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OPTIMISATION OF AN OPEN PIT DIAMONDS MINE'S MINE-TO-MILL VALUE CHAIN USING PROBABILISTIC VALUE STREAM MAPPING

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

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 Researcher 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

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4th day of September 2025

ABSTRACT

This study optimised a mine-to-mill value chain of a case study open-pit diamonds mine that experienced an average of 26% production shortfall between 2017 and 2022. A mixed-methods approach was applied, combining quantitative and qualitative methods. Quantitative analysis of historical data (2018–2022) from production reports, processing plant records, and block models was supported by qualitative insights from expert interviews and field observations. Probabilistic value stream mapping and Monte Carlo Simulation (MCS) were used to diagnose inefficiencies, model variability, and improve process performance. MCS was used to simulate fluctuations in processed tonnes, feed grade, recovered carats and recovered grade, with cumulative distribution functions visualising predictability and variability. Current state mapping and process activity mapping were used to categorise activities across the value chain into Value-Adding (VA), Non-Value-Adding (NVA), and Necessary but Non-Value-Adding (NNVA) activities, helping to identify material flow bottlenecks and inefficiencies.

Blasting, crushing and screening, dense media separation, recovery and sorting were identified as VA activities. NNVA activities included loading and hauling and stockpiling, Activities sending material to the tailings dam were classified as NVA. Excessive stockpiling, unplanned equipment downtime, inefficient haulage cycles, redundant material rehandling, and misalignment between blasting and downstream processing rates were identified as inefficiencies.

A proposed future state map incorporated lean principles, predictive maintenance, real-time density monitoring, and Radio Frequency Identification (RFID) enabled ore reconciliation. The results showed significant improvements in recovery efficiency, throughput, and process stability. Sensitivity analysis further identified feed grade and recovery efficiency as the most critical drivers of variability, while a cost–benefit analysis confirmed the economic viability of the proposed optimisations. The study contributes a scalable methodology for value chain optimisation in high-variability mining environments and recommends the integration of digital tools, standardised operational practices, and continuous improvement to achieve sustainable mine performance.

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LIST OF ACRONYMS AND ABBREVIATIONS

AI - Artificial Intelligence

CB - Closing Balance

CDF - Cumulative Distribution Function

Cpt - Carats Per Tonne

Ct - Carats

CSM - Current State Map

DMS - Dense Media Separation

DMAIC - Define, Measure, Analyse, Improve, Control

FeSi -Ferrosilicon

FSM – Future State Map

IR - Interview Respondent

Kc - Kilo Carats

Kt - Kilo Tonnes

KPIs - Key Performance Indicators

ML – Machine Learning

MCS - Monte Carlo Simulation

NVA - Non-Value Adding

NNVA - Necessary but Non-Value Adding

OB – Opening Balance

PAM - Process Activity Mapping

PVSM – Probabilistic Value Stream Mapping

RoM - Run of Mine

RFID - Radio Frequency Identification

SCM - Supply Chain Management

SOP - Standard Operating Procedure

TOC - Theory of Constraints

TPH - Tonnes Per Hour

VA -Value Adding

VSM - Value Stream Mapping

VSL - Value Stream Losses

1 INTRODUCTION

1.1 Overview of Chapter 1

This chapter provides an introduction of the research. It outlines the research background and problem statement in which the existing inefficiencies at the case study diamonds mine are outlined. Additionally, it provides the aim, objectives, and justification of the research. The name of the mine could not be disclosed in this report for confidentiality reasons. The chapter ends with a summary of Chapter 1 and the structure of the research report.

1.2 Research Background

A mining value chain encompasses all processes from exploration to delivery of a final product. The chain is crucial for generating value and maintaining competitive advantage in the mining industry. Factors such as operational efficiency, resource utilisation, and cost significantly impact the profitability and sustainability of mining operations (Amini *et al.*, 2021). This research report used a mine that extracts diamonds from kimberlite deposits through three open pits namely Pit 1, Pit 2, and Pit 3 as a case study. The materials from these pits are categorised as run of mine (RoM) ore, low-grade ore and waste. Marginal zone ore and ore with granite and xenoliths is classified as low-grade. Additionally, high grade ore with dilution of above 60% as per geological technician assessment is classified as low-grade. The effectiveness of this classification system is influenced by grade losses, material tonnage, and fluctuations in feed grade, all of which can reduce profitability of a mine.

1.3 Problem Statement

The case study mine has faced notable challenges in recovering mineral grades such that actual grades are frequently lower than grades predicted in the geological block model. This has resulted in an average carats production shortfall of 26% from 2017 to 2022. The recovery model shows that the milling stage has lockup factors of 17% and 25% for Pit 1 and Pit 2, respectively. A lockup factor is the proportion of ore that is left unrecovered or unmined within a mineral resource due to geological, economic, or operational constraints, impacting the overall efficiency and profitability of a mine (Coulston and Waugh, 2002). The geological block model estimated a minimum grade of 0.4 carats per tonne (cpt) for Pit 1 and 1.06 cpt for Pit 2 with expected recoveries of 0.33 cpt and 0.80cpt, respectively. The lowest actual recovered grade for Pit 1 was 0.28 cpt in 2022 and 0.42 cpt for Pit 2 in 2018 which are both lower than estimated minimum grades. The gaps between expected and actual recovered grades necessitated a thorough review of the mine's value chain. Figure 1 shows the mine's diamonds production between 2017 and 2022.

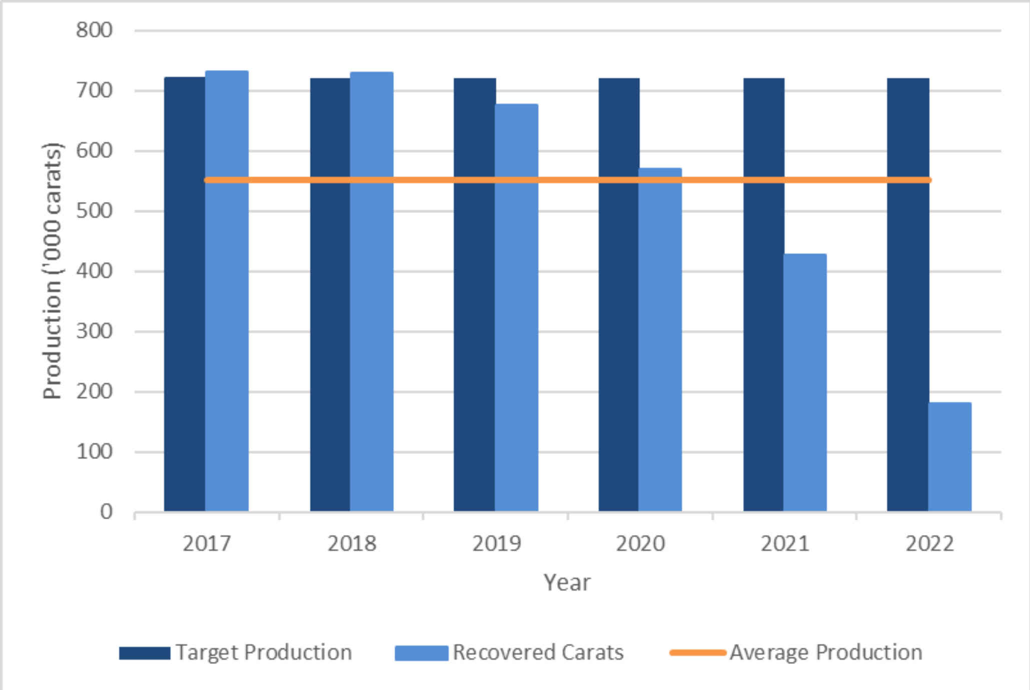

Figure 1: Target versus actual diamonds production between 2017 and 2022

Figure 1 illustrates a consistent decline in diamond production from 2018 onwards, highlighting inefficiencies across the mine's value chain. Initially, the mine's 10-year plan (2017–2026) targeted 720 kilo carats (kc) per year. However, due to repeated shortfalls in meeting this target, the production budget was revised downward to an average of 682 kc per year. As shown in Figure 1, recovered carats remained relatively stable at around 730 kc in 2017 and 2018 before declining to 677 kc in 2019, and further down to 180 kc by 2022. Actual production averaged 552 kc per year from 2017 to 2022, well below both the original and revised budgets.Figure 2 shows actual average ore grade, feed grade, expected recovered grade, and recovered carats between 2017 and 2022.

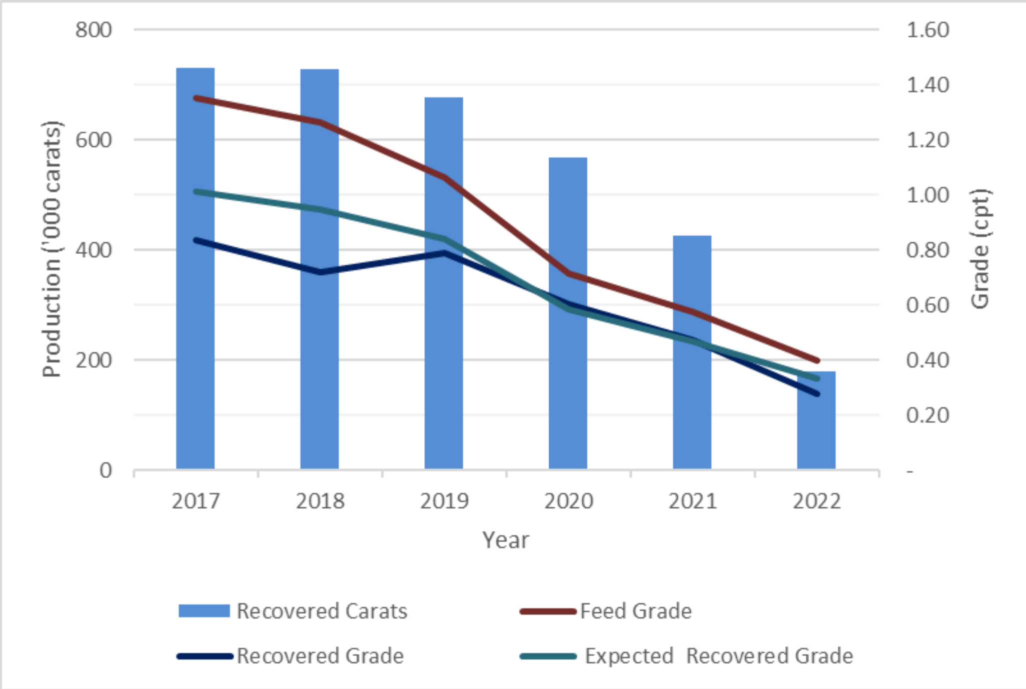

Figure 2: Feed, recovered and expected recovered grade versus recovered carats between 2017 and 2022

Figure 2 illustrates a strong correlation between carats produced and the recovered grade. Recovered grade declined from 0.84 cpt in 2017 to 0.72 cpt in 2018, followed by an improvement to 0.79 cpt in 2019. However, from 2019 onwards, there is a consistent decline in grade up to 2022. Similarly, production exhibits a steady downward trend, decreasing from 732 kct in 2017 to 180 kct in 2022. This represents a 75% decline in output over six years, driven primarily by the fall in feed grade from 1.35 cpt in 2017 to 0.40 cpt in 2022. Expected recovered grade followed a similar downward trajectory (1.02 cpt in 2017 to 0.33 cpt in 2022), but actual recovered grade consistently trailed these values, with the largest shortfalls of 0.18–0.23 cpt in 2017–2018, narrowing to 0.05 cpt in 2019, briefly exceeding expectations in 2020–2021, and then falling short again by 0.05 cpt in 2022. These differences highlight persistent inefficiencies in recovery that compounded the effect of declining feed quality.

The graph clearly demonstrates that increases in recovered grade correspond to higher carat production, while decreases in grade result in lower production levels. Hartman and Mutmansky (2002) argue that operational inefficiencies in grade recovery and processing drive up operational costs and reduce profit margins for mining companies. Similarly, Torries (2020) notes that production inefficiencies often make mining operations more sensitive to market fluctuations and economic pressures, which can threaten their long-term viability. Furthermore, inadequate grade reconciliation and recovery inefficiencies compromise mineral resource management and hinder accurate mine planning, which is essential for aligning operations with market demands and sustaining production targets (Binnemans et al., 2013). Without effective grade reconciliation, mining operations struggle to predict outputs reliably, impacting long-term financial planning and operational sustainability. Additionally, Rosienkiewicz (2012) observes that such inefficiencies frequently cause bottlenecks, reducing production throughput and diminishing profitability.

1.4 Research Aim and Objectives

The aim of the research was to optimise the mine-to-mill value chain for an open-pit diamonds mine using Value Stream Mapping (VSM) and Monte Carlo Simulation (MCS). By integrating VSM and MCS, the study provides a unique way to model operational uncertainties, presenting a strategy to boost efficiency, predictability, and safety in mining operations. This approach not only addresses specific inefficiencies in diamonds mining but also adds insights on the body of literature showing how VSM and MCS, can sustainably improve profitability and competitiveness in the industry. The objectives of the research were to:

1. Review literature on mine-to-mill value chains optimisation using VSM and MCS.
2. Map and assess the current mine-to-mill value chain at the case study mine to identify gaps and justify the use of VSM and MCS.
3. Identify Value Stream Losses (VSL) in the mining system at the case study mine using VSM and MCS.
4. Develop a future value stream map of the case study mine.
5. Create a tailored VSM strategy and develop an implementation plan for the case study mine.

1.5 Research Justification

The case study diamond mine has encountered considerable challenges due to varying mineral grades and inefficiencies throughout its value chain, especially during the mining and processing phases. These inefficiencies negatively affect profitability and safety. Specific challenges included dilution from ineffective grade control and blasting, inconsistent fragmentation affecting crushing and screening efficiencies, haulage constraints due to equipment mismatch and congestion, and suboptimal recovery performance caused by DMS inefficiencies and concentrate tail losses. In addition, there was high variability in feed grade and recovery rates. These operational issues often caused deviations from design specifications, increasing safety hazards and reducing ore recovery, thereby introducing unpredictability into the system (Bester et al., 2016; Rohac and Januska, 2015). All these challenges justified this research.

Despite these challenges, current literature has not fully addressed the unique challenges associated with open-pit diamonds mining. While studies have universally applied lean principles such as VSM in industries such as manufacturing and even in some types of mining, their application in the high-variability context of open-pit diamonds mining remains limited (Duggan, 2012; Hines and Taylor, 2000). Mining environments, present unique challenges, including unpredictable ore grade, inherent variability in ore characteristics, and increased environmental and operational risks. These challenges are particularly prominent in resource intensive and variable mining contexts, where infrastructure and operational conditions can exacerbate inefficiencies (Mukaba and Kinyua, 2020).

Another gap in the literature is the lack of integration of probabilistic modelling methods, such as MCS, with VSM. Although VSM has been valuable for identifying waste and improving efficiency in linear and stable processes, it is less effective on its own in environments marked by high variability and uncertainty, such as diamonds mining. Probabilistic approaches, such as MCS, enable a more dynamic analysis of operational uncertainty by allowing simulations of different scenarios based on fluctuating ore grades, equipment performance, and other unpredictable factors (Metropolis and Ulam, 1949; Dimitrakopoulos and Ramazan, 2008). However, the benefits of combining probabilistic methods with VSM to optimise mining operations are underexplored in current studies, leaving a gap in practical tools for real-time decision making in the diamonds mining sector. This gap also necessitated this research.

This research addressed gaps discussed in above paragraphs by implementing a combined VSM and MCS approach tailored to the unique conditions of open-pit diamonds mining. This interdisciplinary approach not only addressed specific inefficiencies, but also added flexibility to VSM, making it more applicable to the high-variability case study diamond open pit mine. Integrating these methodologies has the potential to improve predictability, safety, and profitability (Rosienkiewicz, 2012; Torries, 2020). This research report contributes insights to the field of mine-to-mill optimisation and demonstrates the value of Probabilistic Value Stream Mapping (PVSM) for sustainable competitiveness in open-pit mining operations.

