Optimised fuel consumption of hauling mobile equipment achieved from speed optimisation using Simulated Annealing

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Abstract

The mining industry is a significant contributor to greenhouse gas emissions and operational costs. The transportation of materials within mining operations, especially using diesel-powered trucks, accounts for a substantial portion of both emissions and costs. Optimizing fuel consumption in this context is crucial for environmental sustainability and financial efficiency.

While there is some existing research on minimizing fuel consumption in mining operations, most of these studies prioritize production over fuel efficiency. Additionally, there is a lack of solutions addressing real-time dispatch problems while also minimizing fuel consumption.

This thesis proposes the development of a model to optimize truck speeds in mining operations, with the primary goal of reducing fuel consumption. The focus is on minimizing waiting times for trucks at loading stations by adjusting their speeds using a metaheuristic algorithm, specifically Simulated Annealing (SA).

To achieve this, a discrete event simulation (DES) model made in HaulSim to replicate a simplified mining site in Nevada, USA. The simulation includes Caterpillar 793 series trucks. The SA algorithm is applied to find optimal truck speeds, with the aim of reducing fuel consumption with the same level of production.

The hypothesis is that lowering truck speeds in mining environments with queueing trucks can significantly reduce fuel consumption. The study explores how speed optimization impacts efficiency across different mining conditions, identifies the most effective optimization techniques, and quantifies potential fuel savings. The research reveals a 27-32% reduction in fuel consumption across various truck scenarios. However, these findings should be interpreted cautiously due to limitations in data constraints and modelling simplifications.

In conclusion, the study highlights the effectiveness of SA in optimizing truck speeds and the potential for substantial fuel savings in mining operations. We recommend the integration of Artificial Neural Networks (ANNs) for a more nuanced approach to fuel consumption estimation and optimization, considering factors like road maintenance intervals and payload. This synergistic approach, combining metaheuristics and machine learning techniques, aligns with sustainable practices in the mining industry and offers promising avenues for further research and application.

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1 Introduction

Mining has played a crucial role in the development of human civilization with signs of mining activity as old as human settlements. Still to this day the mining industry is an essential part of today's society. The demand for raw materials is growing at an unprecedented rate, driven by factors such as energy used, population growth, urbanization, and the increasing complexity of modern technology. Without mining, it would be impossible to produce many of the goods and services that modern society relies on.

As the world's population is projected to reach around 10 billion by 2050, the demand for raw materials such as energy resources, minerals, and metals is also rising (United Nations, 2019). People's consumption patterns have changed significantly over the years, with more people having access to various goods and services. For example, electronics, household appliances, and cars have become more popular, and they all need minerals and metals to be manufactured. The increased consumption of these goods has driven up the demand for raw materials. Recycling can help to provide some of the raw materials needed, but its effect depends on the type of commodity. Some products are very long-lasting and can be used for a long time. For example, around 68% of all nickel ever produced is still in use today (nickelinstitute.org), also some commodities are better recyclable than other, some have such a low economic value that recycling is not feasible or too energy intensive.

However, as the demand for raw materials grows, it becomes increasingly difficult to access them. Many of the easily accessible resources have already been depleted, and mines must now go deeper and extract lower-grade ore to meet the growing demand (Rocky Mountain Institute, 2019). This has led to a significant increase in the energy and costs required to extract these resources, which presents challenges for the mining industry.

The depletion of easily accessible resources also has other consequences. The extraction of minerals and metals from lower-grade ore requires more energy, which leads to higher greenhouse gas (GHG) emissions and a greater environmental impact. It also means that the mining industry must become more innovative and find new ways to extract minerals and metals more efficiently, with less impact on the environment.

Greenhouse gas emissions are a major contributor to climate change, which poses a significant threat to the environment and human well-being. The mining sector together with the oil industry is seen by the public as one of the biggest emitters of greenhouse gas. According to the CEEC the mining sector uses 3.5% of the global energy consumption. A large portion of the energy consumption of mining operation is due to material handling and transportation. Load and haul operation can contribute up to 60% to the total GHG emission of a mine (Zhang et al. 2022) as truck and loader frequently still run on diesel. This part of the mining sector will also take a lot of years to electrify and will contribute to the growing demand in raw materials. Beside the GHG emission reducing diesel consumption can also have financial benefits, diesel consumption can contribute to 50% of operation costs (Zhang et al. 2022).

One approach which will be used in this thesis is to optimize truck speed to safe fuel. A lot of studies have been done on the fuel consumption of mining trucks and which parameters have the most influence. According to Siami-Irdemoosa et al. (2015) waiting time of diesel trucks are the main contributor to unnecessary fuel consumption. Another study by Soofastaei et al. (2018) identifies payload/gross weight vehicle, speed (s) and total resistance (TR) as the three main parameters that influence fuel consumption (FC). Also, a lot of studies have been done about how to optimize dispatch strategies but most of those studies are more concerned with the increase in production.

Metaheuristic and mathematical algorithms have gained prominence in the mining industry, with large-scale mines realizing substantial operational cost savings through enhanced efficiency. As mines expand and incorporate an increasing number of parameters, traditional mathematical algorithms, such as linear programming, often become impractical due to extended computational timeframes. Consequently, this thesis explores the application of metaheuristic algorithms, specifically focusing on optimizing truck speeds to minimize fuel consumption. While several algorithms were evaluated, the methodology and results will exclusively address the Simulated Annealing (SA) optimization.

The dataset employed in this research was generated using a discrete event simulation (DES) model, specifically through Haulsim, which is recognized as a robust mining simulation software. This simulation replicates a simplified model of a mining site located in Nevada, USA. The Haulsim framework for this study incorporates two loaders and multiple trucks from the Caterpillar 793 series. The scope of the simulation is confined to a single production shift, and the loading and dumping events are strictly defined within this timeframe. A crucial aspect of this study is the optimization process, which aims to eliminate excessive waiting times. This optimization is strategically focused on modulating the operational speeds of the trucks, thereby achieving a reduction in fuel consumption.

1.1 Hypotheses

Based on comprehensive vehicle modelling and established principles of physics, it is proven that vehicles moving at reduced speeds consume less fuel. The thesis proposes that reduced fuel consumption can be achieved by advising an optimal speed for the trucks given the mine circumstance. In a mining environment where trucks have to wait in queues, an optimization can be made by reducing the speed of the trucks, thereby consuming less fuel during production.

1.2 Research question:

Can a model for optimizing the hauling speed of mobile equipment be created to eliminate unnecessary waiting times in mining operations, with the ultimate goal of reducing overall fuel consumption?

1.2.1 Sub questions

- How does speed optimization impact efficiency across various mining conditions?
- Which optimization technique is most appropriate for the specific case study?
- What quantifiable fuel savings can be realized by employing optimization techniques to reduce truck speeds?
- How do different optimization parameters affect the outcomes of the proposed algorithm?
- In what scenarios or conditions within the mining environment does the optimization demonstrate the highest effectiveness for both speed reduction and fuel savings?

1.3 Scopes and Limitations

1.3.1 Scope

This thesis focuses on developing and applying an optimization model, which reduces the waiting time of trucks at the loaders. The reduction in waiting time will be achieved by reducing the speed of the trucks through a meta-heuristic algorithm, specifically Simulated Annealing (SA). Optimizing truck speeds in mining operations aims to minimize fuel consumption. The research is based on a custom-designed mine simulation using Haulsim, a robust mining simulation tool. The key aspects of this study include:

- Analysing the influence of truck speed on fuel consumption in mining environments.
- Implementing the SA algorithm to find optimal truck speeds.
- Examining the impact of different truck configurations (varying numbers of trucks) on fuel consumption and operational efficiency.
- Assessing the potential fuel savings through speed optimization in simulated mining scenarios.

1.3.2 Limitations:

While this research aims to provide insights into optimizing fuel consumption in mining operations, several limitations must be acknowledged:

- Data Constraints: The data for this study is sourced exclusively from Haulsim simulations, which may not perfectly mimic real-world mining operations. Limitations in data export capabilities (e.g., inability to export location-based data to Excel or CSV) have necessitated the use of averages for optimization, potentially affecting the granularity and precision of the results.
- Modelling Simplifications: The study focuses primarily on Total Resistance (TR) and speed as the key variables for modelling fuel consumption in heavy-duty machinery. This simplification might overlook other significant factors that influence fuel consumption, such as payload, road conditions, and weather.
- Algorithmic Limitations: The use of the SA algorithm, while effective in certain scenarios, introduces randomness that may not always lead to optimal solutions. Additionally, the performance and accuracy of the algorithm in larger truck configurations and complex operational scenarios may vary.
- Generalization of Results: The findings, particularly the fuel savings percentages, are based on simulated scenarios and may not directly translate to real-world mining operations. The study's conclusions should therefore be interpreted with caution when applying them to actual mine sites.
- Scope of Research: This research predominantly focuses on diesel-powered trucks. With the advent of electric trucks and changing technological landscapes, the optimization strategies and findings might not be directly applicable to these newer technologies.
- Economic Considerations: While the study identifies potential fuel savings, it does not fully explore the trade-offs between these savings and the additional costs that may arise, such as increased labour or capital investment in more efficient technologies.

In summary, the research presented in this thesis offers valuable insights into fuel optimization in mining operations using metaheuristic algorithms. However, the findings are subject to the mentioned limitations and should be considered within the context of the simulated environment and specific parameters employed in this study.

This thesis will have to following eight chapters.

1. Introduction: This chapter provides background information, research questions, and the context of the research.
2. Literature Review: This chapter provides an overview of existing literature relevant to the research questions.
3. Methodology: This chapter describes the research methods and procedures used in the study.
4. Results: This chapter presents the results of the research.
5. Discussion: This chapter interprets the results, discusses the implications of the findings, and provides recommendations for future research.
6. Conclusion: This chapter summarizes the main findings, limitations of the study, and the significance of the research.
7. Recommendation: This chapter outlines practical, actionable suggestions derived from the research findings, addressing their application in relevant fields and proposing future directions for research or practice.
8. References: This chapter includes a list of all the sources cited in the thesis.

2 Literature review

2.1 Computer-aided mine design & Machine learning capabilities

Computer-aided mine design has revolutionized the mining industry by enhancing efficiency, safety, and environmental sustainability. One of the pivotal techniques that have been instrumental in this transformation is linear programming. According to Gholamnejad et al. 2020, linear programming has been employed to optimize the extraction sequence in open-pit mining. This mathematical modelling technique helps in determining the most efficient way to allocate limited resources, such as equipment and labour, to achieve the desired output, such as maximizing profits or minimizing costs.

In addition to linear programming, metaheuristic algorithms have emerged as powerful tools in mine planning and design. These algorithms are used for solving complex optimization problems that are computationally infeasible to solve through exact methods. Denby and Schofield, in their 1994 study, illustrated the utilization of Genetic Algorithm (GA) for optimizing open-pit mine production planning. The standout feature of their approach was their capacity to tackle both the ultimate pit limit and long-term planning issues in tandem. By selecting appropriate genetic parameters, the methodology demonstrated its efficacy in generating commendable outcomes for a small block model within a reasonable timeframe.

A study by Paithankar & Chatterjee (2019), employing a hybrid method using real-world mineral deposit data and benchmark instances. The method, which incorporates Genetic Algorithms (GA), was applied to two sets of problems based on copper and gold deposits, taking geological uncertainty into account. The study conducted a sensitivity analysis of various GA parameters, including population size, crossover probability, mutation probability, and parametric diversification. It was observed that increasing the population size stabilized the results and reduced the gap from the optimal solution but at the cost of increased execution time. Additionally, the study highlighted the significance of weights in source and sink arcs. It was found that incorporating weights for both source and sink nodes as opposed to only the source node had a case-specific impact on the final solution, contingent on the spatial distribution of the material. Another aspect explored was the approach to solving the problem, comparing solving it in stages to solving all periods simultaneously. The latter added complexity and was sensitive to small changes in initial periods. The study concluded that solving the problem in stages was more effective, ensuring a directed search and a better net present value. The hybrid method demonstrated robustness in solving real-world open-pit mine production scheduling under uncertain scenarios. The method did not rely on an initial solution and was adaptable for deterministic models or various uncertainty modelling approaches, as well as additional scheduling constraints.

For short-term planning in mining, the study by Mousavi et al. 2016 tackled the Open Pit Block Sequencing (OPBS) problem, which is essential for optimizing extraction sequences. Three metaheuristic methods, namely Simulated Annealing (SA), Tabu Search (TS), and a hybrid of TS and SA, were employed and compared against a traditional mixed-integer programming (MIP) solver, CPLEX. The findings indicated that the metaheuristic algorithms not only demonstrated minimal deviation from the objective value compared to CPLEX but also executed significantly faster. Importantly, the study showed that large-scale instances, which proved infeasible with CPLEX, could be effectively addressed using the metaheuristic algorithms within a reasonable timeframe. The hybrid TS-SA algorithm, in particular, exhibited superior performance, especially for large-scale instances. The study underscored the limitations of traditional solvers and highlighted the effectiveness of metaheuristic algorithms in handling the complexities of the OPBS problem.

In a 2015 study by Saghatforoush et al., Artificial Neural Networks (ANN) were utilized to predict fly rock and back-break, which are common environmental impacts of blasting in mining. The study analysed 97 blasting operations at the Delkan iron mine in Iran. The ANN model proved to be highly accurate in its predictions. Additionally, the study introduced a novel approach using Ant Colony Optimization (ACO), an algorithm inspired by ant foraging behaviour, to optimize blasting parameters. The integration of ANN with ACO led to significant reductions in fly rock and back-break by 61% and 58% respectively. In essence, the combination of ANN and ACO presented a powerful and efficient method for predicting and optimizing the environmental impacts of blasting operations.

In the 2014 study by Abousleiman & Rawashdeh, an exploration of two metaheuristic algorithms, Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), was undertaken to solve an energy-efficient routing problem for electric vehicles (EVs). It was highlighted that traditional algorithms like Dijkstra's algorithm fell short when applied to EVs due to their energy regeneration capabilities, which can result in negative edge costs. ACO, inspired by the natural behaviour of ants in finding the shortest path, was relatively simple to implement. However, to make it suitable for energy-efficient routing in EVs, a conversion from the shortest path to the energy-optimized path was necessary. In contrast, PSO required a more involved adaptation from its original form and was somewhat more complex to set up. Despite this, it demonstrated a notable advantage in terms of speed, solving the problem in under 400 milliseconds compared to ACO’s approximate 1.8 seconds. The performance of these algorithms was evaluated on a virtual map with 10 nodes and 13 routes. Both ACO and PSO converged rapidly to the optimal solution. The study concluded with the affirmation that ACO and PSO are effective metaheuristic algorithms for energy-efficient routing in electric vehicles.

Despite meta heuristics algorithm for optimization, machine learning has the remarkable ability to learn and make predictions from data, and its applications are virtually limitless and will play a role in future mining related prediction such as fuel consumption, reserve estimation and capital costs. In a study conducted by Guo et al. in 2021, various forms of AI were utilized to predict Mining Capital Cost (MCC) for open-pit mines. The study used a dataset consisting of 74 observations, which was divided into an 80-20 train-test split. In this study, three Artificial Neural Network (ANN) models, Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART) models were developed and evaluated. For the ANN models, the structure was determined through trial and error, and back-propagation was used for training. The ANN models developed included ANN 5-9-1, ANN 5-8-8-1, and ANN 5-12-7-1. The RF model was developed with a forest of 2000 trees, and hyperparameters were optimized using a grid search technique. The CART model was developed using a complexity parameter, and its optimal value was determined through a grid search. The SVM model employed a radial basis kernel function, and its hyperparameters, cost (C) and sigma (σ), were optimized through trial and error. The models were assessed based on Root Mean Square Error (RMSE), R-squared (R2), and Mean Absolute Error (MAE) on both the training and testing datasets. Among the models, the ANN models emerged as the most effective, with ANN 5-12-7-1 standing out with an RMSE of 138.103, MAE of 114.589, and R2 of 0.990 in the testing phase. The SVM model also showed promising results, while the CART model lagged in performance.

2.2 Dispatch strategies

2.2.1 Dispatch strategies

Truck dispatching problems are not exclusive to mining operations. Other areas like shipping, package delivery and emergency services all have a fleet management system in place to operate efficiently. In other literature dispatching problem may also be referred to as Vehicle Routing Problem (VRP). Transportation of hauled materials is often one of the biggest operational costs in open pit mines. Enormous amounts of material have to be transported to a different location. Most of this relocation of material is done by diesel mining trucks, which is why truck dispatching management has a significant influence on the schedule and production but also on the total efficiency of the mine. Poor mine management can lead to queues at dump locations or truck bunching, which increases the operation cost. An optimal fleet management system can also lead to a smaller mining fleet Mirzaei-Nasaribad et al. (2023) which also has an impact on the capital expenditure (CAPEX).

Truck dispatching can be done in the single stage approach or in the multistage approach. The single stage approaches any constraints or production targets are not taking into account, truck allocation is done by some 'rule of thumb' method. Multi-stage approach is divided into two stages, the upper stage is a truck and shovel allocation model with the schedule and production targets as constraints. This stage is often accomplished with a form of linear programming (LP, MIP or SP). The lower stage is the real time truck assignment optimization, where the goal is to minimize the deviation from the upper stage. According to Subtil (2011) using a form of mathematical modelling to solve the lower stage would be very time consuming because of the many constraints created by the real-time aspect. The model should be able to runs every time something changes which has influence on the availability on equipment like trucks and shovels, but also on the availability of locations like dump or production sites.

The optimization in Chaowasakoo et al. (2017) study three different truck dispatching strategies are used, the 1-truck-for-n-shovels dispatch strategy, which is still the most used strategy because of easy implementation. The m-trucks-for-1-shovel dispatch strategy and the m-trucks-n-shovel dispatch strategy. Where the first strategy is to be considered a single stage approach, strategy two and three are based on a multi-stage approach. In Chaowasakoo's paper the m-trucks-for-1-shovel has to worst results with a 27% lower production than scheduled. However, the method had an 8% higher production rate than the realized production. According to Alarie and Gamache this strategy is myopic and lack a global vision because the optimization only considers 1 shovel at the time. Currently only one commercial dispatch software system is using this technique. Both the 1-truck-for-n-shovels dispatch method and the m-trucks-n-shovel dispatch method can be optimized with four different key objectives which are shown in the table below:

Table 1: Heuristic truck dispatching methods (Chaowasakoo, 2017)

Method	Key objectives	Assignment
Minimizing shovel waiting time (MSWT)	To maximize the utilization of both trucks and shovels	An empty truck is assigned to the shovel with the longest idle time or to the shovel that is expected to be idle first
Minimizing truck cycle time (MTCT)	To maximize the total tonnage productivity	An empty truck is assigned to the shovel that allows the shortest truck cycle time
Minimizing truck waiting time (MTWT)	To maximize the utilization of a shovel by minimizing truck waiting time	An empty truck is assigned to the shovel in which the loading operation starts first
Minimizing shovel saturation and coverage (MSC)	To minimize a shovel operating waiting time	An empty truck is assigned to shovel at equal time intervals to keep shovels non-idle

The result for the 1-truck-for-n-shovels method is between 1.2 and 1.7 million bcm's which are around the same as the actual production and the plan respectively. According to Alarie and Gamache this truck dispatch strategy is myopic. A lack of global vision is missing because only one truck at each time instead is considered. The best results by far are m-trucks-for-n-shovels method with at least 60% more production with every heuristic method. The difference in production with different key objective is also very small compared to the other dispatching method. This suggest that the total utilization of the truck and shovels is higher. The study of Mirzaei-Nasaribad et al. (2023) compares the key performance index's (KPI's) production, utilization, and fuel consumption of 3 heuristic optimizations with a mathematical model. Heuristic methods do not always give the optimal solution and are not guaranteed to give the same outcome every time. Nevertheless heuristic methods have been quite popular in the literature because of their easy implementation and they do not need strong computation power. The result of the mathematical model were found in less than a minute with a strong but normal laptop. These results suggest that mathematical models are possible for real time truck dispatching. The production difference between the mathematical model and heuristic optimizations falls within the range of 0.4% to 4%. The difference is negligible when a suitable heuristic model is employed. However, developing a mathematical model for an m-trucks-for-n-shovel dispatch strategy and comparing it to various heuristic models may be challenging. This dispatch strategy is best suited for smaller operations or closed systems since larger numbers of trucks and shovels can significantly increase computation time. The problem with real-time dispatch solutions involving mathematical models and m-trucks-for-n-shovel dispatch strategies may not be solvable within a reasonable timeframe, limiting its practicality in the industry. A perfect truck dispatching system according to Alarie and Gamache (2002) is a multi-stage dispatching system where the upper stage of multistage systems computes a guideline by solving a mathematical program, which is then used as a reference by the lower stage for real-time dispatching decisions. Compared to single stage systems, the mathematical program considered by the upper stage can factor in a range of complex variables such as blending requirements at crushers, stripping ratios, and capacity constraints at shovels. Additionally, constraints arising from practical considerations and mine manager requirements can also be added. Multiple guidelines can be determined based on production constraints, such as maximizing production, minimizing costs, or even maximizing profit if relevant data is available. However, the guideline must be formulated in a way that does not require a homogeneous fleet in the lower stage. A study by Zhang et al. 2022 used a MIP model to optimize the upper stage of the autonomous mine fleet schedule. In this study the real-time speed was controlled to minimized fuel consumption. They also develop a real-time scheduling system based on their proposed model and solution method. This system performs well in the stochastic and dynamic mine environment, making it suitable for short-term decision-making. The fuel consumption was based on static data which only considered 3 stages full, empty, and idle. Also, the speed vs fuel consumption data was not dynamic.

2.2.2 Gap analysis: dispatch strategies

For many years, mining corporations have been scaling up the size of their trucks as a strategy to enhance efficiency and reduce the cost per ton. Additionally, various mining techniques have evolved to accommodate the large-scale mining operations prevalent today. However, with the impending regulations on carbon emissions, continuing to increase the scale of diesel mining equipment will not be feasible. There is a pressing need for innovative, computer-aided mine design to keep pace with modern advancements. Such computerized mine design systems have demonstrated their efficacy in boosting production levels and ensuring better utilization of equipment. Although existing literature on dispatch systems in mining covers aspects like production rates, scheduling, and equipment utilization, there is a conspicuous absence of studies focusing on reducing fuel consumption. This is a critical oversight, considering that fuel expenses, particularly for diesel-powered mining trucks, constitute a significant portion of operational costs in mining. In an era characterized by escalating energy prices and heightened environmental consciousness, it is imperative to explore alternative optimization strategies to sustain and expand mining operations. Optimization focused on fuel consumption can be particularly beneficial in mining operations where various bottlenecks, such as grinding and milling, shipping, stockpiling, or even market demand, can adversely affect profits. By incorporating these factors, the optimization of fuel consumption can also assist in establishing more informed production constraints. This holistic approach not only contributes to reducing operational costs through fuel savings but also ensures a more efficient and streamlined process that takes into account the various challenges and constraints faced by mining operations.

The majority of literature on dispatch systems in mining tends to follow a similar sequence of techniques. Initially, a form of linear programming (such as Mixed Integer Programming or Sequence Goal Programming) is employed to optimize production. Subsequently, metaheuristic algorithms are utilized to execute the dispatch strategy. This approach has been established as effective in achieving near-optimal production levels. However, it is important to note that fuel consumption and production are positively correlated; an increase in either speed or payload will enhance production but will also lead to higher fuel consumption. To address this, an objective function aimed at minimizing fuel consumption, with production targets serving as constraints, can be employed following the aforementioned logic. Nonetheless, fuel consumption can be a multifaceted function, which may lead to the introduction of numerous constraints due to the various parameters that need to be considered. Employing a series of metaheuristic algorithms can be a viable solution to this complexity.

2.3 Fuel consumption in mining trucks

2.3.1 Fuel consumption

The International Energy Agency (IEA) outlined an industry carbon budget in 2014, which requires mining companies, similar to those in other industries, to achieve a 58% reduction in emissions by 2050 compared to their 2010 levels (Rocky Mountain Institute, 2019). However, meeting this emission reduction target is challenging due to the expected increase in mineral demand, coupled with the growing difficulty of mining. The demand for minerals is being fuelled by factors such as a rising global population, increasing average wealth, and a shift toward low-carbon technologies like wind turbines, electric vehicles (EVs), and solar panels. In addition, mining companies typically extract easier-to-mine and higher-grade ores first, resulting in decreasing head grades and yields, and hence, requiring a larger tonnage to be moved over longer distances (Rocky Mountain Institute, 2019). According to the RMI globally, there are approximately 28,000 large mine hauling trucks currently in operation, which are predominantly powered by diesel. These haulers consume an average of 900,000 Liters of diesel per year and account for 30% to 50% of their mines' total energy consumption. The collective emissions of these mining trucks result in 68 million tons of CO_2 ($MtCO_2$) being released annually, equivalent to the entire greenhouse gas footprint of Finland or New Zealand. Despite the advantages of low capital expenditure, flexibility, and a well-established supply chain, diesel haulers present long-term risks, including the emission of various pollutants and susceptibility to diesel fuel price volatility. A higher efficiency can prevent millions of tons of CO_2 entering the atmosphere. A higher efficiency in mining trucks even if they ever switch to renewables like electric or hydrogen powered mining trucks will still be very beneficial. A volatile diesel price like we have seen the last couple years can also have great impact on the operational costs as diesel accounts according to literature for around 50% of the operation costs in an open pit mine, (Zhang et al. 2022, Subtil et al. 2011).

The study of vehicle fuel consumption and emissions has been a popular research topic, and various energy usage models for vehicles have been developed in the past. Heavy-duty vehicles differ significantly from light-duty vehicles in terms of engine performance, aerodynamic drag coefficient, power-to-weight ratio, and tire characteristics. Therefore, they require a different set of parameters for precise modelling Hunt et al. 2011. Mining vehicles are designed to operate at low speeds, with blocky shapes that lack aerodynamic features and contribute to increased air resistance. As mining trucks carry enormous loads, rolling resistance has a more significant impact on their fuel consumption than air resistance. Factors such as payload, road conditions, and tire pressure are crucial parameters that influence fuel consumption in mining vehicles. In the guidelines of mine haul road design by Tannant & Regensburg (2001), all the important parameters on rolling resistance on haul road are shown. Tannant & Regensburg point out that a higher rolling resistance result is a lower overall speed, which directly results in a lower production, another factor which influence the economics of the mine is the fact that lower speeds result in a lower gear shift which consumes more fuel over the same distance. A study by Algere et al. (2021) showed that the rolling resistance can be back-calculated from truck dispatch data. The rolling resistance was calculated with the truck specific speed–Rimpull–gradeability curve on road segments with a continual grade profile. Another method is using the cooper's equations developed by cooper in 2008. The two methods show good results, the performance of trucks is greatly influenced by the condition of haul roads. Having a real-time indication of haul road conditions can result in significant economic benefits by maintaining consistent production and minimizing fuel consumption, without requiring excessive maintenance.

