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DETERMINING THE IMPACT OF HAULAGE OPTIMISATION SOFTWARE ON ADDRESSING OPEN PIT MINING ECONOMIC AND ENVIRONMENTAL CHALLENGES: A CASE STUDY

Priscilla Malepfane

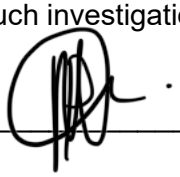
A research report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science.

Johannesburg, 2025

DECLARATION

I declare that this research report is my own unaided work. It is being submitted for the degree of Master of Science in Engineering at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other university.

I have familiarised myself with the University of the Witwatersrand Student Academic Misconduct Policy (SAMP). I hereby declare that the work I am submitting for assessment is my original work. I affirm that I have not plagiarised, misrepresented, or colluded with any other person or source. I have properly acknowledged, cited, and referenced all the sources that I have used in my work. I also declare that where I have used artificial intelligence (AI) tools it has only been as a means of guidance. The ideas and arguments presented in my work are my original thoughts and interpretations. I acknowledge that any academic misconduct, such as plagiarism or collusion, will result in serious consequences. According to the SAMP, these consequences may include a reduced grade, a fail mark, or disciplinary action. The Faculty of Engineering and the University of the Witwatersrand have my consent to investigate any potential academic misconduct in my work. This investigation may include the use of similarity and AI detection software to check the originality of my work. I undertake to abide by the decision of any such investigation.



(Signature of Candidate)

26th day of AUGUST, 2025

(month) (year)

“If you don't ask, the answer is always no.”

_Nora Roberts

ABSTRACT

This study assessed whether optimised surface mining schedules reduce environmental impact, thereby improving ESG-related factors. The study employs both qualitative and quantitative methods. A literature review revealed much research on optimisation and carbon footprint, but few studies on incorporating carbon footprint into strategic mine planning. The quantitative approach entailed the collection of secondary data for running an optimisation on a mine planning software. Hexagon's MinePlan Optimiser was used to run the optimisation.

Two key variables were analysed by contrasting and comparing the baseline and optimised models generated. These variables include Net Present Value (NPV), which helps determine the financial feasibility of the mining models and their carbon emissions. This, in turn, allows us to calculate the carbon footprint and assess the environmental impact. To derive meaning from the data, three main methods of analysis were employed: linear regression, Spearman's correlation, and a P-value hypothesis test.

The study achieved its initial objective by showing that there is a benefit in running an optimised model for mine planning purposes at Mine A. Results show that at Mine A's projected NPV will always be 62% higher than when running a baseline model. Furthermore, the NPV from the baseline model portrayed a high rate of decay at 0.667 versus 0.118 from the optimised model. This indicates the baseline model's sensitivity to long-term project timelines and fluctuating markets.

The optimised method presents an opportunity to manage emissions during the high operational costs phases, which is represented by a 31% improvement in carbon emissions during the periods of high operational costs, whilst maintaining a positive NPV when compared with the baseline model. Therefore, the optimised model presents a better chance of achieving financial feasibility and balancing environmental impact, thereby ensuring that Mine A can align with the environmental aspect of ESG through lowering the carbon footprint resulting from its hauling operations.

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Firstly, To God, for endless opportunities.

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LIST OF ABBREVIATIONS

ASCII	American Standard Code for Information Interchange
CO_2	Carbon Dioxide
CPLEX	Complex Linear Programming Expert
CSV	Comma-separated Values
ESG	Economic, Social, and Governance
GHG	Greenhouse Gas
KPI	Key Performance Indicator
LOM	Life-of-Mine
MILP	Mixed-Integer Linear Programming
NPV	Net Present Value

1 INTRODUCTION

This chapter provides context into the topic being researched by discussing the location of the mine where the study was conducted, the geological and environmental challenges facing the mine and investigates a probable solution. Furthermore, it summarises the research question, problem statement, objectives, elaborates on the research limitations, assumptions made and concludes with a section overview.

1.1 Research Background and Context

For anonymity, the gold mine of study is referred to as Mine A. Mine A is located in the gold mining region of Ghana, 300 km northwest of Accra (Sec & Edgar, 2021). The mine operates using both underground and open pit mining methods, with the majority of the gold being extracted through conventional open pit mining techniques, that is, truck and shovel. There are more than three active open pit areas of varying size, but they can reach depths of 300 m (Sec & Edgar, 2021). These pits can be extensive with robust infrastructure to support the mining and processing operations. Figure 1.1 shows the location of mine A within the Sunyani region of Ghana.

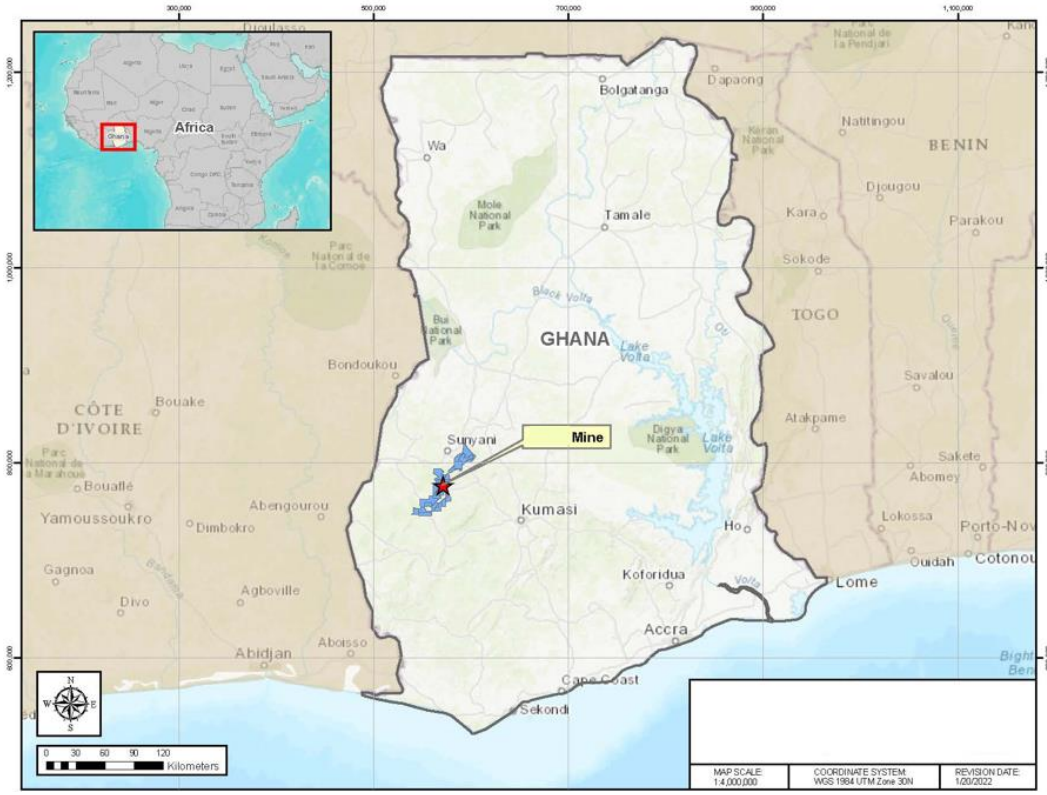


Figure 1.1 A geological representation of the mining site being reviewed in the case study *(Sec & Edgar, 2021)*.

Mine A is characterised by rolling terrain, including valleys and ridges typical of the West African savannah. Forest reserves, farmlands, and rural communities define the region's landscape. It enjoys a tropical climate with a distinct wet and dry season. The gold at Mine A is primarily hosted in structurally controlled deposits within metamorphosed volcanic and sedimentary rocks called Birimian rocks, these rocks are highly favourable for gold mineralisation due to their structural complexity and multiple shear zones (Komla, 1993). The ore bodies are mainly found in greenstone belts, particularly in steeply dipping shear zones, faults, and quartz veins that contain varying amounts of pyrite and arsenopyrite associated with gold mineralisation (Klemd & Hirdes, 1997).

Access to the mine is facilitated by major roads connecting it to the regional capital, Sunyani, and to the capital city of Accra (Sec & Edgar, 2021). The proximity to key infrastructure such as highways, electricity, and water resources ensures that mining activities are well-supported logistically (Sec & Edgar, 2021). However,

managing the mine's geographic impacts—particularly land use and the socio-economic effects on nearby communities—remains a critical concern for the operators and the government (Ghana Chamber of Mines, 2022).

Mine A uses surface mining methods, such as truck and shovel operations to extract the ore. Accessing these ores for economic benefit involves the clearance of vast hectares of land, leading to environmental degradation and excavation, which causes landscape deterioration and a negative impact on air quality (Sasmito et al, 2016). Despite surface mining operations contributing greatly to the global economy, they are not immune to the challenges the mining industry faces today. A surface mining operation, such as Mine A, is more susceptible to the following factors (Phillips, 2016):

- Public Scrutiny – ease of accessibility, operating close to local communities;
- Environmental Conditions – wind can exacerbate dusty conditions, overall shift in climatic conditions; and
- Operational Costs – fuel increases, labour costs, maintenance costs.

All the above-listed challenges are related to the frameworks of economic, social and governance (ESG), which have become a major player in the investment sector. Therefore, it becomes necessary for a surface mining operation to align with these frameworks to obtain future investments and maintain growth that can be used to develop the country further (Mao & Zhang, 2024). However, complying with the ESG standards alone is not enough, especially in the long term; an operation must be able to achieve and maintain profitability to satisfy all stakeholders (Naeem & Cankaya, 2022). Moreover, the world has seen a decrease in underground mining, with more operations looking into surface mining methods due to rising operational costs and safety concerns (Lumadi & Nyasha, 2024).

There is considerable literature detailing the strategies to achieve sustainable mining within the industry (Sasmito et al., 2016). The most recent approach is adopting business improvement strategies to achieve key performance indicators

(KPIs) directly linked to improving net present value (NPV) and meeting ESG compliance.

1.2 Problem Statement

A case study by Amankwa in 2023 indicates that gold mining activities are causing environmental degradation in the Asufiti North district of Ghana. This impacts farming activities within the region vastly, and companies operating within this region have become susceptible to public scrutiny (Amankwa, 2023). Mine A is located within this region, as indicated by Figure 1.1, where mining activities are causing concerns about environmental degradation, thereby emphasising the need for sustainable mining practices. Furthermore, the worldwide shift in energy production practices, international geopolitical instability and low mineral exploration efforts pushes for the adoption of ESG strategies to achieve sustainable mining (Sharaky, 2014).

To manage the effects of mining activities on communities, mining companies adopt and develop strategies in line with ESG requirements. However, these are often reactive and expensive to implement for mining operations that are already in the production stages (Naeem & Cankaya, 2022). Optimising the haul roads and haulage plans allows the technical services departments, as well as the strategic planning team, to incorporate ESG early in the life-of-mine plan. Thereby creating a proactive approach to sustainable mining.

1.3 Research Question

The current cost of operating a surface mine is substantial, with expenses including high fuel consumption and associated emissions, large labour forces and related costs, significant capital expenditures for equipment and infrastructure and rising costs of compliance with ESG (Minerals Council of South Africa, 2023).

The implications of ESG on mining are over-extensive, with mounting pressure from stakeholders to reduce environmental impact, improve social responsibility, and ensure transparent governance. However, reaching these goals without increasing costs poses a significant challenge. Therefore, can the Hexagon's Mine Plan Optimiser aid the industry in improving its current operations without

increasing costs and maintaining alignment with the ESG frameworks to achieve sustainable mining?

1.4 Research Objectives

The main aim of this study is:

- To determine the carbon footprint and NPV arising from Mine A's life-of-mine plan. This was achieved by collecting or requesting access to the database for review and data collection. Then, using the database to run an optimised schedule to review NPV and generate fuel consumption per truck per schedule.
- Comparing and contrasting the NPV and carbon footprint of the baseline model and the optimised model obtained from the Hexagon software.
- Identifying the challenges and opportunities presented by each model concerning achieving sustainable mining in surface mining.

1.5 Research Motivation

This research is important to me because I have travelled to mining sites outside of Africa, where environmental preservation is achieved by proactive decision-making. In these surface operations, there is no conversation of production or productivity without a thorough review of the implications of mining activities on the environment. However, on the continent of Africa, there seems to be a nuanced nonchalance about this.

The approach is rather reactive, resulting in dire consequences for surrounding communities, and I would like to aid in changing this perspective. For Mine A, this research must be conducted because it provides them with an opportunity to rethink the environmental aspect of ESG, to reshape how their employees relate to the impact of the decisions they make daily and their effect on the environment and, inadvertently, the communities from which they may also come.

Though the site may already have optimisation tools, such as Hexagon's Mine Plan Optimiser, on-site. The intent is to show how the proper application of the tool can

aid in solving real-life issues currently faced by the mine through building scenarios (introducing various constraints) in these tools. The findings from this research can empower technical managers and the mine planning team to make well-informed decisions in the initial planning stages for the mine's lifecycle.

1.6 Research Limitations

The research only focused on a single commodity, and the optimisation was done using a single software, that is, Hexagon's Mine Plan Schedule Optimiser. This was the only software available at the time of the study and with which the researcher had experience. Furthermore, the carbon footprint emissions estimation is calculated based on the truck haulage fleet only; no consideration is given to land use, secondary equipment employed to maintain road surfaces, or equipment used to blast the material to be hauled. Due to the technology available, this research only focused on the environmental aspect of the ESG frameworks.

1.7 Research Assumptions

To ensure a successful implementation of this case study, the following research assumptions hold:

- The site has set up an existing haulage plan in their project files to use as a basis for the optimisation schedules and run comparisons against;
- The main KPIs are reduced operational costs and adverse environmental effects to improve NPV; and
- Site uses truck and shovel methods for load and haul operations.

1.8 Structure of the Research Report

This thesis consists of seven chapters. Chapter 1 is the introduction and covers the background of the research topic, the problem statement, the justification for the research, and the research objectives. The research methodologies followed by this study and the sources of the information are introduced.

Chapter 2 reviews the literature within the scope of the research, including a background introduction to surface mining load and haul operations, Hexagon's Mine Plan solutions software, and solver methodology. The section further elaborates on key studies, theories, and concepts covered on this topic.

Chapter 3 outlines the two main methodologies applied to this research and the data collection and validation processes employed, which remove errors and bias to ensure good-quality data for analysis.

Chapter 4 introduces the data collected for the study. It emphasises the importance of each data type in producing good data for analysis.

Chapter 5 provides an analysis of the results obtained from the collected data, which has been processed through Mine Plan Optimiser, and the Greenhouse gases (GHG) estimations calculated from a formula.

Chapter 6 concludes with recommendations after reviewing all chapters and providing an overview summary of the findings, considering the literature reviewed in Chapter 2 and future research work.

2 LITERATURE REVIEW

Chapter 2 reviews the literature within the scope of the research, including a background introduction to surface mining load and haul operations; defines carbon footprint in mining by dissecting the various elements that it covers in general and specifically to surface mining operations. The chapter further discusses Hexagon's Mine Plan solutions software as the tool used for this case study, and the solver methodology it applies. Lastly, the section elaborates on key studies, theories, and concepts covered on this topic.

2.1 Surface Mining Carbon Footprint Studies

Greenhouse gases (GHGs) are often divided into primary and secondary, where primary emissions are necessary for maintaining atmospheric balance, and secondary emissions are a result of the gradual increase in industrialisation (Tuckett, 2019). These secondary GHGs include carbon dioxide (CO_2), methane (CH_4), chlorofluorocarbons (CFCs), tropospheric ozone (O_3), and nitrous oxide (N_2O) (Watson et al., 2018).

When released into the atmosphere at a rate higher than they can be absorbed, these GHGs create a thick film along the ozone layer that prohibits the sufficient transfer of heat, thereby offsetting the temperatures on Earth (Tuckett, 2019). This offset has resulted in the gradual 1-degree Celsius increment in global temperatures, also known as global warming, which has worsened droughts in some parts and flooding in others (Stallard & Poynting, 2024). GHG emissions are classified into three categories (UNFCCC, 2020):

- **Scope 1 Emissions**: These are all direct emissions resulting from an organisation's activities that the organisation can control. An example would include burning fuels by mobile or stationary vehicles.
- **Scope 2 Emissions**: All indirect emissions resulting from activities that directly benefit an organisation. For example, emissions from generating electricity used in the processing plant or from producing the cooling in the workings;

- **Scope 3 Emissions**: These are all indirect emissions not included by either Scope 1 or Scope 2. Such as emissions due to employee travel, goods purchased by the organisation or drinking water.