1.6 Summary of Chapter 1 and Structure of the Research Report

This chapter provided an overview of the research, outlining the background that prompted the research. It presented the problem statement, research aim and objectives and justified the need for the study. The report consists of five chapters and remaining chapters are briefly outlined in the next paragraph.

Chapter 2 reviews the existing literature on mine-to-mill optimisation and the application of VSM and MCS, assessing their effectiveness in tackling challenges faced in mining operations. Chapter 3 describes the methodology employed in the research, including data collection techniques, the research framework, and the approaches used to develop the VSM and MCS-based optimisation model. Chapter 4 presents the data gathered during the study and highlights the findings from the current state analysis of the mine value chain. It analyses the results and discusses the creation of a future state value stream map, along with strategies aimed at enhancing value recovery. Chapter 5 concludes the research and provides recommendations for improving the mine's economic performance through VSM, MCS and value chain optimisation.

2 LITERATURE REVIEW

2.1 Overview of Chapter 2

This chapter reviews key literature on the optimisation of mine-to-mill value chain, with a particular focus on lean methodologies, specifically VSM and MCS. It introduces the mine value chain concept, emphasising its role in aligning upstream and downstream activities to maximise operational efficiency. The chapter discusses challenges unique to mining, including ore grade variability, processing inefficiencies, and the underutilisation of lean tools such as VSM. It explores how VSM helps identify waste and streamline processes, while MCS models operational uncertainties by simulating variable factors. By integrating these approaches, mining operations can develop a comprehensive framework for improving recovery rates and throughput. Additionally, the chapter presents the theoretical foundations of the study, including Lean Thinking, the Theory of Constraints (TOC), and probabilistic modelling approaches. The chapter concludes by identifying the need for context-specific strategies that incorporate both lean principles and probabilistic models to optimise complex mining operations.

2.2 Mine Value Chain

Porter (1985) introduced the value chain concept, defining it as the entire lifecycle of a product—from its conception and design to its delivery to customers and eventual disposal. In the mining context, the mine value chain refers to the interconnected activities involved in extracting, processing, and delivering mineral commodities to end users (Pietrobelli & Rabellotti, 2011). The mine value chain encompasses a series of integrated processes that transform raw mineral resources into marketable products, with a focus on maximising value at each stage (Cucuzza, 2021; Korinek, 2020). It emphasises efficiency, waste reduction, and value optimisation, ensuring that mining operations operate seamlessly across multiple stages to enhance overall productivity. Figure 3 illustrates the mine value chain, highlighting its sequential and interdependent components. Each stage, from exploration to rehabilitation, is essential for maximising value creation and ensuring long-term operational sustainability.

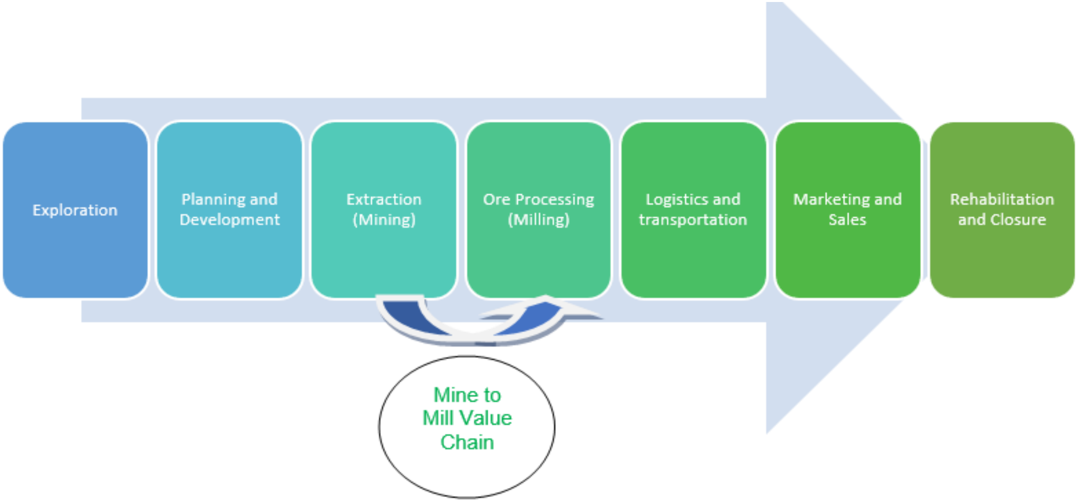

Figure 3: An example of a mine value chain

(Source: Arndt *et al*., 2017)

As illustrated in Figure 3, the mine value chain consists of a series of interconnected activities, each playing a crucial role in the extraction, processing, and delivery of mineral commodities. The exploration and resource identification phase is critical for accurate mineral resource estimation and feasibility studies, laying the foundation for subsequent processes (Marjoribanks, 2010). The mine planning and development phase involves the application of optimisation techniques to align operations with strategic goals, ensuring efficiency and long-term sustainability (Whittle, 2014). The extraction (mining) phase focuses on operational efficiency and environmental considerations, aiming to minimise waste and reduce operational costs (Hartman & Mutmansky, 2002). Ore processing employs advanced technologies to improve energy efficiency and maximise mineral recovery rates (Wills & Finch, 2015). Logistics and transportation involve supply chain optimisation, addressing bottlenecks and reducing costs to enhance overall operational efficiency (Christopher, 2016). Marketing and sales link effective marketing strategies to competitiveness and value realisation within the industry (Porter, 1985). The rehabilitation and closure phase prioritises sustainable practices to ensure long-term environmental health and compliance with regulatory frameworks (Limpitlaw *et al*., 2005). Sustainability, as defined by the World Commission on Environment and Development (1987), is the responsible management of natural resources to meet present needs without compromising the ability of future generations to meet theirs. This research report focuses on the mine-to-mill stages of the mine value chain due to their critical role in optimising production efficiency and ensuring the effective delivery of mineral commodities.

2.3 Mine-to-mill value chain optimisation

A mine-to-mill value chain is an integrated framework designed to synchronise mining and milling processes, optimising performance from ore extraction to product processing. Kanchibotla *et al.* (1999) described this value chain as involving activities such as drilling, blasting, loading and hauling, which determine the quality and size of material delivered to the processing plant. Morley and Milne (2015) highlighted the interdependence of these upstream mining activities with downstream processes such as crushing and milling. The mine-to-mill value chain is central to mining operations because inefficiencies at any stage can disrupt performance of downstream stages.

Mine-to-mill optimisation is described by Jankovic and Valery (2014) as a holistic integration of mining and milling processes to ensure seamless operations. This systems-based approach links upstream activities, such as blasting, to downstream outcomes, ensuring a more efficient and cost-effective value chain. The mine-to-mill optimisation process involves scoping, analysis, optimisation, and implementation. Scoping includes site visits to identify areas for improvement, while analysis surveys the entire operation, from blasting to screening, to identify inefficiencies (Adel *et al.,* 2006a). The optimisation phase focuses on refining blasting practises to achieve consistent material size and enhance milling efficiency (Wills and Finch, 2015). The implementation phase ensures that refinements to mine-to-mill activities are applied, resulting in reduced energy consumption, faster processing rates, and overall improved performance of mine-to-mill value chain. Adel *et al*. (2006b) emphasised the significance of sampling, modelling, and computer simulations to evaluate processes and explore alternatives during the optimisation process.

Optimisation of the mine-to-mill value chain addresses several critical objectives, including maximising throughput by ensuring efficient material flow thus avoiding bottlenecks caused by oversized material (Whittle, 2014). Also, optimisation of this chain reduces operational costs caused by inefficiencies such as poor fragmentation and high energy use (Kanchibotla, 2000). Additionally, optimisation of the mine-to-mill value chain improves mineral resource utilisation by improving grade control, reducing losses, and maximising recovery rates (Jankovic and Valery, 2014). Furthermore, the optimisation ensures sustainability through minimising environmental impacts by reducing waste, energy use, and emissions (Scott and Elbrond, 2003).

Literature underscores the critical role of probabilistic approaches in mining optimisation modelling, particularly in addressing uncertainties related to ore characteristics, recovery rates, and market fluctuations. Frenzel *et al.* (2023) examined geometallurgical performance optimisation, highlighting the integration of geological data into ore behaviour models to manage uncertainty across the mining value chain and account for grade variability in ore deposits. Similarly, Bonfils *et al.* (2021a) developed a structured methodology for multicomponent mine-to-mill optimisation, focusing on tracking mineral components throughout the recovery process for iron and gold ores. Caldas *et al*. (2022) applied stochastic programming to incorporate uncertainties such as ore grade variability and market dynamics into optimisation models. Additionally, Pereira *et al*. (2023) explored optimisation in geometallurgy, emphasising the necessity of understanding ore characteristics and their impact on recovery rates throughout the mining value chain. Bamba *et al*. (2021) demonstrated the effectiveness of combining VSM with probabilistic models, enabling dynamic adjustments to milling processes in response to ore grade variability at Siguiri Gold Mine in Guinea. Collectively, these studies highlight the importance of integrating uncertainty into mine-to-mill optimisation models, demonstrating how such approaches can enhance recovery rates, improve operational efficiency, and support more resilient decision-making across the mining value chain.

2.4 Lean Techniques Used in Optimisation

Mine-to-mill optimisation can benefit significantly from the adoption of lean techniques, which emphasise waste elimination, efficiency improvement, and value maximisation (Womack & Jones, 1996). Paditar *et al*. (2021) define lean techniques as the application of continuous improvement principles aimed at streamlining operations, delivering maximum value to customers, and minimising waste. Originally developed in manufacturing, lean techniques prioritise the elimination of Non-Value-Adding (NVA) activities while fostering a culture of continuous improvement. In the mining context, these techniques can be applied to address challenges such as delays, equipment downtime, and excessive material handling, all of which frequently hinder mine-to-mill operations (Womack & Jones, 1996; Liker, 2004). Various lean techniques have been developed over time. However, this research report focuses on those most commonly applied in mine-to-mill optimisation, specifically Kaizen, Six Sigma, and VSM (Kęsek *et al*., 2019). These are each discussed in the following subsections.

2.4.1 Kaizen

Kaizen is an approach that emphasises incremental improvements to collectively enhance process efficiency (Imai, 1986). It is regarded as one of the most influential lean techniques, focusing on continuous improvement in performance, cost, and quality. Sheller and Nikhil (2012) highlight that Kaizen systematically identifies and eliminates waste while preserving Value-Adding (VA) activities, leading to leaner and more efficient operations. In the mining sector, Kaizen can be applied across the mine-to-mill value chain to improve operational efficiency. For example, regular reviews and refinements of blasting techniques can optimise fragmentation, reducing downstream energy consumption in crushing and milling processes.

A case study by Knight *et al*. (2020) demonstrated the successful implementation of Kaizen principles at a gold mine in Australia, resulting in a 15% increase in mill throughput and a 10% reduction in operating costs over two years. Similarly, reviewing material handling strategies, such as conveyor systems and truck loading operations, can minimise delays and enhance productivity. Moreover, Knight *et al*. (2020) noted that Kaizen contributed to sustainability by reducing waste generation and energy consumption.

However, while Kaizen is highly effective in stable environments, it is less suited to addressing systemic inefficiencies in high-variability contexts like open-pit mining. Therefore, Kaizen was not applied in this research. Sheller and Nikhil (2012) further emphasise that the successful implementation of Kaizen requires consistent and predictable processes. Given the inherent variability in ore grades and equipment performance in mining, more adaptive frameworks are necessary to manage dynamic operational conditions effectively.

2.4.2 Six Sigma

Six Sigma is a data-driven methodology pioneered by Motorola (1986) that seeks to minimise variability and enhance quality through a structured, problem-solving approach. It is a customer-focused methodology for process improvement, employing statistical tools to identify inefficiencies, reduce defects, and optimise performance (DeFeo & William, 2004). In the mining industry, Six Sigma can be instrumental in identifying and addressing bottlenecks within the mine-to-mill value chain. For instance, El Didamony *et al*. (2016) applied the Define, Measure, Analyse, Improve, Control (DMAIC) framework, a core Six Sigma approach, at an iron ore beneficiation plant, achieving a 20% increase in recovery rates and a 15% reduction in process variability. Similarly, statistical analysis of equipment downtime and energy consumption can reveal inefficiencies in haulage and milling operations, enabling targeted interventions. According to the World Diamond Council (2024), the implementation of Six Sigma at a diamond mine in Botswana reduced production losses by 18% within one year, demonstrating the methodology's effectiveness in delivering measurable improvements in controlled production environments.

However, while Six Sigma excels at stabilising processes in controlled environments, its structured and prescriptive nature may be less suited to highly variable settings such as open-pit diamonds mining. These operations are often characterised by fluctuations in ore grade, equipment reliability, and recovery rates, which require adaptive and flexible optimisation frameworks. Nonetheless, the data-intensive foundation of Six Sigma remains valuable. Even if the full methodology may not be directly applicable, its emphasis on data-driven decision-making can be selectively integrated to enhance process control and continuous improvement in dynamic mining environments.

2.4.3 Lean Thinking

Lean Thinking provides the theoretical foundation for continuous improvement and waste elimination, supporting the effective use of VSM in process optimisation. At its core, Lean Thinking focuses on maximising value by streamlining workflows, a principle particularly critical in mining operations where NVA activities, such as waiting times, excessive material handling, and equipment downtime, can significantly affect productivity and operational costs (Womack & Jones, 1996; Liker, 2004). It emphasises the removal of various forms of waste, including overproduction, excess inventory, and unnecessary transportation, asserting that eliminating NVA activities is key to improving efficiency and reducing costs (Womack & Jones, 1996). Furthermore, Lean Thinking advocates for continuous improvement, encouraging organisations to regularly refine processes, adapt to changing conditions, and foster a culture of ongoing innovation (Liker, 2004). Crucially, it aligns all activities with customer-defined value, ensuring that each process step contributes directly to delivering what customers perceive as valuable, thereby enhancing competitiveness and satisfaction (Hines *et al.*, 2004).

However, researchers have identified certain challenges in applying Lean Thinking to the mining sector. These include resistance to change among employees, which can hinder implementation (Hines & Taylor, 2000), and a potential short-term focus that may detract from broader, long-term strategic objectives (Mason & Turner, 2021). Additionally, the inherent complexity and variability of mining operations can complicate the application of lean principles. There is also a risk of over-optimisation, where excessive resource reduction could negatively impact operational flexibility (Mason & Turner, 2021).

2.4.4 Lewin's Theory of Planned Change

Lewin's Theory of Planned Change provides a structured framework for implementing VSM and lean practices within the organisational setting of a diamonds mine. The theory consists of three pillars, unfreezing, changing, and refreezing, which are essential for overcoming resistance to change and embedding new practices into an organisation (Lewin, 1951). The unfreezing stage involves raising awareness of inefficiencies in existing processes, preparing employees for change, and fostering a sense of urgency for improvement (Burnes, 2004). During the changing phase, VSM and lean practices are introduced, providing the organisation with new methodologies to streamline workflows and eliminate waste and enhance productivity (Burnes, 2004). The refreezing phase ensures that optimised processes are institutionalised, reinforcing the new standards as part of the organisation's daily operations (Wojciechowski *et al*., 2016).

Lewin's theory is particularly relevant in the mining sector, where achieving buy-in and sustaining improvements are critical for long-term operational optimisation. In complex environments such as a diamonds mining, a structured change management approach helps ensure that improvements made through VSM and lean initiatives are effectively integrated and sustained.