According to a study conducted by Soofastaei et al. 2016, the fuel consumption of haul trucks is determined by various parameters, which have been classified into the following main groups: Fleet management, mine planning, modern technology, haul roads, design, weather conditions and fuel quality. The most significant parameters that impact energy consumption are payload, speed, and Total resistance. The study investigated the optimal payload for minimum diesel consumption and the best truck ratio (BTR) for a fixed production of 20 million tonnes of material moved. BTR is defined as the ratio of actual energy consumed to the theoretical best use of energy by haul trucks. Furthermore, the study revealed that the truck model and the condition of the haul road also influence BTR and fuel consumption. The total resistance is the sum of the rolling resistance and the grade resistance. Where the grade resistance is the resistance against gravity as the hauled material usually has to be transported up to the surface. The rolling resistance is composed of several factors like road condition, tyre pressure, current precipitation etc. A complete list is shown in the appendix. Another study that predicts fuel consumption was done by Siami-Irdemoosa and Dindarloo (2015). The study focused on two input parameters, namely payload and stage within a cycle time, which consists of five stages: loading time (LT), idled while loaded (LS), loaded travel time (LTR), empty travel time (ETR), and idled while empty (ES). To predict fuel consumption for one cycle, an artificial neural network was developed utilizing these six parameters. The results of the study indicate that empty idle time (ES) of trucks is a major contributor to unnecessary fuel consumption in surface mines. Other studies have also demonstrated the negative impact of ES on production rates in mining. Therefore, it is important to implement proper remedies to reduce the negative effects of ES on both production and energy consumption. Another study by Wang et al. 2021 on fuel consumption concluded that fuel consumption during queueing cannot be ignored. This study utilizes a truck dispatching system to introduce a highly accurate volumetric fuel consumption meter that enables the precise measurement of real-time and cumulative fuel consumption for open-pit mine trucks. In order to improve the accuracy of the fuel consumption pattern and prediction model, a multi-dimensional mine truck fuel consumption database was constructed, taking into consideration the aspects of road design, mine truck status, and personnel operation. Regression analysis was employed to explore the fuel consumption pattern for multi-dimensional features. Another observation by Wang et al 2021 which was also shown in Soofastaei et al. 2016 is that different mining trucks have different fuel consumption indexes which all have a different optimal payload and speed. This often lacking in the literature because homogeneous fleet are used. According to Bajany 2017 When dealing with trucks and shovels of varying transportation and capacity, differences in power, traction, and inter-truck time can arise within a fixed period. In mines these variations in inter-truck time affect the shovels' utilization time and consequently, their fuel consumption. Additionally, a truck's loading time is directly proportional to its capacity and the shovel's capacity, leading to fuel consumption that is a function of the loader's capacity when loaded. Therefore, in the case of a fleet with diverse equipment, technical specifications must be considered when optimizing haulage operations in open-pit mines. Also shown in the study by Soofasteai, Vehicles exhibit varying performance levels in terms of fuel consumption, depending on their payload ratios and weight ratio, which is the GWV (Gross Vehicle Weight) divided by the payload. Another study by Soofasteai et al. 2016 show that payload variance has significant impact on production and fuel consumption. Loading is a stochastic process and is influenced by factors as bench geology, blast design, muck pile fragmentation, operator efficiency, weather conditions, utilization of trucks and shovels, mine planning, and equipment selection. To load a truck effectively, the shovel operator must aim for an optimal payload. This optimal payload is defined in different ways but always aims to maximize the amount of material carried by the haul truck while minimizing payload variance. The range of payload variance is determined by the truck's capacity and power, and it greatly affects productivity in large surface mines due to long distances which the mining trucks have to travel, this is referred to as truck bunching and can decrease production and fuel efficiency drastically. Based on the findings of Soofateai et al. (2016), there is a significant increase in fuel consumption when comparing 0 standard deviations (std) to 30 std, which results in a 260% increase in L/(h*ton). While these are the two extreme points on the charts, even a moderate increase from 5 σ to 10 σ results in a 17% increase in fuel consumption.

In a paper by Alamdari et al. in 2022, a comparative analysis of five different machine learning techniques to determine the most effective method for predicting fuel consumption was made. The techniques evaluated included multiple linear regression (MLR), random forest (RF), support vector machine (SVM), artificial neural network (ANN), and kernel nearest neighbour (KNN).

The researchers found that all the tested techniques yielded r^2 values ranging from 0.8 to 0.9, indicating their suitability for fuel consumption prediction. Among these techniques, MLR showed the lowest correlation of 80% with the following formula:

$$fuel\ conompution\ index\ \left(\frac{L}{h}\right) = 11.112 + 1.111 * P + 0.728 * s + 7.10 * TR$$

Equation 1: MLR of fuel consumption index

Where:

P = payload (ton)

s = speed (km/h)

TR = Total resistance (%)

The best correlation was produced by the ANN, which achieved a 90% correlation and was configured with one hidden layer consisting of 20 nodes.

2.3.2 Gap analysis: fuel consumption

Predicting fuel consumption using machine learning algorithms such as Multi Linear Regression (MLR), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN) has demonstrated promising results. However, there is a noticeable gap in the literature regarding practical implementation strategies. Additionally, mining companies often make substantial capital investments in procuring mining equipment, which makes replacing or upgrading equipment an impractical solution in the near term. One of the most effective and easily implementable strategies for reducing fuel consumption is minimizing idle time of the equipment. Furthermore, an Artificial Neural Network (ANN) approach, as suggested by Soofesteai, can be integrated into both the upper and lower stages of dispatch planning to optimize fuel consumption. This approach can be particularly beneficial in ensuring more sustainable and cost-effective mining operations.

2.4 Rolling resistance

The literature on the relation between rolling resistance and speeds in sometime a little bit controversial. According to Świeczko-Żurek et al. (2017) the force of rolling resistance is the coefficient of rolling resistance times the vertical load. Laboratory measurements by ISO standards have resulted that the C_{rr} is constant with the increase of velocity within normal operation ranges. The same conclusion was found by a study from Taghavifar & Mardani in 2013 where five different vertical loads were tested at 3 different inflation pressures. A literature study done by Ydrefors et al. (2021) calls a lack of harmony in the rolling resistance research. According to this study, "When driving at lower or moderate speeds and suddenly accelerating, you might notice that your tires experience more energy loss (known as hysteresis loss) and increased resistance when rolling. This is because, at slower speeds, the tires tend to deform more, and a sudden speed increase doesn't let them adapt immediately. However, when you pick up speed. The tires heat up due to the increased spinning forces and become less flexible. This, surprisingly, helps counteract the energy loss and resistance. So, in most cases, you'll find that your overall rolling resistance slightly increases as you speed up. But in some situations, especially after the tires have warmed up, you might experience a slight decrease in resistance. It should be noted that the findings from the aforementioned studies may not be directly applicable to mining contexts, given the distinct differences in road conditions and payload characteristics. Adair et al. (2015) observed a clear linear relationship between the coefficient of rolling resistance (C_{rr}) and speed in a mining environment. Nonetheless, the increase from low to very high operational speeds results in only a slight change in the C_{rr}. The variability in calculating rolling resistance in a typical mining setting can eclipse the linear growth associated with increasing speeds, which might account for the discrepancies in the literature's interpretations.

2.5 Research gap:

The first gap identified in the literature is the lack of concrete results showing the effectiveness of minimizing fuel consumption in dispatch strategies in open-pit mines. While previous studies have touched on the option to minimize fuel consumption, most of these optimizations prioritize production, and there is a lack of literature providing concrete evidence of the effectiveness of prioritizing fuel consumption.

The second gap is the lack of solutions for real-time dispatch problems that considering fuel consumption. While there are many studies focused on fuel consumption in open-pit mines, there are few that provide solutions to tackle the real-time dispatch problem while also minimizing fuel consumption.

Finally, while one study found an optimal dispatch strategy with fuel consumption as a mean priority, the fuel consumption was simplified, and the trucks were only modelled with three stages: full, empty, and idle. This oversimplification limits the applicability of the study to real-world scenarios where fuel consumption may be more complex. Thus, there is a gap in the literature for more accurate and practical modelling of fuel consumption in dispatch strategies in open-pit mines.

3 Methodology

After establishing the theoretical framework and reviewing relevant literature in the previous sections, this chapter now turns its attention to the methodology employed to address the research questions posed.

3.1 Research Design:

In this research, the selected design can be characterized as computer-simulation experiment, focusing on the investigation of dispatch strategies to minimize fuel consumption in truck and haul mining operations by optimizing truck speeds to reduce idle time, trucks that are blocked during travel and queues at dumps and loaders.

The motivation behind this research is to address the substantial fuel consumption associated with mining truck operations. Reducing fuel usage not only presents an opportunity for cost savings but also contributes significantly to the reduction of carbon emissions, thus aligning with sustainability objectives.

3.2 Data Collection:

Data collection relies on information sourced from Haulsim, a specialized mining simulation tool. Haulsim boasts an extensive library of truck and loader options that can be readily incorporated into simulations. Furthermore, it comes equipped with pre-defined variable parameters such as loading time, spotting time, and dumping time which can be adjusted accordingly. Additionally, the software takes into account the significant influence of engine power concerning payload and the type of terrain encountered, thereby dynamically adapting vehicle speed to real-life conditions. Haulsim generates structured Excel files, documenting every action within mining operations. Notably, this data lacks location-based information regarding truck positions on the mine road. To enhance data usability, Python is employed for data processing, Python, is a versatile and widely used programming language and serves as the linchpin of our data processing. Known for its simplicity, readability, and robust data manipulation capabilities, Python is an ideal choice for handling complex data tasks. In the realm of advanced data analysis and machine learning, we harness the power of TensorFlow, an open-source library developed by Google. TensorFlow's flexibility and scalability are instrumental in our research, particularly in the application of Artificial Neural Networks (ANN) to model complex data relationships. Additionally, we explore metaheuristics, a class of optimization algorithms, within the Python ecosystem. Python's extensive libraries and packages make it conducive for implementing and experimenting with metaheuristic algorithms. These metaheuristics aid in optimizing mining truck speed strategies, contributing to the depth and breadth of our research analysis.

3.3 Data Source

For this research, we rely on a synthetic dataset from Haulsim, a specialized mining simulation tool. A mining site was replicated to collect data and test the hypotheses. The mine was simplified to reduce the noise that was provided in the data. The mine features two source points and two destination points. We've chosen this tool because it suits our research's specific focus on analysing truck speeds within mining operations.

3.3.1 Haulsim Features

Haulsim offers an extensive library of mining trucks and loaders that can be easily integrated into simulations. It comes with predefined variable parameters like loading time, spotting time, and dumping time, which we can adjust to match specific operational conditions. Haulsim also accounts for the significant influence of engine power, payload capacity, and terrain type, allowing it to dynamically adapt vehicle speeds to mimic real-life scenarios. It's worth noting that Haulsim generates structured Excel files that document every action within mining operations. However, these files lack location-based data regarding truck positions on the mine road.

3.3.2 Data Collection Methods

Haulsim operates as a discrete event simulation, providing a robust mining environment. This simulation tool's versatility allows us to accelerate time, condensing an 8-hour shift into just 3 seconds of simulation. Importantly, Haulsim provides accessible reports on key parameters, such as material movement, haul and loading states, and loader or truck utilization percentages, all without requiring us to download the entire dataset. However, for more in-depth analysis, the raw data can be extracted into an Excel or CSV file for further processing.

3.3.3 Data Variables

Mining software involves numerous variables. In this research, our focus centres on the choice of mining trucks. Specifically, we've opted for the CAT 793F as our truck model. This choice aligns with the widespread use of the CAT 793F in Australian mining operations, a fact well-documented in fuel consumption literature. To ensure accurate fuel consumption calculations, we've selected the same truck models used in these studies. Additionally, the compatibility of the chosen truck model with loaders and its ability to meet the ideal 3 to 5 passes for full loading, as recommended by the SME Mining Handbook, led us to select the CAT back shovel 6060 as the loader model. These initial details provide insight into our data collection process, highlighting Haulsim's capabilities and explaining the reasoning behind our choice of truck and loader models.

In this study, Haulsim incorporates preconfigured dump and load parameters for every truck and loader. The default settings, as provided below, were employed in this research:

Furthermore, Haulsim offers the flexibility to adjust the distribution characteristics, including options such as right-skewed, left-skewed, normal, or uniform distributions. Additionally, users can modify the spread, minimum, and maximum values to simulate various scenarios. For this thesis, we made slight adjustments to the spot time for loading and dumping to explore their potential impacts. Additionally, we examined a scenario where large dump time could lead to queues at the dumping sites. But this had little effect on the performance of the mine or the bunching of the trucks. The default settings for the loaders were used.

Figure 1: Variables for each type of truck

The snapshot below displays the raw data generated by the HaulSim simulation software. While HaulSim produces additional raw data in other sheets, these are not utilized in this thesis. Specifically, the relevant data is extracted from the 'equipment state' sheet. It's worth noting that there are several other columns in the raw data, such as operation cost, electricity cost, TKPH, etc., but these variables are not considered in this thesis. Furthermore, the fuel burn columns are excluded from the analysis because HaulSim provides either a fixed fuel consumption value in liters per hour or a linear value in liters per hour determined by the payload. Given the primary focus of this thesis on vehicle speed, these values are considered nonessential and including them in the analysis would result in overestimating fuel consumption, especially since the trucks are operating for longer durations.

Simulation Time (min)	Equipment Class	Equipment	Current Location	Travelling To	State	Time Usage	Elapsed Time (min	Distance Travelled (km)	Average Speed (km/h)	Quantity (t)	Material
0	Truck	Truck 01	Road Network	Source 01	Idle	Operating Shift Delay	1,5	0	0	0	
1,5	Truck	Truck 01	Source 01		Travel Empty	Operating	12,69	9,01	42,6	0	
14,19	Truck	Truck 01	Source 01		Spotting At Loader	Operating	0,41	0,05	8	0	
14,6	Truck	Truck 01	Source 01		Loading	Operating	3,08	0	0	0	
17,68	Truck	Truck 01	Road Network	Destination 01	Travel Loaded	Operating	4,62	2,1	27,25	0	
22,3	Truck	Truck 01	Road Network	Destination 01	Travel Loaded Blocke	Operating Shift Delay	1,53	0,31	11,99	0	
23,83	Truck	Truck 01	Road Network	Destination 01	Travel Loaded	Operating	0,89	0,18	12,35	0	
24,71	Truck	Truck 01	Road Network	Destination 01	Travel Loaded Blocke	Operating Shift Delay	1,38	0,28	12,32	0	
26,09	Truck	Truck 01	Road Network	Destination 01	Travel Loaded	Operating	0,08	0,02	12,47	0	
26,17	Truck	Truck 01	Road Network	Destination 01	Travel Loaded Blocke	Operating Shift Delay	0,1	0,02	12,02	0	
26,27	Truck	Truck 01	Road Network	Destination 01	Travel Loaded	Operating	0,79	0,16	12,35	0	
27,06	Truck	Truck 01	Road Network	Destination 01	Travel Loaded Blocke	Operating Shift Delay	1,32	0,27	12,32	0	
28,38	Truck	Truck 01	Road Network	Destination 01	Travel Loaded	Operating	0,08	0,02	12,46	0	
28,45	Truck	Truck 01	Road Network	Destination 01	Travel Loaded Blocke	Operating Shift Delay	0,1	0,02	12,02	0	
28,55	Truck	Truck 01	Road Network	Destination 01	Travel Loaded	Operating	0,73	0,15	12,35	0	
29,29	Truck	Truck 01	Road Network	Destination 01	Travel Loaded Blocke	Operating Shift Delay	1,17	0,24	12,34	0	
30,46	Truck	Truck 01	Destination 01		Travel Loaded	Operating	4,65	2,89	37,23	0	
35,11	Truck	Truck 01	Destination 01		Spotting At Dump	Operating	0,31	0,03	6,15	0	
35,42	Truck	Truck 01	Destination 01		Unloading	Operating	0,2	0	0	218,41	Copper Ore
35,62	Truck	Truck 01	Source 01		Travel Empty	Operating	9,9	6,56	39,75	0	
45,52	Truck	Truck 01	Source 01		Queued at Loader	Operating Shift Delay	1,48	0	0	0	
47	Truck	Truck 01	Source 01		Spotting At Loader	Operating	0,41	0,05	8	0	
47,41	Truck	Truck 01	Source 01		Loading	Operating	2,98	0	0	0	
50,38	Truck	Truck 01	Road Network	Destination 01	Travel Loaded	Operating	17,43	6,65	22,9	0	
67,81	Truck	Truck 01	Destination 01		Spotting At Dump	Operating	0,31	0,03	6,15	0	
68,12	Truck	Truck 01	Destination 01		Unloading	Operating	0,2	0	0	224,87	Copper Ore
68,32	Truck	Truck 01	Source 01		Travel Empty	Operating	9,9	6,56	39,75	0	
78,22	Truck	Truck 01	Source 01		Queued at Loader	Operating Shift Delay	1,34	0	0	0	
79,57	Truck	Truck 01	Source 01		Spotting At Loader	Operating	0,41	0,05	8	0	
79,98	Truck	Truck 01	Source 01		Loading	Operating	3,03	0	0	0	
83	Truck	Truck 01	Road Network	Destination 01	Travel Loaded	Operating	16,68	6,65	23,93	0	
99,69	Truck	Truck 01	Destination 01		Spotting At Dump	Operating	0,31	0,03	6,15	0	
99,99	Truck	Truck 01	Destination 01		Unloading	Operating	0,2	0	0	210,24	Copper Ore
100,19	Truck	Truck 01	Source 01		Travel Empty	Operating	9,9	6,56	39,75	0	
110,1	Truck	Truck 01	Source 01		Queued at Loader	Operating Shift Delay	2,52	0	0	0	
112,61	Truck	Truck 01	Source 01		Spotting At Loader	Operating	0,41	0,05	8	0	
113,02	Truck	Truck 01	Source 01		Loading	Operating	2,98	0	0	0	
116	Truck	Truck 01	Road Network	Destination 01	Travel Loaded	Operating	17,44	6,65	22,9	0	
133,43	Truck	Truck 01	Destination 01		Spotting At Dump	Operating	0,31	0,03	6,15	0	

Figure 2: A snapshot of how the data is structured.

3.4 Haulsim mining layout

In the figure shown below, the locations of the sources, destination (dump site), and ancillary facilities are illustrated. To ensure simplicity and accurate routing of trucks, trucks from Source 01 are directed to Destination 01, while trucks from Source 02 are routed to Destination 02. The optimal cycle time for Source 01 to Destination 01 is 30.56 minutes with a standard deviation of 0.99, and for Source 02 to Destination 02, it is 41.62 minutes with a standard deviation of 0.94. This calculation is based on the maximum allowed speed without any other trucks causing queues or bunching. The results will be discussed in greater detail, elaborating on these values. Nevertheless, due to deviations in cycle times, a greater number of trucks are choosing Route 4 to balance the utilization of both loaders.

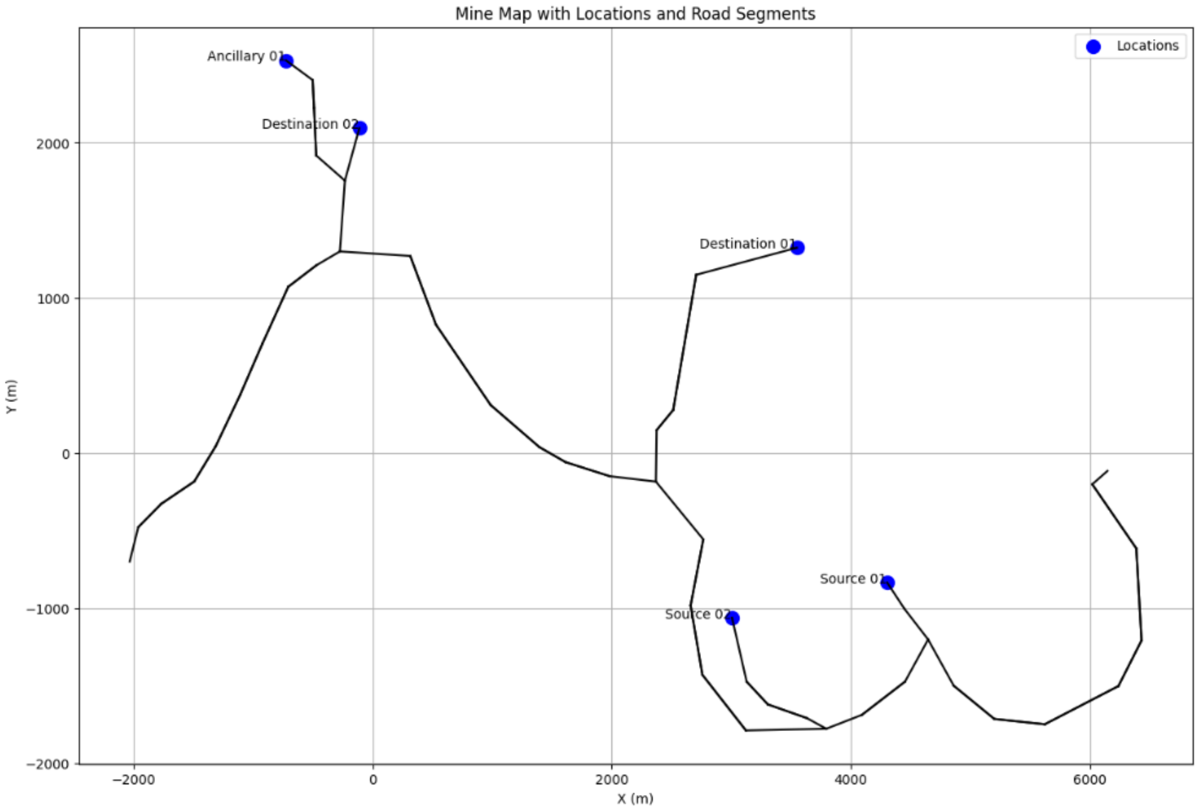


Figure 3: Top view of mine layout

The simulation model utilizes the CAT 793F truck for several reasons. This choice is based on its widespread use in the mining industry and its prominent presence in fuel consumption literature. Opting for this particular truck ensures the closest alignment with real-world calculations. Some of the literature refers to the CAT 793D model. In the interest of simplification for this thesis, trucks are regarded as homogenous entities. The CAT 793F/D, which represents the subsequent model in the CAT 793 series, boasts a marginally larger engine capacity and enhanced capability to operate under more adverse conditions.

The CAT 793F truck has a nominal payload capacity ranging between 218 and 240 tons, with a mean of 225 tons. The net engine power, as cataloged by HaulSim, is 1848 kW. The operational speeds, contingent upon payload and weight considerations, are determined by the rimpull curve specific to this truck, as illustrated in the figure below. It's worth noting that manually interpreting a rimpull curve can introduce a margin of error of a few kilometres per hour. In Appendix, we provide a code that offers a more precise estimation for uphill scenarios.

For instance, with a rolling resistance (RR) value of 2, a grade resistance (GR) of 10, and a maximum payload resulting in a gross weight vehicle (GWV) of 385 tons, the calculated velocity is 12 km/h.

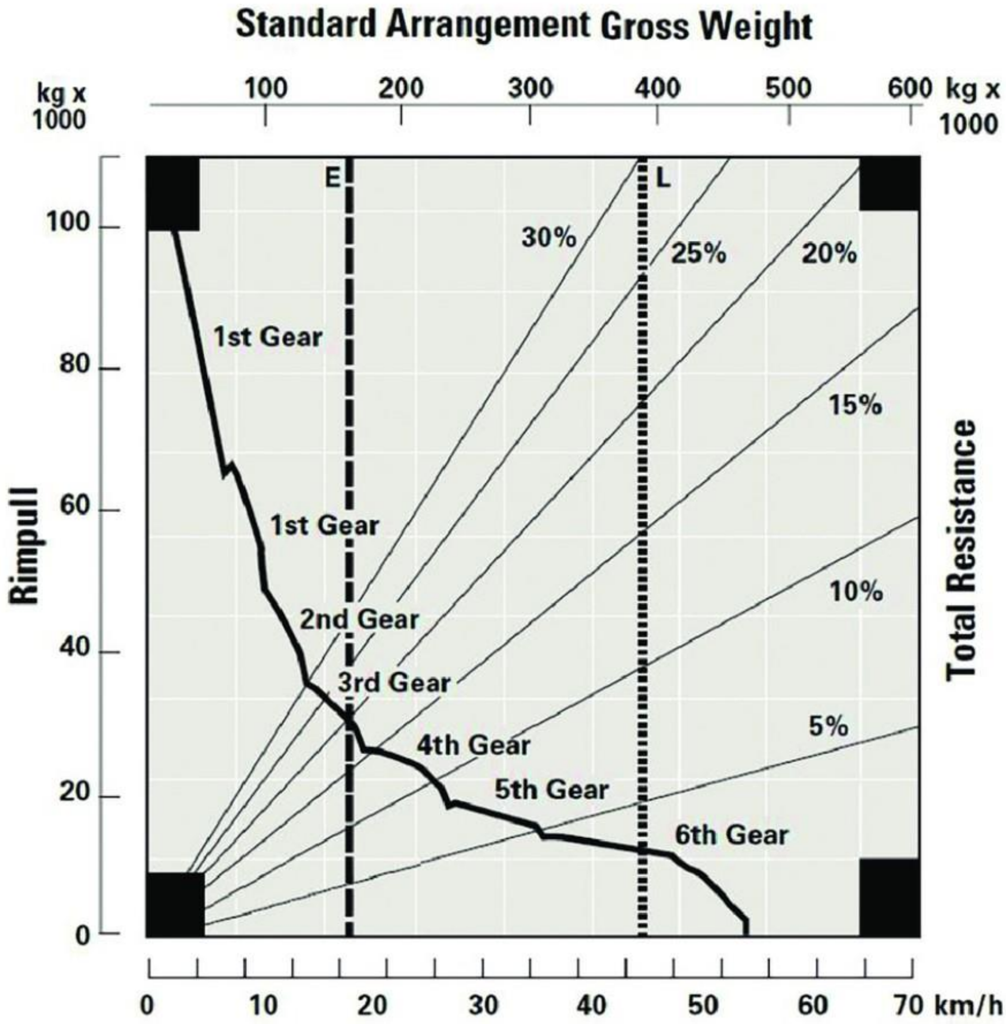


Figure 4: Rimpull curve CAT793D (Soofastaei, 2018)

The selected loader type is the CAT 6060 backhoe shovel. According to the HaulSim library, the mean payload per fill is 45 tons, with 5% variation. This payload capacity implies that all trucks can be efficiently loaded in 5 passes, which falls within the ideal range of 3 to 5 passes as recommended by the SME mining handbook (Darling, 2011).