Treaties such as the Paris Agreement have been developed as a strategy to negate the effects of global warming by reducing the global GHG emissions to cap global warming to 1.5 degrees Celsius (UNFCCC, 2020). The Paris Agreement has had a major influence on managing environmental impact through the conscientisation of investors to progressive funding of current and future projects (Chang et al., 2024). ESG provides guidelines for managing varying factors such as climate change, environmental degradation, social instability, and ecosystem imbalance (European Banking Authority, 2025). The excavation of the ground with the intention of retrieving minerals is a detrimental process that contributes to one or more of these factors. Sustainable mining has become a necessity, and this is supported by the trend of multiple operations adopting environmentally sustainable strategies such as:

i. Seriti (2024) has identified environmental care as one of its core values, indicating its importance by dedicating an entire reporting framework to the public via its website. The company uses this platform to report on energy consumption, GHG emissions, air quality, water management and land use (Seriti, 2024).
ii. Thungela (2023) follows an approach similar to Seriti by publicly reporting on Scope 1 and Scope 2 emissions and further elaborating on the company's plan to achieve the obligations of the Paris Agreement.

Though the abovementioned companies are coal mining companies, they were included because there are no gold mining opencast mines in South Africa to run a comparison against. However, the coal mines above are surface mines (which form part of the scope of the research) and they exemplify a common trend amongst local and multinational companies operating within South Africa and other African countries. It is important to note that there was no rigid framework for ESG pre-2023 quarter 4; however, as of 2024, public companies must report on ESG

performance (Redelinghuys, 2024). This requirement arising due to the Companies and Intellectual Property Commission (CIPC) making it mandatory for public and state-owned enterprises to file ESG performance reports with the annual returns reports, forecasting that this requirement would be fully mandatory in 2025 (XBRL, 2024). Some efforts have been made by the Johannesburg Stock Exchange (JSE) to align with the CIPC requirements by developing a common framework of reporting for all companies in its listings to standardise and structure the reporting practices in line with the International Sustainability Standards Board (ISSB) (Anstey, 2024).

Though undergoing major standardisation processes, ESG reporting has cemented its importance in creating value for developed and developing countries. A recent study shows that though there is a correlation between ESG scores and financial benefit, the quality of reporting plays a major role in that score, with developing countries lagging in the environmental indicators category (Huang & Ge, 2024). This means that many African companies do not realise the full financial benefit of adopting ESG due to weak reporting on environmental performance, poor ESG frameworks and/or poor execution of the frameworks. Figure 2.1 shows South Africa's ESG score performance compared to developed countries. In the graph is clear that between the reporting periods 2019 to 2021, the United Kingdom (UK) scored higher than the sample average in terms of average ESG scores. It is then followed by the United States of America (USA), with South Africa lagging behind both countries. Relating this to Huang and Ge's (2024) report, this would mean that of the three countries, SA would have received the least benefit from ESG due to its low score.

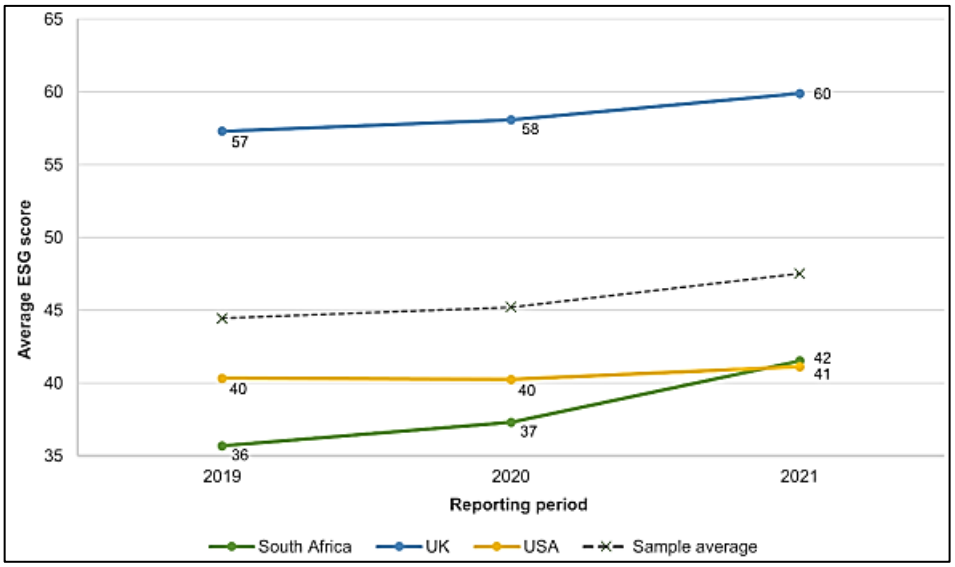


Figure 2.1 Average ESG score per country (Huang & Ge, 2024).

In South Africa, the Department of Forestry, Fisheries, and the Environment (DFFE) releases annual national greenhouse gas inventory reports to track and manage GHG emissions, which is essential for meeting international climate commitments like the Paris Agreement (Department of Environmental Affairs, 2016). The Paris Agreement's frameworks align with the ESGs in addressing key environmental challenges (Cochran & Pauthier, 2019). Released in 2023, the latest report covers the period starting in 2000 to 2020; South Africa's 8th national GHG inventory report indicates a slight overall decrease in emissions from 446 million metric tonnes of CO_2 equivalent ($MtCO_2e$) in 2000 to 442 $MtCO_2e$ in 2020, equating to about a 0.8% reduction (DFFE, 2022). Furthermore, a notable 5.9% drop in emissions between 2017 and 2020 resulted from COVID-19-related industrial activity and transportation reductions, reflecting short-term emissions variability (DFFE, 2022).

Energy production remains the primary source of GHG emissions in South Africa, contributing around 80% of the country's total emissions (DEA, 2016). This high percentage is largely due to the country's reliance on coal for electricity generation, alongside industrial fuel use and transportation.

Amoaka et al. (2018) conducted an extensive study into the GHG emissions from gold mining in West Africa, Ghana. The study of twelve mining companies in the

Birimian complex on the Sewfi Belt found that fuel and electricity use were the main sources of greenhouse gas emissions in Ghana (Amoako et. al, 2018). This indicates that the trend between GHG emissions and the mining industry is prominent in South Africa and globally, necessitating an effective resolution through technology adoption and adaptation. Although ESG's effects on profitability and mining's future are well studied, its practical use is less examined. This study fills that gap.

While developing a systematic engineering approach incorporating ESG into life-of-mine designs, Nehring & Knights (2024) referred to the lack of ESG consideration in mine planning designs in the early stages of mine planning. They argue that though strategic and operational mine planning encompasses decisions determining the feasibility of running a mine, the planning is often conducted separately, lacking continuity and homogeneity. Operating in silos deters collaboration and accountability, thereby resulting in missed opportunities for growth, development and/or improvement (De Waal et al., 2019). To maximise ESG benefits, integrate its principles throughout mine planning, as frequent updates address changing surface mining conditions and unpredictable weather (Leonida, 2022).

2.2 Load and Haul – The Heart of Surface Mining Operations

More than 60% of all surface mining operations are accounted for by surface mines, with haulage costs representing nearly 60% of total operating costs, as shown in Figure 2.2 (Ali, 2015). About 80% of this 60% representing operating costs, is consumed by load and haul operations (Bagherpour, 2007). Furthermore, load and haul operations are the most energy-intensive in the surface mining value chain (Saragih, 2023). Research by Haque & Norgate (2010) indicates that load and haul operations account for the highest contribution to greenhouse gas emissions (GHG) in surface mining operations, where crushing and grinding are ignored. Efficient haulage systems are key to mining goals, and simulation with animation effectively evaluates them (Ali, 2015).

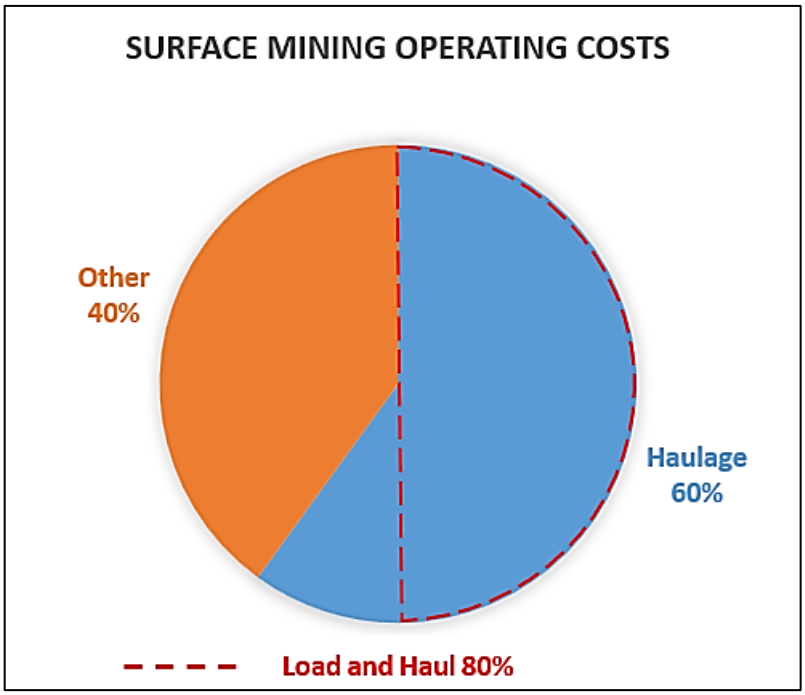


Figure 2.2 Schematic representation of the percentage contribution of load and haul into surface mining operations (Ali, 2015 and Bagherpour, 2007).

A comprehensive approach to optimising mining and processing operations is required to address the prominent economic and environmental challenges in open pit mining. The planning and scheduling of extraction blocks from different mining areas, considering the physical properties of ore types, are crucial for achieving over 63% optimisation, with the remaining 37% obtained from improving measures such as optimal fragmentation and fleet size selection (Aymen, 2013).

Low-grade mineral deposits and inaccessible orebodies present significant challenges. These challenges can be mitigated through mine planning optimisation, focusing on mining selectivity strategies, ore deposit parameters, determining ideal haulage routes, and planning for plant facilities (Findlay & Dimitrakopoulos, 2024). A study by Feng et al. (2020) highlighted that optimised haulage operations could reduce CO_2 emissions by up to 20%, contributing to more sustainable mining practices. If realised, this integrated approach can achieve economic benefits by meeting environmental and production requirements.

Sustainable mining emphasises the need to balance economic growth with environmental protection. Haulage optimisation software can support this by reducing fuel consumption and emissions, which aligns with broader environmental sustainability goals (Gupta et al., 2021). Assessing the environmental impact of mining operations across their entire life cycle can help better comprehend and manage the effects.

Truck fleets are a major component of a haulage plan due to their quantity and ratio to loaders, but they also consume the highest amount of fuel (Dindarloo & Siami-Irdemoosa, 2016). Several studies have proven that haulage optimisation software can substantially improve fuel efficiency by optimising truck routes and reducing idle times (Barnewold & Lottermoser, 2020). For example, a study by Patterson et al. (2017) demonstrated a reduction in fuel consumption at a large open pit mine by applying optimisation algorithms in planning and truck deployment.

2.3 Optimisation Theory

The surface mining industry is not new to optimisation tools and techniques. There is ample research into various methods of optimising surface mines. Companies such as Schauenburg Systems, Micromine, AVEVA, Sandvik, Schneider Electric, Caterpillar, Surpac, Datamine, Vulcan, Komatsu, Hitachi and Razor all have one or more software that provide optimisation solutions throughout the mining value chain (Mining Technology, 2025). Gorai and Chatterjee (2022) explain mine systems explicitly in their work on mining optimisation techniques by referring to the following:

i. The optimisation theory for surface mining is derived from a systems theory. Systems theory is the basic understanding that any mining operation comprises an open or closed system containing other subsystems.
ii. These systems are necessary to the everyday operations of the mine and can vary from linear, non-linear, simple, complex, time variant/invariant, continuous, discrete, deterministic and/or probabilistic.

iii. Applying a systems approach ensures that a complex system can be broken down into manageable systems to aid in achieving the objective. This can be done by understanding the relationship between the input and output parameters, identifying constraints and determining the most ideal equations to apply for the mathematical model. This method is also known as the classification of the optimisation problem and is further illustrated by Figure 2.3.

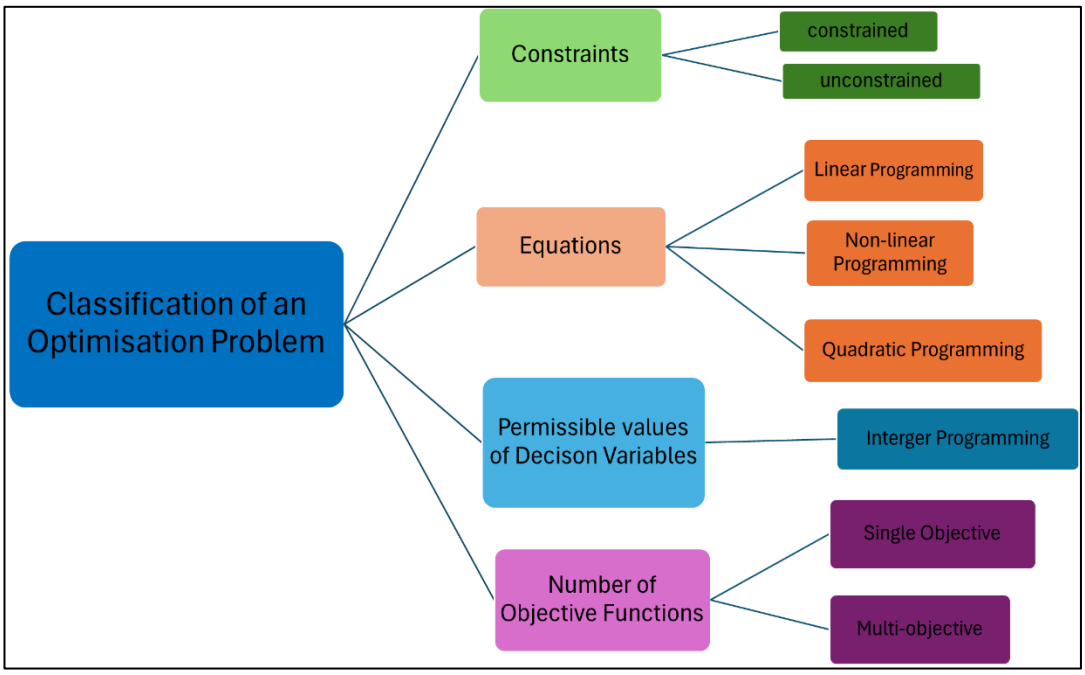


Figure 2.3 Schematic representation of the categories reviewed when classifying an optimisation problem.

Once the classification process is completed, a suitable algorithm can be used to perform the optimisation. Though Gorai and Chatterjee (2022) provide an elaborate list of techniques or algorithms, Venter (2010) argues that all methods can be summed up into local or global algorithms. Local algorithms can be described as those that generate solutions based on a portion of the input data as opposed to utilising the whole dataset, and the converse is true for global algorithms (Javed et. al, 2018). A majority of the local algorithms are gradient-based methods often used to solve engineering problems because they are presumed efficient and require little specificity to the objective or problem at hand

(Venter, 2010). The local and global optimisation techniques are contrasted in Table 2.1.

Table 2.1 A comparison of Optimisation techniques (Venter, 2010).