One of the key advantages of Lewin's model is its clear, step-by-step approach, which helps organisations manage resistance and embed new practices systematically. By following the unfreezing, changing, and refreezing stages, organisations can create a well-defined roadmap for transformation (Lewin, 1951; Wojciechowski *et al*., 2016). However, its linear structure may oversimplify the complexities of dynamic environments, failing to fully accommodate the iterative and unpredictable nature of modern organisational change (Burnes, 2004).

This study used Lewin's Change Management Model as a structured framework to guide future implementation of VSM at the case study diamonds mine. These three pillars of the model will ensure a smooth transition.

2.4.5 Theory of Constraints

The TOC focuses on identifying and managing bottlenecks within a system to maximise throughput (Goldratt, 1990). TOC is particularly valuable in mining, where specific constraints, such as equipment limitations, haulage delays, or inefficiencies in material handling, can significantly impact productivity across the mine-to-mill value chain. By pinpointing these constraints, TOC enables targeted interventions that remove process bottlenecks and improve overall system performance.

TOC complements VSM by guiding the prioritisation of improvements, ensuring that the study focuses on high-impact constraints within the mining value chain. By systematically identifying and optimising constraints, TOC enhances the ability of VSM to streamline operations and increase throughput in diamond mining processes (Braglia *et al.*, 2006a). Figure 4 shows the TOC process model.

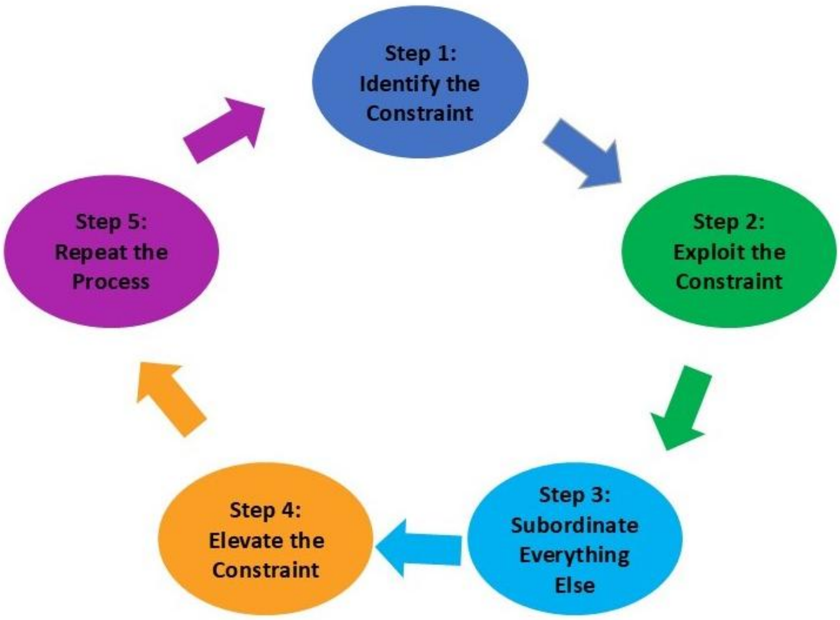

Figure 4: TOC process model

(Source: Adapted from Goldratt, 1990)

Figure 4 presents Goldratt's (1990) TOC process model which follows a structured, cyclical five-step approach to identifying and resolving constraints. The five steps are described below:

1. Identifying the constraint: Determine the weakest link in the system that limits its ability to achieve its goal.
2. Exploiting the constraint: Ensure that the constraint is utilised to its maximum potential.
3. Subordinating other processes: Align all other processes to support the constraint.
4. Elevating the constraint: Increase the capacity of the constraint to improve overall throughput.

5. Repeating the process: Once the constraint is resolved, identify the next constraint and repeat the process.

TOC encourages a holistic view of production processes, aiming to continuously enhance throughput rather than merely optimising individual steps (Catalano, 2020; Rahman, 1998; Größler, 2009). TOC promotes a holistic approach to production processes, focusing on optimising system-wide throughput rather than isolated process improvements. However, its primary limitation is its emphasis on addressing one constraint at a time, which may oversimplify complex systems with multiple interacting constraints. This narrow focus can result in localised optimisations that fail to resolve broader systemic inefficiencies (Rahman, 1998). Given this limitation, TOC was not applied in this research, as a more comprehensive approach was required to account for the interdependencies within the mine-to-mill value chain.

2.4.6 Supply Chain Management

Supply Chain Management (SCM) theory focuses on the integration and optimisation of tasks across the mining value chain. While it is not purely a lean methodology, SCM emphasises the efficient flow of materials and information, aligning with VSM's objective of minimising delays and waste from extraction to processing (Harland, 1996; Kang *et al.*, 2012). SCM provides a broad perspective on how VSM can enhance the coordination and integration of processes across departments, improving the overall efficiency of the mine-to-mill sequence. Its emphasis on supply chain performance evaluation and process control strengthens VSM's efforts to achieve a holistic, optimised flow of materials and resources (Mentzer *et al.*, 2001). SCM prioritises the integration and optimisation of processes across the value chain, enabling efficient material and information flow to reduce delays and costs while enhancing overall performance (Mentzer *et al.*, 2001; Harland, 1996). However, while SCM is effective in ensuring efficiency through process standardisation, its implementation in mining is complicated by fluctuating resource availability and operational conditions. The variability and complexity in resource-intensive industries like mining pose challenges for applying SCM, which relies on predictable supply and demand patterns. For these reasons, SCM was not used in this research report.

2.4.7 Other Lean Techniques

There are several other lean techniques commonly used to enhance efficiency and eliminate waste in various industries which were not utilised in the study. These include the 5S

Methodology, which focuses on workplace organisation through Sort, Set in Order, Shine, Standardise, and Sustain, to enhance operational performance and workplace safety (Bicheno and Holweg, 2009). Just-in-Time (JIT) Production, an approach widely adopted in lean manufacturing, minimises inventory costs by producing materials only when needed, reducing waste and improving responsiveness (Melton, 2005). Total Productive Maintenance (TPM) ensures proactive equipment maintenance to prevent breakdowns and enhance efficiency, ultimately leading to improved equipment reliability and productivity (Ahuja and Khamba, 2008).

Heijunka (production levelling) smooths production flow by balancing demand fluctuations, ensuring efficiency and stability in operations (Liker and Meier, 2006). Additionally, Poka-Yoke (error proofing) reduces process defects by implementing fail-safe mechanisms that enhance quality control (Sahoo, 2021), while Takt Time helps optimise production pace to align with customer demand (Rother and Shook, 2003). Gemba Walks, a technique used in lean management, encourage managers to observe and engage with workers to identify inefficiencies and areas for improvement (Mann, 2014).

Hoshin Kanri (policy deployment) aligns company goals with continuous improvement strategies, ensuring that strategic objectives are effectively translated into operational processes (Witcher and Chau, 2007). The Kanban System, a visual workflow management approach, improves production flow by reducing lead times and limiting work-in-progress inventory (Pérez *et al*., 2010). Theses lean methodologies were not utilised for the study as they tend to lean towards stable and predictable environments. Their focus on incremental improvements, defect reduction, or supply chain efficiency, were deemed less suited to open-pit diamonds mining. VSM is one of the methodologies which is discussed in detail in the next section.

2.5 Value Stream Mapping

VSM is a lean technique used to visualise and analyse the flow of materials and information across a process, identifying Value-Adding (VA) and NVA activities to enhance efficiency and eliminate waste (Rother & Shook, 1999). It provides a structured framework for improving operational efficiency, reducing cycle times, and lowering costs. Key elements of VSM include the value stream (the series of steps required to deliver a product or service), VA and NVA activities, and performance metrics such as lead time and cycle time (Hines & Rich, 1997). Through its visual and systematic approach, VSM simplifies complex processes, engages teams, and fosters a culture of continuous improvement (Womack & Jones, 1996).

The VSM methodology involves visually mapping the flow of materials and information across each step to enhance stakeholder understanding, communication, and collaboration. By distinguishing between VA and NVA activities, organisations can systematically eliminate inefficiencies such as waiting times, excessive movement, and overprocessing. A successful VSM implementation leads to faster throughput, improved resource utilisation, and reduced cycle times (Rother & Shook, 1999; Hines & Rich, 1997).

Furthermore, VSM promotes continuous improvement by designing an optimised future-state process, ensuring that only steps directly contributing to the product are retained. This customer-centric approach fosters a mindset focused on delivering value (Womack & Jones, 1996). Additionally, assigning clear roles and responsibilities within each stage strengthens decision-making and accountability, enabling managers and teams to make informed adjustments that sustain long-term operational efficiency (Patidar *et al*., 2021; Braglia *et al*., 2006b).

Despite its strengths, VSM has several limitations, particularly in dynamic industries such as mining, where workflows and material quality fluctuate significantly. While standard process mapping is effective in structured and stable environments, VSM often struggles to account for variability in key factors such as ore quality and equipment performance (Duggan, 2012).

Additionally, VSM is resource-intensive, requiring substantial time, personnel, and expertise, which can make comprehensive implementation challenging in large-scale or fast-paced operations without disrupting production (Braglia *et al*., 2006b). Another limitation is VSM's focus on incremental improvements, which, while effective for gradual process optimisation, may overlook opportunities for transformative change or the adoption of advanced technologies (Womack & Jones, 1996).

Moreover, while VSM's simplicity enhances process visualisation, it risks oversimplifying complex operations, potentially missing critical interdependencies within interconnected workflows (Patidar *et al*., 2021). Finally, sustaining long-term improvements requires a strong lean culture; without continuous monitoring and commitment to lean principles, organisations may revert to previous inefficiencies, reducing the long-term impact of VSM (Liker, 2004). The VSM concept is outlined in Figure 5 which illustrates the stages in the transportation of raw materials from source to customer.

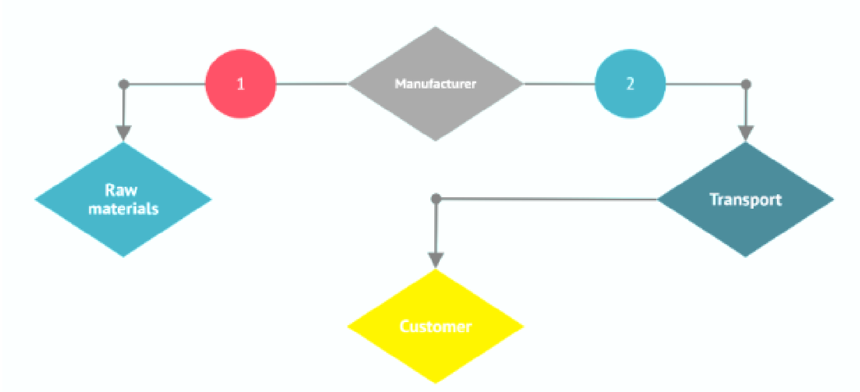

Figure 5: Conceptual value stream mapping

(Source: Andreadis *et al.*, 2017)

Figure 5 illustrates the entire process of extracting raw materials and transforming them into marketable products. In the mining sector, this encompasses ore extraction, processing, and final delivery to customers. VSM plays a critical role in mining operations, directly influencing profitability and market competitiveness. Its application enables the identification and elimination of bottlenecks, including equipment failures, inefficient ore processing, and delays in material transportation (Rother & Shook, 1999; Hines & Rich, 1997). By streamlining these processes, VSM enhances operational efficiency, reduces costs, and optimises resource utilisation, ultimately improving overall mine performance.

2.5.1 The Value Stream Mapping Process

The VSM process consists of several structured steps designed to streamline operations and align production processes for improved efficiency. Figure 6 illustrates these steps, demonstrating how VSM facilitates process optimisation (Azaletskiy, 2022).

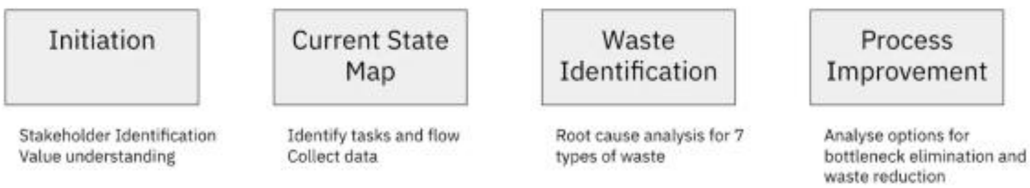

Figure 6: The value stream mapping process

(Source: Azaletskiy, 2022)

Figure 6 outlines four key VSM stages which are initiation, current state mapping, waste identification and process improvement. These are discussed below.

Initiation Stage

The initiation stage ensures that all relevant stakeholders are engaged and that the objectives of the VSM process are clearly defined. This involves establishing the scope of the VSM exercise, outlining process boundaries, and setting measurable goals to maintain focus and relevance (Dinis-Carvalho *et al.*, 2019). Additionally, assembling cross-functional teams enhances collaboration by integrating diverse perspectives and expertise, ensuring a comprehensive understanding of the process (Rother & Shook, 2003).

Current State Map

Current state mapping involves documenting and visualising the existing flow of materials and information within a mining operation (Rother & Shook, 2003). It establishes a baseline for assessing current performance and resource utilisation (Bicheno & Holweg, 2009), helping stakeholders identify key operational bottlenecks and areas for improvement (Almeida & Dias, 2014). By clearly representing workflows, resource allocations, and production pathways, current state mapping provides the necessary context for further analysis through targeted waste identification.

Waste Identification

Waste identification focuses on analysing inefficiencies and activities across operational processes. Azaletskiy (2022) highlights seven primary types of waste in mining operations which are, transportation, inventory, motion, waiting, overproduction, overprocessing, and defects, emphasising their impact on overall process efficiency. These categories serve as a foundation for value stream mapping initiatives aimed at streamlining workflows in complex mining environments. In addition, Dinis-Carvalho *et al.* (2019) extend this framework by introducing an eighth type of waste namely the underutilisation of employee skills, often summarised using the TIMWOODS acronym. Together, these frameworks support the identification of common inefficiencies in mining operations, such as equipment downtime, excessive handling, material misclassification, unnecessary stockpiling, and delays, enabling more targeted and effective improvement strategies. Identifying and addressing these inefficiencies are crucial steps towards optimising the value stream, reducing operational costs, and significantly improving productivity and efficiency (Ohno, 1988; Hines & Taylor, 2000).

Process Improvement

The process improvement phase focuses on designing the Future State Map (FSM) and applying Process Activity Mapping (PAM) to eliminate inefficiencies. The FSM serves as a strategic blueprint for optimising workflows by incorporating solutions derived from previous VSM stages (Rother & Shook, 2003). PAM categorises activities into VA, NVA, and NNVA, enabling a data-driven approach to process enhancement (Hines & Rich, 1997).

Studies have demonstrated the effectiveness of VSM in systematically analysing and minimising inefficiencies, leading to significant reductions in operational delays and improved resource utilisation. Aydin *et al*. (2021) examined the application of VSM in mining operations, revealing that traditional processes suffer from inefficiencies such as excessive transportation and material handling delays. Almeida and Dias (2014) applied VSM in underground mining, identifying NVA activities such as excess movement and waiting times, which contributed to production inefficiencies. Their study proposed actionable strategies to optimise the value stream, resulting in cost reductions and enhanced throughput. Costa *et al*. (2024) highlighted VSM's role in identifying bottlenecks in ore processing and transportation, demonstrating how refining these areas enhanced productivity and minimised costs. Hines and Taylor (2000) applied VSM to mineral processing operations, identifying waste sources such as overproduction and transportation inefficiencies. They concluded that detailed VSM analysis enables mining companies to implement targeted improvements, boosting efficiency and profitability. Frimpong and Hammond (2017) applied VSM at Ahafo Mine in Ghana, demonstrating improvements in fleet scheduling and reductions in transport-related waste.

Despite the recognised benefits of VSM in reducing VSL, limited research has been conducted on its application in mining environments where infrastructure constraints, labour challenges, and equipment variability exacerbate inefficiencies (Nyembo *et al*., 2021). This research report addresses this gap by systematically categorising and analysing VSL at a diamond mine, demonstrating how VSM can mitigate losses such as waiting times and transport inefficiencies. By providing a nuanced understanding of inefficiencies in mining operations, this study contributes to the expanding body of research on VSM applications for optimising mining value chains.