Additionally, it's worth noting that operating at the upper end of this pass spectrum may result in slightly longer loading times. This aspect is particularly valuable for demonstrating the effectiveness of the speed optimization approach, as it could potentially lead to larger queues at the loader due to the extended loading duration.

Figure 5: CAT793F source: CAT

Figure 6: CAT 6060 backhoe shovel source: CAT

3.4.1 The road network

The road network utilized in this study has been adapted and simplified from a mining site located in the United States. The road network data extracted from Haulsim requires preprocessing. The roads are initially represented as discrete points rather than continuous lines. To address this, a Python-based processing method was applied to transform these points into road segments which are subsequently employed in subsequent calculations. The figure below illustrates the route layout of the mine. Within this network, there are 8 distinct routes identified, with 6 of them being unique, while the remaining 2 are simply the reverse of these unique routes. For clarity, we focus on the 6 unique routes below.

During each shift, Routes 1, 2, 5, and 6 are exclusively employed at the start and end of a shift, most vehicle movement occurs along Routes 3 and 4. These two routes share a segment, which is further divided into 5 subsegments, spanning a total distance of 2.62 kilometres. Within these segments, Routes 3 and 4 converge, prohibiting overtaking and presenting a significant operational challenge in this specific case.

Furthermore, the image below depicts the mine's topography, where different colours indicate varying grades, ranging from a minimum of 0.0% to a maximum of approximately 11%.

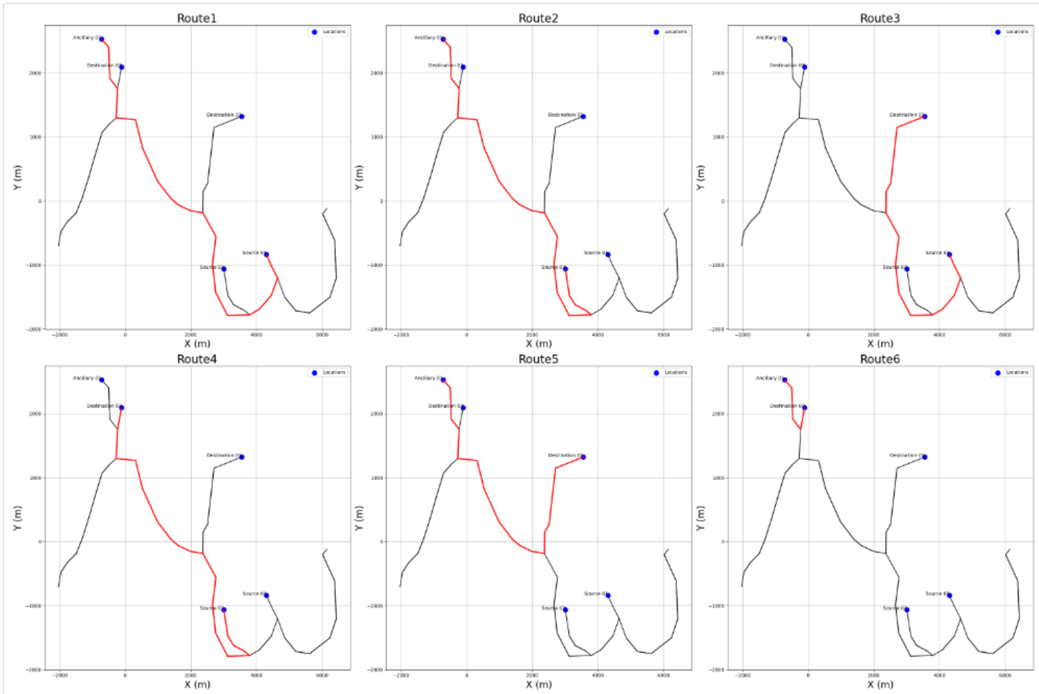


Figure 7: Routes in the case study mine

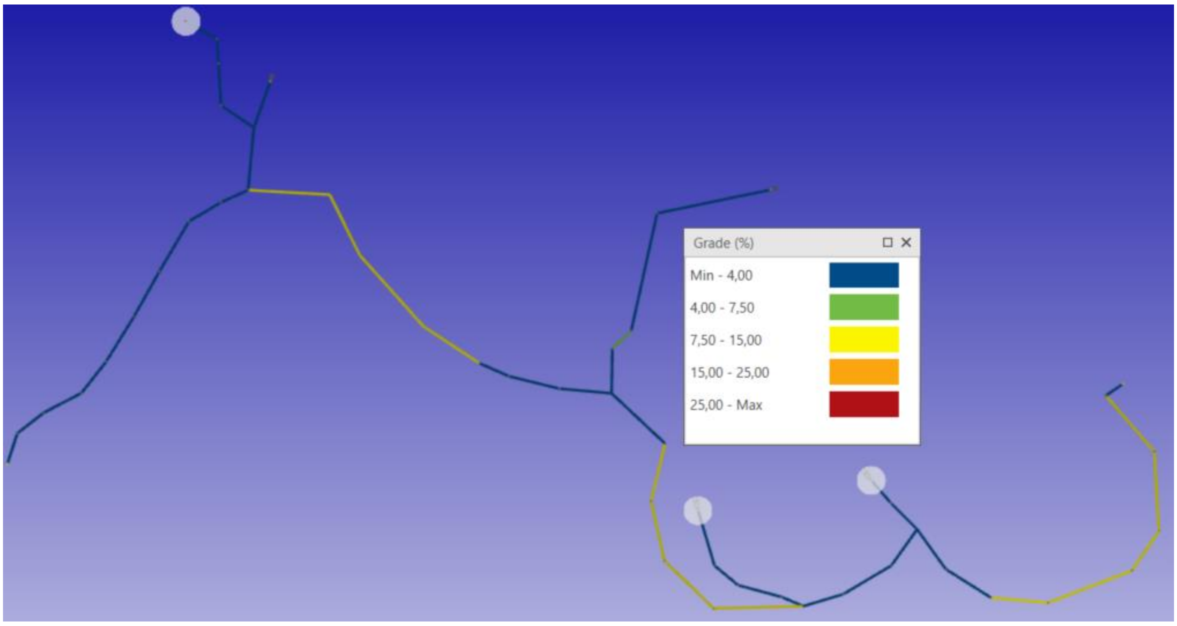


Figure 8: Road grades in in the case study mine

3.5 Data processing

In the Haulsim simulation, a maximum of three trucks is allowed to stand in queue at any given time. Trucks that exceed this limit are flagged by the simulation as 'Travel Empty Blocked,' as illustrated in the figure below.

The appendix contains code that modifies the state of trucks based on three conditions being met: 'state' equal to 'Travel Empty Blocked,' 'Elapsed Time (min)' being longer than 3 minutes, and 'Distance Travelled (km)' being less than 0.3. These three conditions are carefully combined to ensure that the state change is intentional and not accidental.

The state of 'Travel Blocked' can be somewhat confusing because the loaders are not entirely stationary; they do cover distance, but at a slower pace than their maximum speed.

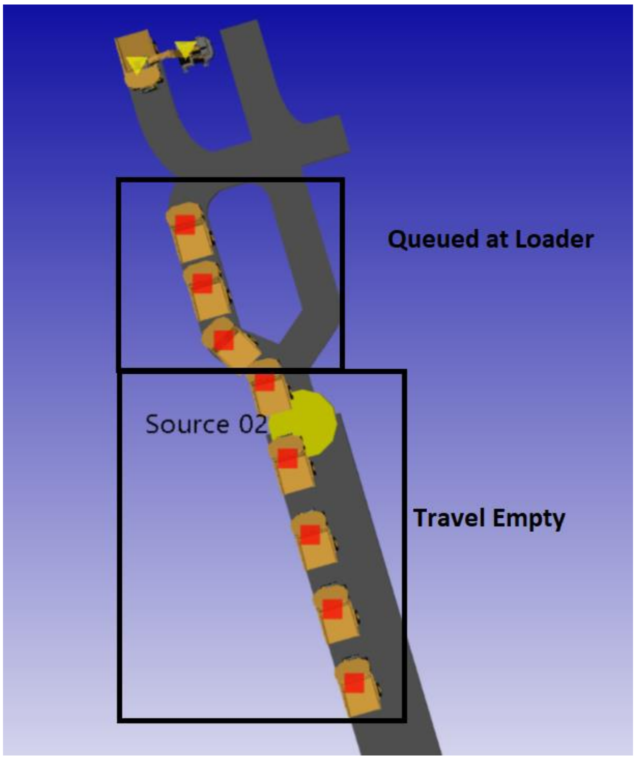


Figure 9: In Haulsim queued trucks.

After changing the state that were misidentified, the data can be inspected with the code from Appendix. The results are shown below in Figure:

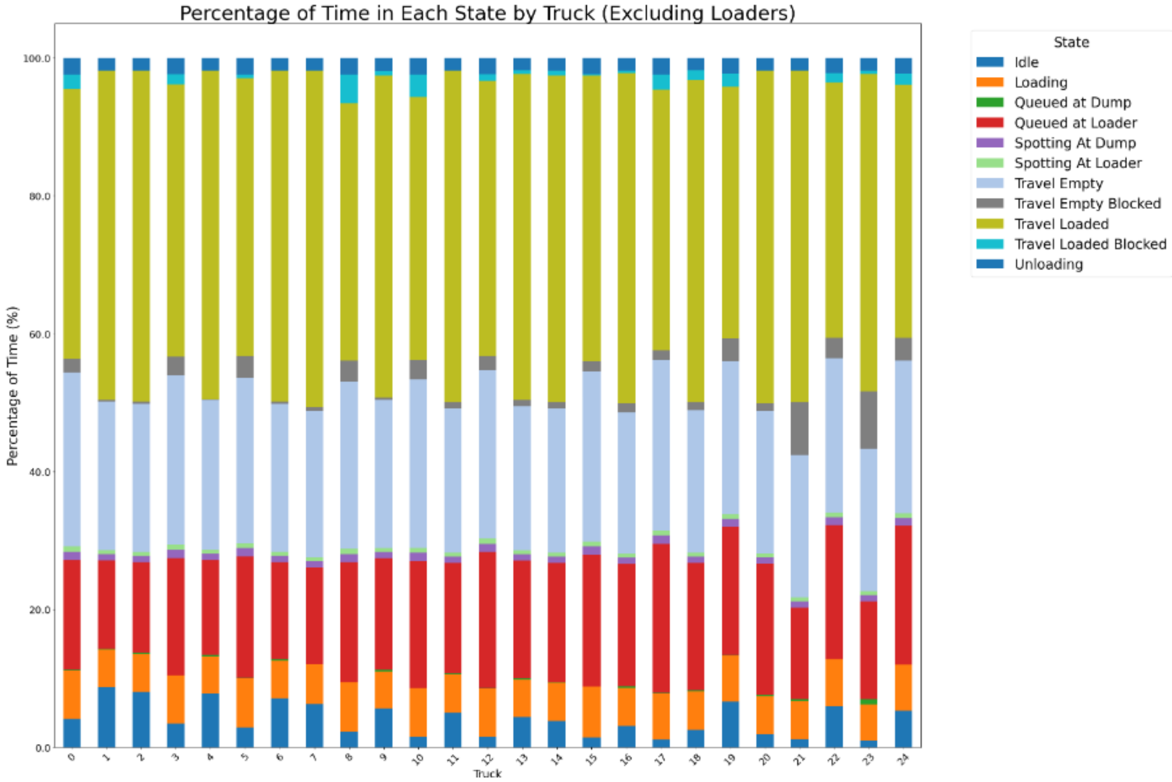


Figure 10: Example of the percentage of time spent by trucks in a particular state.

The states of particular interest for optimization are "Queued at Loader" and "Idle Time." In certain mining operations, similar optimization principles can be applied to "Queued at Dump," but in this particular case, reducing loaded truck speeds without compromising production efficiency is unfeasible. This limitation arises from the characteristics of this mine, where loaded trucks can only operate at approximately one-third of the speed of empty vehicles.

The maximum speed of a truck is determined by its rimpull curve, which factors in variables such as the grade, rolling resistance, and gross weight of the vehicle (GWV) to determine the speed at which a specific truck can effectively operate. Due to the combination of high payload and steep grades, loaded trucks inherently operate at slower speeds. This, coupled with the extended loading time compared to unloading, leads to more frequent instances of queuing at the loader rather than at the dump site.

Some portion of the observed idle time is attributed to the first truck of a shift completing its task, but it's worth noting that in a real-world, non-simulated environment, this would not contribute significantly to idle time beyond the initial shift transition.

The raw data is subjected to processing to distinguish between loaded and empty runs of the trucks, accounting for loading and unloading activities during the transitions between these phases. Within these runs, the optimal speed of a truck is already determined through the following formula:

$$Best\ case\ speed\ \left(\frac{km}{h}\right) = \frac{Distance\ (km)}{(Original\ travel\ time + queue\ time + idle\ time)\ (min)} * 60$$

Equation 2: Best case speed

Importantly, this best-case speed calculation considers only the current run and does not factor in the presence of other trucks following behind.

To maintain consistent production levels, only the truck speed between the loading and unloading phases is taken into consideration. This approach ensures that production remains unaffected by trailing vehicles. It's worth noting that simulation results cannot be applied back to HaulSim. Consequently, any modifications to dump and loading times will yield unpredictable outcomes that cannot be verified.

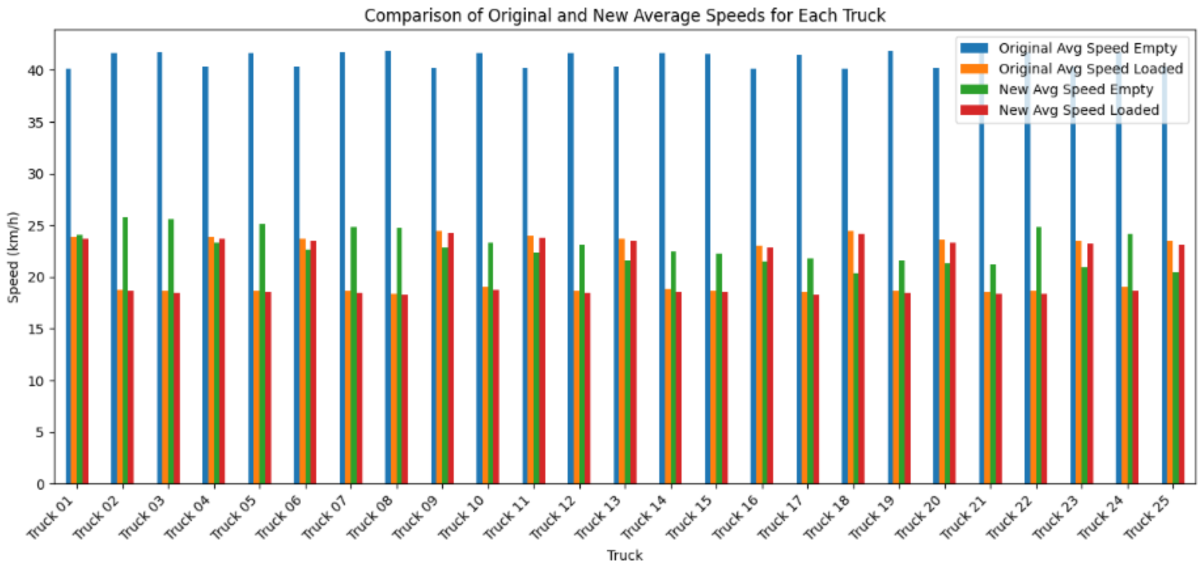


Figure 11: Example of difference in speeds between original speed and best case

The base case has been established through the HaulSim simulation, and the best-case scenario has already been computed. Both scenarios yield identical production within the same time frame. However, the key distinction between the two scenarios lies in the truck speed and the subsequent consequences, such as idle times and queue durations.

The raw data undergoes a division into loaded and empty runs, with the loading and unloading phases serving as the distinguishing markers. This division is crucial to ensure that the relevant parameters align accurately with each stage of the truck's journey.

After the initial data processing steps, the resulting dataframes comprise the following columns:

- Truck ID: Uniquely identifies each truck.
- Run: Tracks and enumerates the individual runs for each truck.
- simtime_start: Marks the departure moment from the unloading point for empty trucks.
- Unloading Time (min): Records the duration of the unloading process just before the truck starts its journey.
- simtime_end: Indicates the moment when the truck is in the process of being loaded.
- Weight: Specifies the weight of the truck, including an additional quantity (in tons) for loaded trucks.
- Distance (km): Logs the distance covered during that particular run.
- Original Speed (km/h): Captures the average speed of trucks in the initial solutions.
- Slowest Possible Speed (km/h): Pinpoints the lowest attainable speeds that still guarantee production requirements are met.

In the second stage of data processing, after inspecting the road segments and shared segments, new columns are appended to the dataset. Most of this additional data is route-specific and serves to identify the operational characteristics of the trucks. The columns are crucial for the optimization of the trucks. The python code of all the extra columns added to the data frame are detailed in Appendix and include:

- Arrive at Loader (min): Specifies the time at which the truck arrives at the loader.
- Route: Indicates the current route in which the truck is operating.
- Pattern: Represents the pattern of routes followed by the truck during its operation.
- Arrival time (shared zone): Records the expected arrival time of the truck at the shared zone.
- Departure time (shared zone): Documents the departure time from the shared zone.
- on_road_trucks: Quantifies the number of trucks traveling in the same direction as the truck in question, located ahead of it as it initiates its run.
- on_road_trucks_same_route: Specifies the count of trucks traveling in the same direction, operating on the same route, and positioned ahead of the truck as it commences its run.

3.6 Limitation

HaulSim stands as a powerful mining software with a wide array of capabilities. Mining companies have the option to integrate their own data into the software, encompassing elements such as topology, road networks, schedules, and fleets. However, generating certain aspects from scratch can introduce uncertainties when attempting to translate them into real-life scenarios. It's important to note that HaulSim has limitations in handling location data. Stationary locations are assigned initial coordinates, and while the road network is location-based, the precise tracking of truck locations during their travel on the road network is not supported within the raw data.

Due to this limitation, only average truck speeds are utilized for analysis. Moreover, the varying length of road segments, with differences often in the order of tens of meters, poses challenges in data interpretation, and even minor errors can lead to significant deviations. To address this, hard-coded distances were implemented to delineate the shared zone of route 3 & 4. However, this approach comes with complexities, especially when trucks are in close proximity, where a mere difference of tens of meters per second can impact the distinction between bunching and smooth operational flow.

3.7 Optimization

Now that the framework is established, it's time to delve into the optimization discussion. As demonstrated earlier, the optimization boundaries are already defined. The upper bound is determined by the data generated by the HaulSim software, while the lower bound corresponds to the best-case scenario. The optimization aims to minimize the collective queue time of all trucks. This approach is grounded in the rationale that if trucks can be held in a queue, they can also operate at reduced speeds, leading to decreased fuel consumption. While the outcome of the optimization is measured in terms of total queue time, it's important to note that the optimization process involves reducing the speed of the trucks. The total queue time is derived by computing 'simtime_end,' which signifies the conclusion of a 'run' and the point when a truck commences loading, and then subtracting the time it takes for the truck to arrive at the loader. The 'simtime_end' for each truck is predetermined and remains unalterable, as any changes to this parameter could potentially disrupt production and would not correlate with the upper and lower bounds of the optimization problem. On the other hand, the truck's arrival at the loader is contingent upon its average driving speed. Slower truck speeds lead to later arrivals at the loader, resulting in a reduced time difference between arrival and 'simtime_end,' ultimately contributing to a shorter queue time.

The upper bound is determined by the HaulSim software, encompassing all the parameters previously discussed. It represents the simulated queue time in the simulation, reflecting the base-case conditions and optimized settings within the given simulation environment. This upper limit serves as a benchmark for evaluating the performance of any alternative scenarios or optimization strategies. In this context, the upper bound is represented by the base case scenario generated by HaulSim. This base case serves as the upper limit because, as we optimize the truck speed – a parameter logically expected to decrease as the goal of the optimization is to minimize total queue time, we refer to the base case as the upper bound.

The lower bound, occasionally described as the slowest speed possible in the python code, represents the minimum speed at which a truck can travel so that as it arrives at the loader, when the loader completes its task with the preceding truck. In such operations, the key bottleneck lies in the loader's performance and utilization. Should the truck speeds drop below the best-case scenario, it would result in underutilized loaders, ultimately leading to a loss in production efficiency.

3.7.1 Bunching

Truck bunching significantly complicates this problem, as it prevents trucks from simply operating at their slowest possible speeds without causing congestion and impeding the overall process. While some trucks may be capable of attaining their best speeds, others must queue strategically to maintain productivity levels and avoid potential bottlenecks. Consequently, assigning an optimal truck speed that prevents bunching becomes the critical constraint in this optimization process.

In this thesis 2 type of bunching are identified:

Type 1 bunching can be described as follows: Each truck possesses both a start time and an arrival time at the loader. It is of utmost significance that when trucks follow the same route, the sequence of their start times mirrors the sequence of their arrival times at the loader. This condition plays a pivotal role in guiding the optimization process towards a more balanced reduction in truck speeds. When the disparities between start times and arrival times become too pronounced, it signifies that trucks are attempting to overtake one another towards the end of their runs.

Type 2 bunching can be described as follows: Initially, all trucks follow a predefined sequence of arrivals. However, due to speed adjustments, this sequence may undergo changes, particularly when trucks are on different routes. In shared road segments where both routes converge and overtaking is prohibited, Type 2 bunching occurs when the sequence of trucks arriving at the shared zone differs from the sequence in which they depart from it, owing to the new assigned speeds. This constraint holds significant influence in steering the optimization process, as a considerable portion of trucks may violate it if random speed assignments are employed.

3.7.2 Pre-optimized adjustments

Trucks within the HaulSim simulation often do not operate at their maximum speeds due to the presence of preceding trucks on the same route, typically occurring within shared zones. In these scenarios, trucks exhibit closely timed arrivals and departures at the shared zones. It's important to note that HaulSim, within the simulation itself, adjusts truck speeds. However, for the purposes of this thesis, only average speeds are considered. Consequently, some trucks are already grouped together in the bunching identification process. For the optimization of the trucks' speed, this is not an issue because the trucks that are behind other trucks will operate at a lower speed, which is what the optimization tries to accomplish.

To resolve this, the algorithm makes an initial adjustment to the truck with the highest index in each identified bunching pair before the primary algorithm begins. This initial adjustment serves the purpose of aligning the starting point of the primary algorithm with the desired direction, effectively addressing the issue of initial bunching pairs to avoid initial penalties.

3.7.3 Metaheuristic

Metaheuristics are advanced optimization algorithms designed to tackle complex problems where conventional methods might not suffice. These high-level, problem-independent strategies guide the search towards optimal or near-optimal solutions. By balancing exploration of the solution space with the refinement of known solutions, metaheuristics can navigate challenges and find solutions that other methods might miss. Their versatility makes them invaluable tools in a wide array of applications, from scheduling to machine learning (Du & Swamy 2016).

One of the standout features of metaheuristics is their generality. Unlike many algorithms that are tailored for specific problems, metaheuristics can be applied to a vast array of optimization challenges. This adaptability is paired with an iterative approach. Typically, these algorithms commence with an initial solution and then, through repeated iterations, refine and enhance the quality of this solution.

A key element in many metaheuristics is their inherent stochastic nature. By incorporating elements of randomness, they can escape the confines of local optima, ensuring a more comprehensive exploration of the solution space. This randomness, however, doesn't mean they operate without direction. On the contrary, they often employ sophisticated strategies to balance exploration which can be seen as searching new areas of the solution space with exploitation as refining known good solutions (Ezugwu et al. 2021).

There are various kind of metaheuristics. Some, like Simulated Annealing and Tabu Search, focus on refining a single solution. Others, such as Genetic Algorithms or Particle Swarm Optimization, operate on a whole population of solutions, enhancing multiple candidates with each iteration (Boussaïd et al. 2013).

While the flexibility and effectiveness of metaheuristics make them a popular choice for many optimization problems, they are not without their challenges. For instance, they don't guarantee an optimal solution, or even the same solution and their performance can sometimes be sensitive to the specific settings of their parameters.

Yet, despite these challenges, the applicability of metaheuristics is vast. From the realms of scheduling tasks in factories to routing data in networks, and even in areas like finance and machine learning, these algorithms have proven their worth time and again. In essence, in the vast landscape of optimization, metaheuristics stand out as versatile and powerful tools, ready to tackle the challenges of today's complex problems.

3.7.4 Simulated annealing

Simulated Annealing (SA) is a stochastic optimization algorithm that draws inspiration from the annealing process in metallurgy, which involves gradual cooling to enhance stability and reduce imperfections. SA combines elements of the Monte Carlo simulation technique and the Metropolis Algorithm (Delahaye et al., 2019). Monte Carlo methods, within the realm of optimization, entail randomly sampling solutions from the solution space and assessing their quality. Meanwhile, the Metropolis algorithm mimics physical annealing and relies on the Metropolis acceptance criterion to determine whether to accept a new state.

$$P(0,1) < e^{-\frac{E_j - E_i}{T}} = e^{\frac{E_i - E_j}{T}}$$

Equation 3: Acceptance criteria Simulated Annealing algorithm.

Where:

P (0,1) = random change between 0 and 1

E_i = energy (or cost) of the current state

E_j = energy (or cost) of the next state

T = temperature

In the Simulated Annealing (SA) algorithm, the exponential function e^x serves as a foundational component guiding the solution acceptance criterion. Notably, this function is always non-negative, with its value at x=0 being 1. When the cost function for the next state is lower, the resulting acceptance probability exceeds one, ensuring that the new state is invariably accepted. Within the SA framework, this exponential curve is instrumental in determining the acceptance probability of a proposed solution. Specifically, if a candidate solution presents a reduced energy level a paramount consideration in optimization contexts it is consistently accepted.