	Optimisation Techniques	
	Local	**Global**
Description	Uses a portion of the dataset to determine the local optima.	Uses the entire dataset to find multiple local optima.
Advantages	Efficient, simple, and can be used in datasets with multiple design variables, without requiring problem specificity.	Efficient and robust, it can conduct multi-search operations at various starting points within the dataset and is more accurate at finding the global optimum.
Disadvantages	Struggles with complex discrete optimisation problems, and therefore, can be erroneous	Time-consuming, requires specificity on the problem, and requires fewer design variables.
Classifications	Gradient-based, non-gradient-based, constraints,	Evolutionary algorithms, deterministic algorithms
Common Examples	Sequential linear programming, Simplex algorithm	Genetic algorithm, Swarm particle optimisation,

For this study, optimisation focuses on two key KPIs (NPV and carbon footprint) or objectives from the planned haulage mining schedules. These objectives are often

viewed as conflicting for a simultaneous optimisation. However, reviewing the arguments presented by Gorai and Chatterjee (2022) and Venter (2010) above, it is clear that the required optimisation is classified as a multi-objective problem with multiple linear constraints, a large dataset requiring a robust algorithm to achieve more than one local optimum. For this reason, a simple linear programming technique will not suffice, but rather a global optimisation technique.

Multi-objective mixed integer linear programming (MOMILP) is one such type of global optimisation technique that allows for the optimisation of more than one objective, where a compromise is required to achieve the desired objectives (Antunes et.al, 2004). This resonates with Mine A because it is a surface mine with multiple pits in different areas. These pits will be mined simultaneously, so it is critical to determine the ideal sequence to follow to achieve the set KPIs. Haulage optimisation is grounded in optimisation theory, which involves selecting the best option from a set of alternatives to minimise or maximise a particular objective (McKelvey & Neves, 2021). Mining typically minimises haulage costs or environmental impact by optimising routes, fuel consumption, and equipment usage (Li et al., 2020). Optimisation theory employs a genetic algorithm or a combination of mixed-integer programming solvers to facilitate decision-making and solution creation (Alipour et al., 2019).

2.3.1 The Optimisation Software

The mining value chain for a surface operation ranges from exploration to rehabilitation, with multiple tasks in between to achieve the operation's financial objectives. However, before any of these activities take place, a strategic plan is drafted to determine the sequence of activities necessary to align with the feasibility study and proposed budget. Operationally, this plan is referred to as the life-of-mine plan, which provides an overview of the required material and resources to meet the expected revenue.

The life-of-mine plan is then broken down into sub-plans in the long, medium and short term to create a more granular trackable plan. Creating these plans can be tedious work, often leaving room for error (Astrand et. al, 2015). Using mine planning software mitigates this issue by reducing time spent on making plans,

improving accuracy, and increasing confidence in decision-making (Kapageridis, 2005).

In his review of the latest and best performing mining planning and scheduling software, Walker (2010) ranked Hexagon's mine planning suite as the second-best performing software for scheduling and optimisation exercises. Referring to its robustness in integrability and enhancement of productivity. Other software included in this list was Surpac by Dassault Systèmes (ranked best), Vulcan by Maptek, Micromine, Deswik, RPM Global and Minex.

Mine A uses Hexagon's Mine Plan Schedule Optimiser to plan and run its long-term to medium-term mining schedules because the schedule optimiser is designed for larger data sets (5 to 10 years) owing to its robust solver. For short-term planning, Mine A uses Hexagon's Activity Scheduler, which allows for a more granular view of operations at shorter periods (hourly, daily, monthly). Activity Scheduler and Schedule Optimiser are tools in Hexagon's MinePlan3D suite (Hexagon, 2024a). The tool (MinePlan Schedule Optimiser) runs on a CPLEX engine using a mixed integer solver to generate solutions. CPLEX Optimiser is known for its robustness in solving Mixed Integer Linear Programming (MILP) problems, for example, the optimisation of production planning (IBM, 2024). MILP aims to identify the optimal solution for problems involving binary or discrete and continuous decision variables (Abolghasemian et al., 2022).

In the context of production planning, key focus areas typically encompass determining production quantities, allocating resources effectively, and scheduling tasks (IBM, 2024). The aim is to minimise costs or maximise profits while meeting constraints such as demand, capacity, and resource availability in line with Mine A's KPI objectives. This approach enhances operational efficiency and supports strategic decision-making within the production process (Aghdamigargi et al., 2024).

MILP or optimisation solvers apply four basics rules (IBM, 2024):

- Decision variables are the unknowns to solve for;

- The objective function shows how these variables impact cost or value to minimise or maximise;
- Constraints limit how decision variables use finite resources; and
- Data defines the relationships in the objective function and constraints.

The solution methodology with CPLEX applies the following algorithm, illustrated by Figure 2.4 (Lima, 2010):

1. Branch & Cut: This reduces computational time by introducing cuts dynamically during a search. This combination of branch bonds and cutting planes refines the search region significantly.

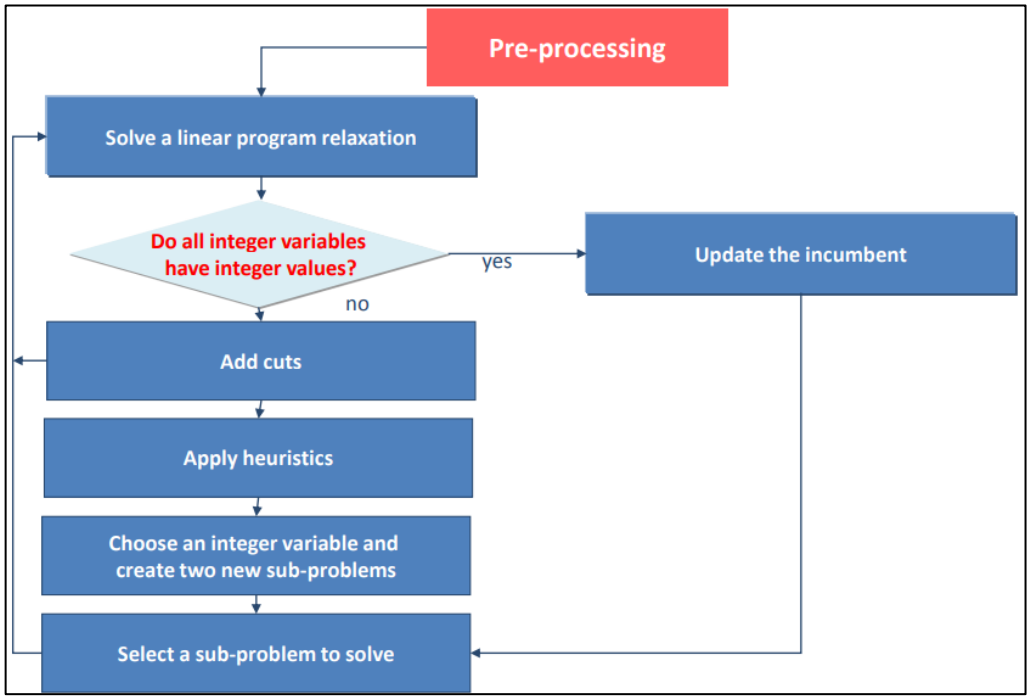


Figure 2.4 Branch and cut algorithm workflow (Lima, 2010).

2. The branch-and-bound method handles the integer constraints;

3. Cutting Planes: improve bounds on the feasible region by excluding portions of the solution that do not contain optimal integer results; and

4. Heuristics: Heuristics, such as rounding solutions from relaxed linear programs (LP), enable speedy results and provide good reference points for further optimisation.

Applying these iterative techniques, CPLEX converges to an optimal solution that satisfies all integer and continuous constraints, balancing production planning requirements and optimising for cost or other objectives.

2.4 ESG Frameworks

The optimisation is expected to align with ESG frameworks to achieve sustainability. Globally, there is a multitude of sustainability accounting frameworks, each one varying from corporation to corporation or from one Non-Governmental Organisation (NGO) to another; however, 3 of the widely accepted and used frameworks are (Bose, 2020):

i. Sustainability Accounting Standards Board (SASB), which is an NGO that focuses on developing and setting the topics, approach and metrics for standardising the disclosure of information by companies and corporations to investors. SASB focuses on five essential topics, such as environment, social and human capital, innovation within the business model and leadership/governance (SASB, 2019).
ii. Global Reporting Initiative (GRI) provides support to organisations requiring a larger number of topics to focus on and aids with multi-stakeholder governance through offering about 44 different standards covering multiple sectors of business for reporting (GRI, 2024).
iii. The Task Force on Climate-Related Financial Disclosures (TCFD) built the frameworks of reporting on environmental impact by focusing its standards on governance, strategy, risk management, and developing metrics to measure progress (TCFD, 2023). Though the organisation has been disbanded, its standards have been fully incorporated into the ISSB under the IFRS S1 and S2 (IFRS, 2023).

Each corporation or organisation may not follow all frameworks provided by all these NGOs but may opt to follow an agreed number of topics to meet the required reporting requirements.

2.5 Key Debates and Controversies

The application of haulage optimisation software in the mining industry has sparked several debates and controversies, particularly regarding its impact on productivity and the environment.

2.5.1 Productivity vs. Environmental Impact

There is a prominent debate about whether haulage optimisation software can simultaneously enhance productivity and reduce environmental impact (Ramdoo, 2019). Proponents argue that optimising haulage routes leads to shorter cycle times, improved truck utilisation, and reduced fuel consumption, thereby achieving both goals (Pasch & Uludag, 2018). However, critics suggest that the primary focus on productivity may overshadow environmental concerns. For instance, the push for maximising output can lead to more intensive resource use, potentially negating environmental benefits (Smith & Hodgkinson, 2021).

2.5.2 Short-term Gains vs. Long-term Sustainability

Another controversy centres on the balance between short-term productivity gains and long-term sustainability. Some argue that haulage optimisation software offers immediate efficiency and cost savings improvements, which can support a mine's financial health throughout the operation's life cycle (Gorman & Dzombak, 2018). However, others warn that focusing too much on short-term gains may lead to long-term environmental ruin, specifically if optimisation is used to justify increased production without effectively addressing its environmental effects (Taha et al., 2023). Both views are valid; incorporating the long-term rehabilitation efforts and plans into the short term could aid in achieving a balance.

2.5.3 Data Privacy and Ethical Concerns

The use of haulage optimisation software also raises ethical questions related to data privacy and the potential misuse of data. As these systems rely heavily on real-time data collection, there are concerns about how this data is used, who has

access to it, and whether it could be exploited for purposes other than improving haulage efficiency (Jones & Wynn, 2023). Critics argue that without specific data management policies, there is a possibility of compromising sensitive information or making decisions that prioritise profit over worker safety and environmental protection (Li et al., 2020).

2.5.4 Technological Dependence and Job Displacement

Increasing use of optimisation software raises concerns about technology dependence and potential job losses as some roles become obsolete. The software boosts efficiency but has led to significant job losses, such as China's coal mining sector where employment fell from 54.8 million to 46.6 million between 2017 and 2020 (Zhang et al., 2024). On the contrary, for technology to be successfully adopted at any operation, there needs to be an upskilling of the workforce. This is one of the critical success factors identified by Lumadi and Nyasha (2024) and can be considered a benefit of technology implementation on the development of the workforce. Moreover, some industry stakeholders argue that over-reliance on technology could cause operational exposure to system failures, interrupting productivity and having environmental consequences if not managed properly (Hassall et al., 2024).

2.5.5 Effectiveness in Diverse Mining Environments

There is also debate about the effectiveness of haulage optimisation software across different mining environments. While these tools are highly effective in large, well-established mines, their applicability in smaller, more variable operations is questioned. Most software companies also rarely have software packages for small-scale mining operations. Critics argue that in complex geological settings or smaller operations with less infrastructure, the benefits of optimisation software may be limited or outweighed by the costs and challenges of implementation (Valerio et al., 2021).

2.6 Chapter Summary

The literature review discusses the importance of haulage optimisation in open-pit mining, focusing on how discrete event simulation, mixed-integer programs and technological solvers embedded within software can improve efficiency and reduce

costs. Haulage costs make up nearly 60% of mining expenses, with load and haul operations consuming more than 80%. Optimising this segment of the mining value chain, particularly through mine planning software, can potentially enhance productivity and reduce environmental impact.

There is an extensive study into haulage optimisation and its benefits on fuel efficiency, operational efficiency, and the overall reduction of environmental impact, like lowering CO_2 emissions. However, several debates around productivity vs. environmental impact, short-term gains vs. long-term sustainability, data privacy, technological dependence and job displacement still exist, including questions about optimisation software's suitability in smaller, less developed mining operations.

The study further discusses GHG emissions, categorising them into primary and secondary emissions. It further divides these secondary emissions into scopes to distinguish the origin of emission and the relevant method reconciliation to be followed. In conclusion, while haulage optimisation offers clear operational and environmental benefits, debates remain around sustainability, ethics, job loss, striking a balance, and adaptability to various mining environments.

3 RESEARCH METHODOLOGY

This chapter outlines the methodology employed in the research to evaluate the benefit of using mixed integer linear programming-enabled software such as MinePlan, to optimise haulage schedules to sustainably combat the rising cost of operating a surface mine. The research utilised qualitative and quantitative data collection and analysis methods to draw an informed conclusion from the findings.

The qualitative approach reviewed relevant literature from the past decade. This literature comprises reports, reviews, journals, books and websites. The quantitative aspect focused on actual data collected from the case study. The qualitative approach aimed to provide a sound background to applying optimisation software in surface mining operations by citing challenges, benefits and areas of improvement, whilst the quantitative aspect provides validated data for analysis. The processes and approaches employed in this study are discussed in depth below.

3.1 Research Design

With the decreasing ore grade, increasing cost of operation, and ever-volatile state of the mining industry, sustainable mineral extraction has become a necessary strategy (Ediriweera & Wiewiora, 2021). In opencast, where more than 60% of the expenditure is in load and haul, how can the industry improve its current operations without increasing costs and aligning with the environmental aspect of ESG frameworks?

A mixed-methods approach was used to address this research question. Through a literature review, qualitative research provided a theoretical framework and a background understanding of the industry's stance on technology and its adoption (Ahmad, et al., 2019).

Haulage schedule data was collected from the site and used as input into the MinePlan software, MinePlan Schedule Optimiser, to optimise the current haulage to improve NPV and reduce environmental effects. The quantitative phase involved the collection of operational data from a mining site, including production rates, costs, and price forecasts, truck fleet specifications, dump and loading area

locations, planned haul routes existing within the pit, shovel fleet specifications, all expenses, capital, mining sequence, equipment availability, cost per tonne, period of operation etc.

3.2 Research Methods

The research methods employed are discussed below.

3.2.1 Qualitative Data Collection

The qualitative research was done by reviewing existing literature covering the topics of optimisation, GHGs, surface mining software and success factors to the adoption of technology in surface mining. Sources included peer-reviewed journals, technical reports, and mining industry best practice guides. The literature review used databases such as ScienceDirect, Scielo, Google Scholar, and industry-specific resources. A thematic search was involved, which looked into key topics such as mixed-interlinear programming vs. genetic algorithm, for large- to small-scale mining operations, operational decision-making, mine planning, and haulage simulations. Table 3.1 indicates the key research papers and which areas of the report they influenced.

Table 3.1 Literature that influences on key areas.

Author	Research Topic	Area of influence in the current study	Year Published
Feng et. al.	Energy efficiency and CO2 emission comparison of alternative powertrain solutions for mining haul truck using integrated design and control optimisation	Fuel consumption	2022
Abolghasemian et. al	Simulation-Based Multi-Objective Optimisation of Open-Pit Mine Haulage System: A Modified-NBI Method and Meta Modelling Approach	MILP optimisation method	2022
Alipour et.al	Production scheduling of open-pit mines using a genetic algorithm: a case study	MILP optimisation methods	2019
Amoako et.al.	Carbon Footprint of the Large-Scale Gold Mining Industry of Ghana	Carbon footprint in surface mining	2018
Barnewold & Lottermoser	Identification of digital technologies and digitalisation trends in the mining industry	Application of digitisation in mining	2020
Chang et.al.	The Paris Agreement effect of consumer awareness and sustainable investing: Some international evidence	ESG frameworks in mining	2024
Davies M.	The Role of Strategic Mine Planning in Decarbonising the Mining Industry	Decarbonisation through mine planning	2024

3.2.2 Quantitative Data Collection

The quantitative aspect of the research focused on data collection from the site and entailed the following:

Data request and collection: The haulage schedule data from the site was collected. This data is part of the bi-annual LOM plan, which is reviewed bi-annually by planning engineers and technical managers. This data comprised equipment specifications, fleet size, loading schedules, and production schedules. The data was cleaned to remove outliers, duplication, and errors and ensure correct file formats, as indicated in Chapter 3, Section 3.3.