2.5.2 Probabilistic Value Stream Mapping

In the context of diamond mining, the mine-to-mill value chain is essential for enhancing operational efficiency and productivity, particularly given the high-value nature of diamonds and the competitive market dynamics of the sector. The extraction and processing of diamonds present unique challenges, including the need to preserve ore integrity, maximise recovery rates, and minimise waste.

Probabilistic techniques play a critical role in process optimisation, as they integrate statistical modelling and probability distributions to account for variability in process parameters, enabling a more adaptive and realistic approach to optimisation (Frenzel *et al*., 2023; Bonfils *et al*., 2021a). VSM has evolved into PVSM, which incorporates statistical modelling to manage dynamic factors such as fluctuating ore grades and equipment performance. Rother and Shook (1998) developed this integrated approach, demonstrating its ability to create resilient systems that maintain efficiency under varying conditions.

Multiple studies highlight the effectiveness of probabilistic VSM in mining. Zhang and Wu (2020) reported that implementing probabilistic VSM at an iron ore mine in Mongolia reduced downtime variability by 20% and increased overall productivity by 18%. Brent *et al*. (2013) found that incorporating probabilistic methods significantly improved recovery rates and reduced processing costs by enabling real-time adjustments based on fragmentation patterns in mining. Gauthier and Pelletier (2013) demonstrated that stochastic inputs in VSM enhance the precision of value chain assessments, leading to better predictions and planning for high-impact variability. This adaptability is particularly relevant in diamond mining, where fluctuations in ore quality can substantially impact production outcomes.

Among probabilistic techniques, MCS is one of the most commonly applied methods. MCS is a computational technique that uses random sampling to estimate mathematical functions and model systems with multiple uncertain variables. This enables the simulation of different scenarios and outcomes, making it a valuable tool for risk assessment and decision-making (Metropolis & Ulam, 1949). Fishman (2013) defined MCS as a method for performing numerical experiments by generating random samples from probability distributions, which helps estimate the impact of risk and uncertainty in complex systems. Figure 7 shows the three most prominent MCS methods.

Figure 7: Monte Carlo Simulation methods

(Source: Pathak, 2021)

As illustrated in Figure 7, MCS employs a predictive approach to define dependent and independent variables, allowing for the estimation of a range of potential outcomes. By conducting repeated simulations, MCS refines predictive accuracy, making it an indispensable tool for process optimisation (Fishman, 2013). Probability distributions play a crucial role in this approach, enabling more accurate predictions of variable conditions (Kroese *et al*., 2014). Rubinstein and Kroese (2016) further emphasised that iterative simulations improve outcome precision, making MCS a valuable tool in uncertain environments that require risk assessment and strategic planning (Metropolis & Ulam, 1949).

In this research, MCS was applied to model uncertainties within the mine-to-mill value chain, providing probabilistic insights that support data-driven decision-making in optimising open-pit diamond mining operations. Unlike conventional VSM, which assumes stable and deterministic workflows, PVSM incorporates statistical distributions to represent fluctuating factors such as ore quality, equipment reliability, and processing times. Rother and Shook (1998) highlighted that this probabilistic adaptation enables a more dynamic and realistic representation of complex systems, particularly in industries with high variability. Zhang and

Wu (2020) demonstrated that probabilistic VSM enhances decision-making by simulating various operational scenarios, providing actionable insights for efficiency improvements. Similarly, Brent *et al*. (2013) illustrated its application in mining, where ore quality and equipment performance are inherently unpredictable, making traditional VSM less effective.

The main proponents of PVSM argue that it offers significant advantages in industries with high variability. By integrating uncertainty into process analysis, it enables a comprehensive understanding of potential outcomes, fostering resilient and adaptable optimisation strategies (Frenzel *et al*., 2023). In mining, where fluctuating ore grades, unplanned equipment failures, and variable processing rates are common, PVSM is a powerful tool for predicting bottlenecks and identifying improvement opportunities (Bonfils *et al*., 2021b). Furthermore, its ability to integrate real-time data enhances dynamic adjustments, ensuring alignment with changing conditions.

PVSM provides several key advantages, including its ability to model uncertainty, enhance predictive accuracy, and support data-driven decision-making. It enables scenario testing, allowing organisations to assess the impact of various operational changes before implementation. However, its adoption presents certain challenges. Its dependence on statistical expertise and advanced software tools can make implementation resource-intensive, particularly for smaller operations or those lacking technical capacity (Zhang & Wu, 2020). Additionally, its complexity may impede communication and collaboration among teams, as its probabilistic outputs are less intuitive compared to the visual simplicity of traditional VSM (Rother & Shook, 1998).

PVSM was adopted in this study instead of traditional VSM due to its enhanced capability to model uncertainty and variability inherent in mining operations (Leporis and Král, 2016). While traditional VSM is valued for its simplicity and ease of implementation, it often overlooks the dynamic nature of mining operations, where variability in equipment performance and ore quality significantly impacts efficiency. PVSM addresses these challenges by incorporating stochastic modelling, enabling a deeper analysis of systemic inefficiencies and potential risks.

Although it requires extensive data collection and advanced statistical tools, the insights provided by PVSM are more robust and reliable. As a result, it serves as a powerful tool for developing long-term, data-driven optimisation strategies that extend beyond immediate operational inefficiencies.

2.5.3 Case Studies on Probabilistic Value Stream Mapping in Mining

Several researchers have explored the application of PVSM in mining to address process variability and uncertainty. Smith and Johnson (2019) investigated the integration of PVSM into lean mining operations, emphasizing its capability to model stochastic delays and resource fluctuations. Their MCS framework was used to quantify variability in equipment downtime and ore quality, enabling mines to prioritise high-impact interventions. While data granularity and computational complexity posed challenges, structured team workshops and leadership alignment helped mitigate these issues (Rubinstein & Kroese, 2016).

Similarly, Jones *et al*. (2021) applied PVSM to optimise mine-to-mill processes in Canadian gold operations. Their study mapped probabilistic workflows, including haulage delays and crusher reliability, ultimately reducing cycle time variability by 22% and improving throughput predictability. Other case studies highlight PVSM's adaptability in diverse mining contexts. Martinez *et al*. (2021) implemented PVSM at a South African platinum mine, modelling stochastic bottlenecks in ore transportation, leading to a 14% efficiency gain and a 20% reduction in lead time variability. Gomez and Lee (2020) applied PVSM in a Chilean copper mine, identifying probabilistic inefficiencies in maintenance scheduling, which resulted in a 12% increase in asset utilisation and a 9% reduction in unplanned downtime. Nguyen *et al*. (2022) demonstrated PVSM's application in Australian iron ore operations, simulating blasting and loading uncertainties, achieving a 17% reduction in truck cycle time deviations.

The literature underscores PVSM's role in enhancing decision-making by quantifying risks through probabilistic distributions, facilitating dynamic resource allocation (Wang & Zhang, 2018). Barrick Gold utilised PVSM to improve recovery rate forecasts, integrating geo-metallurgical variability, which reduced processing cost overruns by 15% (Bott & Chen, 2023). Harmony Gold Mine reported improved stakeholder alignment and a 10% reduction in rework costs following the adoption of PVSM-driven workflows (Mahlangu *et al*., 2022). Hatch (2022) emphasised integrating PVSM with real-time sensor data to refine blast fragmentation models, reducing downstream energy consumption by 8–12%. Brent *et al*. (2023) demonstrated PVSM-enhanced blasting simulations, which minimised misfire risks in Zambian copper mines, improving throughput consistency by 18%. However, successful PVSM adoption requires robust data infrastructure and workforce upskilling to effectively interpret probabilistic outputs (Ouchterlony *et al*., 2021).

PVSM was selected as the primary framework for this research because it builds on traditional VSM by incorporating MCS, a stochastic modelling approach that enables the analysis of complex scenarios involving uncertain equipment performance, ore quality, and processing delays (Zhang & Wu, 2020; Rubinstein & Kroese, 2016). Although VSM provides a structured approach for identifying VA, NVA, and NNVA activities (Rother & Shook, 2003), this study found it insufficient for capturing the dynamic operational fluctuations characteristic of open-pit diamond mining. By addressing these limitations, PVSM offers a more robust and context-appropriate framework for analysing and optimising the mine-to-mill value chain.

2.6 Chapter Summary

The literature indicates that the mine value chain consists of a sequence of activities from exploration to rehabilitation, with each stage requiring optimisation to ensure operational sustainability and efficiency. The mine-to-mill value chain serves as an integrated framework linking upstream and downstream activities, with optimisation efforts primarily focused on improving fragmentation, energy efficiency, and recovery rates. However, challenges persist in aligning upstream and downstream operations, particularly in mining environments with fluctuating material characteristics. Several studies identified inefficiencies in key operational areas, including loading and hauling, crushing, and processing stages, often noting that recovery rates fail to meet expected benchmarks.

This chapter examined lean methodologies, including Kaizen, Six Sigma, Lean Thinking, Lewin's Theory of Planned Change, TOC, and SCM, demonstrating how these frameworks have been successfully applied in various industries to reduce waste and enhance efficiency. Despite its widespread application in manufacturing, VSM remains underutilised in high-variability environments such as open-pit diamond mining. Researchers argue that TOC provides a structured approach to resolving bottlenecks and maximising throughput by prioritising and addressing constraints within mining processes.

The chapter introduced VSM as an effective tool for process visualisation, facilitating the identification of VA, NVA, and NNVA activities (Rother and Shook, 2003). However, findings from reviewed case studies indicate that traditional VSM, though useful in stable manufacturing environments, is often insufficient in dynamic and unpredictable mining conditions. For example, Martinez *et al*. (2021) found that VSM alone could not adequately address stochastic haulage delays in a platinum operation, while Nguyen *et al*. (2022) reported similar limitations when applying VSM to blasting and loading activities in an iron ore mine. These studies highlight the need to integrate VSM with probabilistic techniques, such as MCS, to capture variability and improve applicability in mining contexts. While PVSM has demonstrated potential benefits, the literature still reflects limited research on its integration with MCS for real-time decision making in mining operations (Zhang and Wu, 2020).

The discussion also covered MCS as a modelling tool for uncertainties in operational performance, particularly fluctuations in ore grades, equipment efficiency, and production rates. Studies highlight MCS's advantages in complementing deterministic models, arguing that it provides a dynamic analytical approach that enables scenario-based decision-making. Although MCS has been widely used in financial and engineering contexts, its integration with VSM for real-time operational decision-making in mining remains an underexplored area.

The literature emphasised the need for interdisciplinary frameworks that combine lean methodologies, probabilistic modelling, and constraint-based approaches to effectively address the complexities of mining operations. Chapter 2 established the theoretical foundation for this study, highlighting existing inefficiencies in mining operations and underscoring the necessity of developing a tailored PVSM framework. This integrated framework, combining lean and probabilistic techniques, aims to enhance productivity, improve recovery efficiency, and ultimately increase profitability in diamond mining.

3 RESEARCH METHODOLOGY

3.1 Overview of Chapter 3

This chapter describes the research methods used to analyse and optimise the mine-to-mill value chain of the case study mine. The research report adopted a mixed methods approach, combining both quantitative and qualitative techniques, which ensured a comprehensive perspective by capturing both human and technical factors. Quantitative methods, including regression analysis and archival data review, provided a data-driven understanding of variability in grades, recovery rates, and production volumes. The chapter describes how these methods enabled a thorough analysis of the technical aspects of the mine's operations. Qualitative methods, such as semi-structured interviews and onsite observations, were then used to gain insights into operational challenges and inefficiencies. The chapter also describes the use of purposive sampling to select participants with relevant expertise and validation techniques like triangulation to ensure data reliability. Ethical issues, including participant confidentiality and compliance with research standards, were also considered. By employing a robust methodology, this chapter establishes the foundation for the study's findings and their practical application.

3.2 Research Design

Research design serves as a blueprint for drawing conclusions and addressing research questions (Agresti, 2019; Cooper and Schindler, 2016). Saunders *et al*. (2019) says that research design is a structured framework for collecting and analysing data, outlining clear objectives, data sources, and methods for data collection. There are three main research approaches namely quantitative, qualitative, and mixed methods. Quantitative research is a systematic inquiry that involves gathering and analysing numerical data to reveal patterns, relationships, and trends (Bryman, 2012). Qualitative research, according to Denzin and Lincoln (2018), is a situated activity that locates the observer in the world, involving interpretive practices that make the world visible by studying things in their natural settings and seeking to understand the meanings people bring to them.

This research report utilised a mixed methods approach to analyse and enhance the mine-to-mill value chain of an open-pit diamonds mine. The mixed methods approach integrates both quantitative and qualitative research methodologies to gain a thorough understanding of the research problem (Creswell and Plano Clark, 2018). Two significant benefits of this approach include its ability to offer deeper insights into complex phenomena by merging numerical data with contextual understanding and its potential to improve the reliability of results through methodological triangulation (Tashakkori and Teddlie, 2010; Johnson and Onwuegbuzie, 2004). In this mixed methods research, the quantitative approach worked alongside the qualitative approach by offering objective data-driven insights into operational inefficiencies. This combination of methodologies enabled the study to leverage the numerical accuracy of quantitative data while situating it within real-world practices captured through qualitative methods (Creswell and Plano Clark, 2018). The mixed methods approach provided a more thorough understanding of the mine-to-mill value chain, thereby enhancing the robustness and reliability of the study.

3.3 Quantitative Research

The quantitative part of the research focused on analysing numerical data, including mineral grades, production volumes, and recovery rates, to pinpoint inefficiencies in the mine-to-mill value chain. Quantitative research was suited for this study as it enabled objective analysis of numerical data, identification of inefficiencies and ensured the generalisability of findings for optimising the mine-to-mill value chain.

3.3.1 Quantitative Data Collection

A comprehensive archival search was conducted to gather quantitative data from various records relevant to the case study mine's operations between 2018 and 2022. An archival search involves systematically exploring existing records and documents to collect data pertinent to a research study (Ventresca and Mohr, 2002). The study used production reports from the case study mine covering the years 2018 to 2022 to identify trends in mineral grades and production levels. According to Hartman and Mutmansky (2002), mine production reports provide detailed accounts of the volume and grade of ore extracted and processed within a specific reporting period. In this research report, these reports provided crucial data for analysing trends in mineral grades, enabling evaluation of the consistency and variability of ore quality over time.

The archival search included processing plant reports, which provided key operational metrics such as feed grades, recovery rates, and milling losses. These measures are widely recognised as critical indicators of plant performance in mineral processing (King, 2001). These were essential for evaluating the efficiency of ore beneficiation processes and identifying opportunities for operational improvement. Survey data reports were also examined, particularly for quantifying the volumes of ore deposited on the RoM pad and verifying the originating blocks. This was crucial, as the research was largely based on the results of a bulk sample, whose tonnage was confirmed by survey measurements, and whose spatial location was used to calculate the feed grade.

In addition, geological block model reports were analysed to obtain data on grade variability, ore boundaries, and mineral recovery potential, providing insights for optimising both extraction and processing activities. Block model forecasts were reconciled with actual production and recovery data to confirm reliability and reduce the risk of forecast errors. A geological block model is a three-dimensional representation of an orebody that illustrates the spatial distribution of mineral grades and geological features (Deutsch and Journel, 1998). All mine data is stored in the OpsData database, which provides read-only access across departments while write-access is restricted to the department responsible for generating the data.

3.3.2 Quantitative Data Analysis

The quantitative data collected for this research mentioned in the previous section was analysed using variance analysis of MCS cumulative distribution function (CDF) graphs. Variability analysis is a method used to identify sources of variability in production processes and to evaluate whether the differences in performance observed are statistically significant (Montgomery, 2013). In this research report, variability was measured by the steepness of the CDF curve. The steeper the curve the more stable the metrics are.