However, when the energy of the new system is higher, the algorithm looks to the temperature parameter. Temperature serves as a measure of the algorithm's willingness to explore less favourable states in the search for the global minimum. As the system temperature remains high, the e^x curve approaches the y-axis, and the likelihood of accepting configurations with higher energy increases.

This characteristic serves as a fundamental feature of SA optimization, and it offers a clear advantage over conventional Monte Carlo simulations. SA performs exceptionally well in navigating complex solution spaces, skillfully avoiding the challenges of local minima. This capability is harnessed by systematically lowering the temperature throughout the optimization process.

3.8 Simulated Annealing optimization.

As explained in the preceding section, SA serves as a potent optimization technique capable of overcoming local minima. This optimization approach is highly suitable for the current thesis because it effectively navigates past local minima by accepting slightly less favourable results. To prevent truck bunching, trucks can be adjusted to operate at slightly higher speeds, which can be accommodated by allowing other trucks to slow down. This strategic approach enables trucks to escape local minima, ultimately leading to a collective reduction in queue times across the system to achieve the optimal total queue time. The whole code of the simulated annealing can be found in the appendix.

The optimization process commences with an initial solution derived from the original speeds obtained from HaulSim. To prevent initial bunching, minor adjustments are applied to selected trucks. The optimization code accommodates several configurable parameters where the first 5 are key to any SA optimization:

- T: The initial temperature of the system.
- T_min: The temperature at which the algorithm terminates.
- alpha: The cooling rate that controls the temperature reduction.
- max_operations: The maximum number of operations allowed within each temperature stage.
- max_solutions: max best solution, (not really needed but algorithm got stuck sometimes)

The cost function in this context of the algorithm calculates the cost associated with a particular set of truck speeds. It quantifies how "good" or "bad" a given solution is in the context of the optimization problem. In this specific case, the cost function is designed to minimize the total queue time of trucks. While it also keeps the trucks from bunching.

Here's a breakdown of the steps involved in the cost function:

1. Adjust truck speeds: It starts by adjusting the speeds of the trucks based on the proposed changes.
2. Calculate adjusted arrival times: Using the adjusted speeds, it calculates the arrival times of each truck at the loading point (loader) after traveling a certain distance.
3. Calculate adjusted arrival times in shared zones: It calculates the arrival times of trucks at shared zones, considering the distances and speeds for each truck. This step also involves taking into account the minimum arrival times for trucks on different routes.
4. Calculate adjusted departure times in shared zones: Similar to the arrival times, it calculates the departure times of trucks from shared zones based on their adjusted speeds.
5. Check for bunching: It identifies two types of bunching scenarios: Type 1 (Loader Sequence) and Type 2 (Shared Zone Sequence). Bunching occurs when trucks on the same route do not follow the same sequence of start times and loader arrival times or when trucks on different routes have different sequences of arrival and departure times at shared zones.
6. Calculate queue times: It computes the queue times for each truck, which is the time spent waiting at the loader before being loaded.
7. Calculate the total queue time: The cost function sums up the queue times of all trucks to obtain the total queue time for the entire system (with penalties if bunching occurs).

With the initial parameters set and the cost function defined, the Simulated Annealing (SA) optimization loop can commence. Within this loop, there are a few additional parameters that warrant a brief introduction. Notably, the line where adjustments are calculated (adjustments = np.random.uniform(-2.5, 0.5, size=5)) determines the specifics of speed adjustments for the trucks, including the range of adjustments (-2.5 to 0.5) and the number of trucks whose speeds are adjusted simultaneously (size=5). These parameters influence the exploration of the solution space and performance during the SA optimization.

1. Initialization:
    - Initialize the current speeds (current_speeds) with the original speeds from the HaulSim data.
    - Set various parameters, including (T), (T_min), (alpha), (max_operations), (max_solutions).
2. Outer Loop (while T > T_min):
    - Continue until the temperature drops below the minimum temperature (T_min).
3. Inner Loop (for i in range(max_operations):
    - Repeat a maximum of max_operations times within each temperature stage.
4. Generate Proposed Speeds:
    - Create a set of proposed_speeds by making random adjustments to a subset of truck speeds from the current speeds (current_speeds).
5. Limit Proposed Speeds:
    - Ensure that the proposed speeds do not go below a certain minimum speed (min_speeds) by taking the maximum between proposed and minimum speeds.
6. Calculate Costs:
    - current_cost: Cost associated with the current truck speeds (current_speeds).
    - proposed_cost: Cost associated with the proposed speeds (proposed_speeds).
7. Calculate Delta:
    - Determine delta as the difference between proposed_cost and current_cost. This represents how much the cost changes with the proposed speed adjustments.
8. Accept or Reject Proposed Solution:
    - Decide whether to accept or reject the proposed speeds based on delta and a random factor (np.random.rand()). If delta is negative (improved solution), it is accepted. Even if delta is positive, there's a chance to accept it probabilistically.
9. Update Best Solution:
    - If the proposed solution is accepted, it becomes the new current solution (current_speeds). If its cost is lower than the best-known cost (best_cost), it becomes the new best solution, and best_speeds is updated accordingly.
10. Stopping Conditions:
    - If the maximum number of improved solutions (max_solutions) is reached, terminate the SA process early.
    - If no more improved solutions can be found within the current temperature stage (i.e., no more accepted solutions with negative delta), reduce the temperature T using the cooling rate alpha, and proceed to the next temperature stage.
11. Repeat:
    - step 3 -11 while T is above T_min

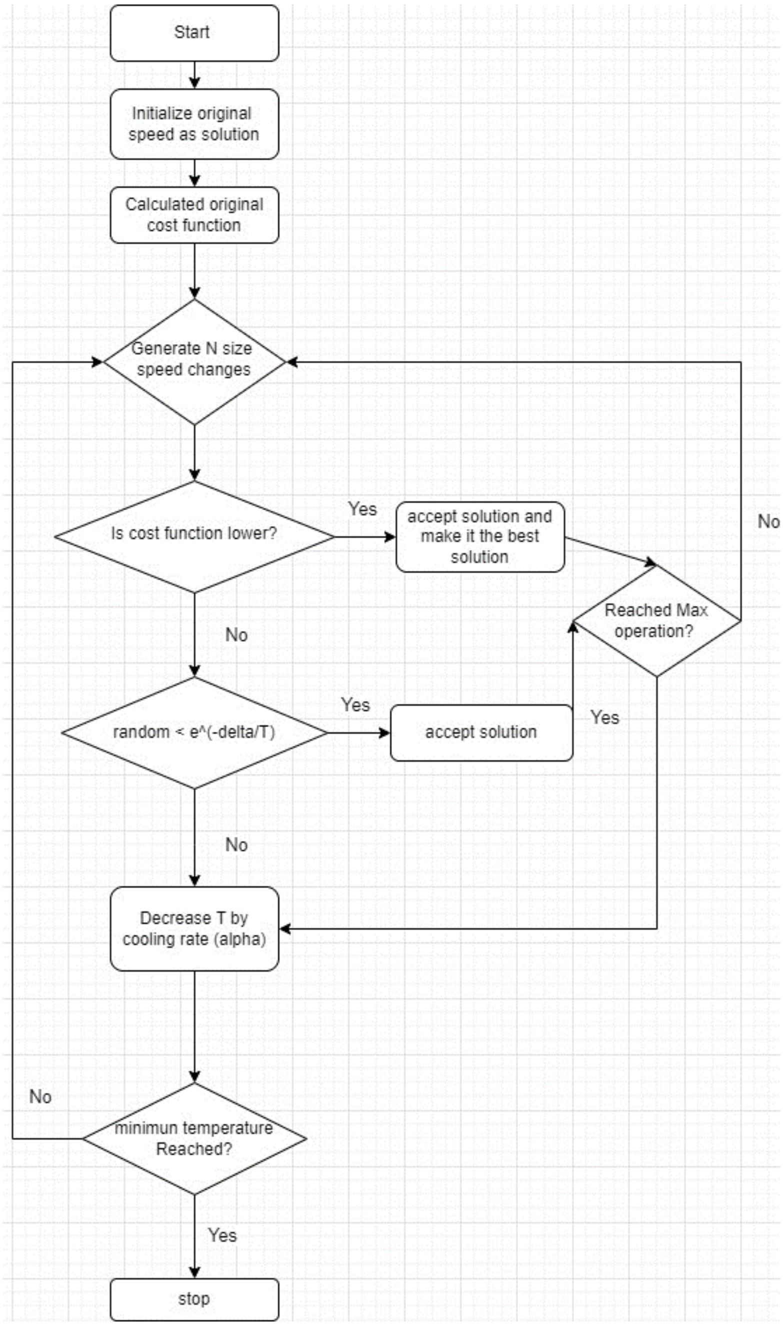


Figure 12: Flowchart of the SA algorithm

The algorithm aims to explore the solution space gradually, searching for better solutions while considering both cost improvement (delta) and a probabilistic acceptance criterion based on temperature. Overall, the SA algorithm seeks to optimize the truck speeds to minimize the total queue time by iteratively adjusting speeds and gradually reducing the temperature. It balances exploration (acceptance of non-improving solutions) and exploitation (acceptance of improving solutions) to navigate complex solution spaces and potentially escape local minima. The goal of the SA optimization is to find a set of truck speeds that minimize this total queue time. Therefore, the cost function returns a value that represents the total queue time associated with the proposed truck speeds. The SA algorithm aims to minimize this cost function by adjusting truck speeds iteratively until an optimal (or near-optimal) solution is found.

3.9 Fuel consumption

The understanding of fuel consumption in conventional vehicle use is a well-established aspect within the multitrillion-dollar automotive industry. This comprehension is largely consistent worldwide, given that most cars operate on asphalt roads at similar speeds. However, when it comes to mining trucks, they operate at significantly lower speeds, resulting in substantially reduced air resistance compared to typical road trucks. This difference in air resistance is particularly impactful when these trucks are fully loaded and operate at very low speeds, as the effect of air resistance increases exponentially with velocity. Furthermore, mining trucks often exhibit a much greater weight, sometimes reaching up to 10 times the weight of standard trucks. Consequently, the significance of rolling resistance far surpasses that of air resistance. Additionally, these trucks are frequently used on roads with a high coefficient of rolling resistance, such as sandy or gravelly surfaces. Our comprehension of rolling resistance is not as comprehensive as our understanding of air resistance. While this disparity may not be apparent in controlled laboratory settings, it becomes highly significant in real-world scenarios due to the dynamic and variable road conditions that vehicles encounter during their operations. These changing road conditions have a substantial impact on the fuel consumption performance of vehicles. In the literature review, it is evident that most scientific papers have provided a consistent scientific response regarding the influence of speed on rolling resistance. However, those papers do not uniformly assert that there is no observed increase in rolling resistance (C_{rr}) with an increase in speed. However, it is essential to emphasize that this conclusion is derived from studies conducted in non-mining environments, where vehicle weight and road conditions differ substantially. In a study by Adair et al. (2015), a notable correlation between speed and rolling resistance is discernible. It is worth noting that rolling resistance increases by a modest 0.1 when the speed is raised from 10 to 40 km/h. While this finding may not be particularly striking, it is indeed a discernible trend in the data. However, different studies may interpret these findings differently, and further research may yield varying perspectives on this relationship.

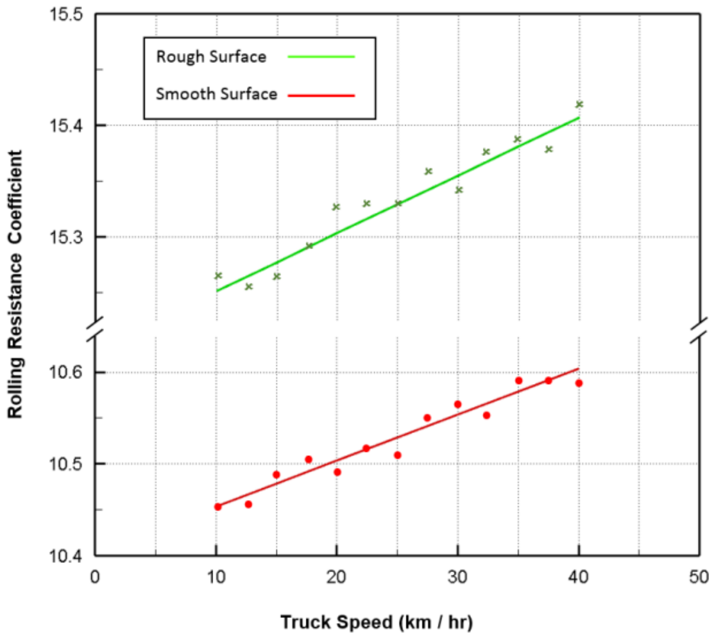


Figure 13: Rolling resistance coefficient vs speed (Adair et al. (2015))

In a study conducted by Soofastaei et al. in 2015, a fuel consumption index was established, expressing the FC index in units of liters per tonne per kilometer (l/tonne*km). It is noteworthy that most publications by Soofastaei predominantly present graphs utilizing the FC index in units of liters per tonne*hour (l/tonnehr). Furthermore, these graphs frequently feature Gross Vehicle Weight (GVW) on the x-axis, often illustrating data line for both 10 and 15 km. However, due to the relatively small differences observed, it becomes challenging to apply these findings directly to our case, as the potential reductions in fuel consumption are offset by the extended travel time taken by trucks to reach their destinations.

The data utilized for this thesis is presented in the figure below:

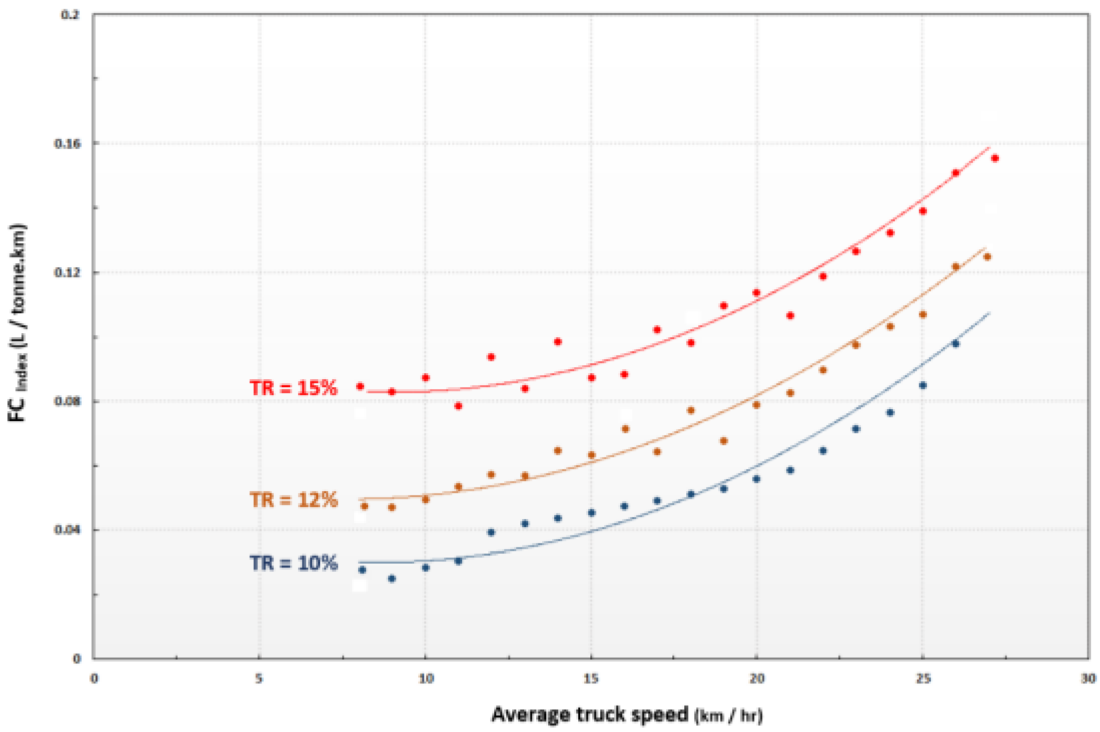


*Figure 14: Fuel consumption index (L/(ton*km)) vs speed (Soofastaei et al. 2015)*

An exponential fitting approach was employed to derive three distinct fuel consumption curves, each corresponding to different total resistance levels. These curves are expressed by the following mathematical formulas:

$$Fuel\ consumption\ index\ \left(\frac{L}{ton * km}\right) at\ TR\ 10 = 0.00510 * \ e^{0.10337*S} + 0.01807$$

$$Fuel\ consumption\ index\ \left(\frac{L}{ton * km}\right) at\ TR\ 12 = 0.00609 * \ e^{0.10024*S} + 0.03505$$

$$Fuel\ consumption\ index\ \left(\frac{L}{ton * km}\right) at\ TR\ 15 = 0.00254 * \ e^{0.12891*S} + 0.07544$$

Equation 4: Fuel consumption index at TR 10, 12 and 15

As depicted in the figure, the rise in speed exhibits an exponential pattern, leading to noteworthy fuel economy improvements. To harness this relationship, an exponential fit was generated using the raw data, incorporating the total resistance (TR) as a variable. Although the exact translation of this trend to low total resistance consumption remains somewhat uncertain due to limited data, for the purposes of this thesis, an assumption has been made. To facilitate calculations, the formula that considers total resistance as a variable is presented below:

$$Fuel\ consumption\ index\ \left(\frac{L}{ton * km}\right) = 0.0039 * \ e^{0.1143*S} + (0.0103 * TR) - 0.00834$$

Equation 5: Fuel consumption index with TR and speed variable

Based on the available data, this formula appears to be the most suitable. However, it's important to note that the model has been trained specifically for total resistance (TR) values of 10, 12, and 15. Given the similarity in shapes of the fitted curves, adjustments have been made to the formula to enhance its applicability to lower TR values. This modification is aimed at offering a more accurate representation of fuel consumption across various total resistance (TR) and speed levels. To achieve this, adjustments have been made to the formula to account for specific TR variations, as will be elucidated later. These adaptations are visually represented by the inclusion of TR lines in the accompanying figure, along with their corresponding formulas:

$$Fuel\ consumption\ index\ \left(\frac{L}{ton * km}\right) = 0.0039 * \ e^{0.1143*S} + (0.00413 * TR)$$

Equation 6: Adjusted fuel consumption index with TR and speed variable

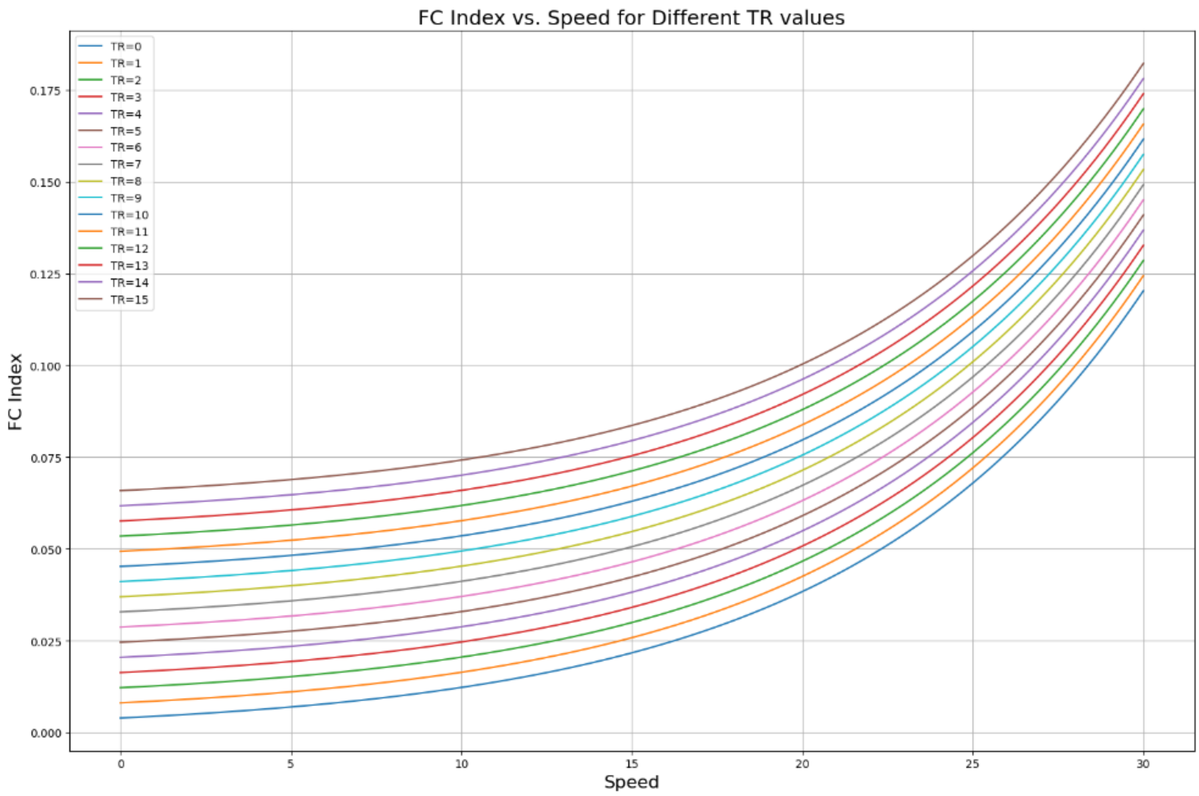


*Figure 15: Altered fuel consumption index (L/(ton*km)) vs speed for different TR's*

Dealing with grade and its resulting Total Resistance (TR) calculations presents challenges. A negative grade can lead to a negative TR, which, however, does not correspond to negative fuel consumption, especially for diesel trucks. Diesel trucks cannot emit negative fuel. While the situation may differ with electric trucks who can regenerate power, it's important to note that this thesis primarily focuses on diesel trucks.

To address this issue, the TR function has been modified to handle negative values as well. An adapted TR function is presented and utilized in the calculations in the figure below. This modified TR function tends to slightly overestimate TR, as observed in the figure. Conversely, the figure above tends to slightly underestimate Fuel Consumption (FC). The combination of these equations and adjustments aims to closely emulate fuel consumption in various scenarios. This approach strives to provide both logical values for low or negative TRs and a close approximation for TR values that align with the available data.

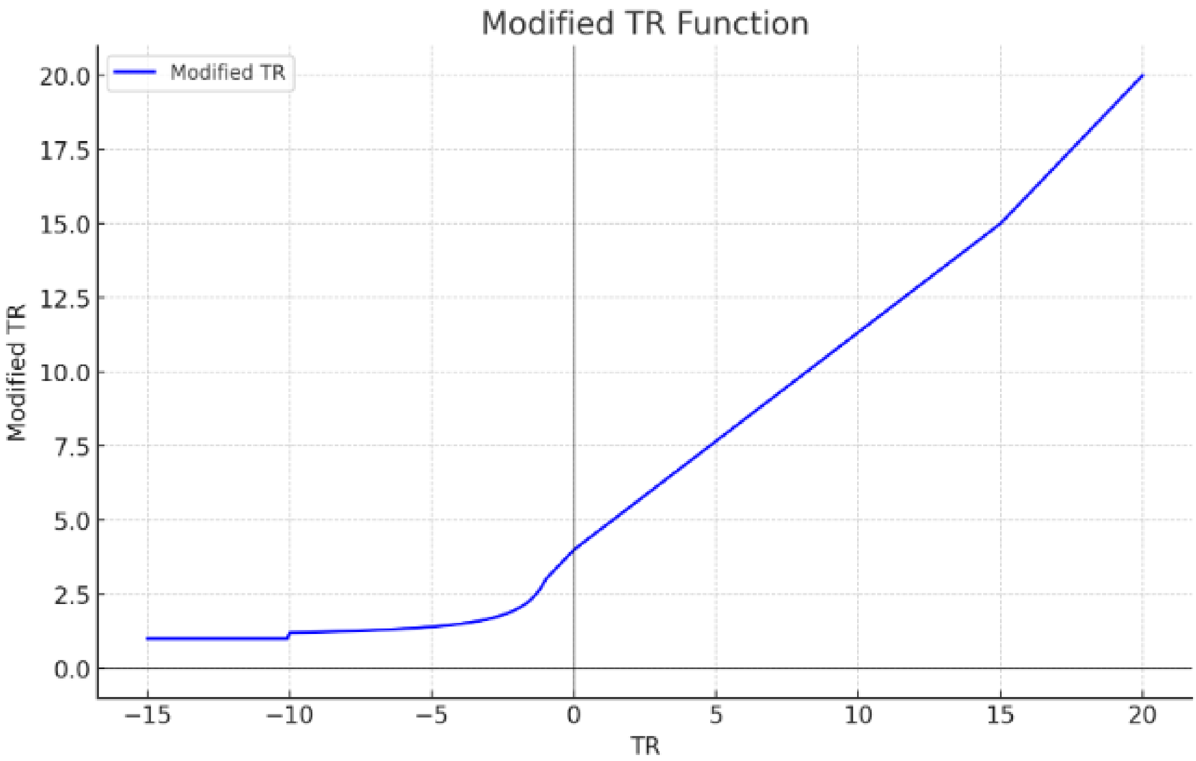


Figure 16: Modified TR function

Considering the detailed modifications and fuel consumption formulas outlined previously, the "Results" section will provide a more lucid understanding of the derivations of specific figures and metrics. Within this section, we will present heatmaps that represent fuel consumption at varying speeds. It's crucial to note that the fuel consumption index is expressed in Litres / (km × ton) To derive the absolute fuel consumption, both the weight or payload and the distance travelled must be integrated into the calculations.

An essential assumption made in our analysis is the addition of supplementary weight to the trucks. This is incorporated because trucks must have a baseline weight for the calculations to remain logical and meaningful. If a truck weighs 150 tons plus its payload, the fuel consumption is specified per ton moved of the payload. In our calculations, however, we assume the truck to be 50 tons. This adaptation ensures that even empty trucks have a weight to calculate with. The reduction in weight is implemented so that the weight of the trucks does not become too dominant in the calculations.

It is good to acknowledge that the fuel consumption calculations are based on certain assumptions. The extraction of data, limited to cases with TR values above 10, can yield fuel consumption calculations that may not directly correlate with real-world scenarios. This is particularly evident in situations such as the downhill sections of the mine, where the grade leads to negative TR calculations.

Nevertheless, with the incorporation of specific assumptions, all translations are consistently applied across different speeds. This uniform approach serves to demonstrate an approximation of the percentage of diesel saved, offering insights into the potential fuel conservation under various conditions.