The site is an existing Hexagon Mining client with the MinePlan scheduling software package. Before optimisation, a baseline project was created and saved onto the client's database. This baseline was used as a reference point during the scenario analysis. The data sits on the Mine A database and can be extracted and shared with other individuals as a .hlg file, the primary file format for MinePlan's haulage optimiser, for further analysis.

Secondary data, including market forecasts and commodity price predictions, were also integrated from publicly available reports by industry analysts (PWC, 2024). Other data, such as the equipment specifications, operating costs, mine layout and ore reserves were shared via a .CSV file and other MS Excel file sheets. This data was pivotal to generating the discounted cash flow used for NPV calculations and generating fuel consumption by the truck fleet using Mine Plan's schedule optimiser.

3.2.3 Mine Layout

The mine layout file was shared as an *ASCII* file and imported into MinePlan3D. This allowed for visualisation of the data and data cleaning. During import, some data points can be displaced or duplicated. Visual inspection provides for correcting any such points, polylines, and polygons. Mine A is divided into two mini pits hosting cuts C1 and C2, and the main pit hosting cuts C3, C4, and C5. Currently, the site has two main dumps, D1 and D2, with stockpiles and the crusher clustered near the main pit, as indicated in Figure 3.1. The distance between the

main pit and the mini pit in the Southwest is approximately 4 km, whilst the one in the Northeast is less than 1 km.

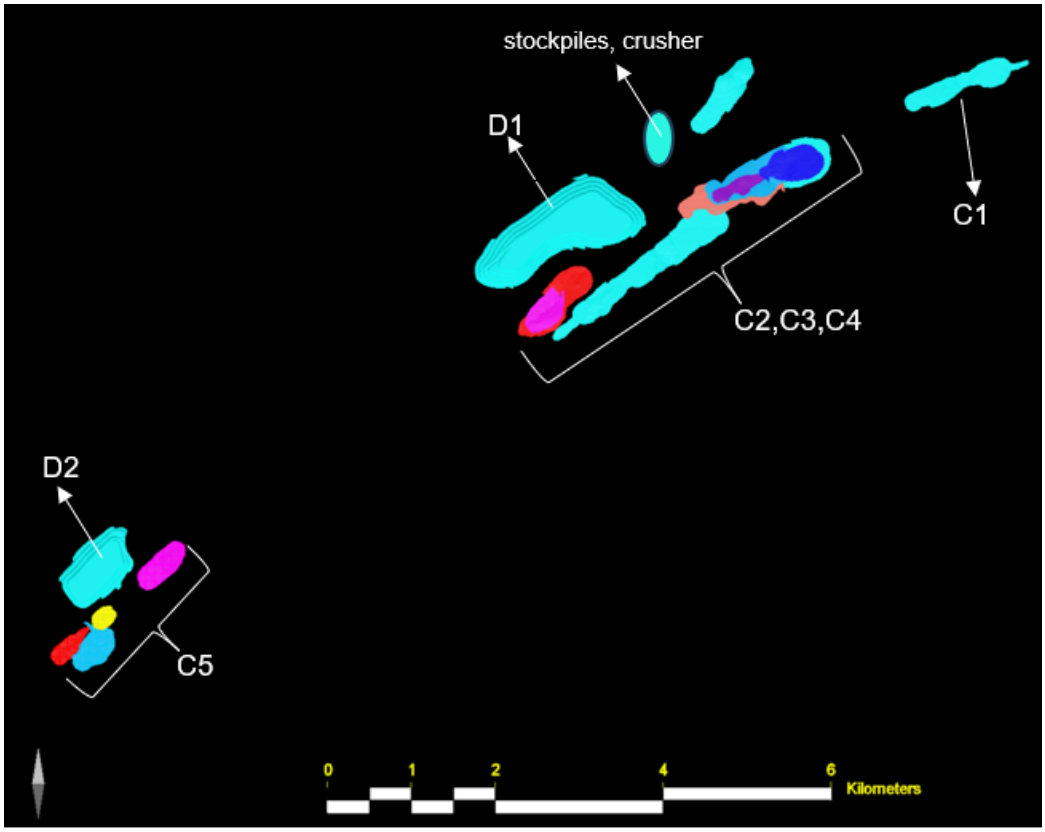


Figure 3.1 Mine A mine layout.

3.2.4 Material Mapping

Mining occurs in four main material zones: waste rock, saprolite rock (SAP), primary unweathered rock (PRI), and transitional partially oxidised rock (POX). The material to be loaded and hauled is categorised into four bins by grade: grams per tonne (g/t), the unit measure for gold (AU) ore. Material is categorized as follows: waste (0 g/t, bin 0), low grade (>0–1 g/t, bin 1), medium grade (>1–<1.5 g/t, bin 2), and high grade (>1.5 g/t, bin 3), as detailed in Table 3.2.

Table 3.2 Material type, bin and description.

Type	AU min (g/t)	AU max (g/t)	BIN	Label	Description
Waste			0	Waste	Waste material
Ore	0	1	1	LG	Low-grade material
Ore	1	1.5	2	MG	Medium grade material
Ore	1.5	3	3	HG	High-grade material

Ideally, this data should be encoded into the block model to ensure that the attributes are assigned as per assay and geology data. To verify this, the block model provided by Mine A was run through MinePlan's Reserve Logic. This tool allows for assessing the block model or reserves to ensure that all material data, such as material type, grade and density, are attributed to the block model. All other components were coded for this data except for the cut-off grades in each material zone. Therefore, as part of data validation, the cut-off grades were assigned to the correct material code as shown in Figure 3.2.

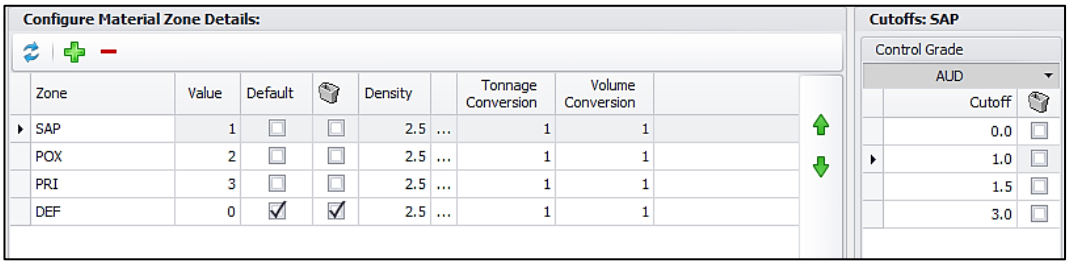


Figure 3.2 Cut-off and material zone configuration.

3.2.5 Equipment Properties

This study's main concern is the primary haulage fleet, which consists of trucks and loaders. Table 3.3 outlines and categorises the data according to the different equipment types. The fleet comprises 16 CAT777D trucks with a rated payload of 91 tonnes (t) and an average fuel consumption of 65.6 litres/hour. For the average truck speeds on various road surfaces of the haulage routes, see Table 3.4.

Table 3.3 Truck specifications.

	Trucks
Type	CAT777
Payload, t	91
Availability, %	90
Utilisation, %	80
Average rolling resistance, %	4

Table 3.4 Truck speed specifications.

Road Surface	**Truck speed, km/hour**
Level Loaded Travel	45
Level Empty Travel	50
Uphill Loaded Travel	15
Uphill Empty Travel	30
Downhill Loaded Travel	20
Downhill Empty Travel	35
Switchback (Empty and Loaded)	20

Table 3.5 provides the CAT9030 excavator specifications. The site has three of these loaders to use for the five mining cuts. To meet Mine A's production objectives, these shovels were planned to produce 1530 t/h.

Table 3.5 Loader specifications.

	Loader
Type	CAT6030
Rated payload, t	33
Availability, %	90
Utilisation, %	78

3.2.6 Processing and Economic Constraints

The following economic constraints were provided as per the plan and shown in Table 3.6. These constraints were used as input parameters in the Mine Plan schedule optimiser as they form the basis for building the financial and processing capacities. The capital investment is the initial investment into the project injected

in the first year. The description of constraints is elaborated below (Hexagon, 2024b):

- Discounting convention: refers to when the engine will apply the discount rate to the cashflow. For this project, this is set to discount at the end of the year;
- Discount rate: the rate applied to the cashflow to provide the relevant time value of money;
- Mining cost: total cost of loading and hauling material in the mining value chain as per the mine's budget;
- Processing costs: the cost of crushing, grinding and extracting the mineral of interest from the hosting rock;
- Price: this is the average price of gold;
- Plant capacity: maximum annual capacity that can be processed by the plant based on the plant's hourly processing rate;
- Plant rate: maximum amount of ore to be processed in an hour; and
- Mill head grade: This is the maximum gold quality that can be produced under the plant's current configuration.

All the descriptions can be obtained from Mine Plan's info tab within the software for clarity.

Table 3.6 Constraints for the processing plant and cash flow in MinePlan Scheduler optimiser.

Processing and Economic Constraints	
Discounting convention	End of period
Discount rate, %	8
Capital investment, USD	588 000 000
Mining Costs, ($/t)	4
Processing costs, ($/t)	15
Price ($/t)	2 000
Plant capacity, (t/annum)	3 500 000
Plant rate, (t/hour)	463
Max Mill head grade,(g/t)	5
Max plant hours, per annum	8 000

3.2.7 Quantitative Process

The quantitative process focused on two main areas, which are the NPV and the Fuel Consumption. To determine these key focus areas, the validated operational data from the mine was input into a financial optimisation solver in MinePlan. The model was built using optimisation software, which runs multiple simulations to test different operational scenarios. The model's primary objective was to maximise the NPV and generate the equivalent fuel consumption by adjusting key variables such as mining rate, operational cost, and production schedules and observing constraints such as equipment fleet and dump capacity. A baseline model was created and the constraints further adjusted to derive an optimised model. These models were then compared and contrasted to determine which one offered the highest NPV and the lowest greenhouse emissions. This input data, as outlined in Chapter 3 Section 3.2.2, was used for these models, and all constraints were applied to the models to align with the reality on site.

A scenario analysis is derived using the information obtained from the engineers, such as the loading area, dump capacity, material type, the desired output NPV and fuel burned to achieve the desired NPV. Figure 3.3 shows the material mapping performed on the multiple routes that material can travel from each loading area to the various dumping areas based on the shortest or most ideal route. For example, mining cut C2 contains material that can be dumped at two D1 dumping areas and all the D2 dumping areas; however, to honour the constraints and maximise NPV, no material will be routed to the D1 dumps due to longer travelling distances, resulting in higher cycle times. The total travel distance (empty travel and full travel) is then multiplied by the fuel burn rate per truck over a specified period to provide the total fuel consumption, an essential aspect of this research for carbon footprint calculations.

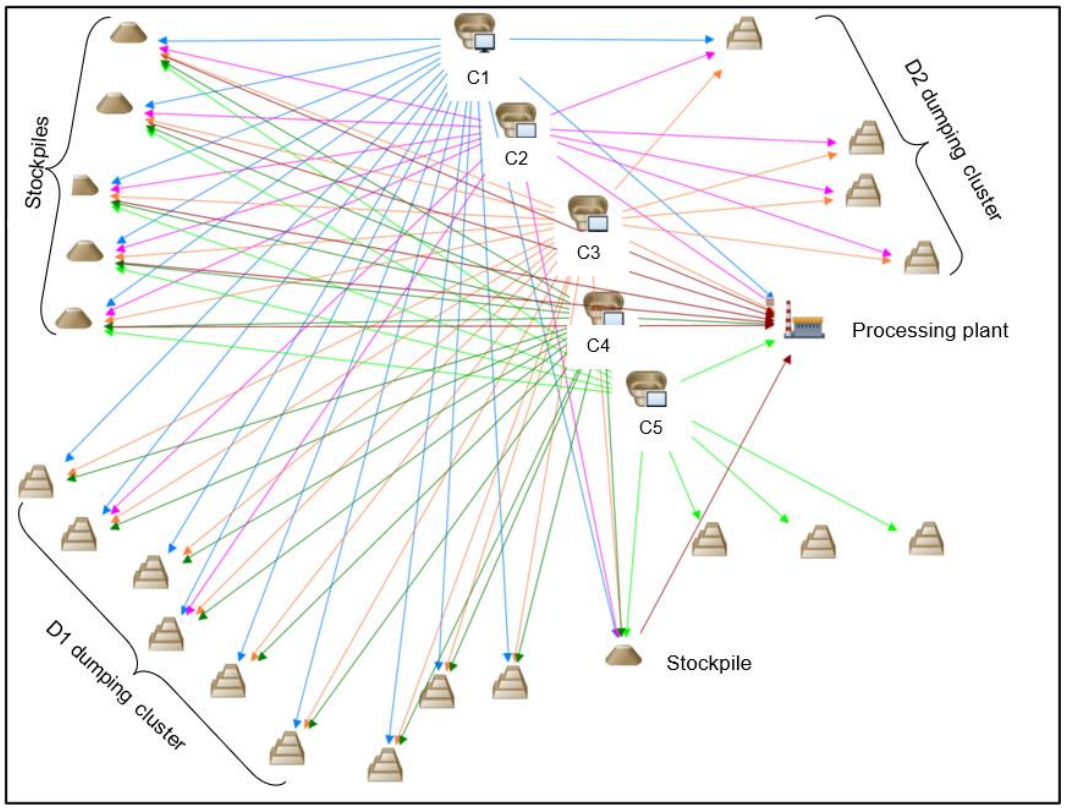


Figure 3.3 Schematic diagram showing the material mapping network for Mine A.

The software repeats this methodology described in section 2.3 multiple times to produce the results in Appendix A and Appendix B.

Fuel Consumption

The second aspect of the quantitative method involved obtaining data on the fuel consumed by the baseline and optimised mining models. Using section 3.3.2 data and a 10-year limit for both models, with loading and dumping per Appendices A and B, the Mine Plan's Schedule Optimiser generates the fuel burn rate report in Table 3.7. Table 3.7 provides us with the amount of fuel consumed annually by the truck fleet in alignment with the financial performance in Tables in Appendix A and B.

Table 3.7 Total fuel consumed by trucks at Mine A annually.

Fuel Consumption by CAT777D Trucks in litres		
Year	**Baseline Model**	**Optimised Model**
1	3 048 210	3 402 000
2	3 641 504	2 104 995
3	7 181 181	6 734 976
4	2 254 678	3 951 084
5	2 898 138	1 914 075
6	2 842 127	1 545 456
7	2 605 061	1 727 363
8	6 107 370	3 239 001
9	2 778 394	1 008 865
10	1 441	4 765 203

Furthermore, under the same ideal conditions, the calculation for carbon footprint was conducted to determine coherence between the optimised NPV and the resulting carbon footprint. The final output of the model was a set of recommendations for operational adjustments that would optimise the NPV (sustainably) of the mining site within the set constraints.

Calculating Carbon Footprint

Carbon footprint estimation calculations can be complex and may differ from operation to operation; to simplify the approach, it is best to start by identifying the key sources of GHG emissions (IPCC, 2019). In a chronological sense, mining requires vast land; some processes must be employed to resize the rock from this land into smaller mineable units; energy will be required to break the rock and move the rock from one point to another. Processing at the plant must be employed to obtain the mineral of interest. These are all categories of GHG emissions at Mine A elaborated in Figure 3.4.



Figure 3.4 Mine A's GHG emissions by category (Amoako et. al, 2018).

As stated in Chapter 2, this research only focused on scope 1 emissions, that is, emissions resulting from Mine A's direct activities. Based on the literature reviewed by Amoako et al. (2018) and the DEA (2016), energy-related activities account for the highest GHG emissions globally. Therefore, the category of interest for this research was scope 1 emissions within the energy category. The energy category is divided into two subcategories: mobile combustion and electricity. The key focus of this research is on mobile combustion, which includes activities such as the transportation of personnel and the hauling of materials and goods (IPCC, 2019).