Value Stream Mapping

The study employed the VSM methodology as mentioned in the previous chapter. For the process observation exercise, a bulk sample was mined and processed through the plant. An ore bench was identified, marked by surveyors, drilled and blasted, loaded and hauled to the RoM stockpile and fed into the crushing and screening plant for resizing and screening. Crushed material then went through the dense media separation (DMS) plant for concentration and then the recovery plant for recovery, sorting and cleaning. During the whole process, tonnage passing through the value chain was noted and the expected grades calculated from the recovery model. The VSM steps discussed in Section 2.5.1 were followed as described in the following steps.

i. Initiation:

The VSM process began with an initiation stage, where key stakeholders, including mine operations and processing teams, were engaged. The scope of the mapping exercise was defined, inefficiencies to be assessed outlined, data collection strategies identified and interview participants identified.

ii. Current State Mapping:

A current state map (CSM) was crafted to visually represent the existing processes, workflows, and inefficiencies within the mine-to-mill value chain of the case study mine. Data from observations and interviews enabled the CSM to identify areas where operational flow could be streamlined, permitting the prioritisation of improvement opportunities. The CSM covered the following mine to mill activities:

1. Mining (drilling, blasting, loading, hauling).
2. Stockpiling (RoM, low-grade, tailings, crushed stockpile).
3. Processing (crushing and screening, DMS, sorting, recovery).

On each of the activities, tonnage and grade were tracked. The current state data was tabulated and mapped graphically to show the flow of material throughout the process. The tonnage and grade were indicated on each activity on the CSM diagram.

iii. Waste Identification:

Waste identification was conducted through process observations, focusing on blasting, loading and hauling, stockpiling, material handling and processing activities. The analysis provided insights into waste reduction opportunities.

iv. Process Activity Mapping:

PAM was conducted to classify activities based on their contribution to the recovery of diamonds (carats). Diamonds movement (in carats) was tracked throughout the mine-to-mill value chain, allowing activities to be grouped into three categories. VA activities are those that contributed significantly to net carat movement. Activities with minor net carat change, primarily related to stockpiling, were categorised as NNVA. Activities with minimal net carat contribution were identified as NVA. This classification provided a clear framework for assessing process efficiency and identifying areas for optimisation.

v. Monte Carlo Simulation:

The study utilised MCS to model fluctuations in historical (2018 to 2022) processed tonnes, ore grades and recoveries. This was done to define probability distributions of those parameters to develop the FSM. The mean and standard deviations of historical data (current state) were calculated and used in data simulation. MCS was conducted in Microsoft Excel using 10,000 iterations to ensure statistical stability and reliable probabilistic predictions. Studies suggest that 10,000 iterations are generally sufficient for stabilizing standard deviations and ensuring convergence of probability distributions in complex simulations (Rubinstein & Kroese, 2016; Law, 2015). While MCS provides a powerful means of modelling variability, its application is limited by computational intensity and the need for technical expertise, in this study, these challenges were managed through structured sampling and iterative validation.

The first forty six iterations are presented in Appendix A for illustration purposes. Frequency histograms of simulated data, which are a graphical representation of the distribution of a dataset, showing how often different values occur, were created in Microsoft Excel. Histogram spread indicated data variability with wider bars indicating greater variation and narrower bars suggesting more consistency. After data simulation, the mean and the standard deviations were calculated and used as inputs in the future state data simulation. Matplotlib was used to draw CDF graphs because of its ability to plot thresholds lines quicker than Microsoft Excel. CDFs were used to measure the probability that a random variable takes on a value less than or equal to a given value. Percentile values at 10%, 50% and 90% were used to identify thresholds. Steepness of the CDF curves was used to measure predictability and stability. Steeper CDFs indicated less variability while flatter CDFs suggested more spread and uncertainty. Comparisons between current and future states CDFs revealed how each process has changed in terms of distribution, central tendency, and variability.

vi. Future State Mapping:

Monte Carlo Simulation CDFs were used to model the FSM by forecasting key parameters namely processed tonnes, feed grade, recovered carats and recovered grade. The CSM was analysed and expected changes defined. Historical data's CDFs were used to understand the current variability. MCS was used to model future performance based on expected changes and CDFs were used to validate future state improvements by comparing the before-and-after distribution changes. According to Montgomery (2013), process improvement and statistical quality control methods involve adjusting key parameters such as mean and standard deviation. The future mean was calculated using Equation 1 (Montgomery, 2013):

$$\boldsymbol{Future\ mean} = \boldsymbol{Current\ mean\ x}\ (\boldsymbol{1} + \boldsymbol{expected\ improvement}) \qquad (1)$$

while variability reduction was calculated using Equation 2 (Montgomery, 2013):

$$\boldsymbol{\sigma_{future}} = \boldsymbol{\sigma_{current}} \times (\boldsymbol{1} - \boldsymbol{expected\ improvement}) \qquad (2)$$

These adjustments helped in modelling process improvements effectively. The FSM figures were used for simulation using 10,000 iterations, the first forty six of which are presented in Appendix B. Histograms and CDFs were created from the resultant data. Histograms gave an understanding of the future distribution. Future CDFs were super imposed for comparison with current CDFs to analyse variability. Four parameters namely processed tonnes, feed grade, recovered carats and recovered grade were of interest.

3.4 Qualitative Research Methods Used

The research used the ethnography and case study qualitative research methods to provide in depth insights into the mine-to-mill value chain of the case study mine. Ethnography allowed for immersive observation of organisational practices and culture, while the case study method facilitated a detailed, context rich examination of the specific operational challenges faced by the open-pit diamonds mine.

Ethnography entails a thorough examination of people and cultures by engaging in immersive observation and taking part in their everyday settings (Hammersley and Atkinson, 2019). The method enables researchers to deeply understand organisational cultures, practices, and interactions, providing detailed insights into real-world situations. In this research, ethnography was used to gather first-hand knowledge of the operations of the diamonds mine. Various activities along the mine-to-mill value chain were observed and recorded. A significant benefit of this method is its ability to capture the intricacies of social processes and offer a comprehensive perspective of the environment under investigation (Brewer, 2000).

The case study methodology offered valuable insights into the operational dynamics and challenges faced in specific value chain processes at the mine. Yin (2018) mentioned that a case study involves a detailed and context rich examination of a particular phenomenon within its real-life context. This method is especially useful for investigating complex issues where various factors interact, as it enables the use of multiple data sources to validate findings

(Stake, 1995). As mentioned in Chapter 1, this research used an open-pit diamonds mine as a case study.

A study's population refers to the entire group of individuals, objects, or elements that share certain characteristics relevant to the goals of a research from which a sample is selected (Bryman, 2012). In this research, the eligible population consisted of 40 employees at the case study mine involved in various activities of the mine-to-mill value chain. This population was marked by diversity in departmental roles, organisational levels, expertise, and demographics, ensuring a thorough representation across the mine-to-mill value chain. Employees were sourced from the technical services and mining departments which includes crushing and screening, DMS, and recovery. This enabled the study to capture insights from all stages of production. The population included superintendents, supervisors, and operators who offered perspectives that cover strategic, technical, and operational roles. As noted by Patton (2002), a diverse mix of participants is crucial for a good understanding of organisational processes. Varying levels of experience and expertise within a workforce, especially in mining and processing, provides valuable insights into the technical challenges faced at a mine (Etikan *et al*., 2016).

Purposive sampling, a non-probability technique in which participants are intentionally selected based on traits relevant to the research objectives, was used to identify participants from key mine departments (Etikan *et al*., 2016). This approach ensured that individuals with the necessary experience and knowledge were included, allowing the study to capture in-depth insights and achieve a nuanced understanding of the research problem. By targeting participants with specific expertise, purposive sampling also helped to mitigate bias and enhance the credibility of the data collected.

From a total population of 40 eligible employees across various organisational levels and departments, 15 individuals were invited to participate in the study. Of these, seven responded and took part in the interviews. While the final sample size was smaller than anticipated, it was still adequate to capture diverse perspectives within a relatively small and homogenous population, consistent with recommendations for purposive sampling in qualitative research (Etikan *et al*., 2016). The seven respondents are classified as shown in Table 1 which details their department, age and the code they were assigned for the presentation of the findings.

Table 1: Classification of respondents

Department	Age	Assigned Name	Classification Code
Mining	48	Interview Respondent 1	IR 1
Processing	38	Interview Respondent 2	IR 2
Processing	34	Interview Respondent 3	IR 3
Processing	44	Interview Respondent 4	IR 4
Technical	36	Interview Respondent 5	IR 5
Mining	34	Interview Respondent 6	IR 6
Mining	34	Interview Respondent 7	IR 7

As shown in Table 1, there were three respondents from mining, three from processing and one from technical service departments with varying ages. Patton (2002) mentioned that purposive sampling helps researchers focus on individuals who have the necessary expertise, experience, or roles to provide valuable and relevant data. The selected participants' ages ranged from 34 to 50 years, which allowed a variety of experiences and viewpoints to be included, ensuring comprehensive and valid findings (Palinkas *et al.,* 2015).

3.4.1 Qualitative Data Collection

Qualitative data was collected using semi-structured interviews and onsite observations. Semi-structured interviews targeted personnel, who are essential to the mine-to-mill process while onsite observations helped to identify the operational inefficiencies in the mine-to-mill value chain.

Semi-structured interviews were conducted with key personnel, including engineers, mine operators, and managers, who were essential to the mine-to-mill process. This method combines the flexibility of open-ended questions with the structure of a predesigned interview guide (Kallio *et al.,* 2016). This allows researchers to delve deeper into specific topics while keeping the discussion focused on predetermined themes, ensuring that the data collected are both in depth and relevant. To explore operational challenges and gather expert insights into the mine-to-mill value chain, a semi-structured interview guide (Appendix C) was created.

This guide served as a framework for discussing important issues, such as process inefficiencies, grade variability, and bottlenecks, while also giving participants an opportunity to share their experiences and propose potential solutions. Semi-structured interviews allowed the collection of rich, detailed accounts of daily operations and challenges. Brinkmann and Kvale (2015) highlight that this interview style is particularly useful for examining complex phenomena, as it enables questions to be adjusted based on the participants' expertise and responses, ensuring that vital insights are captured. In this research report, semi-structured interviews helped to gather a variety of perspectives from personnel at different hierarchical levels, contributing to a comprehensive understanding of the mine-to-mill value chain and pinpointing areas for optimisation.

Onsite observations were conducted from 15 to 25 August 2023, covering 11 consecutive days and including both day and night shifts. Although limited in duration, this period captured routine operational conditions and provided a representative cross-section of typical mine-to-mill performance and was complimented by historical data (2018–2022), which captured long-term variability. The researcher, based in the technical services department, was not embedded within the processing plant team but was granted special access to observe the passage of a bulk sample through the plant. This enabled first-hand examination of ore flow and material handling processes without disrupting operations.

The observation exercise tracked activities across the value chain, from drilling, blasting, loading and hauling through to crushing and screening, DMS, recovery, and sorting. Data were recorded in tabular form, supplemented with process flow diagrams and value stream maps. As Kawulich (2012) notes, onsite observation provides a systematic method of collecting data in natural settings, and in this case it yielded context-rich insights into workflows, bottlenecks, and inefficiencies that would not have been fully captured by other techniques. These findings were triangulated with semi-structured interviews and archival reports, thereby strengthening reliability and ensuring a more comprehensive understanding of the operational value chain (Patton, 2002; Yin, 2018).

3.4.2 Qualitative Data Analysis

The research used grounded theory to analyse qualitative data. This enabled the identification of patterns and development of theories based on real-world experiences and practices of mine personnel (Charmaz, 2014). This approach enhanced the understanding of operational dynamics and the perspectives of employees.

The qualitative data gathered from interviews and onsite observations was analysed using thematic analysis, which focused on pinpointing recurring themes like process inefficiencies, grade variability, and bottlenecks in the mine-to-mill value chain. As outlined by Braun and Clarke (2006), thematic analysis involves identifying, analysing, and reporting forms and themes within a set of data, which allows for a deeper understanding of complex phenomena. This approach helped to reveal significant patterns related to operational challenges, offering valuable insights into the factors influencing the mine's productivity.

Thematic coding was employed to categorise challenges into distinct groups, providing a more organised method of interpreting the qualitative data collected. It also aided in the organisation and prioritisation of issues based on their frequency and impact on the value chain. Thematic coding is an essential part of qualitative data analysis, as it condenses large volumes of data into manageable themes for further exploration (Saldana, 2016). Through thematic analysis and coding, the study was able to identify key areas for optimisation and suggest targeted solutions to optimise the mine-to-mill value chain.

3.5 Lewin’s Change Management Model

Lewin’s Change Management Model which comprises unfreezing, changing, and refreezing pillars was used as a structured framework to guide the proposed implementation of VSM at the case study mine. As discussed in Chapter 2 (Section 2.4.4), this model provides a theoretical foundation for managing resistance to change and embedding process improvements into organisational operations. The model was applied to structure the transition towards a more optimised mine-to-mill value chain through three interlinked phases: unfreezing, changing, and refreezing.

The unfreezing stage involved diagnosing inefficiencies through the development of the CSM and fostering awareness among stakeholders regarding the need for process improvements. This phase emphasised the identification of bottlenecks, engagement with key personnel, and the establishment of a case for change. The change phase entailed designing a structured roadmap for the transition from existing practices to a more efficient state. This included the development of the future state map, incorporation of lean principles, and the planning of workflow modifications, training initiatives, and stakeholder alignment strategies.

The refreezing stage was conceptualised to ensure long-term stability of the improvements once implemented. It introduced standardisation procedures, monitoring tools, and continuous improvement frameworks to prevent regression to earlier inefficiencies. Although the full implementation of Lewin’s model was beyond the scope of this study, the proposed framework offers a practical pathway for future application. It facilitates a smoother transition and strengthens organisational readiness for change across the mine-to-mill value chain.

3.6 Data Validation Process

A combination of cross validation, expert validation, and triangulation techniques were employed to ensure the accuracy, reliability, and suitability of the collected data. The cross-validation technique assesses the reliability and generalisability of data by comparing various data sets or methods to check for consistency (Stone, 1974). Historical production data was cross referenced with real-time observations to confirm that the patterns and trends identified in the historical data remain relevant under current operational conditions. This process helped to uncover any discrepancies between past and present data, ensuring the accuracy of the information used for analysis.

Expert validation means obtaining feedback from professionals who have specialised knowledge or experience in the relevant field to verify the accuracy and relevance of the information (Patton, 2002). Engineers and geologists assessed the gathered data to confirm its technical validity. The technical validation was undertaken by the same domain experts who generated the reports during the study period, with feedback obtained through site observations and interviews to ensure accuracy and contextual relevance. This expertise was crucial in confirming that the data utilised in the analysis accurately represented the mine's operational processes and aligned with the research objectives.

Data triangulation refers to the practice of using various data sources or methods to verify and validate the consistency of findings (Denzin, 1978). In this research report, insights gathered from interviews, production data, and site observations were cross checked to ensure the reliability of the results. This approach, which draws from multiple sources, offered a more thorough understanding of the mine-to-mill value chain and strengthened the validity of the study's conclusions. Collectively, these validation techniques created a comprehensive approach to validate the data, reinforcing the integrity of the research outcomes.

3.7 Ethical Clearance

An ethical clearance (Protocol number: EMINN/2024/141) for the study was granted by the University of the Witwatersrand’s Human Research Ethics Committee. The clearance assured that the interviews conducted in this research had minimal risks to participants and complied with ethical standards concerning human rights and privacy. Permission was obtained from the case study mine to use its data in this research report.