4 Results

4.1 Results of SA optimization

In this section, we'll delve into the outcomes of the application of the SA optimization method. This technique reduces the waiting time of trucks at the loading point by adjusting their speeds. Once we've determined the optimized truck speeds, we can compute fuel consumption and estimate overall savings. Additionally, we'll conduct a sensitivity review on specific factors within the optimization to discern their influence on this simulation. In each scenario, two loaders are consistently present. However, the number of trucks varies across different scenarios. Despite these variations, production remains consistent, and the production time is unchanged. The loader's utilization is seen as the limiting factor in the operation. All numbers which are represented in the table below can have a very small alteration of less than half of a percent because of the random factors in the simulation.

Table 2: Production of mine

Production	60000 tons
Simulation time	9 hours
Loaders	2

The table below presents the six distinct truck scenarios, each accompanied by its initial queue time and a corresponding diagram illustrating the initial queue size. Over the subsequent four pages, the results for the initial queue sizes of loaders 1 and 2 are displayed, spanning all the various truck combinations. It's worth noting that due to the mechanics of Haulsim and the optimization approach of the model, there will always be a queue time. This persists even if the trucks operate at their slowest possible speeds. This phenomenon is attributed to the first pass delay inherent in the simulation environment.

Table 3: Number of trucks, initial queue time

Number of trucks	Initial queue time	Split
22	665	12/10
26	2381	15/11
30	4139	17/13
34	5819	19/15
38	7420	22/16
42	9065	24/18

The first graph in figures 17 and 19 show the results for the 22-truck scenario. The graphs indicate that truck queue time is not fully optimized, even though there is little queue time. The data shows instances of two trucks in the queue, and specifically on Route 4, there is a notable period of no queue time, which suggests that a loader is not being fully utilized in this scenario. Subsequent graphs within Figures 17, 18, 19, and 20 suggest full utilization of loaders, as evidenced by the consistently non-zero queue sizes. As depicted across these figures, the queue size largely fluctuates around an equilibrium, with a maximum deviation of +1 and a minimum of -1 for the majority of the simulation duration. Moreover, the results indicate that an increase in the number of trucks correlates with a considerable augmentation in the overall queue size.

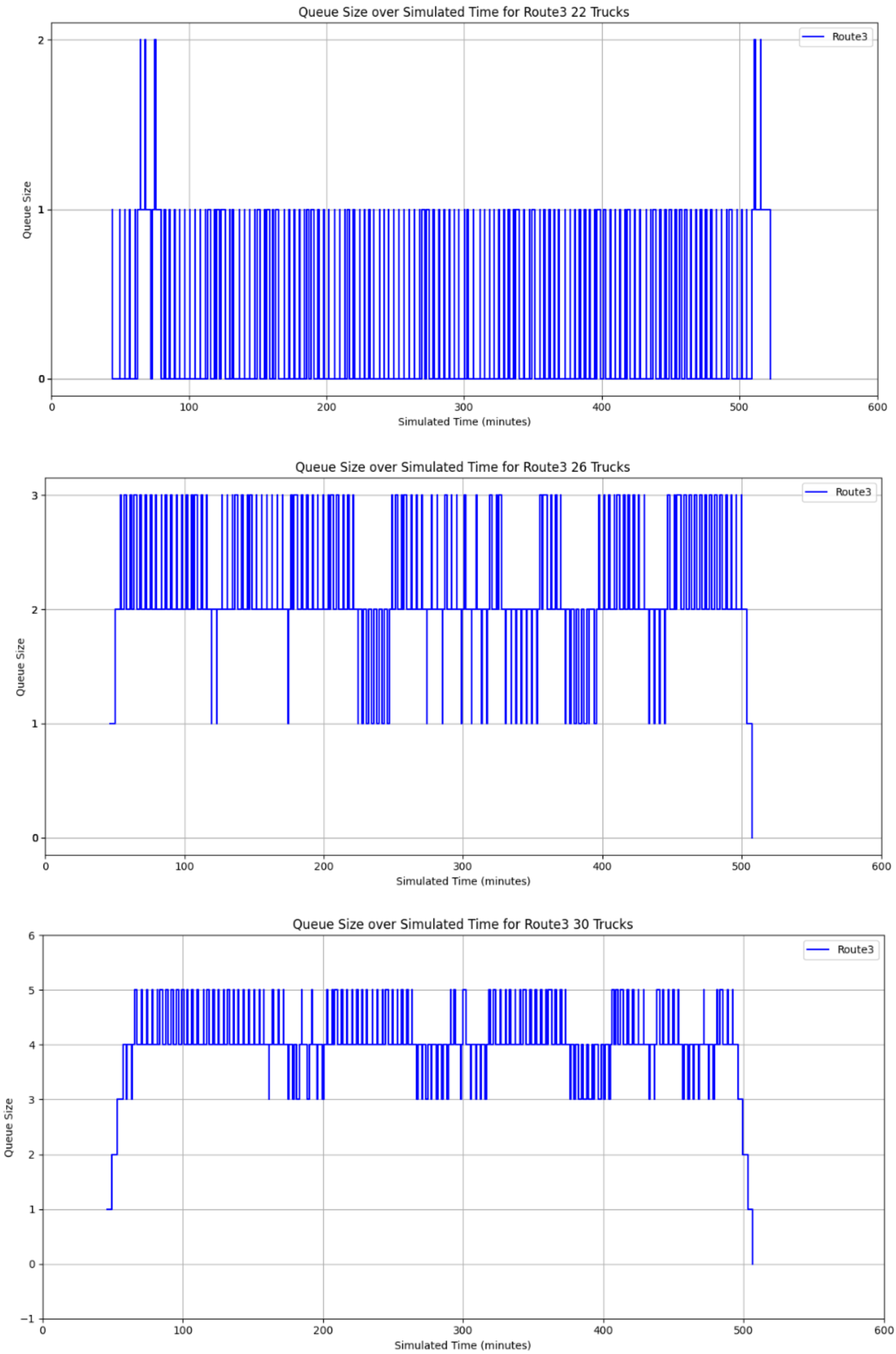
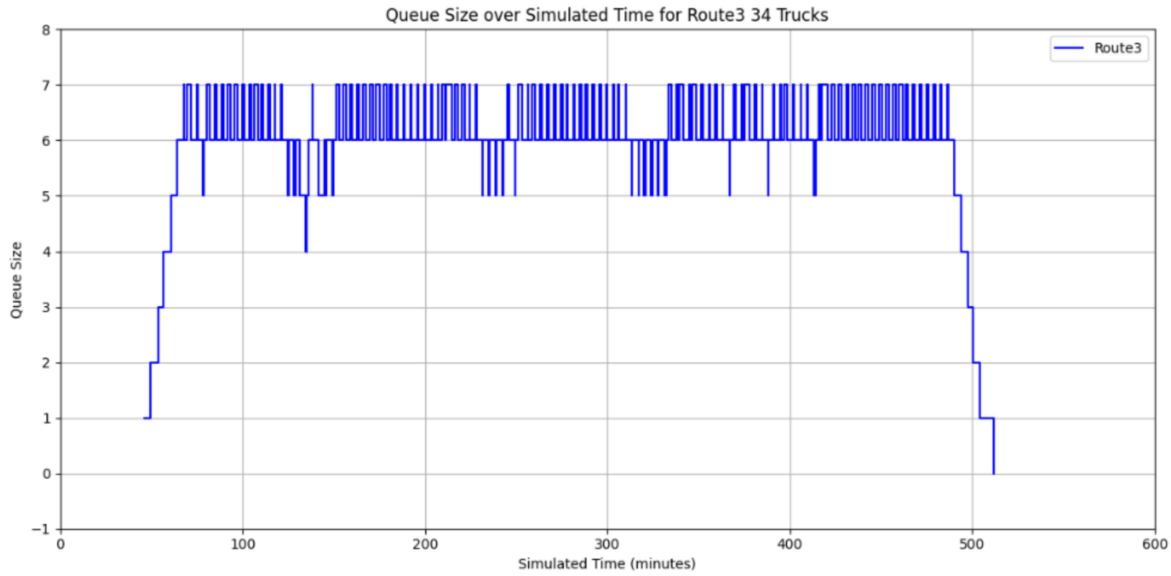
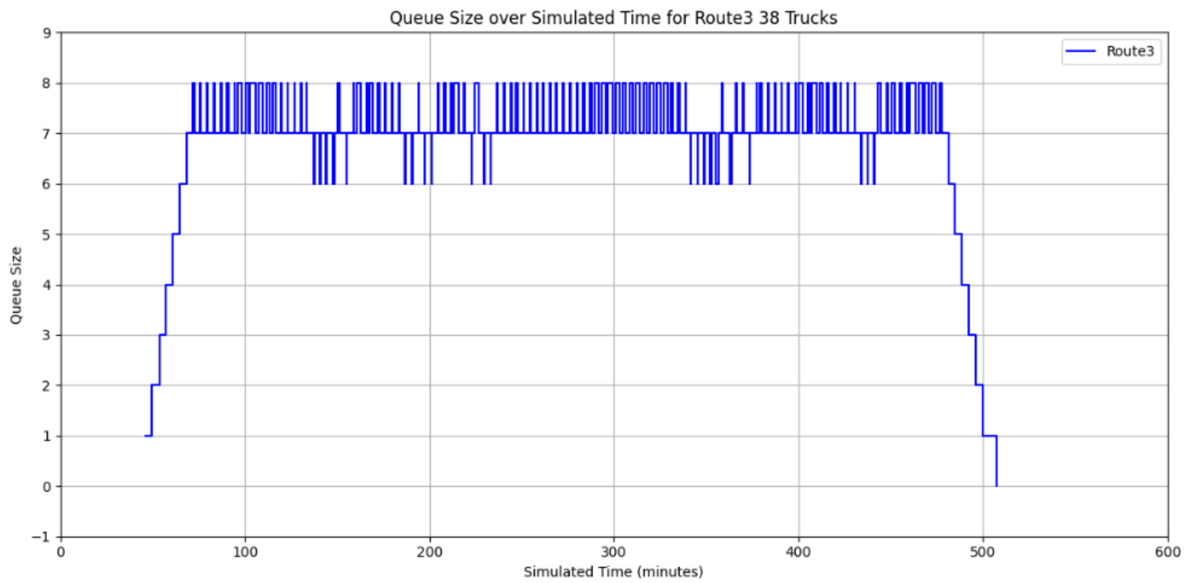


Figure 17: Initial Queue size route 3 (22,26,30) trucks





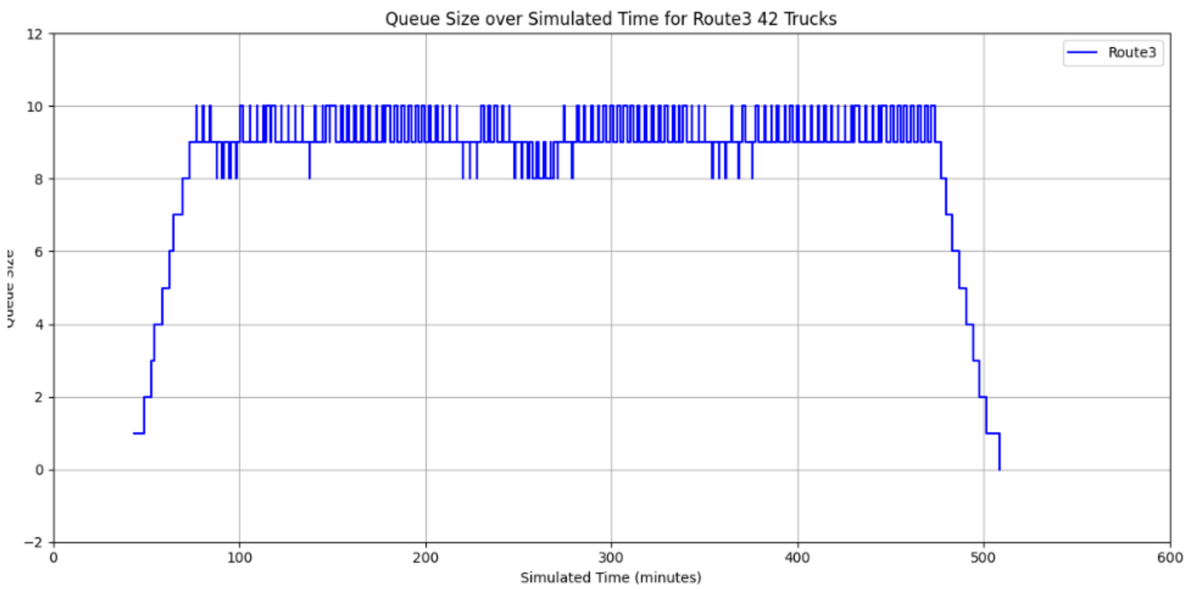


Figure 18: Initial Queue size route 3 (34,38,42) trucks

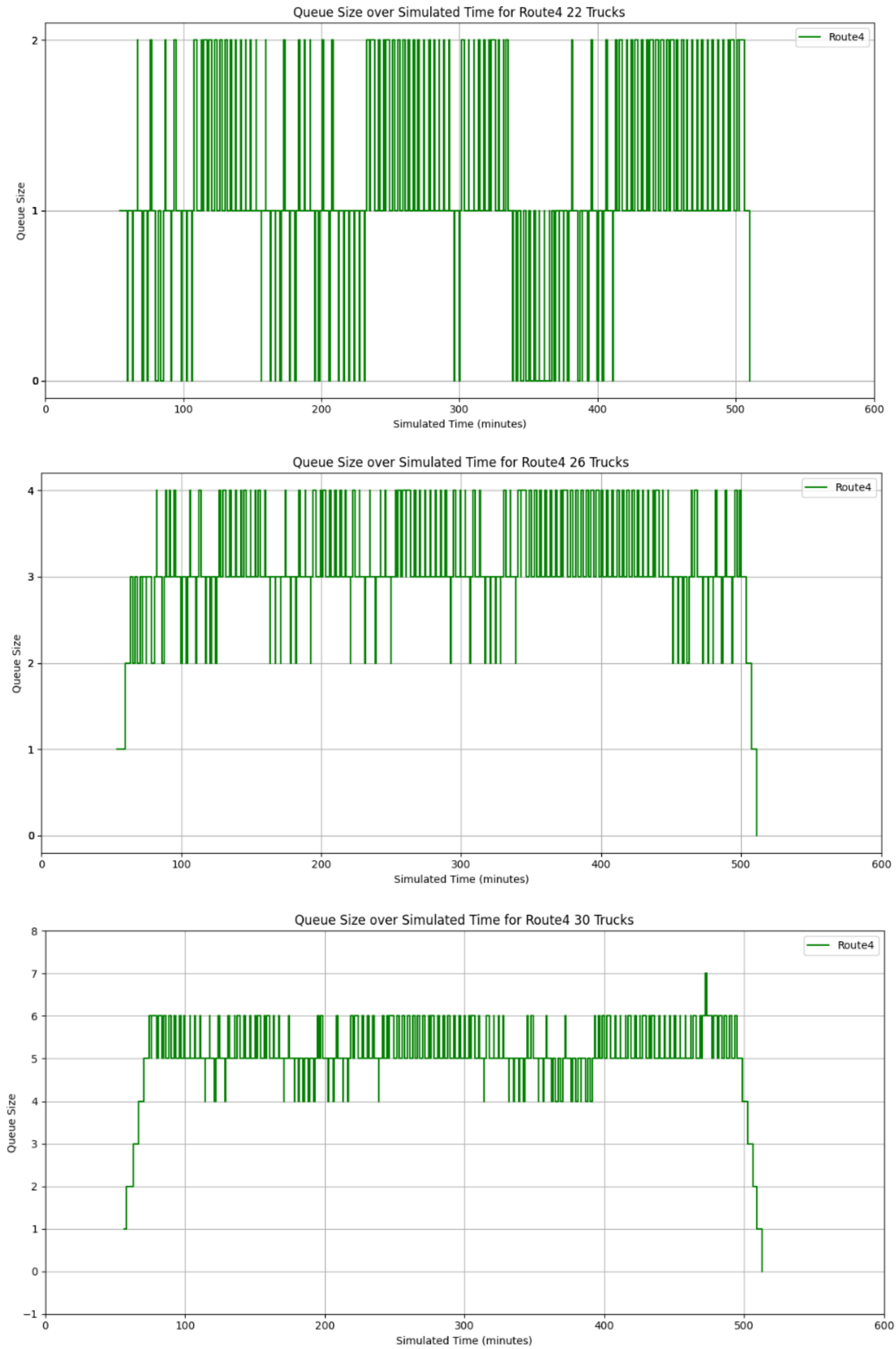


Figure 19: Initial Queue size route 4 (22,26,30) trucks

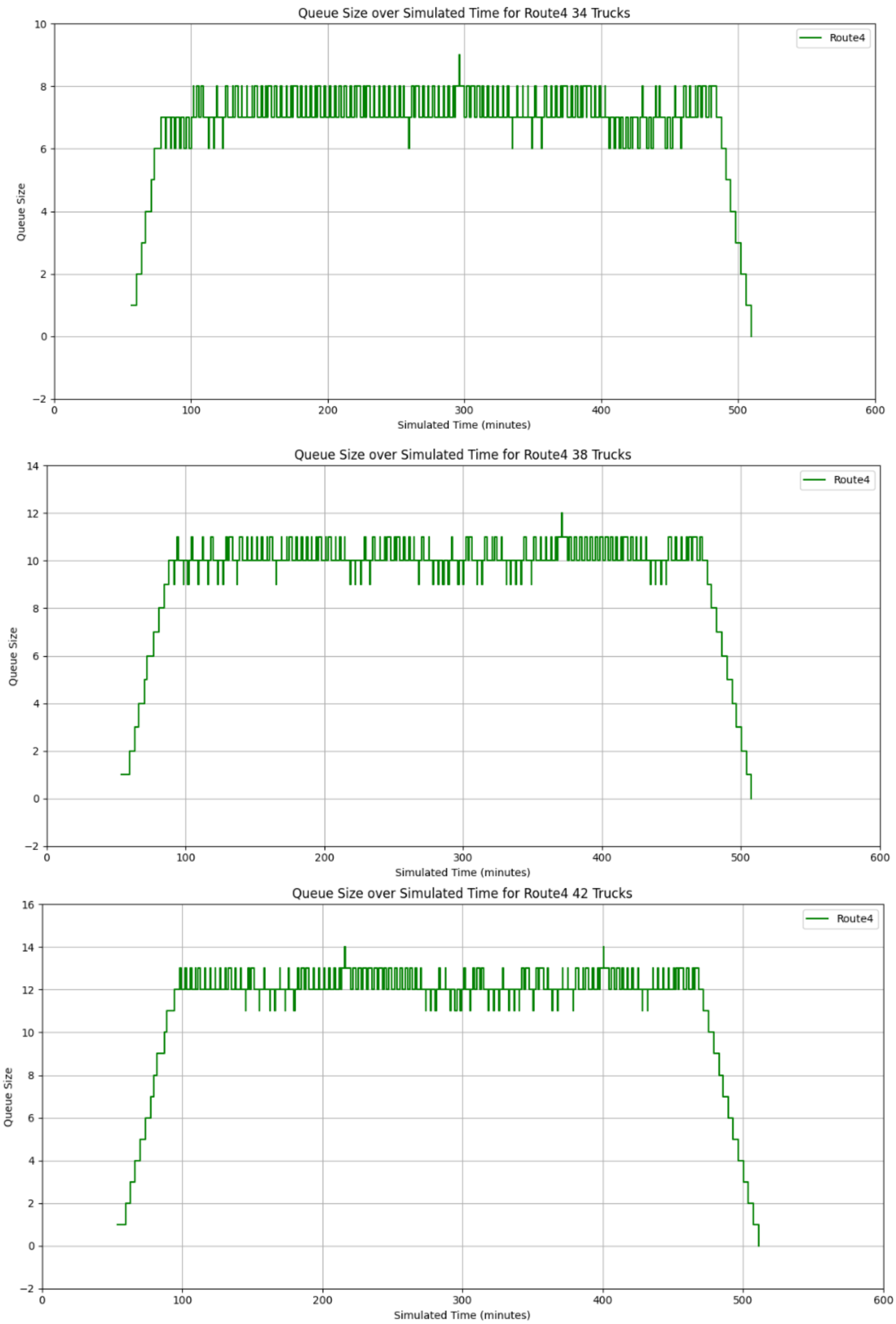


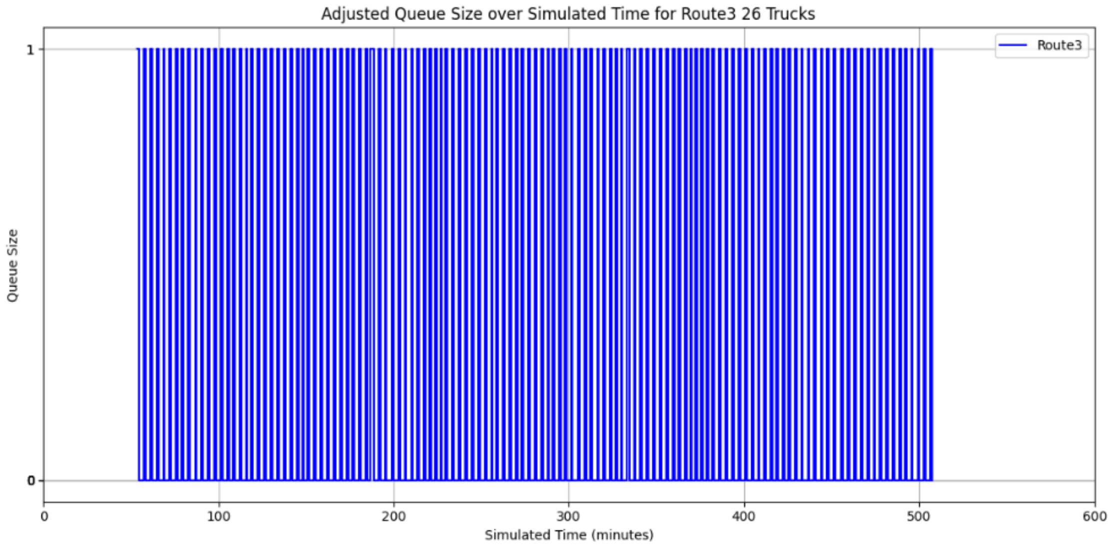
Figure 20: Initial Queue size route 4 (34,38,42) trucks

The Simulated Annealing (SA) algorithm, used to optimize the speed of the trucks, is a probabilistic technique used for approximating the global optimum of a given function. Due to its inherent randomness, SA may not always yield identical outcomes in successive runs. This stochastic nature allows SA to escape local minima, providing a more comprehensive search for optimal solutions. However, it's worth noting that while SA can often bypass local minima, there's no guarantee it will always find the global optimum. Additionally, it's essential to consider the key parameters that significantly influence the SA optimization process. Proper parameter tuning can greatly enhance the algorithm's efficiency and accuracy in finding optimal solutions. Two critical metrics are pivotal for the results: the final queue time and the duration required for the algorithm to compute the solution. These calculations were performed on an Intel(R) Core (TM) i7-6700HQ CPU @ 2.60GHz 2.59 GHz. However, it's noteworthy that this laptop, being eight years old, has experienced some performance degradation over time.

The results specify the boundaries, both maximum and minimum, for the number of trucks this particular model can effectively manage under the current conditions. In the case of the 22-truck model, it didn't optimize in the same fashion as other configurations. This 22-truck setup exemplifies what we label as an "under-trucked mine." the loaders aren't being fully utilized. Observations indicate that there are moments when one of the loaders experiences idle time, leading to situations with no queue. This also suggests that trucks cannot further decrease their speed without affecting production levels. Due to the stochastic nature of truck selection, a more favourable result might be achievable. Yet, it's essential to ensure that truck bunching doesn't occur, as it would adversely affect the optimization, leading to penalized outcomes. The 22-truck scenario was tested multiple times, but no improvement was observed from the initial run. This suggests that the model doesn't guarantee a feasible solution in situations with insufficient trucks. The table below presents the parameters that are used to determine the initial solutions of the SA optimization for the different truck scenarios.

Table 4: Initial parameters SA optimization

Starting temperature (T)	10
Minimum temperature (T_min)	0.001
Cooling rate (alpha)	0.9
Max operation in a temperature stage	275
Max speed adjustment above	+0.5
Max speed adjustment down	-2.5
Adjustment size	5



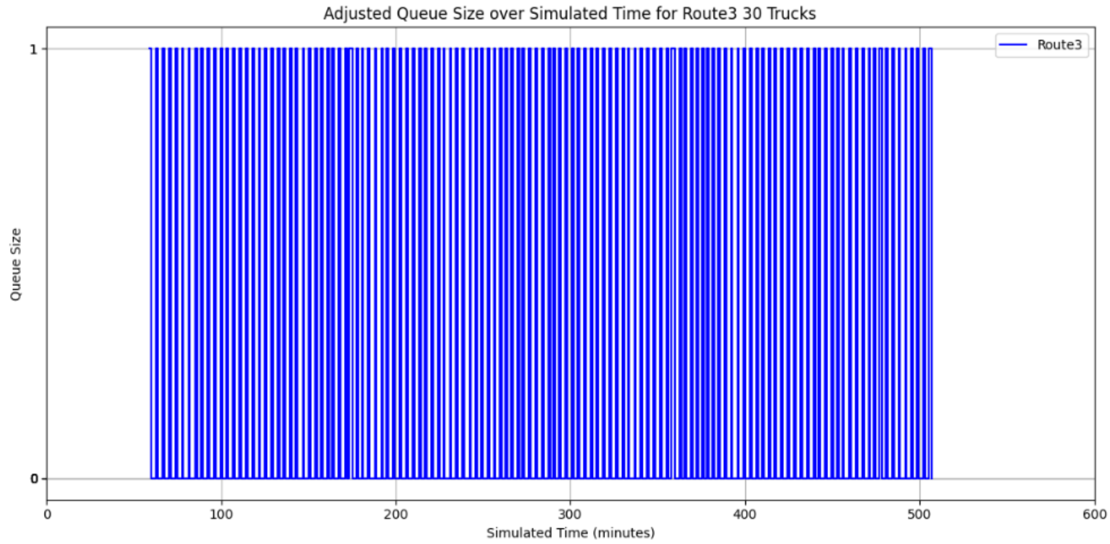


Figure 21: Optimized queue route 3 (26, 30) trucks

Figures 21 and 22 presents the outcomes for the 26 and 30 truck scenarios. As depicted in the SA optimization figures, the queue size does not exceed one, indicating the optimization's efficacy in minimizing queue time for these scenarios. While the results might appear indistinguishable and challenging to discern at first glance, a closer examination of the subsequent numerical data will highlight the distinctions between the two scenarios.