As per the guidelines from the IPCC (2019), mobile combustion can be calculated in three methods:

- Tier 1 methods include calculations for CO_2 emissions arising from the carbon content of fuels supplied as a whole; this method is referred to as the Reference Approach. A second method within Tier 1 calculates CO2 emissions from fuel combustion activities. This method often requires the least amount of data points (IPCC, 2006); and
- Tier 2 and Tier 3 methods are refined versions of Tier 1 and focus on more complex CO2 emissions, such as aviation fuel emissions computed by digital technologies. These methods often require more data points to improve accuracy (IPCC, 2006).

Choice of Method

Due to the size of the data and focus point, the tier 1 CO_2 estimation method was applied to estimate the carbon footprint resulting from the baseline and optimised models. Tier 1 methods used two key equations to estimate the carbon emissions as indicated below by equations 3.1 and 3.2. It is important to note that though the

emitted gases do not only comprise CO_2, but they are also reported in CO_2 equivalents for ease of comparison (IPCC, 2006). For example, a single kilogram (kg) of methane (CH_4) equals 28 kgs of CO_2 (IPCC, 2019). Furthermore, under the guidelines of the United States Environmental Protection Agency (USEPA) (2020) and Amoako et al (2018), the following assumptions are necessary for more accurate estimations:

- Regarding CO_2 equivalents, CH_4 and N_2O account for 5% of diesel engine combustion emissions. All CO_2 estimates will be multiplied by 1.05 to account for this; and
- Any emission of CO is rendered negligible compared to CO_2.
- Fuel is converted to CO_2 during combustion.

Tier 1 method equations

Equation 3.1 Emissions calculation (USEPA, 2020).

$$\boldsymbol{Fuel\ Emissions\ (GHG) = Fuel\ consumption * CO2\ Emissions\ factor} \quad \textbf{(3.1)}$$

where:

Fuel consumption is the total fuel burned over a particular period by a source.

CO2 Emissions factor is a given GHG's default emission factor by fuel type.

Equation 3.2 CO2 Emissions factor calculation (USEPA, 2020).

$$\boldsymbol{CO2\ Emissions\ factor = Mass\ of\ diesel * CO2\ Oxidation\ factor * Molecular\ weight} \quad \textbf{(3.2)}$$

where:

Mass of diesel, in this instance, equates to 1 gallon of diesel, covert litres to gallons.

Oxidation factor for CO_2 is usually 1; however, for this research, it was assumed to be 0.99 to account for residual fuel that may be left uncombusted.

Molecular weight is the ratio of the molecular weight of CO_2 to carbon.

Taking fuel consumption outlined in Table 3.7, applying the assumptions and Equations 3.1 and 3.2, the carbon footprint is derived as indicated in Table 3.8 below.

Table 3.8 Carbon footprint estimations derived for the Baseline and Optimised models.

Carbon Footprint Estimation		
Year	**Emissions Baseline Model in tCO_2**	**Emissions Optimised Model in tCO_2**
1	9 206	10 275
2	10 998	6 357
3	21 688	20 341
4	6 809	11 933
5	8 753	5 781
6	54 686	41 238
7	41 733	27 672
8	97 840	51 889
9	44 510	16 162
10	38	45 803

To analyse the relationship between the datasets generated from the software and calculations, three methods will be applied that is :

i. Simple Linear Regression. This method of analysis was chosen because it allows for the investigation of the relationship between two variables: time in years and NPV (Sykes, 1993);
ii. Spearman's correlation. The Spearman rank test uses data ranks to aid in deriving a linear relationship from data that would have been considered non-linear and not fit for parametric analysis (Al-Hameed, 2022); and
iii. P-value hypothesis test to test the validity of the results against a set hypothesis.

3.3 Data Validation Process

This report used peer-reviewed journals to validate the importance of software in the optimisation of surface operations and the success of software applications. The data validation process ensured the accuracy and reliability of the data collected from the mining site. The following procedures were used:

i. Qualitative Data Validation: To ensure credibility, peer-reviewed and industry-recognised sources were prioritised. All literature sources were cross-referenced to confirm the relevance of key NPV optimisation strategies; and
ii. Quantitative Data Validation: Operational data were verified against historical records and confirmed by mine engineers for accuracy. The data were cleaned to eliminate outliers, gaps, and errors. Spot checks ensured data consistency and removed any anomalies.

3.4 Chapter Summary

This mixed-methods research methodology combines a literature review with site-specific data analysis to evaluate and optimise a mining site's NPV. The literature review provides a theoretical foundation, while quantitative analysis of operational data allows for practical application through an optimisation model. The integrated approach ensures that the findings are theoretically grounded and practically relevant.

The sub-section starting from Chapter 3.3 details the collection and analysis of secondary data from the long-term planning department at Mine A over 10 years. Key data collected includes mine layout, schedule duration, material categorisation, economic factors, and primary equipment properties. The mine layout was imported into MinePlan3D for visualisation and data cleaning, revealing two mini pits and a main pit with designated dump and processing areas.

The material is classified into four grade bins based on gold content measured in grams per tonne (g/t), ranging from waste (0 g/t) to high-grade (over 1.5 g/t). This classification assists in organising materials for loading and hauling. The data is intended to be encoded into a block model to reflect assay and geology data accurately. The block model was assessed using MinePlan’s Reserve Logic to

ensure material attributes such as type, grade, and density were correctly assigned. Most components were successfully coded except for the cut-off grade. As part of the data validation, the cut-off grade data was requested and then coded to the various materials to ensure accurate loading and dumping areas.

The qualitative approach mainly focused on reviewing historical research within the sphere of sustainable mining, ESG, technology in mining and the applicability of the technology in mining. Overall, though research focuses widely on these topics, it is clear from the literature review that not much work has been done to corroborate the benefits of ESG within mine planning to improve productivity. MinePlan's schedule optimiser was used to help build two models for comparison: the baseline model and the optimised model. The software produced both models' NPV and fuel consumption for further analysis. The IPPC (2006) & (2010), Amoako (2018), and USEPA (2010) guidelines were followed through the application of Tier 1 mobile combustion calculations for carbon dioxide emissions estimations.

4 ANALYSIS OF RESULTS

This chapter presents the results of the data obtained from Mine Plan's schedule optimiser, NPV and fuel consumption from the baseline and optimised models. Furthermore, it analyses this data to determine trends that can be applied to everyday mine planning.

4.1 Introduction

The analysis of the results offers a detailed examination of Mine A's NPV and carbon footprint, contrasting the original haulage and mining schedule (baseline) with the optimised schedule over 10 years. By analysing the data, valuable insights can be derived into the underlying factors that should be considered during the planning phase to address current ESG compliance and productivity challenges effectively.

4.1.1 Analysis of the NPV and Carbon Emissions at Mine A.

The period was constrained to ten years to provide a clearer picture of the overall cash flow performance. The NPV values obtained from MinePlan's optimiser, as tabulated in the second last lines of Appendix A. and B., are graphed as a scatter plot in Figure 4.1. Simple linear regression analysis was employed to analyse this data because it is linear. In this analysis, the period is kept as the independent variable, while the NPV is the dependent variable. Applying a line of best fit, a linear regression model of y= -2268.4x + 22275 is derived for the baseline model and y= -1652.3x + 22882 for the optimised model, indicated by Figures 4.1 and 4.2.

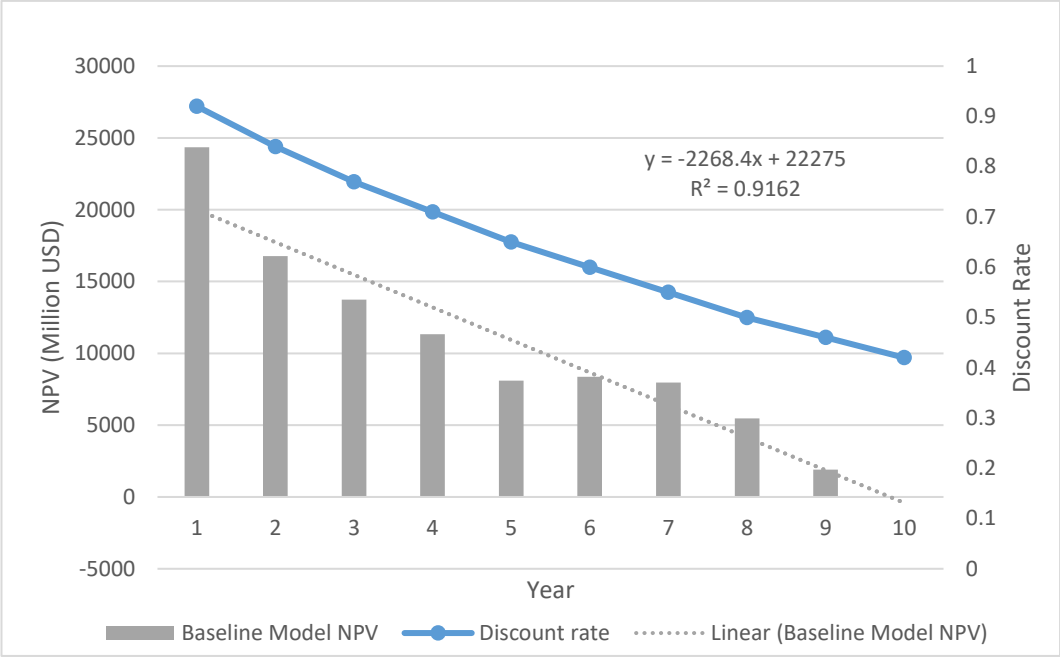


Figure 4.1 Linear regression model for the baseline model.

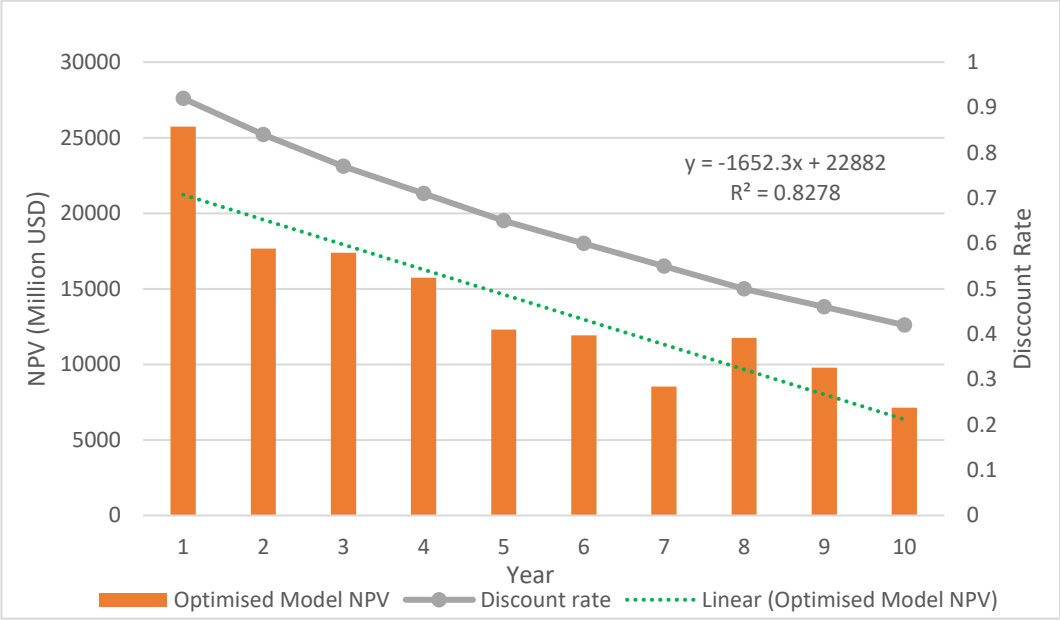


Figure 4.2 Linear regression model for the optimised model.

By comparing the gradient values of the trend lines, it is clear that the baseline model's NPV trend line produces a much steeper decline than the optimised model's NPV between year 1 and year 10. To test the correctness of this

observation, let x=6.5 for both models. When x=6.5 for the baseline model, the regression model gives y= 7530.4, and the regression model for the optimised model gives y=12142.1. This means that for any given period in time, the optimised model will yield an NPV approximately 62% higher than the baseline model, indicating that the optimisation has indeed improved the overall financial performance of the baseline model by yielding the optimised model. The accuracy of this prediction is further substantiated by the strong R^2 values that are R^2=0.9162 for the baseline model and R2=0.8278 for the optimised model. This means that 92% and 83% of the data are represented by the predicted model, respectively. As a rule of thumb, for time-series data, the R^2 mean is normally expected to represent the model well if greater than 80%, the 11% drop in correlation from baseline to optimised is mainly because the optimised models data is not concentrated towards the mean; however the correlation is good enough to allow for a linear regression analysis (Nau, 2014).

A second analysis, the residual plots, was employed to further test the accuracy of the linear models above. To perform this test, it is assumed that the linear model does not violate nonlinearity or homogeneity of variance. Nau (2014) provides guidelines on this approach in his work on statistical analysis. The dispersion of the points on both residual plots aligns with our assumptions in that there is no identifiable pattern in the data a correlation with the predicted models. It is important to note that in both Figures 4.3 and 4.4, the residual plots show outlier points A and B for a 0.92 discount rate which is expected as that is the beginning of mining, NPV is high attributed to the low operational costs.

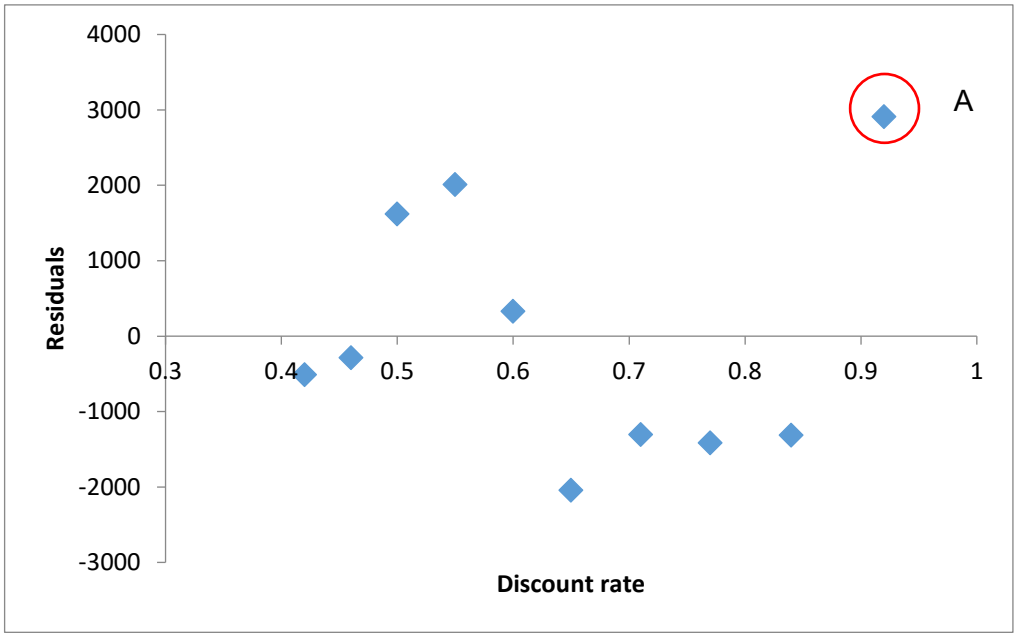


Figure 4.3 Baseline model residual plot.