3.8 Chapter Summary

The study adopted a mixed methods approach, with quantitative analysis focusing on numerical data to identify operational patterns and inefficiencies. Archival searches of production reports, geological block models, and processing plant data provided historical performance insights, while VSM and PAM classified activities into VA, NVA, and NNVA categories. Tonnage and grade were tracked across the mine-to-mill chain to quantify inefficiencies. MCS modelled ore grade and equipment variability through 10,000 iterations, supported by CDF graphs to assess variability in feed grade, processed tonnes, and recovery rates. Cross-validation compared historical production data with real-time observations to ensure data reliability.

Qualitative insights were gathered through semi-structured interviews with engineers, operators, and managers, alongside ethnographic immersion and onsite observations of workflows, cultural practices, and inefficiencies. Thematic coding categorised interview and observational data into key patterns, such as equipment downtime and blasting challenges. Triangulation combined interview findings, archival records, and observational data to enhance validity, while expert validation ensured technical accuracy. Lewin’s Change Management Model (Unfreezing, Changing, Refreezing) provided a structured theoretical framework guiding the proposed implementation of improvements identified through VSM and MCS. Ethical practices, including informed consent and confidentiality, maintained research integrity.

4 FINDINGS AND ANALYSIS

4.1 Overview of Chapter 4

This chapter examines the current state of the mine-to-mill value chain of the case study mine, identifying inefficiencies, bottlenecks, and variability in production processes. The chapter also presents a proposed future state value stream map of the case study mine, which incorporates optimised processes aimed at reducing waste and enhancing throughput. MCS results are also presented in the chapter. The chapter concludes by outlining an implementation plan for the identified improvements, ensuring a systematic approach to enhancing efficiency and profitability.

4.2 Value Stream Mapping of the Case Study Mine's Mine-to-Mill Value Chain

4.2.1 Mine-to-Mill Value Chain

As mentioned in preceding chapters, the study utilised the PVSM approach to produce the CSM and FSM of the case study mine. Building on the conventional VSM framework, PVSM integrates probabilistic modelling to capture operational variability. Using onsite observations, the mine-to-mill value chain of the diamond mine was mapped. The value chain is summarised in Figure 8.

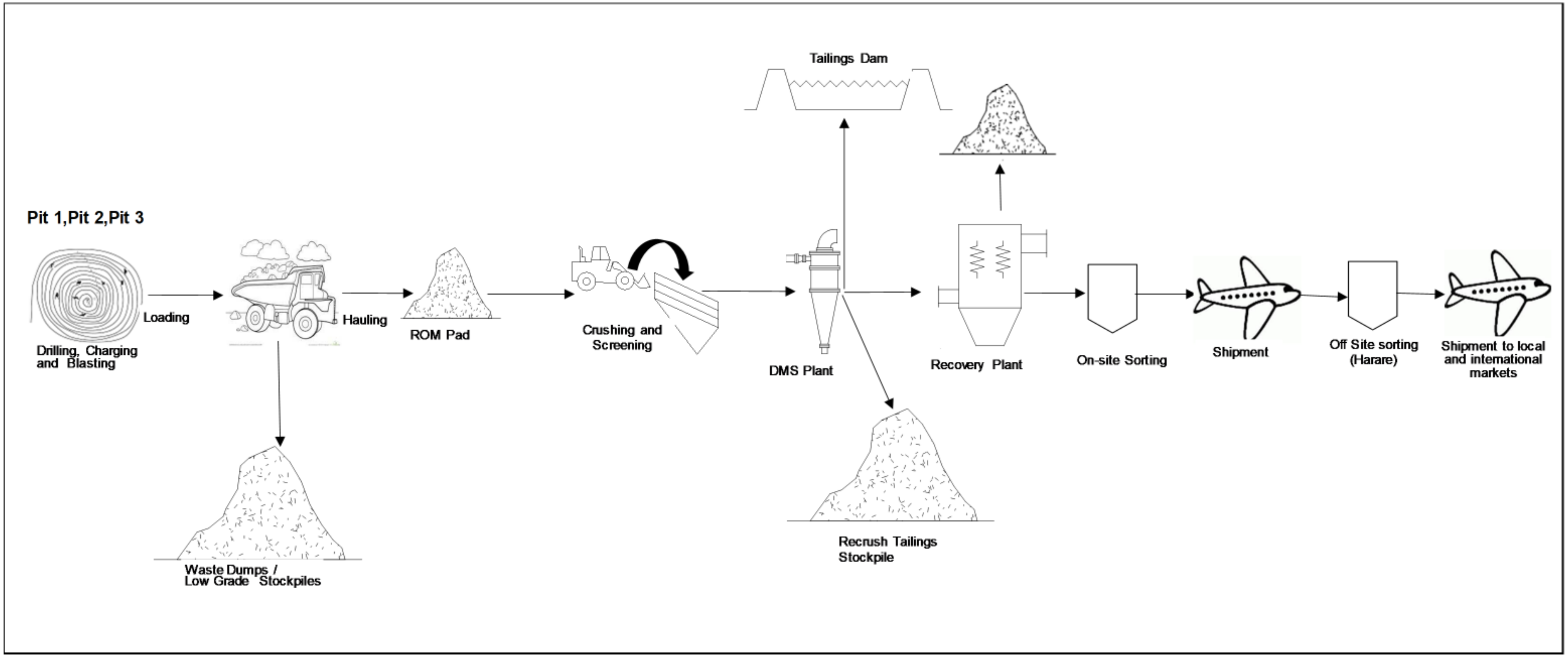

Figure 8: Case study mine's value chain

A detailed description of the mine-to-mill value chain summarised in Figure 8 is provided in the paragraphs below. The value chain begins with drilling followed by charging, and blasting to loosen material, loading and hauling, where materials are categorised and transported to their destinations. High-grade ore is sent to the RoM pad, low-grade material to the low-grade stockpile while waste is sent to the waste dump. From the pits, some high-grade ore is fed directly into the primary crusher through a grizzly (feed size of 500 mm) with some being stockpiled at the RoM pad to be fed when there is no material coming from the pits.

The crushing and screening plant has a capacity of 210 tonnes per hour (tph). The primary jaw crusher reduces the sizes of rock from the grizzly and the material passes through a sizing screen which then sends different particle sizes to the secondary and tertiary crushers for further crushing and resizing. The jaw crusher reduces rock sizes from 500 mm to 90 mm, secondary crusher reduces rock sizes from -90 mm to 25 mm, and the tertiary crusher reduces rock sizes from -25 mm to 16 mm. The -16 mm material is then sent to the DMS through a conveyor belt and some material is stockpiled in the plant.

The DMS plant has a capacity of 170 tph (two 80 tonne DMS and a 10 tonne DMS) hence the stockpiling of some crushed material. The crushing and screening process is cyclic. Fine material measuring -1 mm is sent to the tailings dam. At the DMS plant, material ranging from -16 mm to 6 mm is sent to the course DMS module (80 tonne), material ranging from -6 mm to 1 mm is sent to the fine DMS module (80 tonne) and -1 mm material is sent to the degrit module. At the degrit module, material is sent to the tailings stockpile or to the tailings dam. In the DMS modules, the material, after preparation, is discharged into a mixing box where it is mixed with ferrosilicon (FeSi) and water, and the mixture is pumped into cyclones. FeSi, due to its high density and recyclability, is used as a high-density medium in diamonds processing. Centrifugal force is used to separate denser material from floats. The less dense material, in the inner vortex, comes out into the overflow at the top of the cyclone as floats. The denser material, in the outer vortex of the cyclone sinks at the bottom into the sinks. Floats go into a combined deck where FeSi is recovered. Floats fall into the conveyor and are deposited into the tailings stockpile as course tailings. Sinks go into a 10 tonne DMS for further concentration. Floats from the 10 tonne DMS (reconcentrate tails) are stockpiled in the recon stockpile for further processing after oxidation. Sinks from the 10 tonne DMS (concentrate) are pumped into the recovery plant for recovery and sorting.

In the recovery plant, the concentrate is degritted and screened to remove residual FeSi. The concentrate then passes an X-ray machine where fluorescent material is detected, and a jet of air automatically separates diamonds from non-fluorescent particles. Diamonds in the sort house, are then hand sorted while the no-fluorescent material (recovery tails) is stockpiled in the recon stockpile. The diamonds are sorted according to cut, colour, clarity and carats (4Cs). After sorting, the diamonds are sent to an off-site sort house for further sorting, valuation and distribution to local and international markets.

Reconcentrate tails are added into the DMS circuit with material from the crusher (-16 to 6 mm) for another concentration. The recovery grade from this material is referred to as the adjusted recovery grade. The recovery grade from the crushed material, without addition of tails, is referred to as the recovered grade.

4.2.2 Current State Map based on the bulk sample

As discussed in Section 3.3.2, the CSM was generated from a bulk sample which was run through the value chain. Firstly, a map tracking tonnes and grade of ore along the value chain is shown in Figure 9 with its description shown in Appendix E. The green colour represents the main processes in the diamonds mine's mine-to-mill's value chain. The yellow colour represents material storage on the RoM stockpile, crushed stockpile (c/stockpile) and recovery tails, and long-term storage in low-grade and tailings stockpile (tls stockpile). In the figure thicker arrows indicate the physical flow of ore across the value chain, while thinner arrows denote the flow of information both within the mine and externally between the mine, its suppliers, and customers.

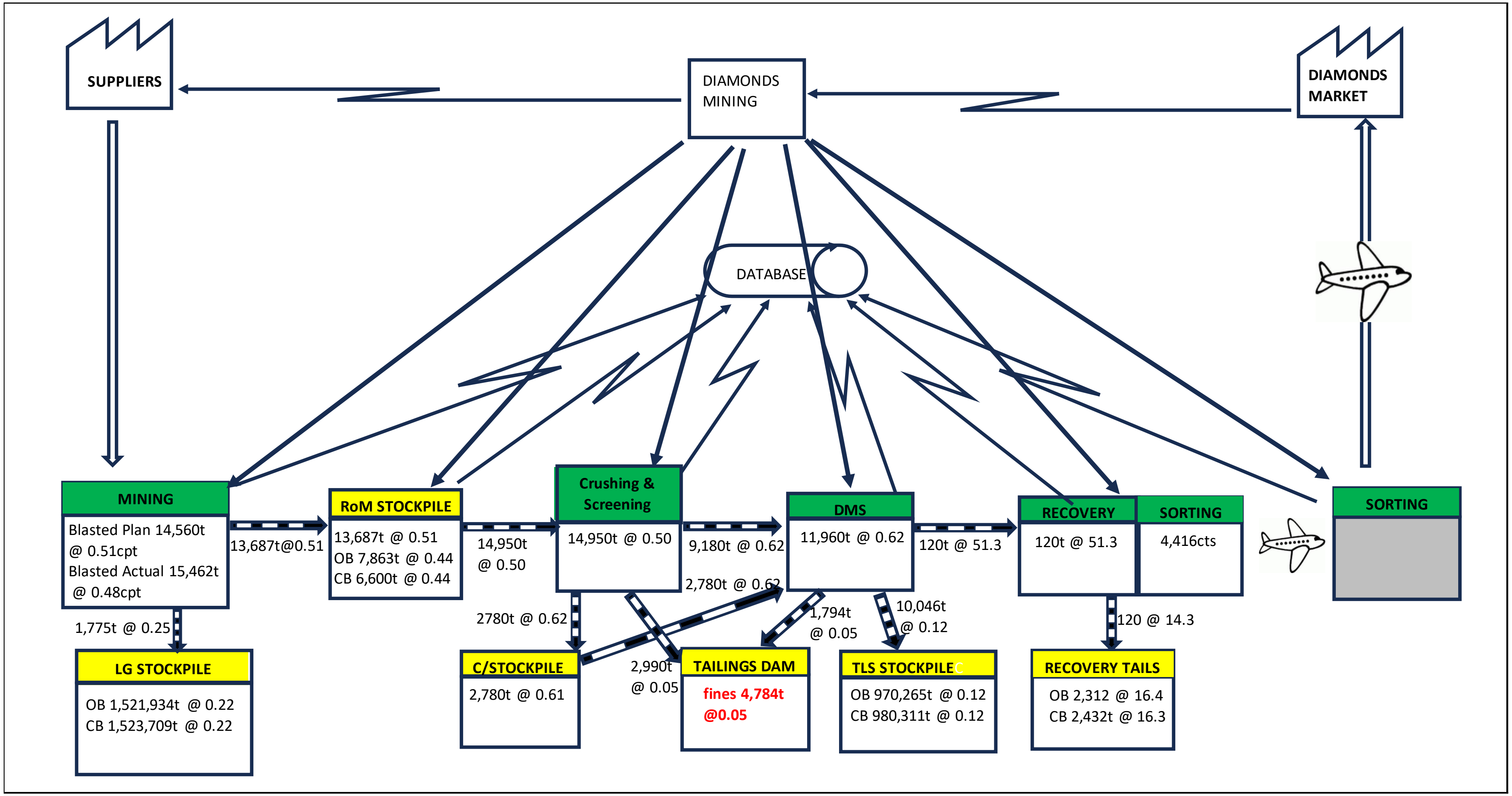

Figure 9: The current state map tracking bulk sample tonnes and grade of ore

To clearly illustrate and understand the flow of carats through the mine-to-mill value chain, Figure 10 was developed. This figure displays both the flow and the percentage of carats progressing from one processing stage to the next. The green and yellow colours on Figure 10 correspond directly to the same activities highlighted in Figure 9, providing visual consistency and aiding easier interpretation of material transitions between stages.

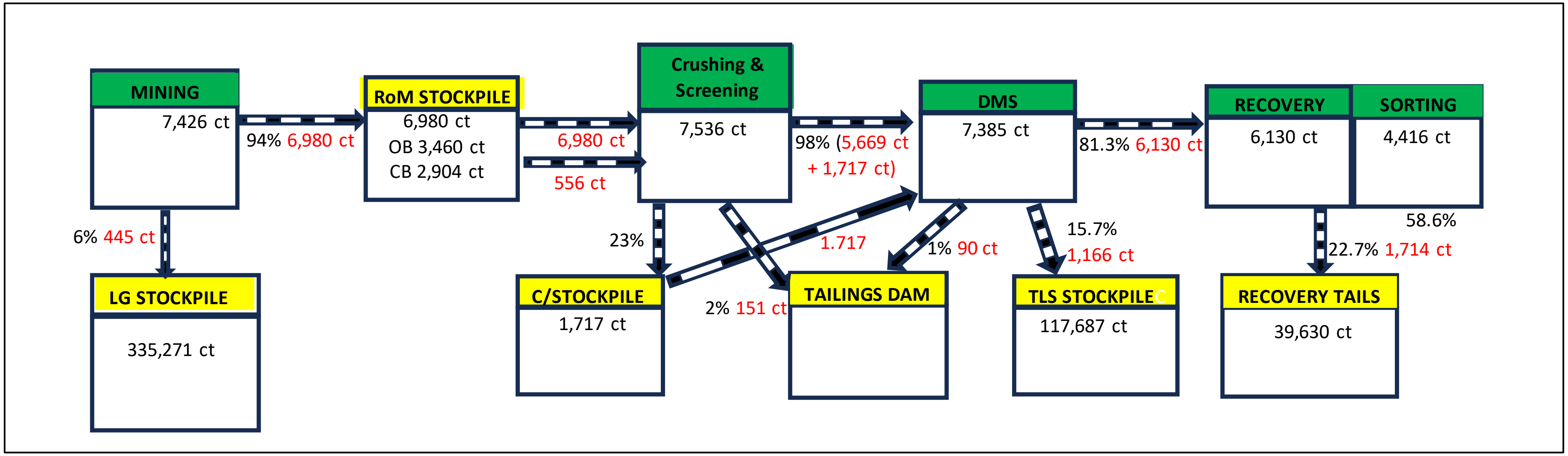

Figure 10: The current state map carats flow

Figure 9 and Figure 10 are described in the following subsections.