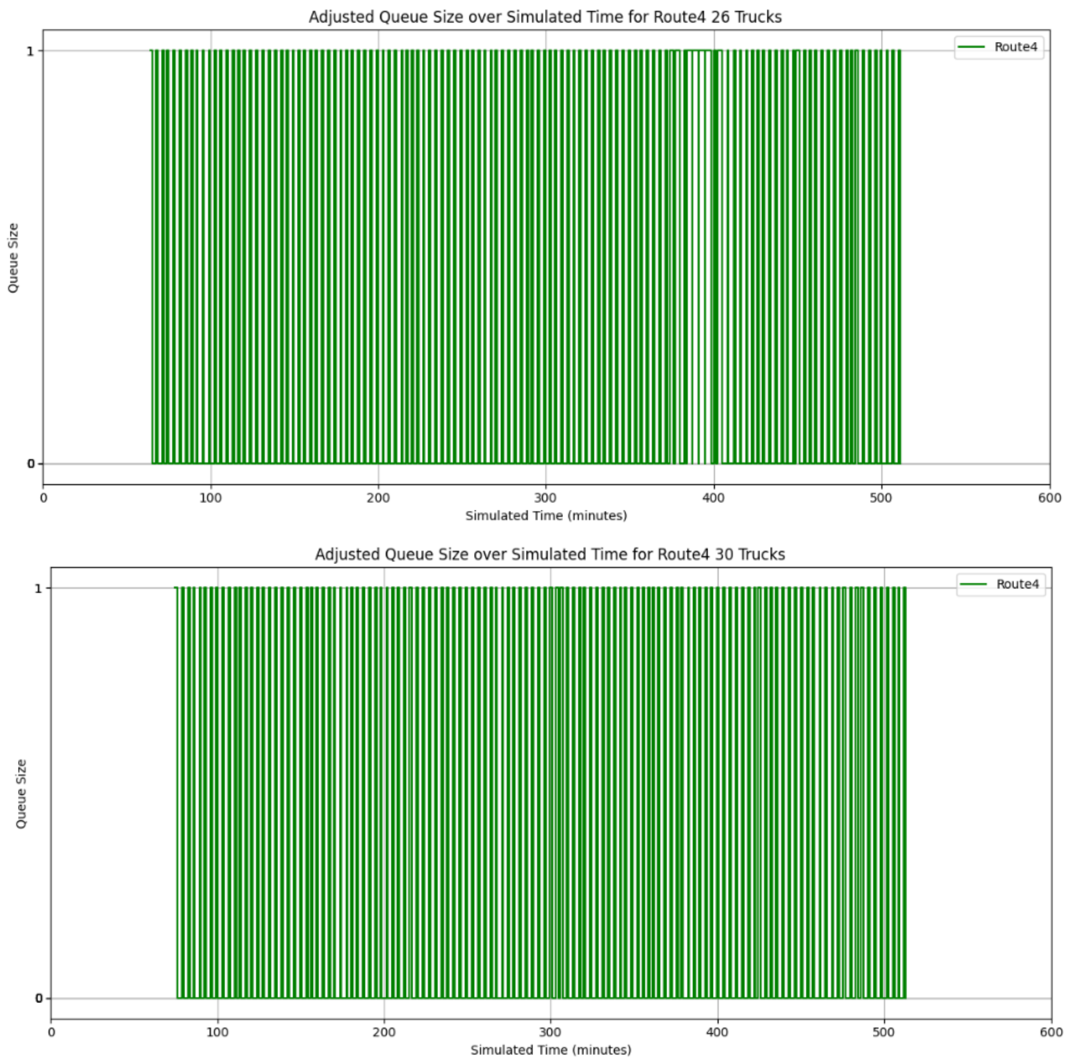
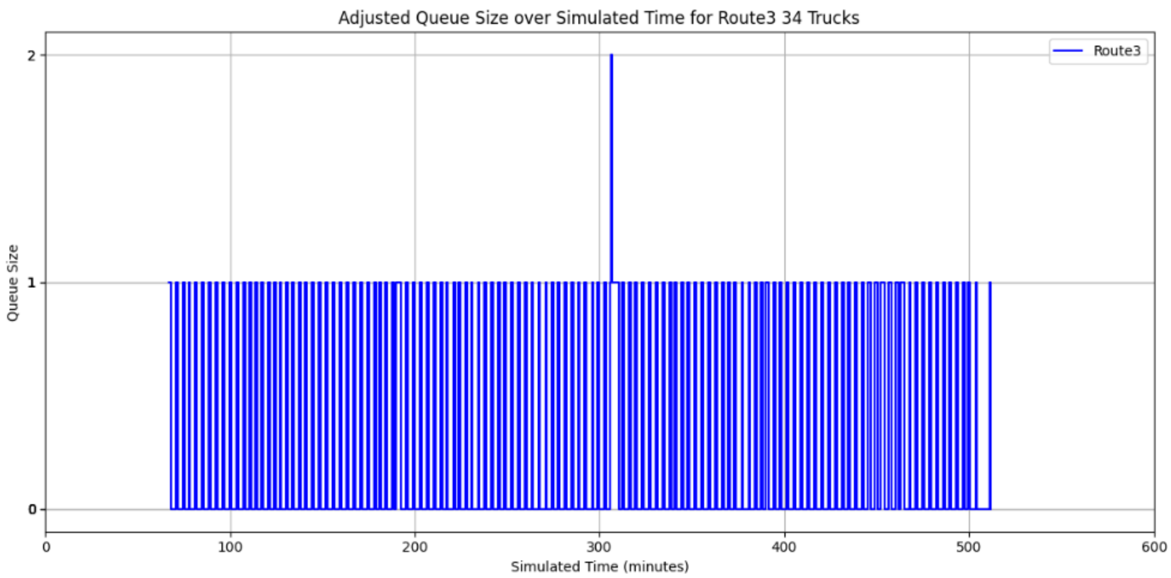


Figure 22: Optimized queue route 4 (26, 30) trucks



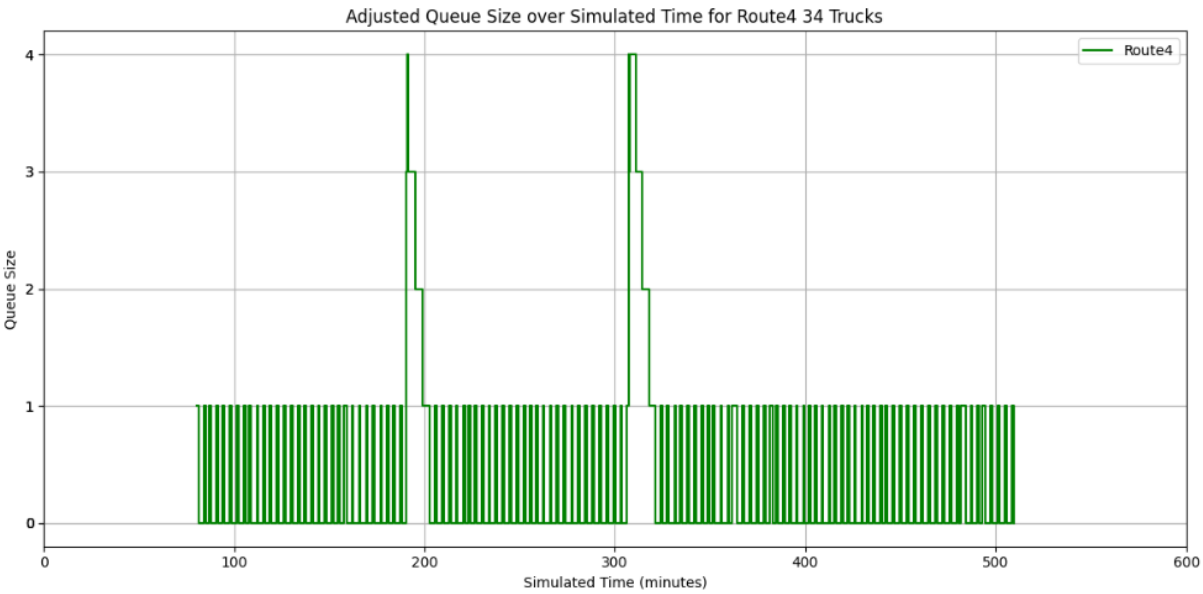
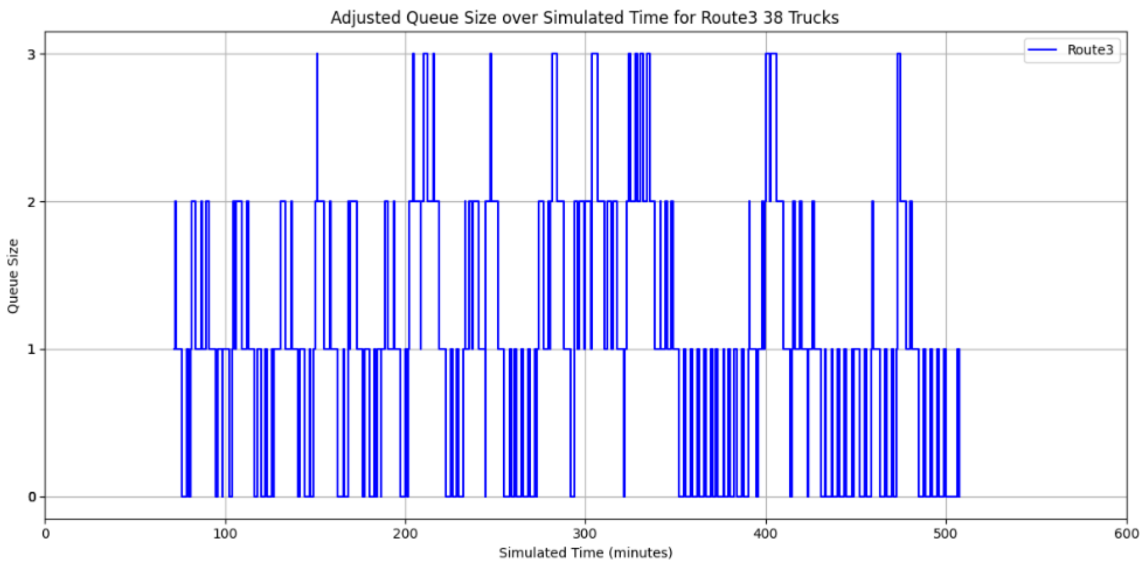
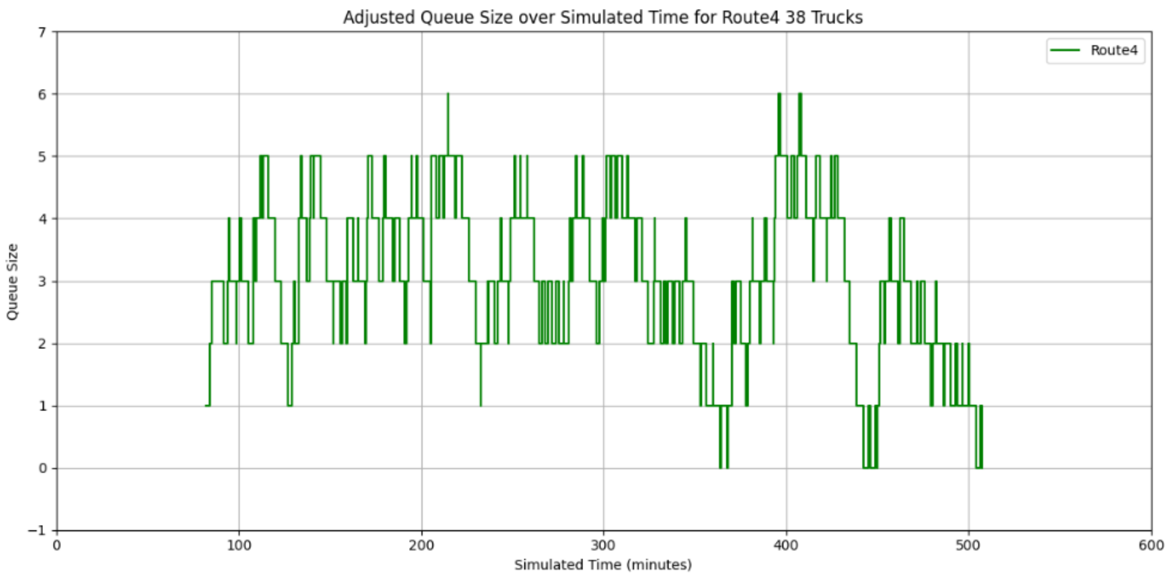


Figure 23: Optimized queue route 3 & 4, 34 trucks





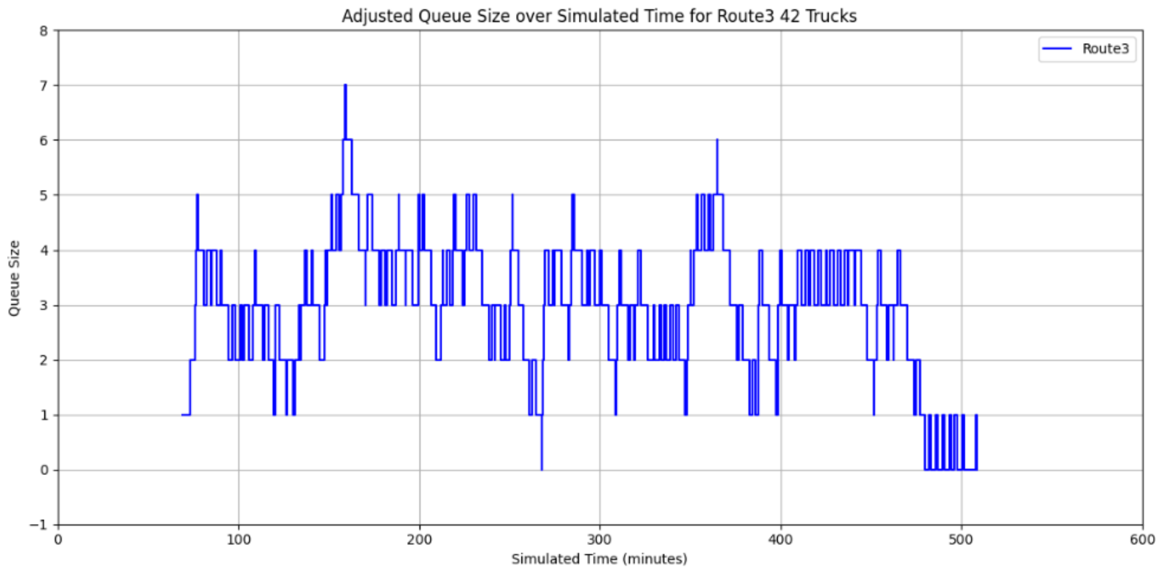


Figure 24: Optimized queue route 3 (38, 42) trucks & route 4, 38 trucks

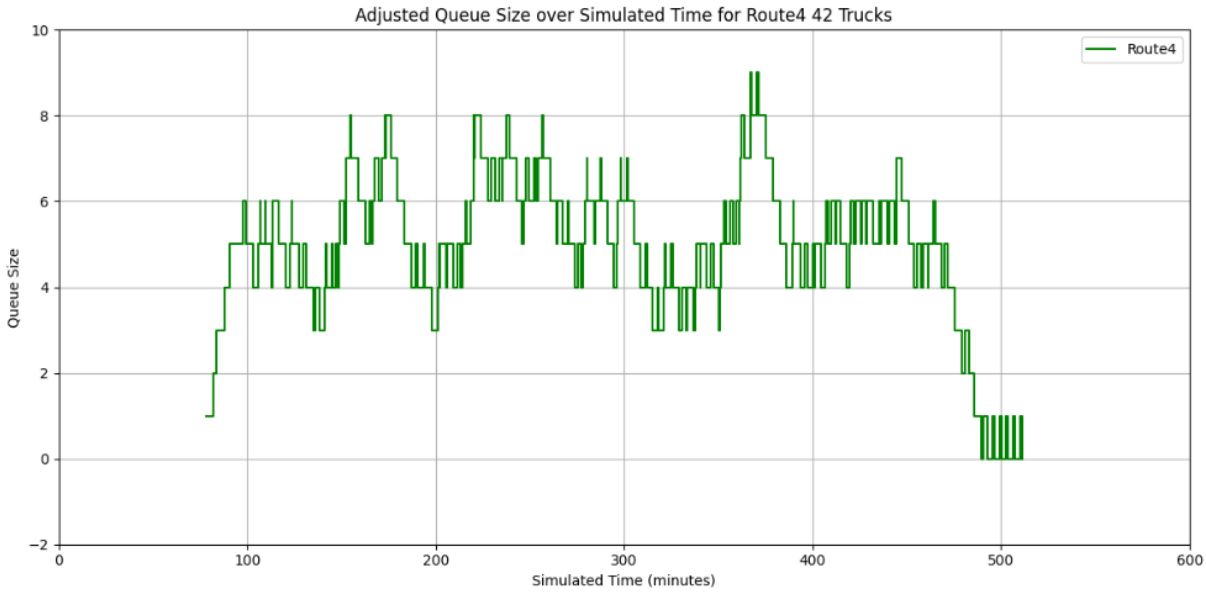


Figure 25: Optimized queue route 4, 42 trucks

In the figures 23, 24 and 25, we observe the results for the 34, 38, and 42 truck scenarios. Interestingly, the outcomes of the first two scenarios are almost identical. As we increase the number of trucks, it becomes evident that the speed optimization algorithm struggles to reach the desired optimal outcome. Particularly in the 34-truck scenario, the algorithm performs relatively well, with seldom more than one truck in queue, except on a few occasions. However, with larger truck configurations, the model's efficiency isn't as pronounced as with the smaller ones. This diminished performance can be traced back to two main factors: firstly, the initial queue is notably large in both scenarios, so even though a significant chunk of the queue time is eliminated, a considerable queue still persists. Secondly, the minimum achievable speeds decrease substantially as the queues grow longer. This scenario sets a broader boundary within which the algorithm operates. Given the algorithm's inherent randomness, this can sometimes lead to larger differences and potential truck bunching. However, it's worth noting that by adjusting some parameters, a more favourable outcome might still be attainable, as alternative parameters might help the algorithm sidestep early settling into a local minimum. The table presented below outlines the outcomes of the SA optimization based on the initial parameters. To account for the inherent randomness of the algorithm, each configuration has been executed a minimum of three times and the results given are average.

Table 5: initial and optimized queue time for different truck scenarios

Truck scenario	Initial queue time (min)	Optimized queue time (min)	Solving time (s)	Shovel idle time (min)	Shovel idle (%)
22	665	NA	NA	149	13.9
26	2381	277	729	136	12.8
30	4139	262	753	133	12.6
34	5819	322	738	134	12.7
38	7420	1479	699	134	12.7
42	9065	3468	723	133	12.5

The solving time for the SA optimization is independent of the number of trucks and is primarily influenced by its initial parameters. A statistical analysis of the optimization times suggests a distribution that approximates a normal distribution. The data has a mean solving time of approximately 736 seconds, with a standard deviation of about 45 seconds. The observed times range from a minimum of 649 seconds to a maximum of 864 seconds.

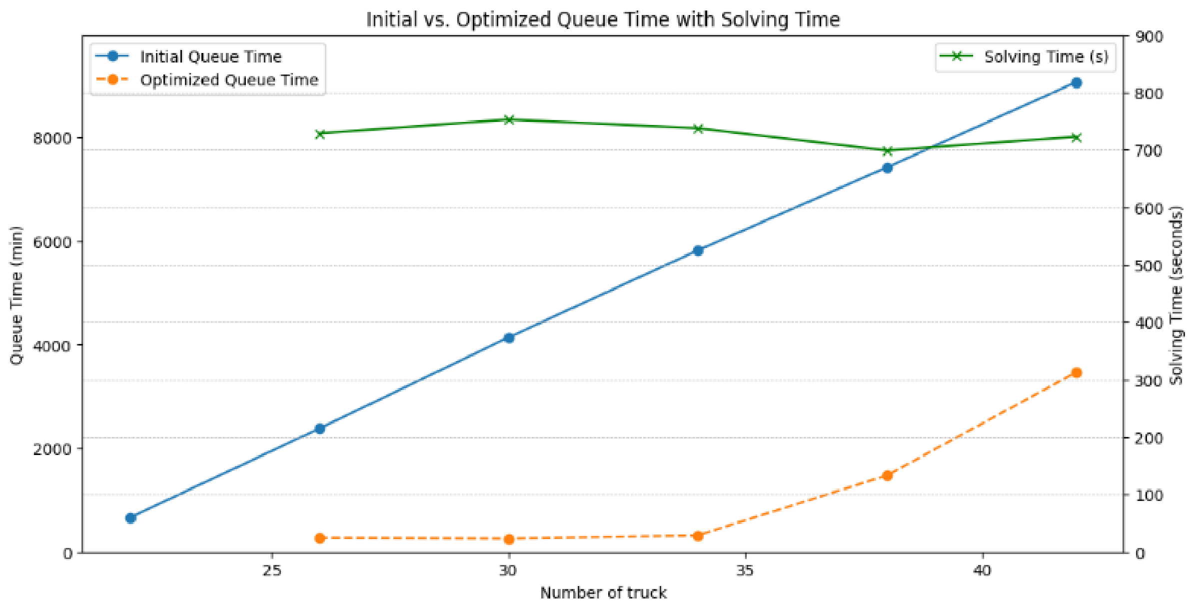


Figure 26: Initial vs optimized queue time

4.2 Sensitivity analysis

In the subsequent section of this thesis, we will adjust the SA optimization parameters to examine their impact on the results. Given the inherent probabilistic nature of SA, it's paramount to understand that the algorithm is deeply dependent on its parameters to navigate towards optimal solutions. The selection of these parameters profoundly affects the algorithm's performance, its rate of convergence, and the performance of solutions it yields. The parameters of SA optimization, such as the initial temperature, cooling rate, and the number of iterations, among others, dictate the algorithm's exploration and exploitation balance. A well-tuned parameter set can enable the algorithm to effectively navigate the solution space, avoiding local minima and converging to a near-optimal or optimal solution.

The preliminary results of the thesis can be categorized into two distinct groups: the truck cases of 26, 30, and 34 trucks, which all could be optimized to sub-optimality solution, and the scenarios involving 38 and 42 trucks which still had considerable total queue times. For the first group, fine-tuning the parameters to bring the algorithm closer to near-optimal performance has a marginal impact on the algorithm's efficacy. However, it does increase the computational time required for resolution. Given that a near-optimal solution has already been identified for this group, the focus shifts to enhancing the algorithm's speed and examining the interplay between near-optimal performance and the algorithm's processing speed.

Conversely, in the initial solutions for the larger truck scenarios, the algorithm did not pinpoint a near-optimal solution. While it managed to significantly reduce idle time, there remained evident avenues for enhancement. The computational times for these solutions were consistent, barring the inherent randomness of the algorithm. Modifying the parameters to increase the processing speed for these larger scenarios might inadvertently lead to even less favourable outcomes. Nevertheless, the parameters governing the search space can be expanded. While this adjustment may necessitate increased computational time, it offers a promising likelihood of yielding superior results.

During the initial temperature phase, there exists an opportunity to expand the search space. Given the elevated temperature, there's an increased probability of accepting less favourable solutions, which can be instrumental in evading local minima. In this segment of the results, the parameters are fine-tuned to identify a near-optimal solution for the larger truck configurations.

Three key parameters will be examined to discern their impact on the results. Firstly, by elevating the initial temperature, the algorithm possesses an augmented likelihood of accepting suboptimal solutions, thereby broadening the solution space, and potentially enhancing the prospects of superior outcomes. A heightened initial temperature, given a consistent cooling rate (alpha), inherently leads to a greater number of solutions being explored.

Secondly, the minimum temperature, denoted as Tmin, can be reduced to delve deeper into the prevailing solution domain of the local search space. At exceedingly low temperatures, the algorithm is less inclined to accept inferior solutions, compelling it to meticulously navigate within the current local search space.

Lastly, the system's cooling rate, termed as alpha, dictates the temperature's decrement rate. With $0<\alpha<1$, a larger alpha value signifies a more gradual cooling process, characterized by prolonged stages at elevated temperatures, thereby expanding the search space.

It's imperative to note that modifications to all three parameters lead to an increase in the number of temperature stages, invariably exerting upward pressure on the algorithm's computational time.

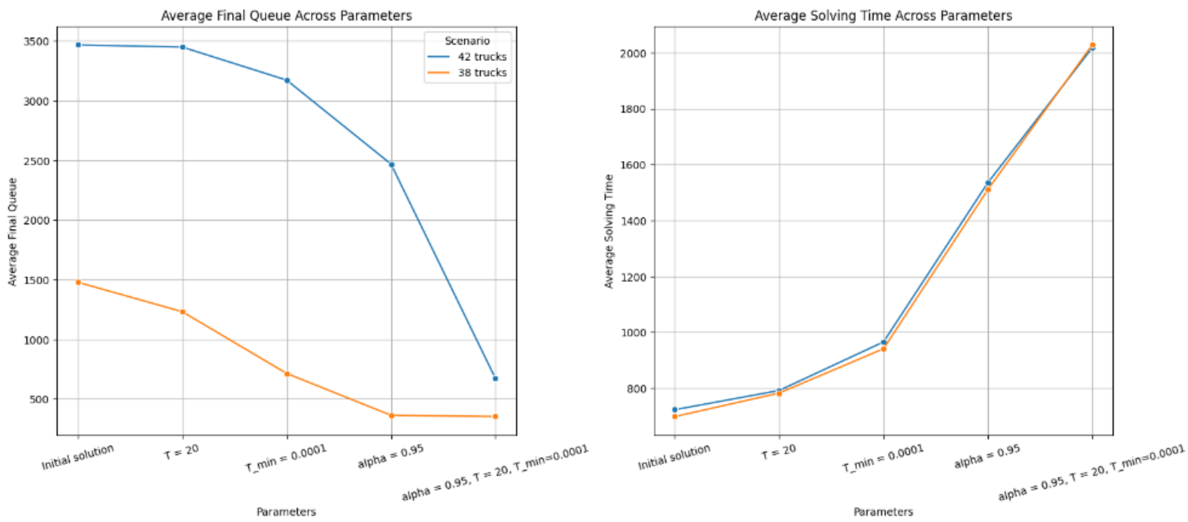


Figure 27: Average queue time and solving time with different parameter changes.