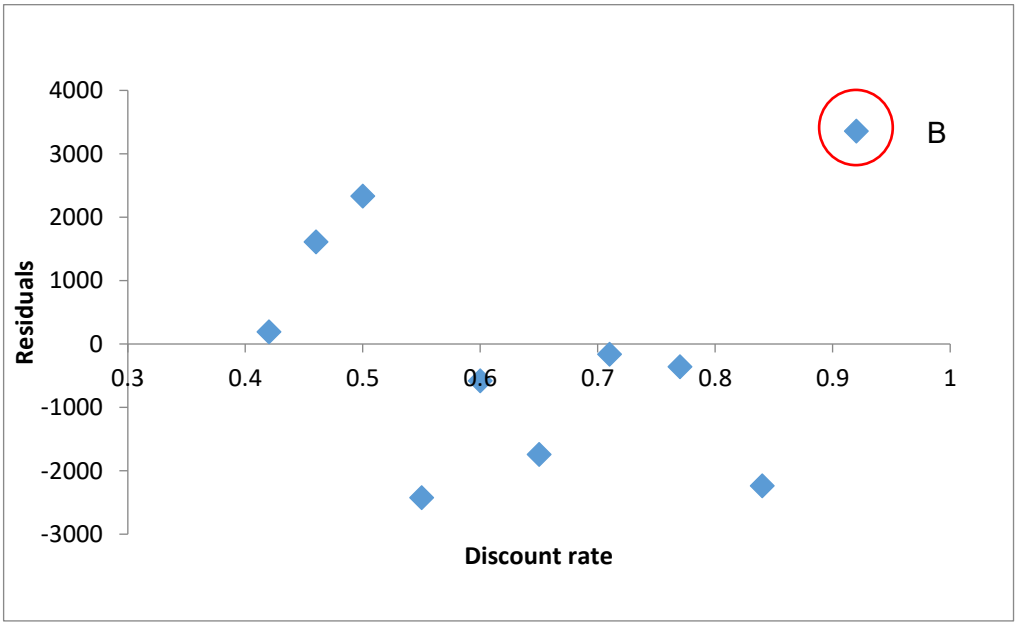


Figure 4.4 Optimised model residual plot.

The intention of this study was not only to optimise the haulage schedule to produce a higher NPV but also to determine if this approach will assist in achieving sustainable mining by reducing the environmental impact, which we measure by

analysing the carbon footprint. The data on carbon emissions against NPV is shown in Figures 4.5 and 4.6.

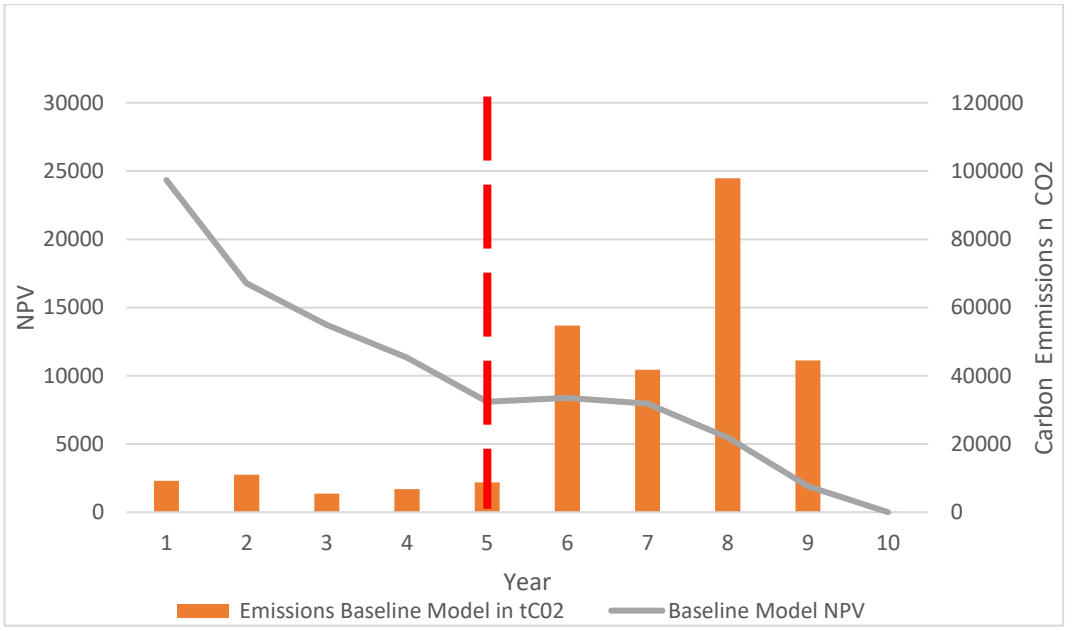


Figure 4.5 Baseline Model's NPV vs Carbon emissions over 10 years.

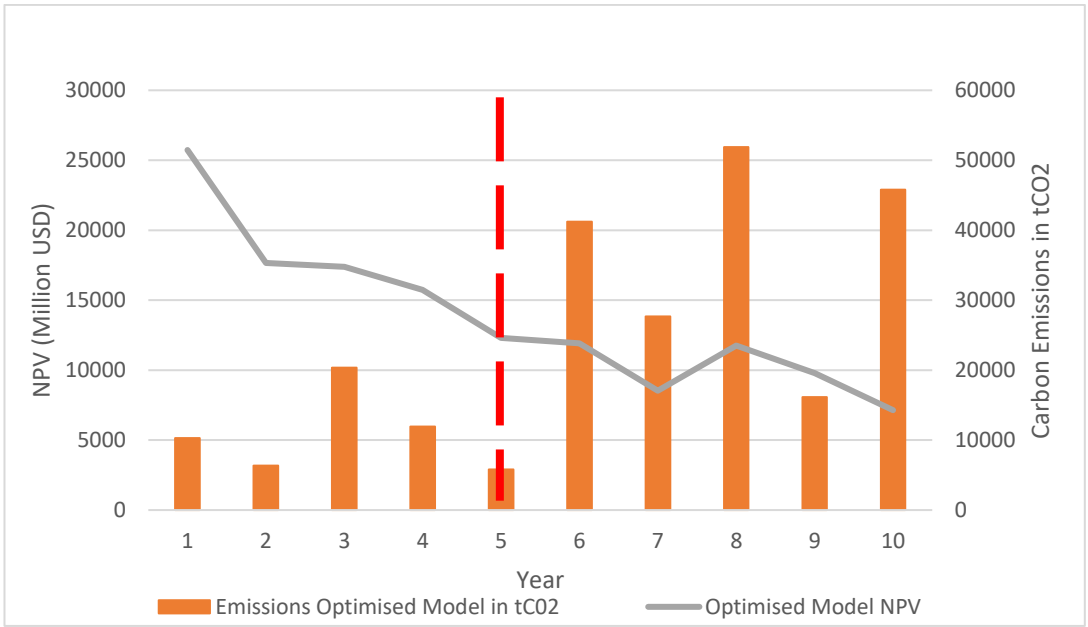


Figure 4.6 Optimised Model's NPV vs Carbon emissions over 10 years.

Both Figures exude a similar trend between Years 1 to 5 and Years 6 to 10. In the first 5 years, both models indicate that the NPV is higher than the carbon emitted. This is expected in that in the first 6 years, both models are mining mainly in pits C1 to C4 within proximity of the main dump D and the stockpiling area. Furthermore, the baseline model's NPV is lower than that of the optimised model throughout this period, as indicated by Figure 4.7.

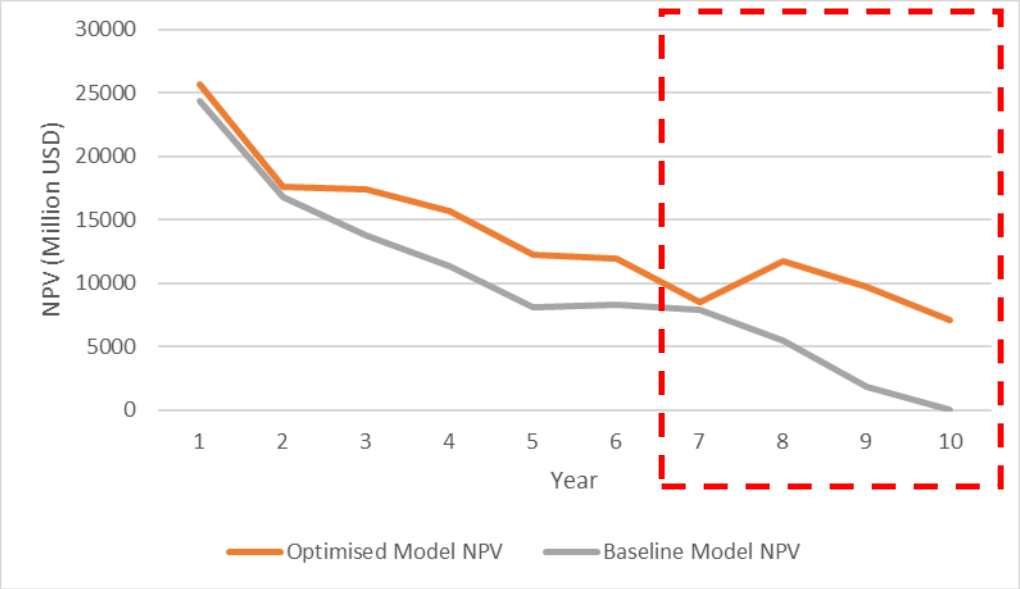


Figure 4.7 Baseline NPV versus Optimised NPV over 10 years.

Though the NPV of the optimised model is higher, the carbon emissions from the baseline model are 25% lower than those of the optimised model in the first 5 years, see Figure 4.8. The optimised model was not constrained to mine the closest pit first but sequentially, such that a single blast must be mined and finished before moving to the bench below. This model also abides by the rule that access to pushbacks must be mined during the mining or production phase of one or more pushbacks, thereby ensuring access is ready by the time the current pit's inventory is depleted. Resulting in higher cycle times during certain periods, which overall causes a higher fuel consumption. It must be noted that Mine Plan's schedule optimiser was set to improve NPV as the main objective.

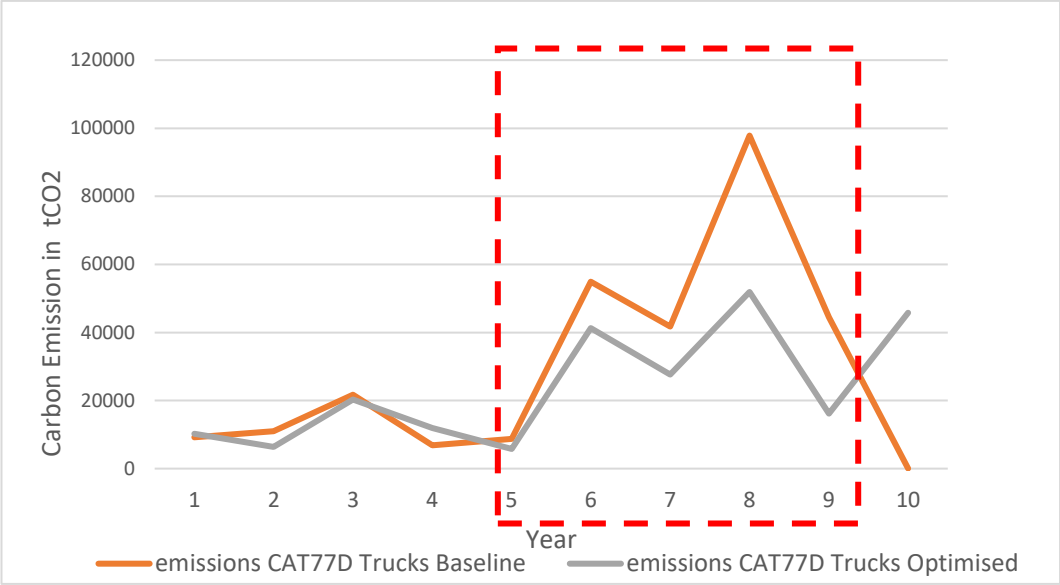


Figure 4.8 Carbon Emissions from the baseline and optimised models over 10 years.

Between Years 5 to 9, another trend is identified that proves true for both the baseline and optimised models. The carbon emissions from the baseline model are approximately 31% more than the optimised model, as indicated by the dashed line in Figure 4.8. This is because the baseline model is hauling most of its material from the pits, which are further from the main stockpile areas and the processing plant. Further elaborating on this is the NPV, which reduces year on year from year 6, as shown in Figure 4.7. The amount of waste material to be hauled increases, particularly in year 8 when mining shifts to pit C5 (refer to Appendix A for cashflow and production reporting), resulting in significantly longer hauling distances. In the optimised model, although it follows a trend similar to the baseline, the program (due to the previously mentioned constraints and rules) creates a balance to maintain a positive equivalent NPV. This is achieved by initiating mining activities in pit C5 earlier, in year 6, thereby reducing the total waste to be mined in year 8. The ore deficit is compensated for by utilising stockpiles directly (refer to Appendix B for production reporting). A similar trend is observable in year 9 as well.

4.1.2 Analysis of the relationship between NPV and Carbon Emissions

By observation of the analysis above on NPV and emissions, it could be assumed that in both the baseline and optimised models, there is an inverse relationship between the NPV and the carbon emissions resulting from hauling material from one design point to another at Mine A. However, to test this assumption, a non-parametric test be employed since the relationship between NPV vs carbon emissions results in a distribution that is not normal and cannot be explained directly by linear regression. To run this test, the following holds:

a) Each numerical variable is assigned a representative number by rank from smallest to largest; and
b) The ranks represent the data from which a relationship or correlation between the original data can be derived.

Table 4.1 indicates the original data and the assigned ranks per value for the baseline model, which is employed in performing the Spearman rank test. Equation 4.1 can be used together with Table 4.1 to determine Spearman's correlation coefficient (rs). The sum of the squared differences is 190 and the number of years is 10. This gives a rs of – 0.2, meaning that there is a negative relationship between the NPV and carbon emissions of the baseline model at Mine A.

Table 4.1 Baseline model original data vs Spearman ranks assigned.

Year	Emissions Baseline Model in $tC0_2$	Baseline Model NPV	Emissions Baseline Model in $tC0_2$ rank	Baseline Model NPV rank	Difference in ranks (d)	Squared Difference (di)
1	9 206	24 340	5	10	-5	25
2	10 998	16 769	6	9	-3	9
3	5 472	13 736	2	8	-6	36
4	6 809	11 339	3	7	-4	16
5	8 753	8 089	4	5	-1	1
6	54 686	8 373	9	6	3	9
7	41 733	7 962	7	4	3	9
8	97 840	5 478	10	3	7	49
9	44 510	1 900	8	2	6	36
10	38	0	1	1	0	0

Equation 4.1 Spearman's correlation equation (Al-Hameeda, 2022).

$$Spearman's\ correlation\ (r_s) = 1 - \frac{6 * \sum d_i^2}{n * (n^2 - 1)} \quad \textbf{(4.1)}$$

where:

$Spearman's\ correlation\ (r_s)$ is between -1 and 1.

$\sum d_i^2$ is the sum of the squared difference in ranks between the NPV and the carbon emissions.

n is the number of years.

A similar analysis is then applied to the optimised model using Table 5.2 and Equation 5.1. For the optimised model, the sum of squared differences is 274, and the number of years is 10. This yields an rs of – 0.7, implying that the relationship between the NPV and the carbon emissions of the optimised model at Mine A is also negative.

Table 4.2 Optimised model original data vs Spearman ranks assigned.

Year	Emissions Optimised Model in $tC0_2$	Optimised Model NPV	Emissions Optimised Model in $tC0_2$	Optimised Model NPV	Difference in ranks (d)	Squared Difference (di)
1	10 275	25 732	3	10	-7	49
2	6 357	17 667	2	9	-7	49
3	20 341	17 388	6	8	-2	4
4	11 933	15 730	4	7	-3	9
5	5 781	12 298	1	6	-5	25
6	41 238	11 921	8	5	3	9
7	27 672	8 532	7	2	5	25
8	51 889	11 748	10	4	6	36
9	16 162	9 791	5	3	2	4
10	45 803	7 140	9	1	8	64

The Spearman's rank test has determined that from the data presented for both models, the relationship between the NPV and the carbon emissions is negative, meaning that an increase in one variable results in a decrease in the other.

However, the true benefit of this analysis is in determining whether this finding holds true at any given point in time. In order to determine that, another test can be performed, the probability test, to determine the probability that the hypothesis above is true at any given time. The following assumptions hold:

- Null hypothesis (H0): There is no inverse relationship between NPV and carbon emissions at Mine A for both the baseline and optimised models.
- Alternative Hypothesis: There is an inverse relationship between NPV and carbon emissions at Mine A for both the baseline and optimised models.
- The Null hypothesis is rejected when the probability value is lower than the significance level; and
- Accepted when the probability value is equal to or greater than the significance level.