i. Mining

The planned production from drilling and blasting a 20 m wide, 28 m long and 10 m high bench was 14,560 tonnes of ore with an average estimated grade of 0.51 cpt. Therefore, the bench was estimated to contain 7,426 carats. From the planned 14,560 tonnes, the actual realised production was 15,462 tonnes at 0.48 cpt after blasting. Actual production exceeded the planned tonnage by 920 tonnes of waste as a result of overbreak. Surveyed bench boundary re-marking indicated boundary displacement, confirming the occurrence of overbreak. This resulted in a 6% dilution (where the acceptable external dilution is 4%). Of the 15,462 tonnes of actual blasted material, 13,687 tonnes with the planned grade of 0.51 cpt resulted in 6,980 carats (94%) which were selectively loaded and hauled to the RoM pad. The remaining 1,775 tonnes, classified as low-grade ore at 0.25 cpt, containing 445 carats (6%), were hauled to the low-grade stockpile. Excavator operators receive geological training to enhance their effectiveness in carrying out selective mining, thereby managing ore quality and dilution.

ii. RoM Stockpile

The RoM stockpile opened with 7,863 tonnes of ore at an estimated average grade of 0.44 cpt (3,460 carats). Ore amounting to 13,687 tonnes at an estimated grade of 0.51 cpt, from the pit, was added to the stockpile, all of which were subsequently fed into the crushing and screening plant. Additionally, 1,263 tonnes (were drawn from the opening balance and processed through the crusher, resulting in a closing stockpile balance of 6,600 tonnes (2,904 carats).

iii. Low Grade Stockpile

The low grade stockpile opened with 1,521,934 tonnes of ore at an average estimated grade of 0.22 cpt (334,825 carats). A total of 1,775 tonnes of low grade ore, at an estimated grade of 0.25 cpt were hauled from the pit and added to the stockpile resulting in a closing balance of 1,513,709 tonnes at an estimated average grade of 0.22 cpt (335,271 carats).

iv. Crushing and Screening

Due to the difference in processing capacities between the crushing and screening plant (210 tph) and the DMS plant (170 tph, with 10 tph reserved for reconcentration), excess crushed material is stockpiled. From the 14,950 tonnes processed through the plant:

- 9,180 tonnes, with an estimated grade of 0.62 cpt (5,669 carats accounting for 75% of carats delivered to the plant), were directly fed into the DMS plant for processing.
- 2,780 tonnes, also with an estimated grade of 0.62 cpt (1,717 carats, accounting for 23% of the carats delivered to the plant), were stockpiled for later processing.
- 2,990 tonnes, containing a lower estimated grade of 0.05 cpt (150 carats, accounting for 2% of the carats delivered to the plant), were removed as fines and discarded into the tailings dam.

The ore emerging from the crushing and screening plant reported an increased grade of 0.61 cpt, compared to the initial feed grade of 0.50 cpt. This improvement is attributed to the removal of 2,990 tonnes of fine material, which contained a significantly lower grade. After the direct DMS feed was completed, the stockpiled ore (2,780 tonnes) were processed after three days, completing the full sample within four days.

v. Dense Media Separation

A total of 11,960 (9,180 plus 2,780) tonnes of crushed ore with an estimated grade of 0.62 cpt (7,385 carats) were fed into the DMS plant. Of this:

- 120 tonnes at 51.3 cpt (6,130 carats, accounting for 81.3% of carats into the processing plant), were directed to the 10-tonne DMS for reconcentration,
- 10,046 tonnes went to the tailings stockpile at 0.12 cpt (1,166 carats, accounting for 15.7% of carats into the processing plant), and
- 1,794 tonnes at 0.05 cpt (90 carats, accounting for 1% of carats into the processing plant) were sent to the tailings dam.

vi. Recovery

From the 120 tonnes of concentrate that was fed into the 10 tonne DMS, for reconcentration, 4,416 carats (58.6% of carats delivered to the processing plant) were received at the sort house for sorting and cleaning. The 120 tonnes of reconcentrate tails, with an estimated grade of 14.28 cpt (1,714 carats, accounting for 22.7% of carats delivered to the processing plant) were sent to the recon tailings stockpile for storage. The recovered grade was calculated to be 0.3 cpt at a recovery efficiency of 60%.

4.2.3 Process Activity Mapping of the bulk sample

Primary data was used to conduct PAM. Variance analysis was done and a process activity map was drafted. The results of PAM are shown in Table 2. The table shows the mine value chain activities with tonnages, recovered carats and grade.

Table 2: Process activity map

Activity	Tonnage (t)	Grade (cpt)	Carats	Net Carats	Catergory	Comments
Blasted ore plan	14,560	0.51			VA	
Blasted ore actual	15,462	0.48	7,426	**7,426**		Caracts Mined
Loading and Hauling to RoM	13,687	0.51	6,980	445	NNVA	Carats to low-grade stockpile
Loading and Hauling to low-grade	1,775	0.25	445	445		
RoM stockpile Opening Balance	7,863	0.44	3,460	556	NNVA	Carats fed to the crushing and screening plant from RoM
RoM stockpile Closing Balance	6,600	0.44	2,904			
Low Grade Stockpile Opening Balance	1,521,934	0.22	334,825	445	NNVA	Carats added to the Low grade stockoile
Low Grade Stockpile Closing Balance	1,523,709	0.22	335,271			
Crushing and Screening	14,950	0.50	7,536	**7,536**	VA	Carats into the crushing and screening plant
Crushing and Screening Fines	2,990	0.05	150	150	NVA	Carats to the tailings dam
DMS direct feed	9,180	0.62	5,669		NNVA	
Crushed Stockpile	2,780	0.62	1,717		NNVA	
DMS	11,960	0.62	7,385	**7,385**	VA	Carats into the DMS Plant
Tails Stockpile	10,046	0.12	1,166	1,166	NNVA	Carats to the tails stockpile
Tailings Dam	1,794	0.05	90	90	NVA	Carats to tailings dam
Reconcentration	120	51.25	6,150		NNVA	
Tails Stockpile Opening Balance	970,265	0.12	116,432	1,166	NNVA	
Tails Stockpile Closing Balance	980,311	0.12	117,598			
Recovery	120	51.25	6,130	**6,130**	VA	Carats into the recovery plant
Recon Tails	120	14.30	1,714	1,714	NNVA	Carats to tails stockpile
Recon Tails Opening Balance	2,312	16.40	37,917		NNVA	
Recon Tails Balance Balance	2,432	16.30	39,630			
Sorting			4,416	**4,416**	VA	Recovered Carats

Process activity map (Table 2) categorised activities into VA, NVA, and NNVA. VA activities included drilling and blasting, crushing and screening, DMS, recovery, and sorting, as these processes received and transferred significant carats to the next stage. NVA activities comprised crushing and screening fines, along with DMS slurry, both of which were discharged to the tailings dam with minimal carat movement. Lastly, all stockpiles were classified as NNVA, as they do not directly contribute to carat recovery but serve an essential function in material handling.

4.2.4 Production Losses based on the Bulk Sample Current State Map

During the observation exercise, the following inefficiencies were observed. Drilling and blasting created an overbreak which was confirmed through survey. Loading and hauling had an idle excavator (low utilisation) on Day 2 due to a truck breakdown. During loading and at the RoM pad, boulders were visible forcing the loader to do sorting to avoid crusher chokes. The crushing and screening plant generated a lot of fines which are estimated to lose 10% of the grade, according to the study mine's recovery model. The

DMS plant, coming from maintenance, had no observed inefficiencies except for the lower capacity compared to the crushing plant leading to stockpiling of crushed material. Due to the amount of reconcentrate tails, it was clear that there is recovery inefficiency at the recovery plant. The following calculations were performed using data from the bulk sample.

Production losses were quantified by comparing actual throughput rates to optimal throughput rates across the mine-to-mill value chain. Interview respondents identified key inefficiencies such as truck unavailability, prolonged maintenance delays, and frequent spare part shortages, all of which significantly reduced plant throughput. These challenges contributed to a reduction in plant availability. Actual availability was found to be 79%, falling short of the planned availability of 83%, representing a 4.8% shortfall. From the bulk sample data, the mine processed an average 2,215 tonnes per day through the DMS plant.

Lost production was calculated using a standard throughput loss equation (Equation 3), which estimates performance losses by comparing optimal and actual throughput. This approach aligns with methods used in mining productivity (Montgomery, 2013; Hartman & Mutmansky, 2002).

$$\textbf{Lost production (tonnes)} = \textbf{Optimal throughput} - \textbf{Actual throughput} \tag{3}$$

$$= 2390.4 - 2214.5 \text{ tonnes per day}$$

$$= 176 \; tonnes \; per \; day$$

This shortfall highlights the critical impact of operational constraints on productivity, aligning with respondent observations about plant downtime and logistical inefficiencies.

Utilisation analysis was conducted to measure standby time or delays. Equipment utilisation was found to be 73% against planned utilisation of 75% which is based on 18 hours of 24 hours. Production loss due to utilisation was calculated using Equation 4. To assess the impact on throughput, the hourly DMS throughput was found to be 123 tonnes per hour.

$$\textbf{Lost production (tonnes)} = \textbf{Lost time} \times \textbf{Production rate/hr} \tag{4}$$

$$= (18.96 \times 0.02) \times 123$$

$$= 47 \; tonnes \; per \; day$$

Production loss due to idling was found to be 47 tonnes per day.

Material losses were assessed by evaluating the grade and recovery inefficiencies associated with blasting, DMS, and recovery stages. Using bulk sample information, average recovery loss was calculated using Equation 5.

$$Recovery\ loss = Model\ recovery - Recovery\ efficiency \tag{5}$$

Where recovery efficiency is calculated using Equation 6.

$$Recovery\ Efficiency = \left(\frac{Recovered\ grade}{Feed\ grade}\right) * 100 \tag{6}$$

$$Recovery\ loss = 83\% - 60\%$$

$$= 23\%$$

The bulk sample came from Pit 1 with a model recovery of 83%. Recovery loss was calculated to be 23%. This quantification underscores the need for improved blasting techniques and parameter control in the DMS stage to minimise material losses, as echoed by respondent observations on recovery inefficiencies.

The financial impact of delays was calculated by combining production losses due to low equipment availability and idle time losses. Using total production loss and the average recovered grade, production loss in carats was calculated. Additional recovery loss was added to the total carats loss. To get the financial loss, a historical price of $120 per carat (as per case study mine historical information) was used. Equation 7 was used for the calculation.

$$Total\ lost\ production = Lost\ production\ (Availability)\ + Lost\ production(Utilisation) \quad (7)$$

$$= 176+47$$

$$= 223\ tonnes\ per\ day$$

This was calculated to be 223 tonnes per day. To calculate total lost carats, Equation 8 was used.

$$Production\ lost\ carats = Total\ lost\ production\ \times Expected\ recovered\ grade \quad (8)$$

$$= 223 \times 0.63\ carats$$

$$= 141\ carats$$

Number of lost carats using an average grade of 0.63 cpt is 141 carats. Equation 9 was used to calculate total lost carats.

$$Total\ lost\ carats = Lost\ production\ carats + Recovery\ loss \quad (9)$$

$Total\ lost\ carats = 141\ \text{carats} + (141 * 0.23) =\ 173\ \text{carats}$ per day

The total financial loss was calculated using Equation 10.

$$Total\ loss\ (\$) = Total\ lost\ carats \times Average\ price/carat \quad (10)$$

$$Total\ loss\ \ = 173\ carats \times \$120/carat$$

$$Total\ loss = \$20{,}736\ per\ day$$

Evidently, this is a significant financial loss. The price per carat applied in the analysis was based on the average selling price from the previous years.[1]

[1] *Information obtained from case study mine management records.*

4.2.5 Current State Map based Historical Production Data

The study retrieved historical processed tonnes, feed grade, recovered carats, adjusted recovered carats, recovered grade, adjusted recovered grade, expected recovered grade, model recovery and sources of feed ore from 2018 to 2022. Feed grade refers to the grade of ore from mining, being fed into the crushing and screening plant which is the initial stage of the processing plant. Recovered carats are total carats recovered every month. Adjusted recovered carats are carats recovered after adding reconcentrate tails into the circuit. Model recovery is the budgeted recovery rate according to the recovery model, taking into consideration lockup factors (17% lockup for Pit 1 and 25% lockup for Pit 2), balancing the lockup in the months with mixed feed from two pits. Expected recovered grade is the planned recovered grade calculated from the feed grade and the model recovery lockup assumptions. Recovered grade is the actual grade after processing the recovered diamonds after sorting, in relation to the quantity of ore that was fed into the plant. Adjusted recovered grade is the recovered grade after the reconcentrate tails have been added into the crushing and screening circuit, into the DMS plant through to recovery. Recovery efficiency is the process effectiveness calculated using Equation 6. The historical data is presented in Table 3 and detailed month on month data is presented in Appendix F.

Table 3: Historical production data

	Processed Ore (t)	Feed Grade (cpt)	Recovered Carats	Adjusted Recovered Carats	Model Recovery (Plan) (%)	Expected Recovered Grade (cpt)	Recovered Grade (cpt)	Adjusted Recovered Grade (cpt)	Recovery Efficiency (Actual) (%)
2018	1,015,090	1.26	729,939	973,252	75.00	0.95	0.73	0.96	58
2019	858,391	1.07	677,357	865,166	79.00	0.84	0.80	1.01	75
2020	946,110	0.71	569,030	694,014	81.68	0.58	0.60	0.73	84
2021	901,937	0.56	426,782	521,930	82.02	0.46	0.47	0.58	85
2022	650,206	0.40	179,828	215,252	83.00	0.33	0.28	0.33	69
MEAN	**874,347**	**0.80**	**516,587**	**653,923**	**80.14**	**0.63**	**0.58**	**0.72**	**74.02**
STDEV	123,461.34	0.32	197,782	267,603	2.89	0.23	0.19	0.25	10.15

The historical data table (Table 3), for the five-year period, shows average processed ore as approximately 874,347 tonnes, with an estimated mean feed grade of 0.80 cpt. The model (planned) recovery averages about 80.14%, but the actual recovery efficiency averages only 74.02%. This indicates an overall shortfall of around 6% in converting feed material into recovered product. The estimated average recovered grade is 0.58 cpt, while the estimated average adjusted and expected recovered grades are 0.72 cpt and 0.63 cpt, respectively. On variability, 2018 feed grade was high (1.26 cpt) but recovered grade was 0.73 cpt, with a planned recovery of 75% falling to 58% actual efficiency. In 2019, recovery improved (80%

vs. 84% expected, and 75% actual). The recovery process performed well between 2020 and 2021, with actual recovery exceeding plan (84–85% actual vs. 82% plan). Recovery efficiency dropped in 2022 (actual 69% vs. 83% planned), indicating issues that need addressing. The CSM from historical data, in terms of flow of carats, is shown in Figure 11.

