	41.58	49.68	46.66	41.58
8	0:00:17	41.58	56.62	41.58	54.44
9	0:00:22	20.84	54.44	54.44	20.84
10	0:00:01	20.84	23.03	20.84	22.99
11	0:00:01	22.99	24.17	22.99	24.17
12	0:00:06	24.17	30.34	24.17	27.67
13	0:00:06	27.67	27.69	27.67	27.67
14	0:00:44	14.54	27.67	27.67	14.54
15	0:00:19	14.54	21.47	14.54	21.29
16	0:00:24	15.65	35.8	21.29	15.65
17	0:00:13	0	17.38	15.65	0
18	0:00:13	0	17.38	0	15.65
19	0:00:24	15.65	36.62	15.65	21.29
20	0:00:13	21.29	35.31	21.29	30.1
21	0:00:20	27.67	43.59	30.1	27.67
22	0:00:06	27.67	27.69	27.67	27.67
23	0:00:06	24.17	30.37	27.67	24.17
24	0:00:01	22.99	24.17	24.17	22.99
25	0:00:01	20.84	23.03	22.99	20.84
26	0:00:22	20.84	53.75	20.84	53.75
27	0:00:16	41.58	57.22	53.75	41.58
28	0:00:09	41.58	51.84	41.58	48.52
29	0:00:13	29.46	48.52	48.52	29.46
30	0:00:18	29.46	55.59	29.46	55.59
31	0:00:06	52.08	56.23	55.59	52.08
32	0:00:15	29.61	52.08	52.08	29.61
33	0:00:07	19.59	30.03	29.61	19.59
34	0:00:33	0	34.51	19.59	0
Index	Average Speed (km/h)	Elevation Change (m)	Fuel Consumed (L)	Fuel Burn Rate (L/h)	Duty Cycle (%)
1	20.2	2.23	0.88	95.7	41.53
2	25.01	0.74	0.19	95.69	74.91
3	38.83	1.8	0.42	95.7	100

4	50.6	2.31	0.16	95.7	91.15
5	42.96	2.03	0.48	95.7	5.81
6	38.57	2.6	0.34	95.7	97.99
7	46.69	1.2	0.25	95.7	41.41
8	50.25	4.12	0.45	95.7	91.47
9	37.64	3.42	0.6	95.7	0
10	21.95	0.03	0.04	95.69	86.01
11	23.58	0.16	0.02	95.7	36.14
12	27.8	0.55	0.16	95.7	62.58
13	27.69	1.32	0.17	95.7	82.62
14	16.08	17.21	1.17	95.7	100
15	19.42	5.23	0.52	95.7	99.56
16	27.2	1.29	0.65	95.7	42.85
17	9.4	0.01	0.34	95.7	6.31
18	9.4	0.01	0.34	95.7	16.22
19	27.33	1.29	0.64	95.7	28.86
20	29.49	5.23	0.34	95.7	5.56
21	36.19	17.21	0.52	95.7	0
22	27.69	1.32	0.17	95.7	0
23	27.8	0.55	0.16	95.71	18.33
24	23.58	0.16	0.02	95.7	4.06
25	21.95	0.03	0.04	95.69	0.76
26	37.61	3.42	0.6	95.7	78.21
27	51.75	4.12	0.44	95.7	36.78
28	47.56	1.2	0.24	95.7	69.56
29	38.99	2.6	0.34	95.7	0
30	42.96	2.03	0.48	95.7	83.52
31	55.07	2.31	0.15	95.69	53.42
32	40.85	1.8	0.4	95.7	0
33	25.01	0.74	0.19	95.69	2.57
34	20.21	2.23	0.88	95.7	16.78

Index	Velocity Limit	Performance Limit	Corner Speed (km/h)	Equivalent Corner Radius (m)	Actual Power Curve
1	TopSpeed	FinalSpeed	19.59	34.5	Rimpull
2	TopSpeed	Retard	29.61	78.82	Rimpull
3	TopSpeed	Rimpull	0	0	Rimpull
4	TopSpeed	Rimpull	0	0	Rimpull
5	TopSpeed	FinalSpeed	29.46	78.02	Rimpull
6	TopSpeed	Rimpull	0	0	Rimpull
7	TopSpeed	FinalSpeed	41.58	155.4	Rimpull
8	TopSpeed	Retard	0	0	Rimpull
9	TopSpeed	FinalSpeed	20.84	39.06	Rimpull
10	TopSpeed	FinalSpeed	22.99	47.5	Rimpull
11	TopSpeed	MaximumAcceleration	0	0	Rimpull
12	TopSpeed	FinalSpeed	27.67	68.81	Rimpull
13	TopSpeed	Retard	27.67	68.81	Rimpull

14	TopSpeed	Retard	30.1	81.43	Rimpull
15	TopSpeed	FinalSpeed	21.29	40.76	Rimpull
16	TopSpeed	FinalSpeed	15.65	22.02	Rimpull
17	TopSpeed	FinalSpeed	0	0	Rimpull
18	TopSpeed	FinalSpeed	15.65	22.02	Rimpull
19	TopSpeed	Retard	21.29	40.76	Rimpull
20	TopSpeed	Retard	30.1	81.43	Rimpull
21	TopSpeed	FinalSpeed	27.67	68.81	Rimpull
22	TopSpeed	Retard	27.67	68.81	Rimpull
23	TopSpeed	Retard	0	0	Rimpull
24	TopSpeed	FinalSpeed	22.99	47.5	Rimpull
25	TopSpeed	Retard	20.84	39.06	Rimpull
26	TopSpeed	Rimpull	0	0	Rimpull
27	TopSpeed	FinalSpeed	41.58	155.4	Rimpull
28	TopSpeed	Retard	0	0	Rimpull
29	TopSpeed	FinalSpeed	29.46	78.02	Rimpull
30	TopSpeed	Rimpull	0	0	Rimpull
31	TopSpeed	Retard	0	0	Rimpull
32	TopSpeed	FinalSpeed	29.61	78.82	Rimpull
33	TopSpeed	Retard	19.59	34.5	Rimpull
34	TopSpeed	FinalSpeed	0	0	Rimpull