The level of statistical significance is assumed to be 0.05 or 5%. This is an ideal assumption for statistical analysis, where the intention is to measure probability against a null hypothesis for time series data sets (Vaidyanathan, 2023). For this study, probability value (p-value) refers to the strength of evidence against the null hypothesis, which states that there is no difference in the relationship identified between or more variables in a sample and a population (Thiese et al., 2016). Table 4.3 indicates the output regression statistics generated from the carbon emissions and the NPV. It can be noted that for the baseline model, the NPV indicates a p-value of 0.68, which is greater than the threshold thereby suggesting that the Null hypothesis is true. This means that the inverse relationship between NPV and carbon emissions is always true for any given period in the baseline model.

In the optimised model, the NPV generated a p-value of 0.04, which is slightly lower than the threshold, implying a strong rejection of the null hypothesis regarding an inverse relationship between the NPV and carbon emissions. There is, therefore, not enough statistical evidence in the data collected at Mine A to conclusively state that the relationship between NPV is inversely proportional to carbon emissions at any given time. Though it may appear to be the case by visual inspection, it is not statistically significant. This means that attempting to generate a predictive model

from this data set based on the assumption of inverse proportionality may significantly yield incorrect results in the optimised model.

Table 4.3 Regression statistics for the baseline and optimised models.

		Coefficients	Standard Error	t Stat	P-value	Analysis	Outcome
Baseline Model	Intercept	6.33	2.17	2.92	0.02		
	Baseline Model NPV rank	-0.15	0.35	-0.43	0.68	p-value > significance	Accept H0
Optimised Model	Intercept	9.13	1.65	5.55	0.00		
	Optimised Model NPV	-0.66	0.27	-2.49	0.04	p-value < significance	Reject H0

4.1.3 Analysis of the relationship between discount rate and NPV at Mine A

The discount rate is a major factor in discounted cash flows as it provides a more realistic value of money over time. In this study's data, the discount period is set to end of period, starting at 9 percent in year 1 and decreasing gradually. This makes it important to identify how it relates to the NPV over the specified period to understand the financial viability of the mine plan. Table 4.4 shows the regression statistics of the baseline model and the optimised model NPVs against the discount rate over 10 years. A multi-linear regression methodology is applied to explain this relationship because a simple linear regression method does not give a clear indication of the impact of discount rate on NPV. Therefore, an approach similar to the one described in sub-section 4.1.2 is applied. For the NPV vs Discount rate, the H0 states that at any given time at Mine A, the discount rate has little to no effect on the NPV.

Table 4.4 Discount Rate vs NPV.

	Discount Rate vs NPV		
	R Square	**P-value**	**t Stat**
Baseline Model	0.93877457	0.00000245	11.78973053
Optimised Model	0.86033131	0.00006846	7.51253664

This data indicates a trend similar to NPV vs time. There is a strong correlation (93% for baseline and 86% for optimised model) of the NPV and the discount rate with the baseline model, indicating a stronger relationship at 93% due to a better dispersion of data about the mean. For both models, the p-value is well below the 5% level of significance, meaning that the H0 hypothesis is rejected. Though there is a high correlation in the data, it is clear that the discount rate does have an effect on the NPV. This may imply that the NPV is sensitive to the discount rate. To substantiate this, a sensitivity analysis is performed on the NPV by assuming a constant 10% decrease in discount rates from 1 to 10. The results, indicated by Figures 4.9 and 4.10, show an overall decrease in total NPV by 33 % in the baseline model and 30% for the optimised models.

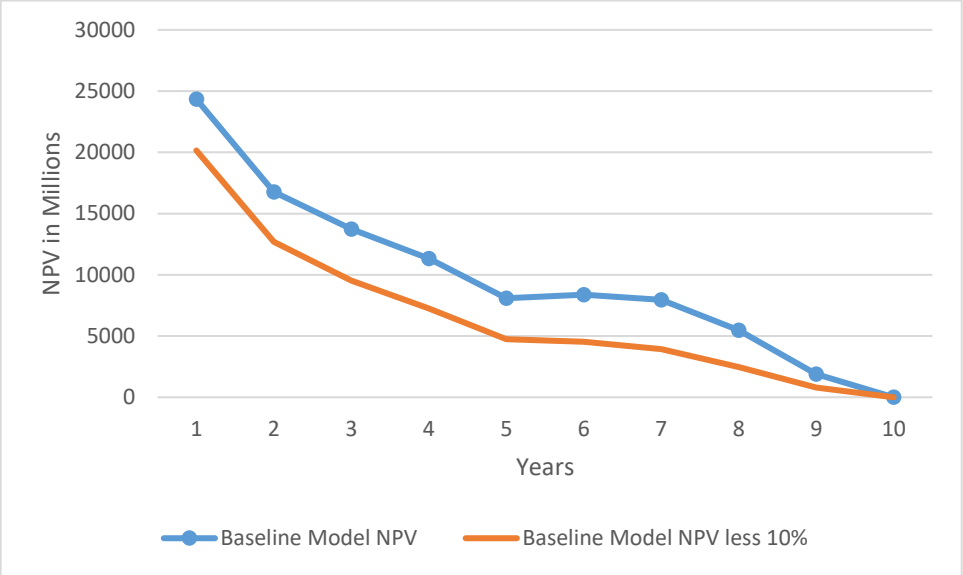


Figure 4.9 Baseline Model sensitivity analysis.

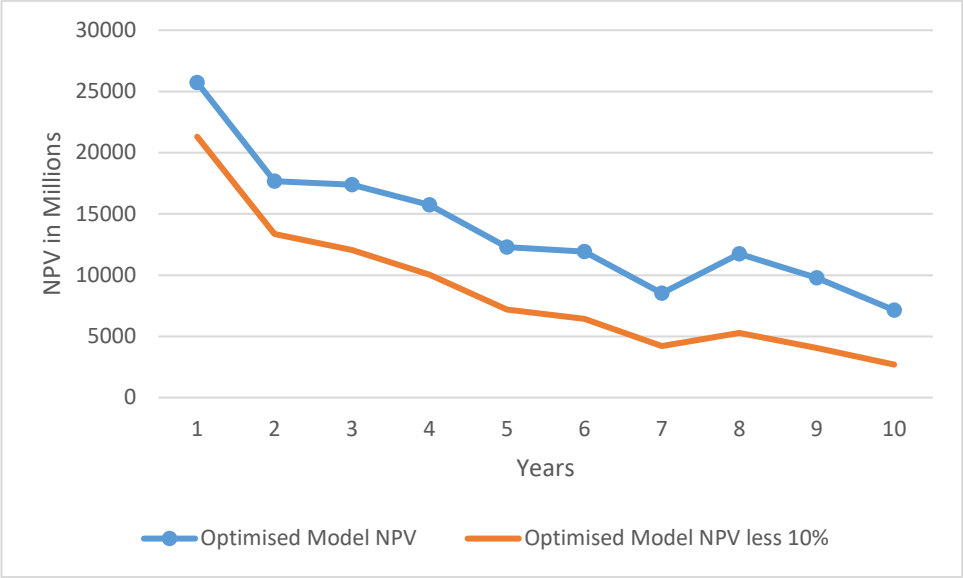


Figure 4.10 Optimised Model sensitivity analysis.

It must be noted that though both models relate similarly to the discount rate, the optimised model outperforms (3% more) the baseline in its ability to cushion the NPV from fluctuating markets and volatile environments.

4.1.4 Analysis of the relationship between NPV and Time at Mine A

It is well known that discounted cash flows exhibit an exponential relationship with time (Campos et.al, 2015). Generally, in the NPV calculation, time is defined as the independent variable and is plotted on the x-axis, while NPV is the dependent variable plotted on the y-axis. This is further elaborated in the equation:

Equation 4.2 Equation for computing NPV (Campos et.al, 2015).

$$NPV = \sum_{t=0}^{n}(CF_t)/(1+r)^t \quad \textbf{(4.2)}$$

Where:

CF_t is the cash flow in year t

n is the life of the project

r is the discount rate

Plotting the annual NPVs generated for both models, see Figures 4.9 and 4.10, the following trends were identified:

i. The graphs decline (steep and flat) from year 1 to 10 due to the discounting factors applied.
ii. The graphs decrease asymptotically towards zero due to a decreasing NPV as time progresses.

These trends indicate exponential decay or negative growth, meaning that the present value contribution of each year's cash flow decreases exponentially over time. To test the validity of this, an exponential analysis was applied. An exponential line of best fit was derived from the NPV datasets of both models. The exponential decay equation is generally of the form described by equation 4.3:

Equation 4.3 Equation for computing exponential decay (Torrontegui et.al, 2010).

$$y = ae^{-bt} \quad \textbf{(4.3)}$$

Where:

a is the initial undiscounted value or CF_t

b is the rate of decay from discounting or ln(1+r)

t is the period

e exponential function

This equation implies that a higher rate of decay (high discount rate) results in a faster exponential decay, impacting long-term investments negatively, and the converse is true. Applying this to the case study models, the baseline model

portrays a steeper decay (Figure 4.11 versus Figure 4.12) as opposed to the optimised model, though the same discount rates were applied for both models. In the baseline model, b is equal to 0.667, whilst in the optimised model, it is only 0.118. It therefore means that the baseline model is susceptible to longer project periods, making it least ideal for a long-term 10-year project.

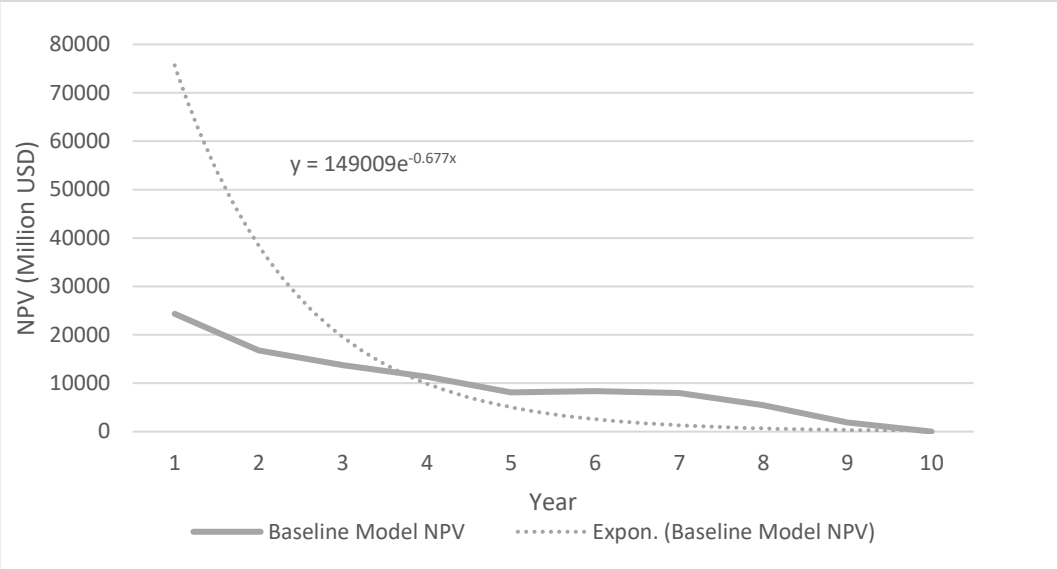


Figure 4.11 NPV versus Time for baseline models.

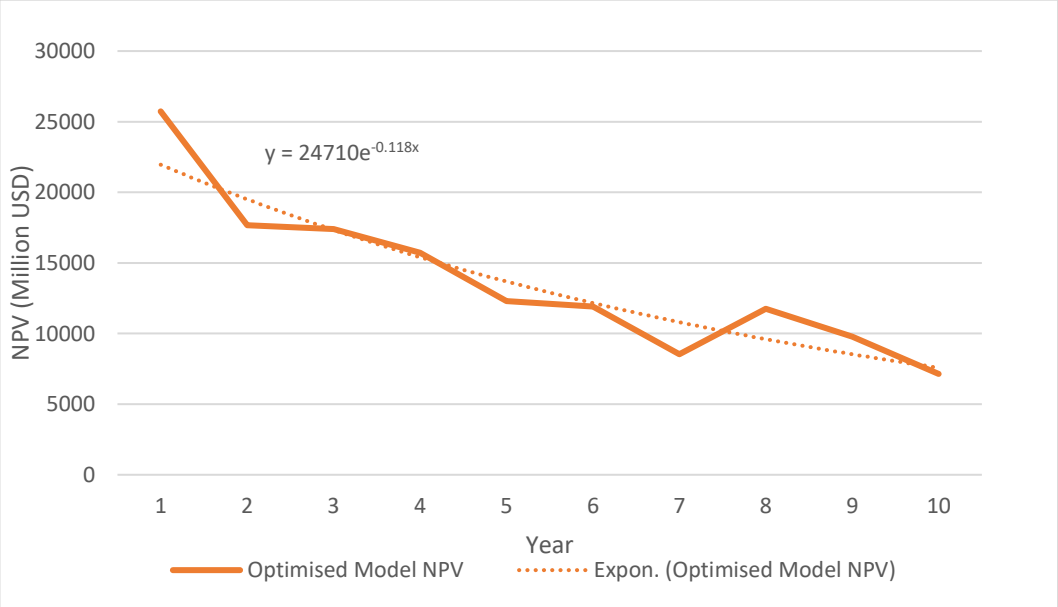


Figure 4.12 NPV versus Time for optimised models.

Section 4.1.3 showed the sensitivity of the models to a volatile economic environment. Increasing the discount rate can impact the models negatively; however, the most affected model is the baseline, indicated by the high rate of decay. Mining operations rely on long-term NPV to cushion against capital-intensive projects such as a processing plant enhancement. High rates of decay, such as that of the baseline model, provide an idea of the level of risk associated with a particular investment or, in this case, a particular model. Also, if Mine A continues to mine per the baseline model (to combat the effects of a lower NPV), they may need to opt for more intensive resource depletion in the earlier years of mining. This can result in high fuel consumption and inadvertently high carbon emissions.

4.2 Chapter Summary

The analysis evaluates Mine A's NPV and carbon footprint by comparing the original haulage and mining schedule (baseline) with an optimised schedule over 10 years. Key points include:

- The NPV analysis indicates that the NPV has an exponential relationship with time. Over time, the baseline models' NPV decays faster than the optimised. Making the optimised model more ideal for a mining operation intending to operate profitably over the long term.
- For the first 5 years, the baseline model produces carbon emissions that are 25% lower than the optimised model. However, between years 5 to 9, the emissions increase to surpass the optimised model by 31%.
- A linear regression model was applied to test the relationship between the baseline and optimised model's NPV over the 10 years. The optimised model yields an NPV that is 62% higher than the baseline model at Mine A.
- From Spearman's correlation, the negative relationship identified between the NPV, and carbon footprint indicates that NPV is inversely proportional to the carbon footprint; and
- Though the relationship is true, applying a P-value hypothesis indicates that the baseline model remains inversely proportional at any given time. This

implies that it may not be possible to find a balance between NPV and carbon footprint. However, the optimised model rejects the hypothesis that the inverse proportionality is true at any given point. This implies that there is a possibility that a balance can be achieved in NPV and carbon footprint with some compromise on NPV.

5 CONCLUSIONS AND RECOMMENDATIONS

This chapter provides the report overview by breaking down individual aspects of the research and their contributions to achieving the research objective. This breakdown includes a summary, key findings, contributions, and recommendations.

5.1 Research Observations and Concluding Remarks

5.1.1 Initial and complementary studies

Amoako et al.'s (2018) study on the Carbon Footprint of Ghana's large-scale Gold Mining Industry aligns greatly with the scope of research for Mine A. This study provides a detailed approach to understanding the baseline carbon footprint for gold mines in the West Africa region, which is within the location of Mine A. A similar approach was employed to determine the carbon footprint of haulage trucks at Mine A. The data and results obtained from the calculations are further discussed below.