As depicted in Figure 27, alterations to the parameters of the SA optimization algorithm can significantly influence its performance. The graph demonstrates that the magnitude of influence from these parameter changes remains consistent across scenarios. However, within this consistency, there are distinct variations. For instance, an increased starting temperature has a minimal impact on the 42-truck scenario but presents a more pronounced effect in the 38-truck scenario. Notably, in the 38-truck scenario, a near-optimal solution is already achieved using the initial parameters and an alpha value of 0.95. In contrast, for the larger 42-truck scenario, a near-optimal solution is attained only after adjusting all parameters. For the 42-truck scenario it's worth mentioning that while most results closely approached an optimal solution, one iteration produced a solution of 1700, which is five times higher. Such discrepancies can be attributed to the inherent randomness of the algorithm, and adjusting parameters can reduce the chances of these variations.

It's noteworthy that the algorithm's solving time exhibits no correlation with the results within specified parameters, nor does it correlate with the number of trucks. However, there's a pronounced correlation between the increase in solving time and the model's performance when parameters are altered. This observation aligns with expectations, especially considering that the number of temperature stages is determined by the subsequent formula:

$$number\ of\ temperature\ stages = \frac{\ln\left(\frac{T\_min}{start\ T}\right)}{\ln\,(alpha)}$$

Equation 7: Number of temperature stages

In the table below the result of the amount of temperature stage are shown.

Table 6: Temperature stages with given parameters

Start temperature	Minimum temperature	Cooling rate (alpha)	Number of temperature stage
10	0.001	0.9	87
20	0.001	0.9	94
10	0.0001	0.9	109
10	0.001	0.95	180
20	0.0001	0.95	238

The correlation coefficient between the number of temperature stages and the solving time is 0.99. This indicates that, aside from the inherent randomness that can influence solving time, there is a direct correlation with the number of stages. There exists a robust correlation between the number of temperature stages and the algorithm's performance. For the 38-truck scenario, a near-optimal solution is typically achieved within 180 temperature stages. In contrast, the 42-truck scenario frequently approaches a near-optimal solution around 238 temperature stages. To evaluate the algorithm's performance, random parameters are chosen that yield 238 temperature stages. These parameters range from being proximate to, to deviating significantly from, the initial set of 238 parameters. The table with the random parameter is given below:

Table 7: Random parameter with same temperature stage

	Start temperature	Minimum temperature	Cooling rate (alpha)	Number of temperature stages
Initial stage	20	0.0001	0.95	238
Stage 1	10	0.0001	0.953	238
Stage 2	10	0.00000001	0.916611	238
Stage 3	100000	0.00001	0.907785	238

Al the results were tested and yielded similar solving times in the figure below are the spreads of the results given:

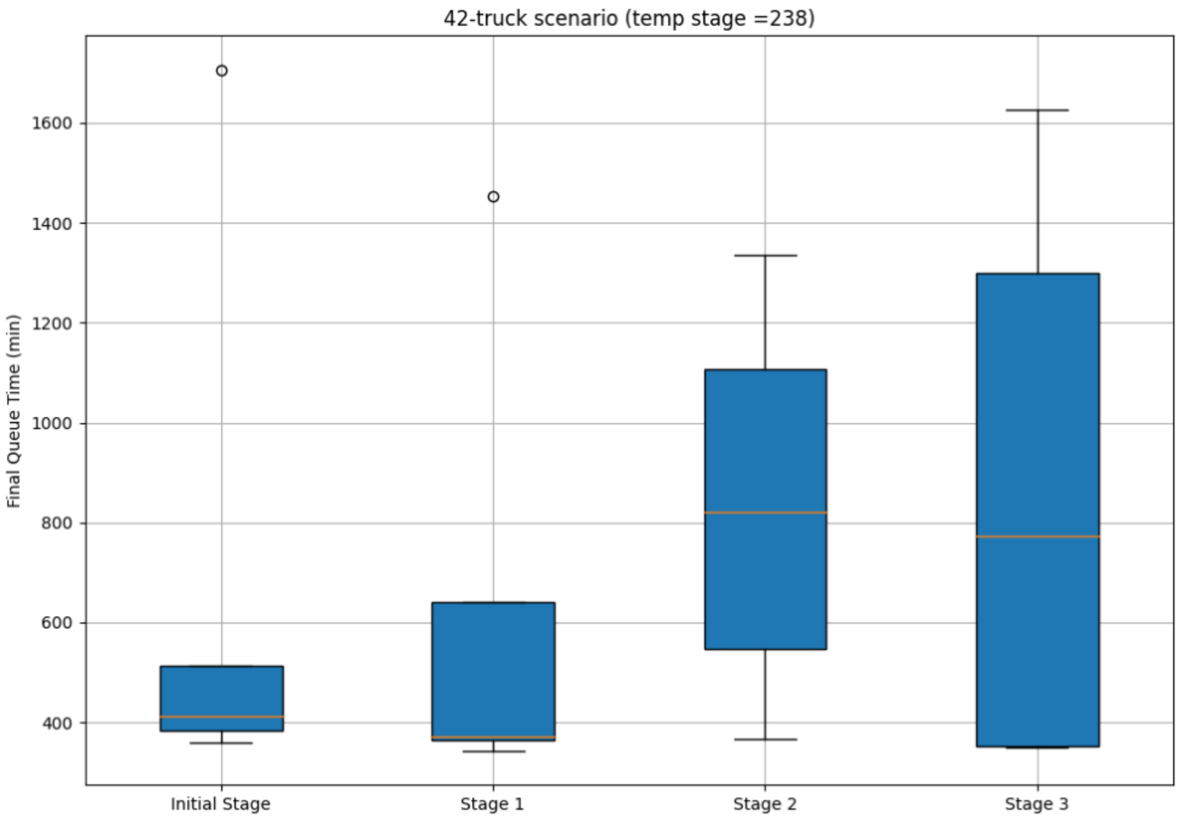


Figure 28: Boxplots of final queue time

From Figure 28, it can be inferred that merely relying on the number of temperature stages does not consistently ensures that the algorithm approaches a near-optimal solution. While outliers exist in every stage, for the 42-truck scenario, an algorithm with an increased number of temperature stages does enhance the likelihood of achieving a near-optimal solution. However, this augmentation is accompanied by extended solving time, which may not be preferable in many contexts. Notably, each stage did succeed in obtaining a near-optimal solution, suggesting that the proximity to a near-optimal solution is significantly influenced by the number of temperature stages.

In the subsequent section of the results, attention is directed towards the smaller truck scenarios, which already achieved a near-optimal solution using the initial parameters of the SA optimization. As observed in the previous section, the cooling rate, alpha, significantly impacts the number of temperature stages, which in turn influences the algorithm's solving time. The table below illustrates the effects of a reduced cooling rate on the number of temperature stages.

Table 8: Temperature stage with different cooling rates

Start temperature	Minimum temperature	Cooling rate (alpha)	Number of temperature stage
10	0.001	0.9	87
10	0.001	0.8	41
10	0.001	0.7	26
10	0.001	0.6	18

A reduced cooling rate is anticipated to decrease the algorithm's solving time, but it may also impact its efficacy in minimizing the total queue time. The figure below showcases the final queue time across various truck scenarios.

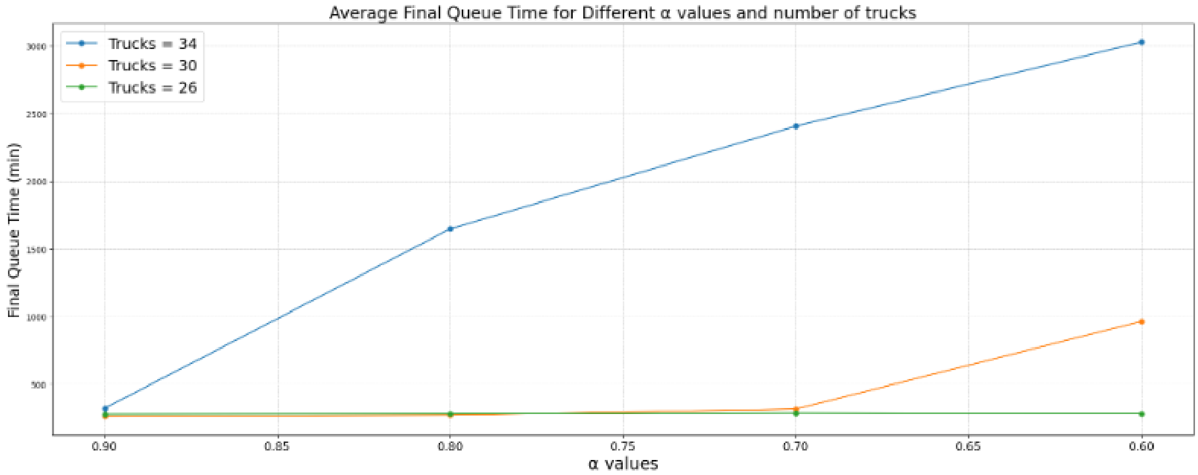


Figure 29: Final queue time with different alpha (truck scenario 26, 30 and 34)

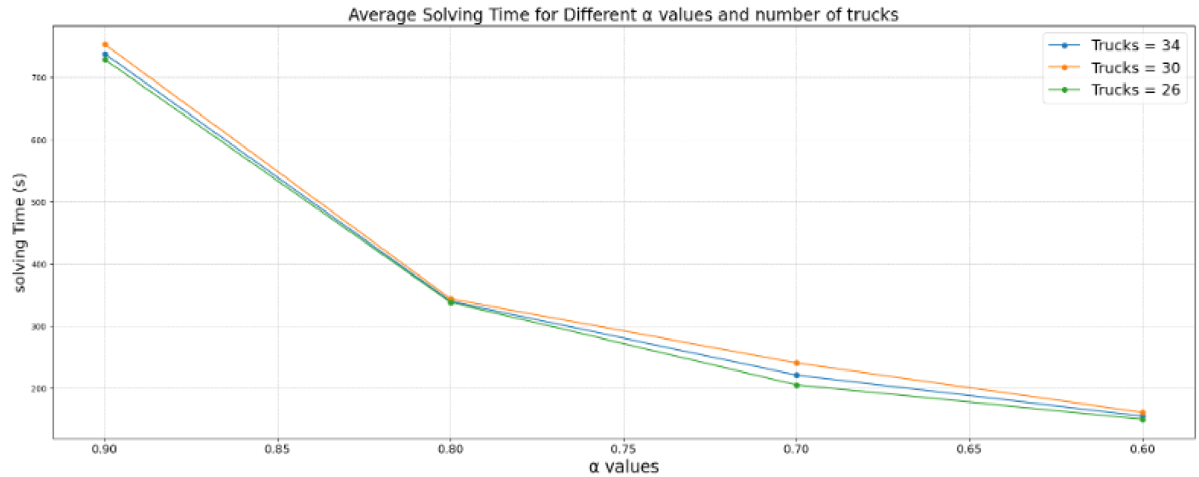


Figure 30: Average solving times with different alpha (truck scenario 26, 30 and 34)

In the depicted figure, it is evident that the solving time decreases as α diminishes. Similar to prior observations, the truck scenarios do not influence the solving time. Only the SA optimization parameter exerts an effect on this metric.

Furthermore, figure 29 illustrates that for an α value of 0.9, all scenarios consistently yield near-optimal solutions. However, for the 34-truck scenario, the model's performance begins to wane when α is reduced below 0.9. In the 30-truck scenario, there is a gradual increase in queue time at an α of 0.7, and the model ceases to provide near-optimal solutions when α falls to 0.6. Remarkably, the 26-truck scenario maintains near-optimal performance even at an α of 0.6, suggesting its potential compatibility with lower alpha which results in faster algorithms.

Upon examining the aggregate data, a distinct correlation emerges between the solving time and the number of trucks. As the number of trucks increases, the solving time correspondingly rises. This can be attributed to the fact that the algorithm necessitates more iterations to reach the lower bound of its operational framework. A higher truck count in the system invariably leads to elongated queue times, implying that trucks can operate at even lower speeds than a scenario with fever trucks, consequently escalating the overall duration of the algorithm. However, various parameters concerning speed adjustment were evaluated. Surprisingly, a pronounced reduction in speed did not enhance the performance. In fact, outcomes with considerably reduced truck speeds underperformed compared to the baseline parameters. This indicates that excessive reductions in speed might induce issues such as bunching or entrapment in sub-optimal local minima, leading to less than ideal results.

In all scenarios, a near-optimal solution is achievable. Table 9 presents the outcomes, showing a comparison of the average optimized speeds against the optimal speeds.

Table 9: Original vs optimized average speed for the empty runs in different truck scenarios.

Number of trucks	Average original speeds (km/h)	Average optimized speeds (km/h)
26	40.93	23.11
30	41.66	16.78
34	41.29	13.05
38	41.96	10.80
42	42.07	9.09

4.3 Fuel consumption

For the fuel consumption calculations in this sub-chapter, we employ the 34-truck scenario as a basis. It's important to note that the figures might vary, with fuel consumption per truck increasing when there are fewer trucks. As shown in chapter 5.4. The disparity between the original and optimized fuel consumption tends to widen with an increasing number of trucks, primarily because a greater number of trucks implies the potential for slower optimal speeds. However, excessively increasing the truck count in the mine can introduce additional associated costs, and it's essential to maintain a certain speed for the trucks to operate efficiently.

The calculations for fuel consumption were conducted using the formulas of equation number 3 presented in the methodology section. For the initial three computations, the fuel consumption, delineated at specific TR levels, aligns most closely with data found in existing literature. The subsequent graphs in figure 31 display the fuel consumption calculations for TR levels 10, 12, and 15. The 'original speed' denotes the velocities recorded in the Haulsim simulation. The 'slowest speed' is identified as the optimal speed achievable, as calculated by Equation 2. The 'optimized speeds' are generated through SA optimization. In near-optimal solutions, these optimized speeds will be close to the best speeds and result in similar levels of fuel consumption.

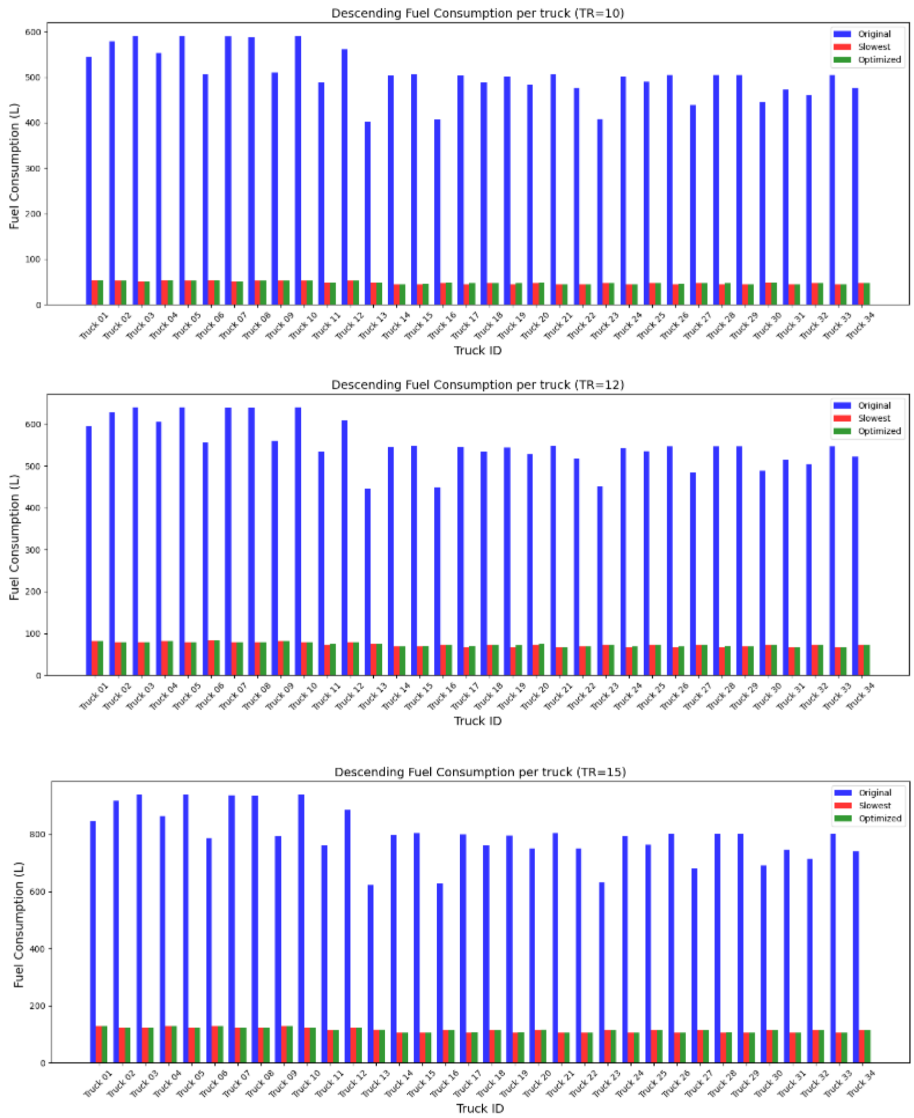


Figure 31: Fuel consumption (original vs slowest vs optimized) at different TR's

Figure 31 exclusively illustrates the fuel consumption of the descending trucks, as these are the trucks subject to optimization. Notably, there is a substantial reduction in fuel consumption during the descent of these trucks. In mines where ore transportation is primarily upward, the fuel consumed during ascent constitutes a significantly larger fraction of the total fuel consumption. The subsequent graphs in figure 32 provide a comparison of total fuel consumption between the original and optimized scenarios.

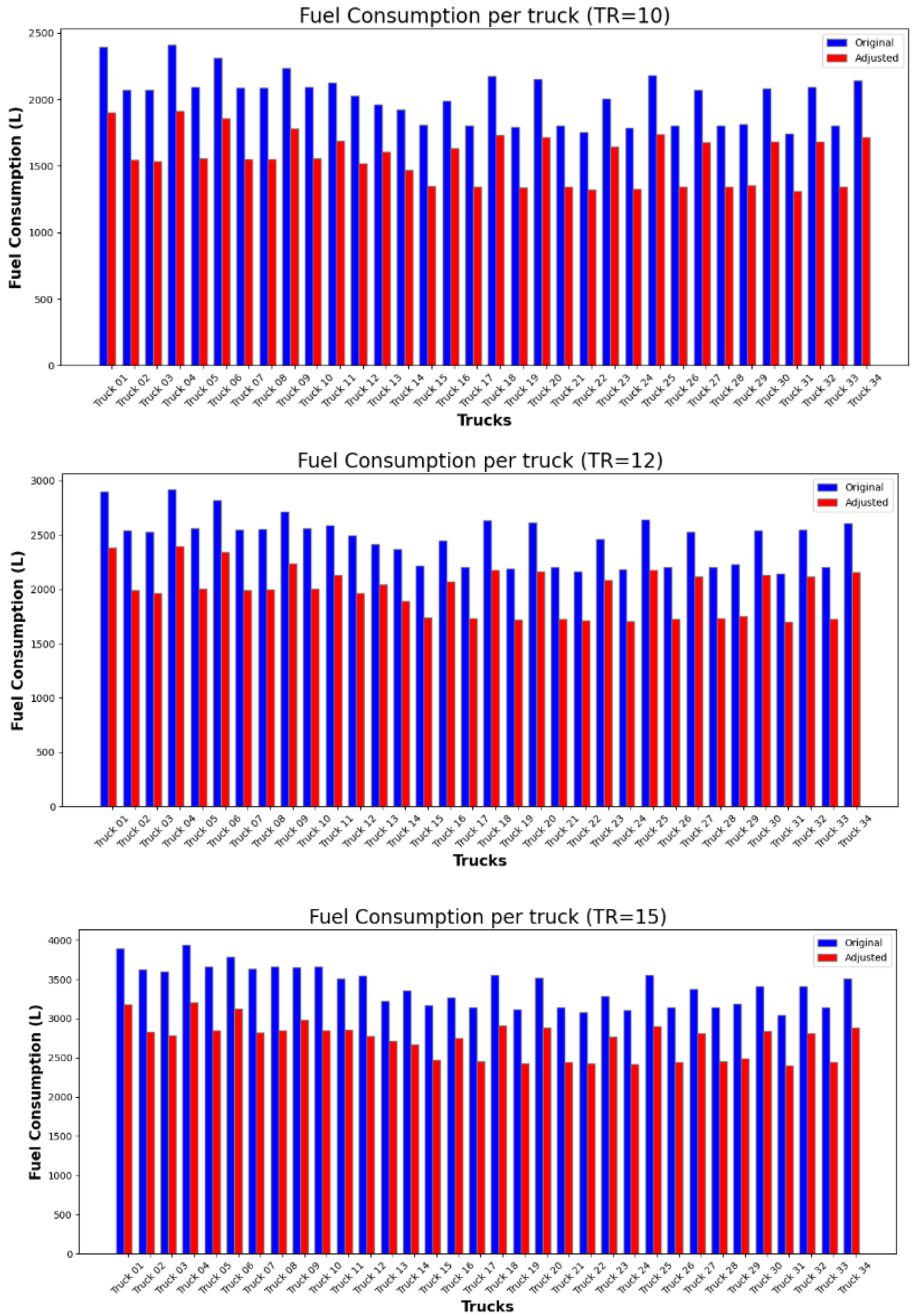


Figure 32: Total fuel consumption for different TR's

The total fuel savings at TR 10, 12 and 15 are recorded at 23%, 19%, and 20% respectively. It's imperative to note that these savings are based on a scenario of constant TR, which does not accurately mirror real-world conditions; assuming an opposing grade would be an unrealistic representation.

In order to model fuel consumption variations due to grade changes, a fuel emission heatmap was developed. This was achieved by employing Formula 17 to adjust the TR and Formula 16 to calculate fuel consumption, with TR and speed serving as variables. These calculations are further elucidated in the methodology section. Shown in figures 33 and 34. The two heatmaps represent the optimized and original speeds. Owing to the fact that a majority of the empty runs are downhill, there is a diminished fuel emission on the mine's steep roads, with more pronounced emissions observed on the extended flat terrains.

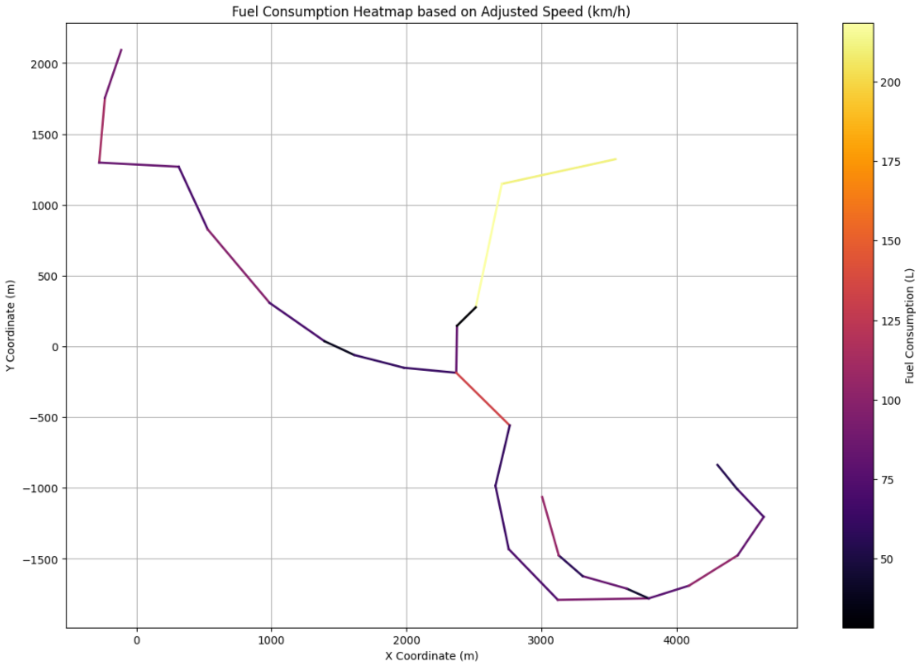


Figure 33: Empty runs fuel consumption heatmap optimized speeds

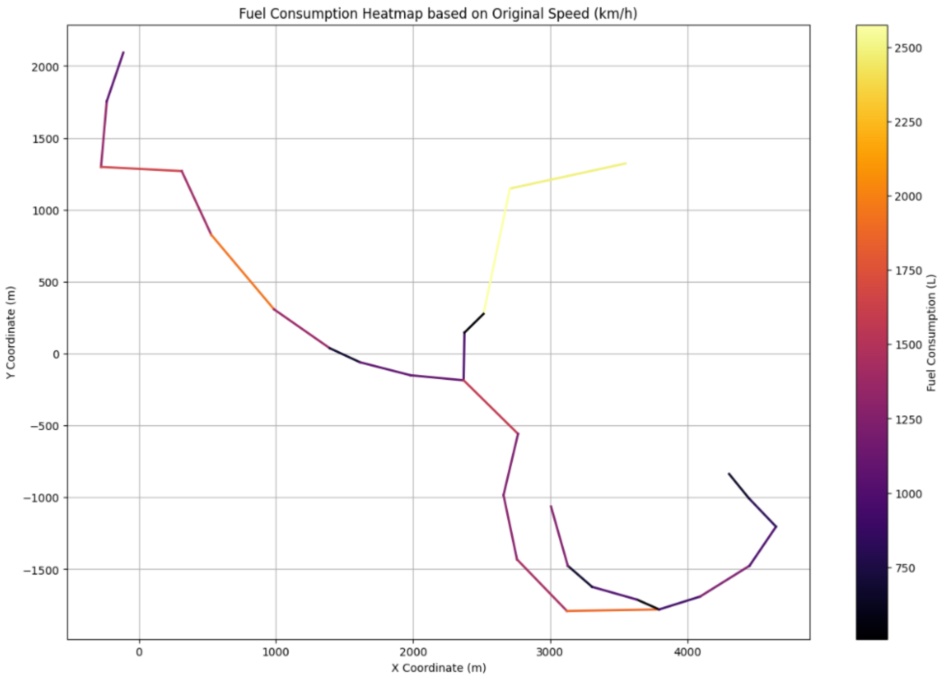


Figure 34: Empty runs fuel consumption heatmap original speeds

The two heatmaps figures 33 and 34 exhibit striking similarities, as both pertain to the empty runs. As illustrated in the subsequent figure, which displays the fuel emission map for the mine's loaded runs, there's a markedly increased fuel consumption for these runs. This elevated consumption is observed despite the trucks operating at merely a third of the original speed of the empty trucks. Such heightened fuel usage can be attributed to the steep gradients and substantial payloads with which they operate.

In Figure 35, the figure illustrates the fuel consumption associated with loaded runs, revealing a notable disparity when compared to empty runs. This increase can be attributed to the fact that loaded trucks must contend with the opposing force of gravity, leading to an increase in their total resistance (TR). Moreover, the presence of a payload effectively more than doubles the weight of the trucks, further accentuating the fuel consumption differential between loaded and empty runs.