5.1.2 Key findings and observations

The following key findings surfaced from the research:

- Based on the analysis in Chapter 4, the optimised model proves to be a better schedule in comparison to the baseline model, which was one of the objectives of the study. It is indicated by the NPV analysis resulting in a linear predictive model that shows that the baseline model will always yield an NPV that is 62% lower than the optimised model at Mine A. A residual plot analysis was further employed to substantiate this statement. From these residual plots, it is clear that the predictive linear model is true and presents an accurate representation of the data analysed. Furthermore, an outlier was identified in the baseline and optimised models' residual plots. This outlier is a result of the first year of mining, where operations are slowly ramping up and operational costs are lower. It is a common phenomenon and is to be expected for new projects such as Mine A. Therefore, based on the NPV analysis, the Mine Plan software has been able to optimise the baseline to yield a better and positive projected NPV throughout the

planned 10 years. However, it cannot be conclusively said that the model will yield the same improvement with a different dataset.

- Though the objective of this study was not only to optimise NPV, but also to determine if the optimised NPV would yield a sustainable mining plan. This was tested by also reviewing the carbon footprint resulting from these mining models. The total fuel consumption associated with each model's NPV was collected and analysed. This fuel data was then (through the application of calculations discussed thoroughly in section 3.3) converted to carbon emissions to improve comparability. By analysing the carbon emissions, the carbon footprint of each model was derived. At a glance, the carbon footprint of the baseline model and the optimised model may exude a similar trend. However, further analysis indicates that between Year 1 to 5, the carbon emissions of the baseline model are 25% lower than the optimised. This is because the baseline model operates on the shortest and easiest access routes during this period, whereas the optimised model seeks to ensure that it mines in sequence. Between Year 6 to 9, the baseline and optimised models both show an increase in carbon footprint owing to an increase in fuel consumption due to an increase travelling distances, that is, pit expansion further from the main surface infrastructure and stockpiles. During this period, the baseline model's carbon footprint exceeds that of the optimised by 31% owing to the fact that the model has exhausted the shorter hauls and often hauls from C5 to the stockpiles. This finding indicates that when operational costs increase, the optimised model is the ideal model in that it produces the highest NPV, has a more stable rate of decay and the lowest carbon footprint for the 10-year period at Mine A.
- It would not do the research justice to only analyse NPV and carbon footprint independently, as it is not clear how the two variables relate. Therefore, another analysis was performed to determine if a relationship exists between the NPV and carbon footprint. By observation of the graphical representation of the data, one can assume that NPV is inversely proportional to carbon footprint for both the baseline and optimised models. Hence, the Spearman's correlation test was conducted. The purpose of the test was to determine if a correlation (relationship) exists between the two variables. By applying Spearman's equation to the baseline and optimised

models' data set, a correlation coefficient of – 0.2 and – 0.7 were calculated for the baseline and optimised models, respectively. The negative sign indicates a negative relationship meaning that it can be conclusively stated that for both the baseline and the optimised models, the NPV is inversely proportional to the carbon emissions. This means that an increase in one variable will result in a decrease in the other at Mine A. Do note that this remains true for the baseline model, especially when operational costs are high. However, the optimised model offers a chance to mitigate this by reviewing multiple scenarios and maintaining the sequence to achieve all set objectives.

- The Hypothesis test was conducted employing the P-value test to determine if this conclusion is true at any point in time at Mine A. Results show that the conclusion holds for the baseline model only. It appears that the optimised model's inverse proportionality is only representative of this particular data set. This means that using a predictive model to determine carbon emissions outside this data range could provide incorrect data. Furthermore, this elaborates the need for concurrent incorporation of the carbon footprint calculations simultaneously with the cash flow projections during the planning phase to ensure that the correct values are obtained, and the informed assumptions are made.
- The final Hypothesis test was employed to determine the relationship between NPV and discount rate. It can be said that NPV is indeed dependent on the discount rate. This can be observed by analysing the sensitivity of the NPV against a changing discount rate, showing direct proportionality to the discount rate for both models. However, the optimised model is less sensitive to the discount rate when compared with the baseline model.

Overall, the research has confirmed that primarily focusing on NPV as a success criterion can be short sighted in this time and age. This is because the optimisation engines do not have a carbon emissions estimator built into the planning software. Therefore, by default, the system always optimises for productivity and profitability instead of striking a balance, as seen in Chapter 4 in the NPV analysis and the carbon footprint analysis.

To achieve sustainable mining, the relationship between NPV and carbon footprint must be investigated simultaneously and concurrently with long-term planning. This way, a more proactive approach is adopted towards reducing carbon emissions from the initial stages rather than only proactively in mine rehabilitation and mine closure. A proactive approach enables informed decision-making, for example, at Mine A, opting for the optimised model indicates a higher probability on return on investment, but it also allows the strategic team to decide how much to compromise in NPV for the years where carbon emissions surpass NPV. This compromise is only for a short while; however, the ability to report this efficiently in the annual ESG reports, which will become mandatory, may improve access to funding and future investments by showing proactive and sustainable mining operations. This is how we build a more conscientised mining industry.

5.2 Recommendations for Future Research Work

The following recommendations apply:

i. Expand the study

The study was constrained to a single type of software and equipment to optimise the schedule. Data on the entire production fleet, land use, and energy consumption by the processing plant to produce the final product are required to have a holistic understanding of the Mine A's contribution to carbon emissions. In this study, it is not possible to model the assumed plant energy consumption as this optimisation is conducted using a mine planning software.

ii. Expand the literature review or qualitative research

Apply the literature review beyond a single commodity. This will help to determine niches of problems or the universality of issues facing surface mines across the commodities.

iii. Apply to other industries

Optimisation is not only a concept in mine planning; other industries have similar challenges to which they have already applied solutions. Comparing solutions and challenges across industries provides a better perspective.

iv. Incorporative planning approach

Conscientise buyers to incorporate planning consultants and/or support personnel to assist with software applications. Beyond training, much attention is required to realise the full value of these expensive software applications.

v. Integrating ESG into mining for insightful planning

The current reactive approach towards mining and mine planning is regressive. A progressive approach requires a proactive approach. This means planning to mine sustainably before engaging the ground. More studies need to be conducted into the benefits of integrating MILP solvers with a predetermined ability to estimate the potential carbon emissions of a mine plan design before implementation.

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APPENDIX A. Cash Flow and Production Reporting for the Baseline Model over 10 years

		Period										
Cash Flow Group	**Cash Flow Description**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Grand Total (million)**
Revenue	AUD, in gold (in million USD)	27277.18	20104.21	17990.37	16215.91	12638.94	14220.91	14749.40	11108.40	4237.77	0.06	138543.00
	Crusher_dst	15.84	15.20	11.51	8.47	12.67	15.34	12.33	12.26	3.08	0.00	106.70
	WD110_dst	3.65	4.58	1.20	1.46	0.00	0.00	1.80	4.73	2.96	0.00	20.39
	WD121_dst	1.91	0.00	0.11	0.47	0.00	0.00	0.00	0.50	1.26	0.00	4.26
	WD122_dst	1.17	22.27	0.00	0.04	0.00	0.00	0.13	1.24	1.19	0.00	26.05
	WD200_dst	3.96	3.42	1.80	0.79	45.24	16.34	6.77	31.73	15.48	0.06	125.59
	WD211_dst	33.57	0.98	1.74	0.37	0.69	8.67	4.59	0.19	1.39	0.00	52.19
	WD212_dst	9.26	7.75	0.10	1.55	5.09	8.24	3.58	31.65	1.53	0.00	68.75
	WD213_dst	1.41	16.61	0.38	0.52	2.00	11.69	3.75	0.95	0.70	0.00	38.02
	WD220_dst	1.75	0.44	32.63	0.08	0.46	9.02	1.97	0.96	0.90	0.00	48.20
	WD241_dst	0.66	0.00	6.44	0.32	1.79	5.85	2.87	0.78	0.85	0.00	19.56
	WD242_dst	1.19	0.89	0.38	0.27	1.37	4.63	3.53	0.81	1.39	0.00	14.45
	WD243_dst	2.14	0.22	0.51	0.00	1.32	4.53	1.43	0.26	1.61	0.00	12.02
	WD252_dst	3.02	14.60	0.51	0.41	1.10	7.36	4.47	4.46	0.93	0.00	36.86
	WD310_dst	0.70	0.00	1.72	19.13	5.82	0.00	14.68	0.00	0.02	0.00	42.06
	WD320_dst	0.79	0.00	0.01	7.85	5.13	0.00	14.53	0.00	0.00	0.00	28.32
	WD330_dst	0.24	0.00	24.37	44.08	7.04	0.00	13.79	0.00	0.13	0.00	89.66
Mining Cost Total	Mining Cost Total	81.27	86.96	83.39	85.83	89.73	91.67	90.19	90.53	33.43	0.06	733.06
	Crusher_dst	74.00	74.00	74.00	74.00	74.00	74.00	74.00	74.00	47.56	0.00	639.56
Processing Cost Total	Processing Cost Total	74.00	74.00	74.00	74.00	74.00	74.00	74.00	74.00	47.56	0.00	639.56
	PRILG_STK	0.00	0.00	0.00	14.00	3.39	1.31	8.84	5.09	0.02	0.00	32.66
	PRIMG_STK	0.00	2.16	6.03	1.92	1.05	0.24	0.87	0.87	0.00	0.00	13.15
	SAPLG_STK	0.00	0.00	0.00	8.98	6.28	0.12	2.18	6.15	24.03	0.00	47.75
	SAPMG_STK	0.00	0.00	8.61	0.05	0.00	0.00	0.00	0.00	0.00	0.00	8.66
Reclaim Cost Total	Reclaim Cost Total	0.00	2.16	14.64	24.95	10.72	1.67	11.89	12.11	24.05	0.00	102.21
Hauling Operating Cost	MS_777D ROCK	0.87	0.09	0.45	7.40	0.85	0.35	0.53	0.21	0.33	0.00	11.09
	MS_777D SAPRO	8.18	9.57	10.55	11.66	10.28	5.46	12.79	9.92	2.79	0.01	81.20
Hauling Operating Cost Total	Hauling Operating Cost Total	9.05	9.66	11.00	19.06	11.14	5.80	13.32	10.12	3.12	0.01	92.29
Hauling Fuel Cost	MS_777D ROCK	0.32	0.03	0.11	1.10	0.30	0.10	0.18	0.05	0.07	0.00	2.27
	MS_777D SAPRO	2.58	3.43	1.61	1.04	2.45	1.37	1.46	3.02	0.89	0.00	17.85
Hauling Fuel Cost Total	Hauling Fuel Cost Total	2.90	3.46	1.72	2.14	2.75	1.47	1.64	3.08	0.96	0.00	20.12
Loading Operating Cost	SHOVEL-ROCK	0.41	0.04	0.22	2.02	0.42	0.23	0.29	0.15	0.33	0.00	4.11
	SHOVEL-SAPRO	3.80	4.19	4.01	2.21	3.81	4.00	3.94	4.08	1.49	0.00	31.53
Loading Operating Cost Total	Loading Operating Cost Total	4.21	4.23	4.23	4.23	4.23	4.23	4.23	4.23	1.82	0.00	35.65
Capital Cost	Capital Investment	575.00	0.00	13.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	588.00
Net Cash Flow	Net Cash Flow	26530.76	19923.75	17788.37	16005.70	12446.37	14042.06	14554.12	10914.33	4126.83	-0.01	136332.00
Discount Factor	Discount Factor	0.92	0.84	0.77	0.71	0.65	0.60	0.55	0.50	0.46	0.42	
Present Value	Present Value	24340.14	16769.42	13735.89	11338.84	8089.28	8372.82	7961.60	5477.53	1900.11	-0.01	97985.63
Cumulative Present Value	Cumulative Present Value	24340.14	41109.56	54845.45	66184.29	74273.57	82646.39	90608.00	96085.53	97985.64	97985.63	

APPENDIX B. Cash Flow and Production Reporting for the Optimised Model over 10 years

		Period										
Cash Flow Group	**Cash Flow Description**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Grand Total (million)**
Revenue	AUD, gold (in million USD)	28827.59	21207.58	22771.50	22479.49	19156.26	20262.79	15820.03	23693.87	21535.44	17177.32	212931.88
	Crusher_dst	15.84	11.54	15.83	15.64	11.30	15.79	9.87	15.84	11.22	12.44	135.28
	WD110_dst	0.00	0.00	0.00	1.68	0.00	0.00	3.72	1.61	54.53	0.58	62.12
	WD121_dst	0.00	0.00	0.00	26.16	0.00	0.00	0.59	0.00	0.00	0.00	26.75
	WD122_dst	90.29	1.49	114.98	85.62	22.52	0.42	60.89	156.41	40.25	0.95	573.82
	WD220_dst	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	8.59	0.00	8.60
	WD241_dst	2.67	1.35	2.70	1.09	15.26	0.00	27.14	1.88	2.49	3.31	57.88
	WD243_dst	0.02	0.24	0.53	40.21	0.00	155.03	5.82	0.21	18.12	0.92	221.11
	WD252_dst	0.66	2.41	2.36	1.33	0.73	1.58	2.68	0.32	23.39	144.26	179.71
	WD310_dst	0.00	0.29	0.00	3.08	17.63	0.00	0.00	0.00	0.13	0.00	21.12
	WD330_dst	0.96	83.39	0.00	0.80	50.74	0.83	1.59	0.00	0.00	0.00	138.31
Mining Cost Total		110.43	100.70	136.40	175.61	118.18	173.64	112.29	176.28	158.72	162.45	1424.70
	Crusher_dst	74.00	74.00	74.00	74.00	74.00	74.00	74.00	74.00	74.00	74.00	740.00
Processing Cost Total	Processing Cost Total	74.00	74.00	74.00	74.00	74.00	74.00	74.00	74.00	74.00	74.00	740.00
	PRIMG_STK	0.00	14.56	0.01	0.67	7.71	0.00	5.35	0.00	15.65	9.07	53.03
	SAPMG_STK	0.00	0.00	0.00	0.00	7.67	0.16	14.87	0.00	0.00	2.45	25.15
Reclaim Cost Total	Reclaim Cost Total	0.00	14.56	0.01	0.67	15.38	0.16	20.22	0.00	15.65	11.52	78.18
Hauling Operating Cost	MS_777D ROCK	7.16	5.89	4.70	11.21	3.93	7.51	8.22	15.81	6.80	2.67	73.90
	MS_777D SAPRO	3.74	15.77	11.94	2.00	15.38	2.97	1.08	4.84	4.33	10.88	72.92
Hauling Operating Cost Total	Hauling Operating Cost Total	10.89	21.66	16.64	13.21	19.31	10.48	9.30	20.65	11.13	13.56	146.82
Hauling Fuel Cost	MS_777D ROCK	2.02	0.98	1.90	3.35	1.14	2.16	2.26	4.07	1.75	0.88	20.53
	MS_777D SAPRO	1.21	1.02	4.50	0.40	0.68	0.54	0.21	1.73	0.89	3.64	14.82
Hauling Fuel Cost Total	**Hauling Fuel Cost Total**	**3.23**	**2.00**	**6.40**	**3.75**	**1.82**	**2.70**	**2.47**	**5.80**	**2.64**	**4.53**	**35.35**
Loading Operating Cost	SHOVEL-ROCK	3.79	1.75	1.51	7.85	2.59	5.54	5.16	6.63	4.16	1.58	40.56
	SHOVEL-SAPRO	1.98	3.06	5.22	0.81	3.18	3.12	0.61	2.02	3.84	6.43	30.26
Loading Operating Cost Total	Loading Operating Cost Total	5.77	4.81	6.73	8.65	5.77	8.65	5.77	8.65	8.01	8.01	70.82
Capital Cost	Capital Investment	575.00	0.00	13.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	588.00
Net Cash Flow	Net Cash Flow	28048.27	20989.84	22518.31	22203.59	18921.81	19993.16	15595.97	23408.49	21265.30	16903.26	209848.01
Discount Factor	Discount Factor	0.92	0.84	0.77	0.71	0.65	0.60	0.55	0.50	0.46	0.42	
Present Value	**Present Value**	**25732.36**	**17666.73**	**17388.27**	**15729.58**	**12297.88**	**11921.27**	**8531.53**	**11747.93**	**9791.14**	**7140.12**	**137946.80**