It is noteworthy that the fuel consumption calculations for loaded runs yield a higher degree of accuracy than those for empty runs. This enhanced accuracy is primarily attributable to the fact that loaded trucks operate with total resistances (TR) that align more closely with the provided data. Additionally, they operate within the specified speed range, contributing to the improved precision of fuel consumption estimations.

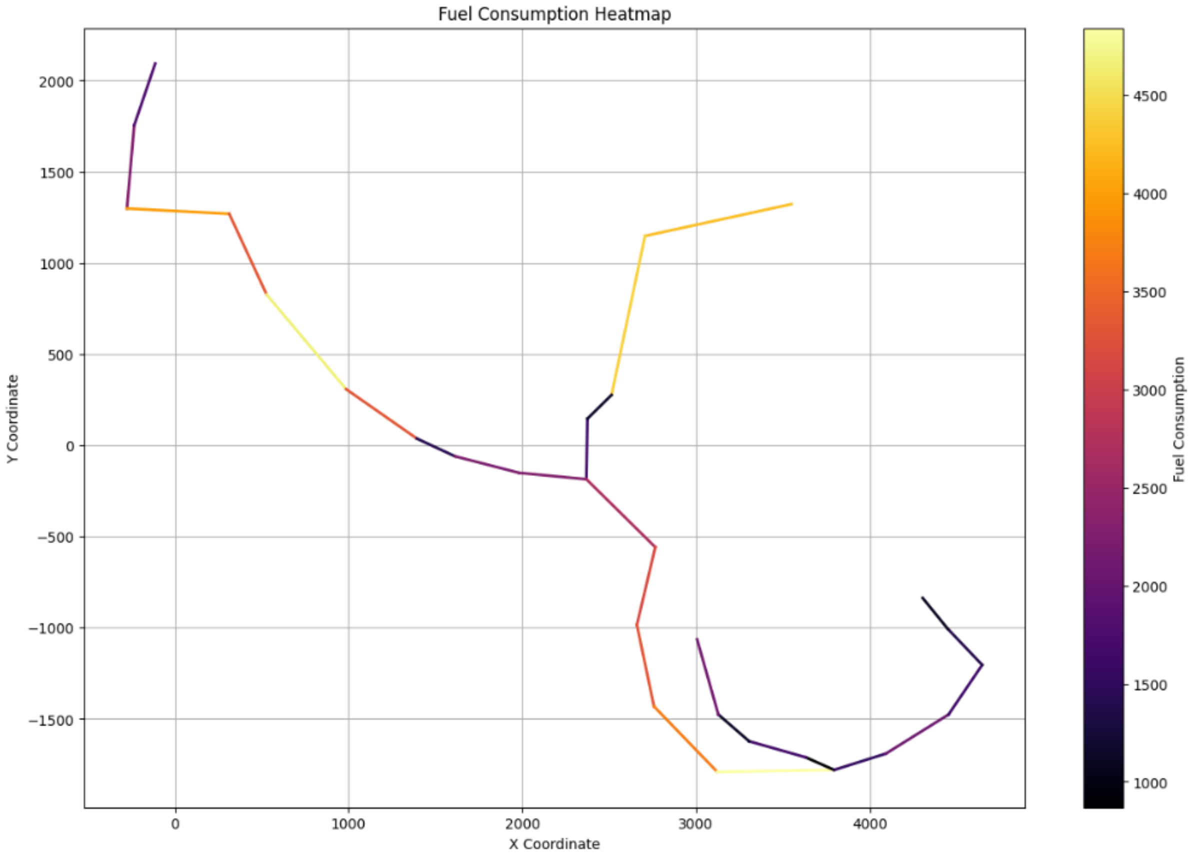


Figure 35: Loaded runs fuel consumption heatmap original speeds

In the table below the total fuel consumption of all the truck are given.

Table 10: Total fuel emissions of heatmaps

	Fuel emission (L)
Loaded run original speeds	67805
Empty runs original speeds	33333
Empty runs optimized speeds	2310
Fuel saving on only empty runs	93.1%
Fuel saving total	30.7%

4.4 Fuel saving comparison

In every optimized truck scenario, the loaders were fully utilized, rendering the integration of additional trucks into the system suboptimal. This research incorporated extra trucks solely to explore the boundaries of the algorithm's capabilities and to facilitate a robust comparison. It also considered the impact of varying parameters within the Simulated Annealing (SA) optimization algorithm. Moreover, an increase in the number of trucks led to extended queuing times, which in turn could lead to reduced optimized speeds. According to the methodology employed for data extrapolation, this deceleration is likely to result in diminished fuel consumption, thereby contributing to greater economic savings. In the next section of the results the fuel consumption saving of the different truck scenarios will be compared.

Table 11: Fuel consumption in Liters at specific TR's in different truck scenarios

Truck scenario	26	30	34	38	42
TR = 10 empty runs original speeds	17103	18082	17189	17418	17413
TR = 10 empty runs optimized speeds	3378	2112	1654	1423	1304
TR = 10 loaded runs original speeds	34077	34152	34125	33939	34044
TR = 12 empty runs original speeds	18689	19668	18716	18918	18900
TR = 12 empty runs optimized speeds	4435	3049	2522	2244	2104
TR = 12 loaded runs original speeds	46170	46263	46221	46015	46141
TR = 15 empty runs original speeds	26641	28439	27024	27457	27508
TR = 15 empty runs optimized speeds	5753	4390	3899	3627	3506
TR = 15 loaded runs original speeds	61903	62009	61950	61722	61873

Figures 36 and 37 illustrate the fuel savings accrued solely from the unladen journeys of the truck, where the saving are represented as a percentage of only the empty runs and as a percentage of the total emitted fuel. The data presented in these figures indicate a positive correlation between the number of trucks and the magnitude of fuel savings. Notably, an anomaly is observed in the scenario involving 30 trucks at TR 10; this deviation can be attributed to that in this instance the lowest possible speed is reached, which, in turn, corresponds to an optimal solution in terms of fuel efficiency. The fuel savings ff the empty runs at a TR of 10 increase from 80% to 93.5% which result in a total saving increase from 27% to 31%.

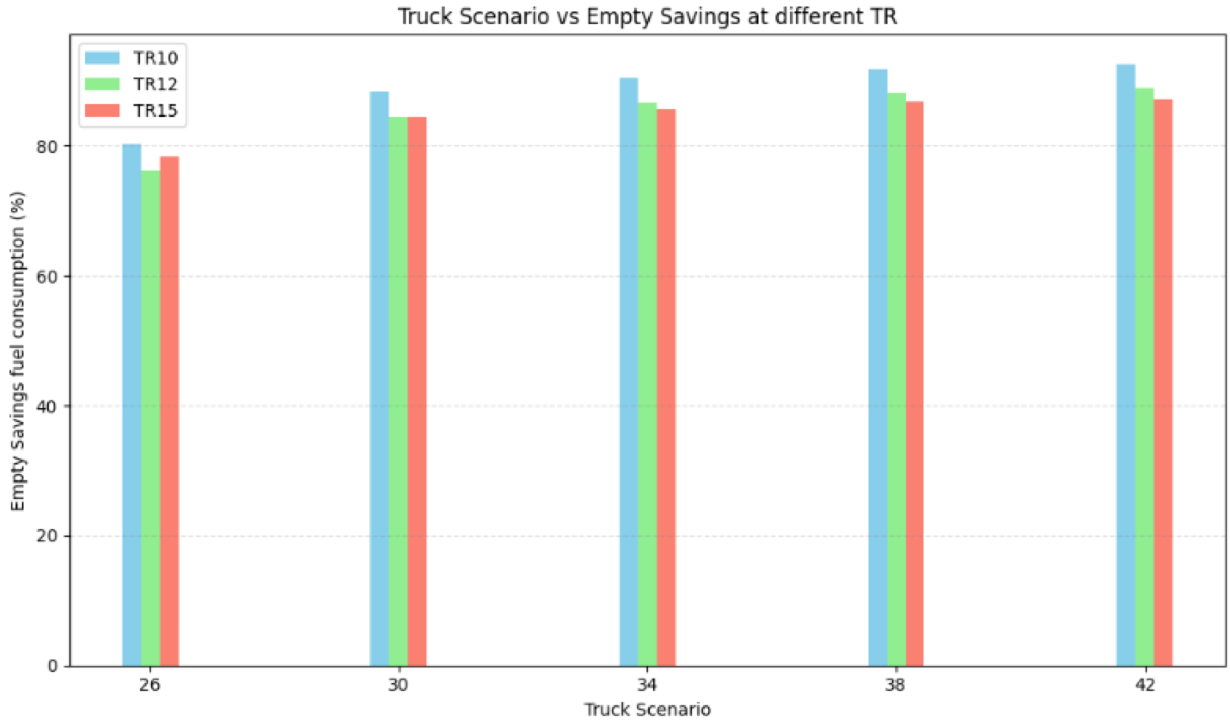


Figure 36: Percentage of savings for empty runs

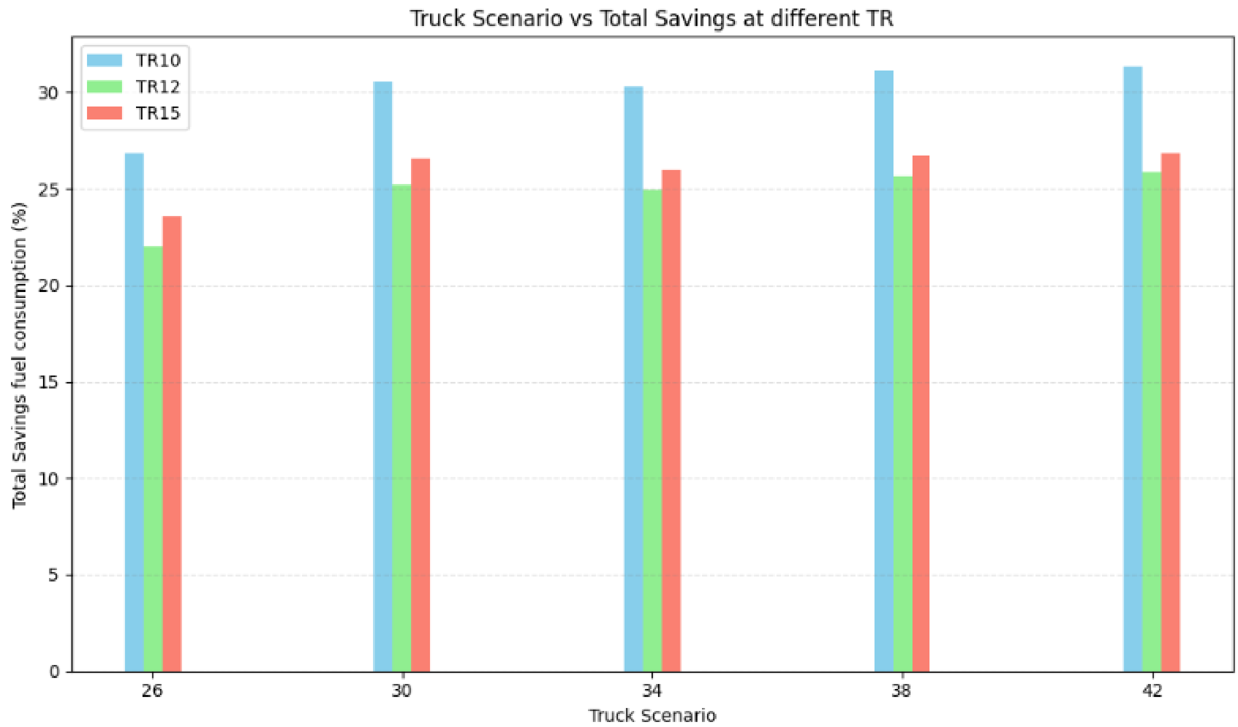


Figure 37: Total fuel consumption saving for different truck scenarios.

Table 11 presents the fuel consumption data derived from the heatmaps, where the consumption is calculated based on the speed and TR's associated with specific road segments. The observed discrepancies with the specific TR's can be attributed to the fact that the underlying formula was originally developed for scenarios characterized by high TR values. The formulas, as originally formulated, would result in negative values when applied to low TR scenarios. As outlined in the methodology, these formulas have been revised to preclude negative values, a modification that may, in some cases, lead to an overestimation of fuel consumption. The resulting savings are shown in figures 38 and 39.

Table 12: Fuel emitted on heat map in Liters for different truck scenarios.

Truck scenario	26	30	34	38	42
Empty runs original speed	5498	3306	2310	2224	2048
Empty runs optimized speed	32785	35232	33333	34494	34745
Loaded runs original speed	67712	67853	67804	67445	67639

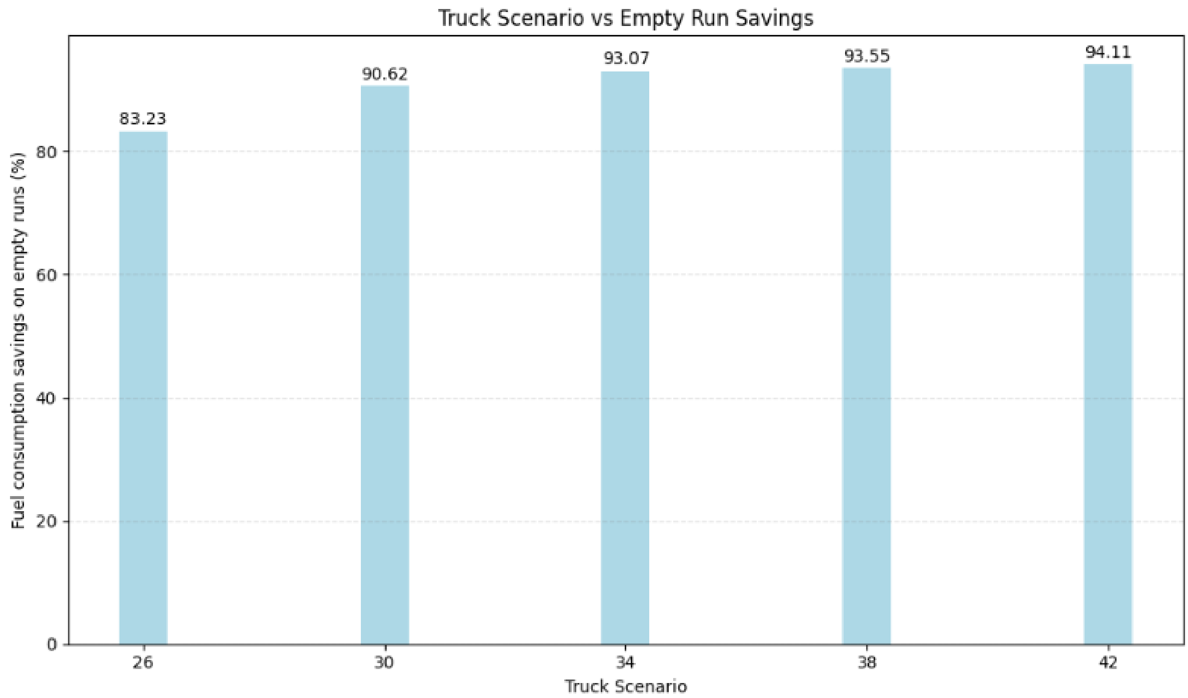


Figure 38: Fuel consumption savings on the empty runs

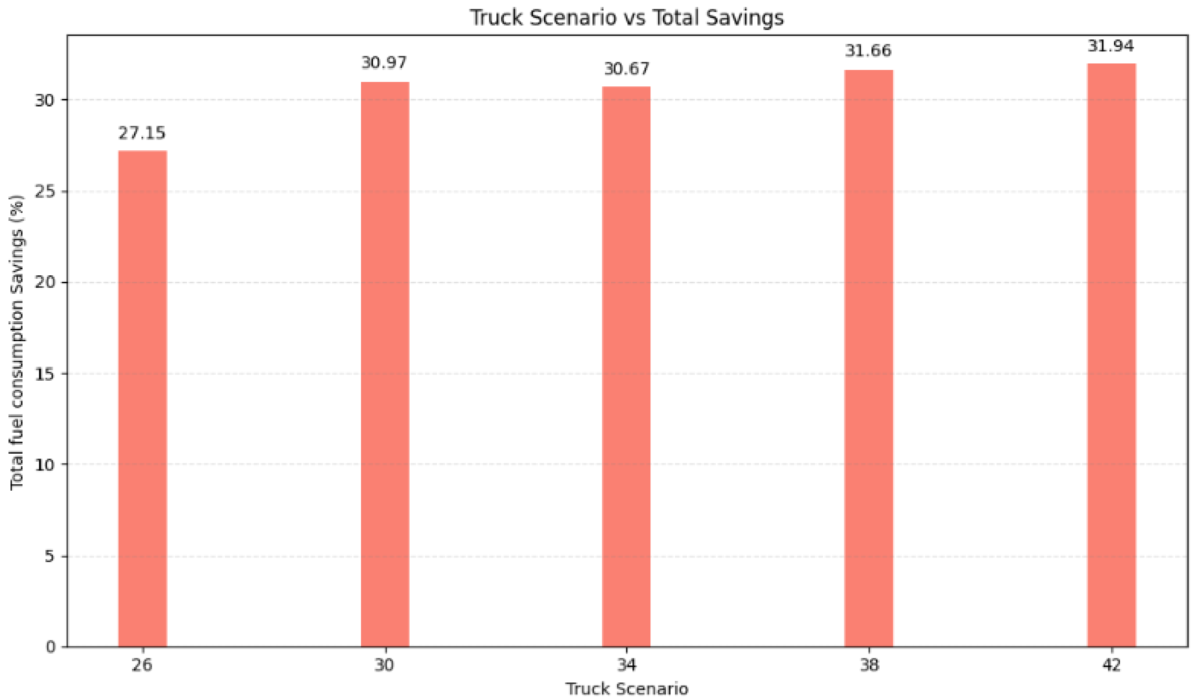


Figure 39: Total fuel consumption savings

The data presented in Figures 38 and 39 indicate a proportional increase in fuel savings corresponding with an increase in the number of trucks. The exception at the 30-truck scenario is attributable to the Simulated Annealing (SA) optimization reaching an optimal solution.

5 Discussion

The Haulsim software's limitations, particularly its lack of location-based, exportable data, represent a significant barrier to achieving more precise results. The average speeds of mining trucks provide an initial view of the potential efficiencies, yet we are constrained by the parameters of the Simulated Annealing (SA) optimization process. Due to Haulsim's inability to simulate the secondary effects of loading and unloading delays, our optimization is limited to the intervals between these events. In the dynamic environment of mining operations, being able to adjust and enhance these aspects would greatly increase the utility of the tool in realizing the full extent of possible optimizations.

In the realm of heavy-duty vehicle modelling, there exists a conspicuous gap in extensive research, or perhaps much of the research remains inaccessible to the public. While the current optimization paradigm posits that lower speeds are invariably preferable, real-world scenarios paint a more nuanced picture. Trucks, under specific circumstances, may have an optimal operational speed that diverges from the minimum. It's imperative to calibrate mining trucks' speeds to these optimal benchmarks, particularly when considering the diverse and often harsh conditions found in mining environments. "Presently, existing models are not designed to evaluate the outcomes of reduced speeds in mining trucks. Typically, a reduction in speed leads to an increase in fuel consumption as per these models. This is attributed to the unit conversion employed in the models, due to the fact that lower speeds result in decreased distance coverage. Consequently, the implications of speed reductions on fuel efficiency and overall operational efficacy remain inadequately explored within these frameworks."

Existing datasets, while comprehensive, often present highly specific data, delineating fuel consumption based on particular payloads, speeds, and Total Resistance (TR) values. A distinct delineation for TR and speed alone could significantly enhance our understanding of fuel consumption modelling. Notably, many models predominantly utilize a TR value of 10 or higher, which typically represents scenarios of exiting mining pits. The domain of fuel consumption modelling could benefit from broadening its scope to investigate scenarios where trucks, under certain payloads and negative TR, may not require more fuel than the idle state. If feasible, mine design could incorporate such considerations to optimize and reduce fuel consumption.

The observed savings in total fuel consumption amount to approximately 27-32% in the different truck scenarios. This percentage of savings is overstated. This can be attributed to the manner in which the speed formulas are extrapolated. The fuel consumption data is derived from moderate to high TR levels, where the operational speeds range between 5-30 km/h. Given that fuel consumption increases exponentially with speed, higher speeds inevitably lead to heightened fuel usage. However, the empty runs exhibit low to moderate TR levels, at which elevated speeds of 40+ km/h are readily achievable. This phenomenon tends to overestimate the fuel consumption during the empty runs at their native speeds. Due to the limited availability of data on fuel consumption modelling at low TR values, it remains challenging to ascertain its precise impact. The impact on scenarios involving more trucks is difficult to predict. In this study, increasing the number of trucks leads to fuel savings because their optimized speed is lower. However, in actual practice, trucks emit fuel while idle, a consideration that might become irrelevant if electric trucks become the norm. Still, it's important to assess whether the savings in fuel outweigh the extra capital investment and labour costs associated with electric trucks.

6 Conclusion

The primary aim of this thesis was to create a model capable of optimizing truck speeds for reduced fuel consumption. This research utilizes a custom-designed mine, where simulation data is generated using Haulsim. The data from Haulsim is subsequently processed using Python, and the optimized truck speeds are determined through the application of the Simulated Annealing (SA) optimization algorithm.

In summarizing the outcomes, Simulated Annealing (SA) has emerged as an effective tool for optimizing truck speeds to extensive queue times. With its initial parameters, the algorithm exhibited commendable performance, producing near-optimal solutions, particularly for scenarios with 26, 30 and 34 trucks. While adjusting the parameters expedited the optimization for these smaller truck configurations without compromising results, the 38 and 42 truck scenarios necessitated a more nuanced approach. Although parameter modifications led to improved outcomes for these larger configurations, they were accompanied by extended solving times. Furthermore, these scenarios occasionally fell short of achieving near-optimal results.

A discernible correlation was observed between the number of temperature stages and the solving time. This suggests a general heuristic: larger truck scenarios typically require a greater number of temperature stages to gravitate towards a near-optimal solution. However, the intrinsic randomness of the SA algorithm presents challenges. While it offers adaptability, it also introduces an element of unpredictability, meaning that reaching an optimal solution isn't guaranteed in every instance.

Concerning fuel consumption, this study, while predominantly employing hypothetical scenarios, demonstrated a reduction in total fuel usage ranging from 27% to 32%. This decrease was observed both in specific Total Resistances (TRs) and in the heat map analysis, where TR and speed were varied as parameters. While these results may not translate directly to real-world contexts, they underscore the vast optimization potential that exists in actual mining operations. Even marginal savings in fuel consumption can translate into significant economic and environmental benefits, given the colossal scale of mining activities.

The larger truck scenarios in this simulation suggest that an increase in number of trucks does increase the fuel savings. However, it is important to recognize that these savings might not directly translate to real-world scenarios. Even if such fuel savings are achievable, it's critical to consider that they may not offset the additional costs incurred, including the capital investment required for procuring more trucks and the accompanying increase in labour expenses.

In light of these findings, it is imperative for mining operations to leverage advanced optimization techniques, like SA, in conjunction with tools like Artificial Neural Networks, which will be explained more in the recommendations chapter. Such an approach not only ensures efficient operations but also paves the way for sustainable practices in the mining industry.

7 Recommendation

Each mining site presents its unique set of challenges, necessitating a flexible framework capable of being seamlessly integrated across varying situations. Such a framework should be adept at estimating the fuel consumption of mining trucks at specific Total Resistance (TRs) and speeds. This would facilitate accurate determinations of areas of high fuel emission, zones where trucks can decelerate, or even instances where acceleration is feasible, provided it is counterbalanced by a reduction in speed elsewhere.

Artificial Neural Networks (ANNs) present a promising avenue in this context. Given the vast reservoir of data points typical of mining operations, ANNs can be trained to discern patterns and behaviours in fuel consumption specific to each mine. Beyond fuel consumption, ANNs can be harnessed to predict aspects like road maintenance intervals, potentially leading to further reductions in fuel usage.

As highlighted in multiple studies by Soofastaei, the three principal parameters influencing the fuel consumption of mining trucks are Total Resistance (TR), speed, and payload. The unit of measurement in the Multiple Linear Regression (MLR) model, which incorporates these parameters, is liters per hour (l/h). However, the l/h-based MLR is not directly applicable to scenarios where speeds are adjusted, as lower speeds result in fewer kilometers traveled but increased fuel usage per kilometer, contrary to the conclusions of other studies. Consequently, the development of an alternative Artificial Neural Network (ANN) is necessary, wherein the unit of liters per kilometer per ton (l/km*ton) is more appropriate. This unit allows for the calculation of specific fuel consumption based on road segments, considering the three aforementioned parameters. With this data, a real-time model could be constructed to advise optimal truck speeds, taking into account both production and operational constraints.

Mining conglomerates, in their bid to remain competitive and reduce their carbon footprint, must leverage the immense data at their disposal. While significant fuel savings can be harvested from optimizing loaded runs, the empty runs too offer considerable opportunities for fuel conservation. Frameworks for developing Artificial Neural Networks (ANNs), which incorporate variables like distance, speed, Total Resistance (TR), and payload, can be established. Such comprehensive frameworks would enable the integration of all pertinent data, thereby facilitating more accurate estimations of fuel consumption across various mining environments. This approach would also be beneficial in accommodating the diverse range of mining truck types, ensuring applicability and accuracy in a broader spectrum of operational contexts.

The advent of electric trucks, equipped with regenerative braking, introduces an added layer of complexity to the optimization puzzle. Unlike their diesel counterparts, which continue to consume fuel even during descent or when idling, electric trucks recapture energy during downhill trajectories. This fundamental shift necessitates a re-evaluation of prevailing optimization models, ensuring they are attuned to the changing landscape of vehicular technology in mining operations.

A comprehensive understanding of fuel consumption can significantly enhance the effectiveness of optimization tools employed to predict and optimize said consumption. A synergistic approach, integrating meta-heuristics with Machine Learning (ML) techniques, particularly Artificial Neural Networks, is a promising strategy. Such a combination facilitates the simultaneous consideration of multiple salient parameters. Historically, both meta-heuristics and ANNs have demonstrated adaptability and efficacy across diverse scenarios, thus making them optimal candidates for addressing the complexities inherent in predicting and optimizing fuel consumption.

8 Reference

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9 Appendix

All of the code can be found in the git repository: https://github.com/Floris-4604784/ThesisSAP/