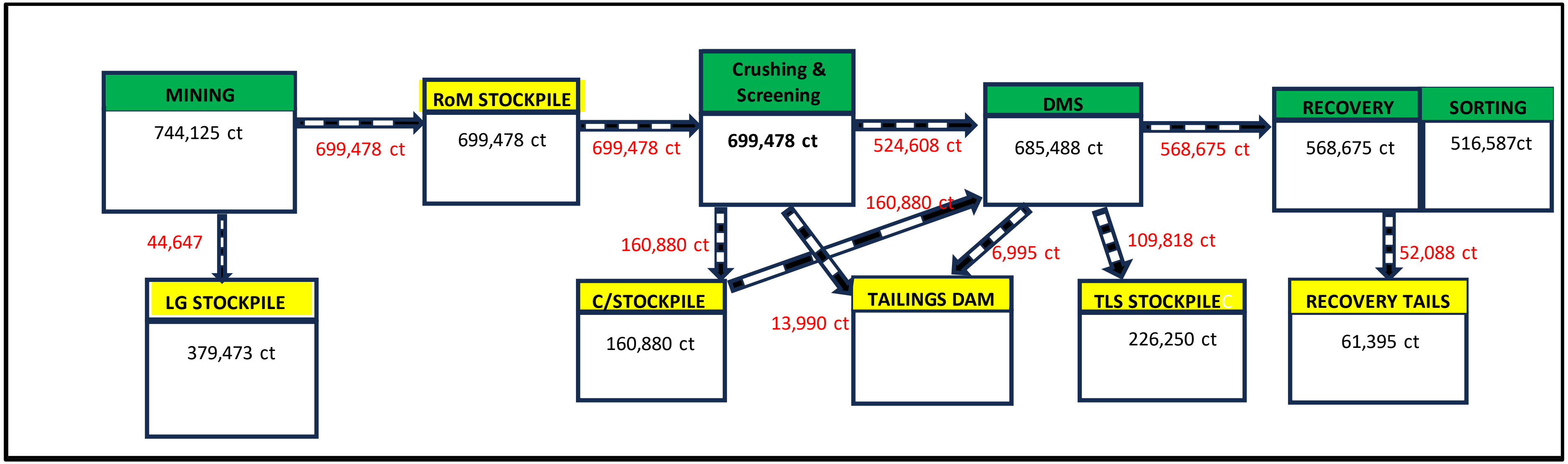

Figure 11: Current state map based on historical production data

From Figure 11, out of 744,125 carats (973,788 tonnes of blasted ore), 699,478 carats went through the crushing and screening plant (from 874,347 tonnes of ore). From the carats that were fed into the crushing and screening plant, 516,587 carats reported to the sorting plant. This constitutes 74% of the carats that went into the crushing and screening plant. The recovered grade is 0.59 cpt at a recovery efficiency of 74%.

4.2.6 Monte Carlo Simulation

As explained in Section 3.3.2, MCS was done on processed tonnes, feed grade, recovered carats, adjusted recovered carats, model recovery, expected recovered grade, recovered grade, adjusted recovered grade and recovery efficiency. The resulting means and standard deviations are presented in Table 4. Percentiles were calculated from the simulated data.

Table 4: Simulated data summary

	Random Processed Ore (t)	Random Feed Grade (cpt)	Random Recovered Carats	Random Adjusted Recovered Carats	Random Model Recovery (Plan) (%)	Random Expected Recovered Grade (cpt)	Random Recovered Grade (cpt)	Random Adjusted Recovered Grade (cpt)	Random Recovery Efficiency (Actual) (%)
MEAN	875,464	0.8	517,169	651,218	80.15	0.63	0.58	0.72	74.08
STDEV	123,181	0.32	201,546	267,544	2.91	0.23	0.19	0.25	10.22
10th Percentile	717,956	0.39	252,310	308,251	76.45	0.33	0.34	0.4	60.99
50th Percentile	875,385	0.8	516,599	651,366	80.15	0.63	0.57	0.72	74.09
90th Percentile	1,032,875	0.21	775,834	999,006	83.87	0.92	0.81	1.03	87.11

Probability distributions highlighted variability across operational parameters, with medians (50^{th} percentile) closely aligning with means. The MCS demonstrated moderate variability in recovered and adjusted recovered grades, with the adjusted recovered grade showing consistent alignment with the recovered grade but failing to fully compensate for losses. The mean adjusted recovered grade (0.73 cpt) is higher than mean expected recovered grade (0.63 cpt) while the mean recovered grade is lowest (0.58 cpt). This indicates incomplete initial recovery leaving recoverable diamonds in the concentrate tails, highlighting a higher recovery potential. Figure 12 to Figure 20 show different variable frequency distributions from ten thousand iterations.

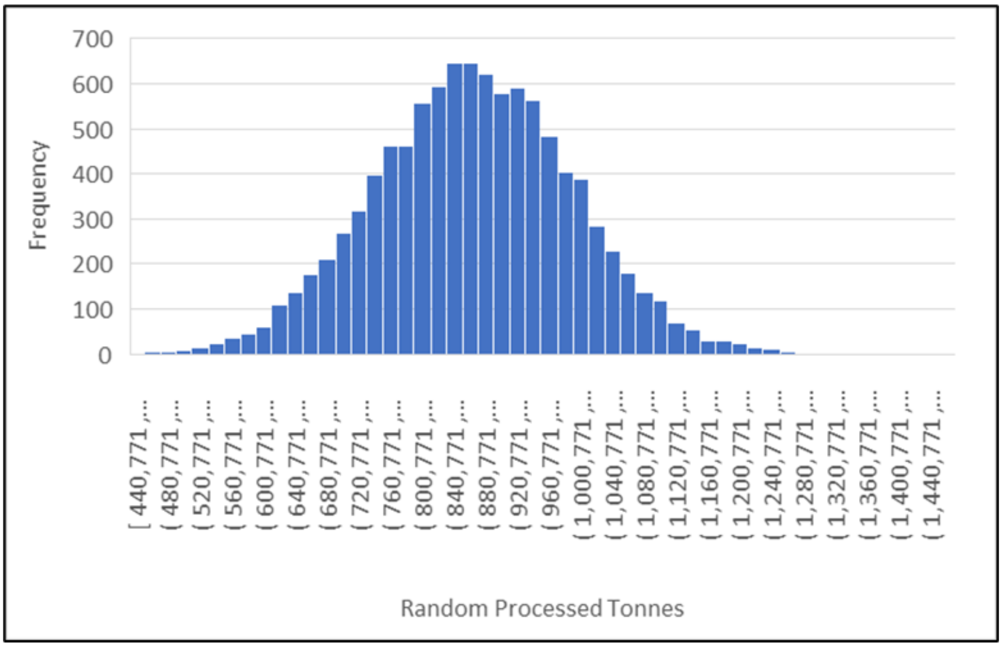

Figure 12: Processed tonnes probability distribution

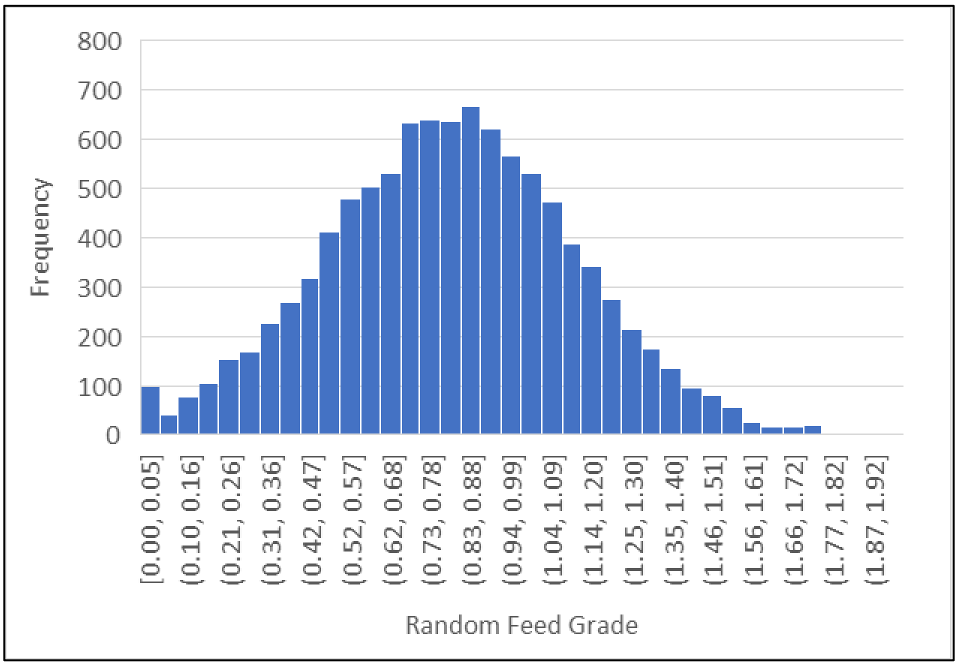

Figure 13: Feed grade probability distribution

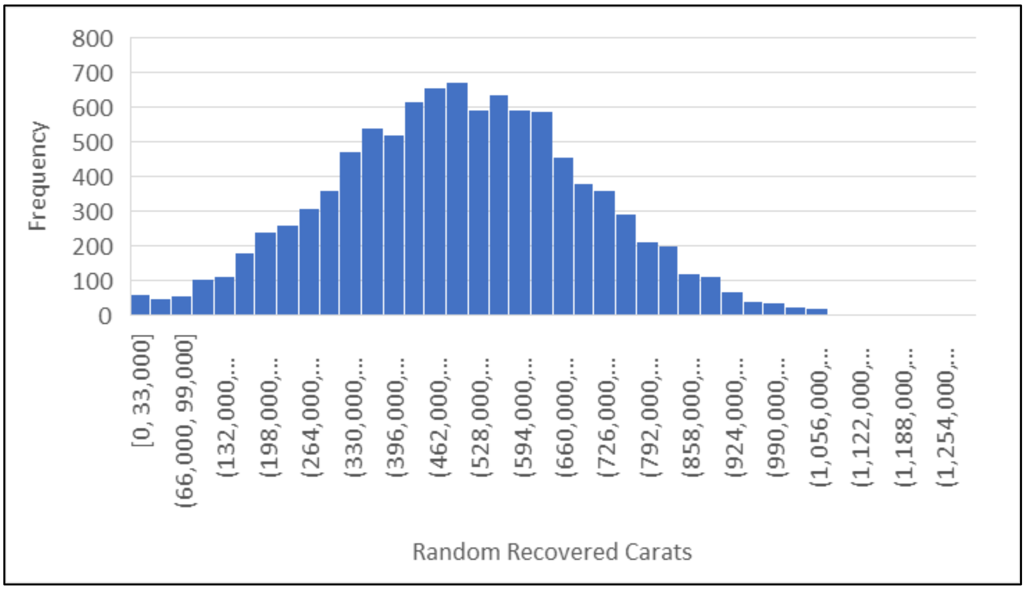

Figure 14: Recovered carats probability distribution

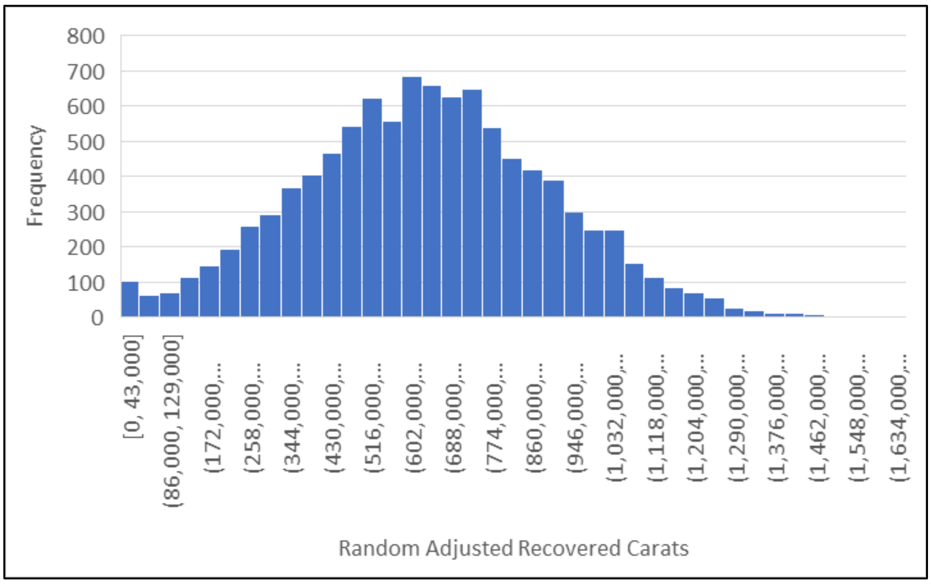

Figure 15: Adjusted recovered carats probability distribution

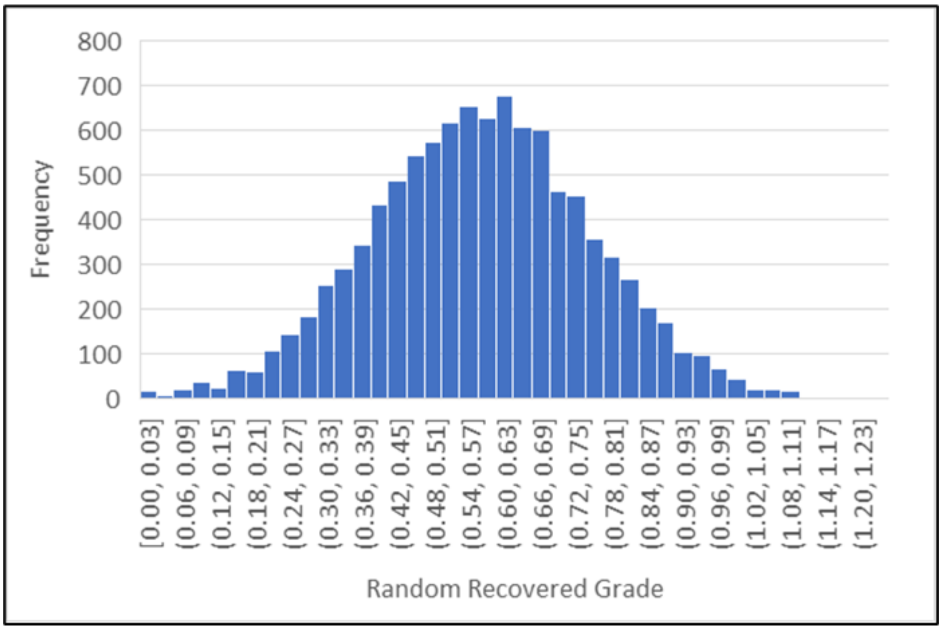

Figure 16: Recovered grade probability distribution

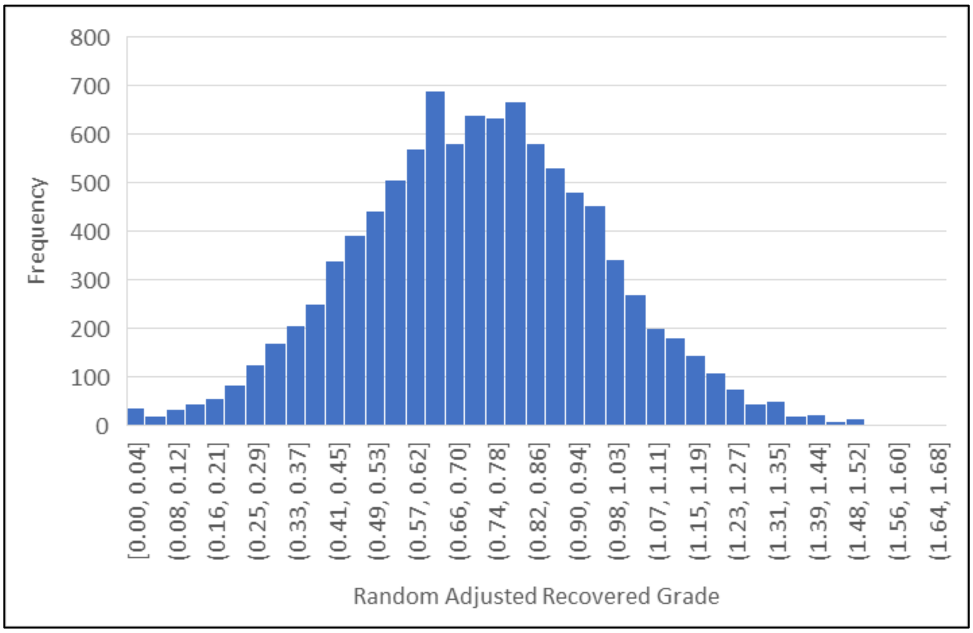

Figure 17: Adjusted recovered grade probability distribution

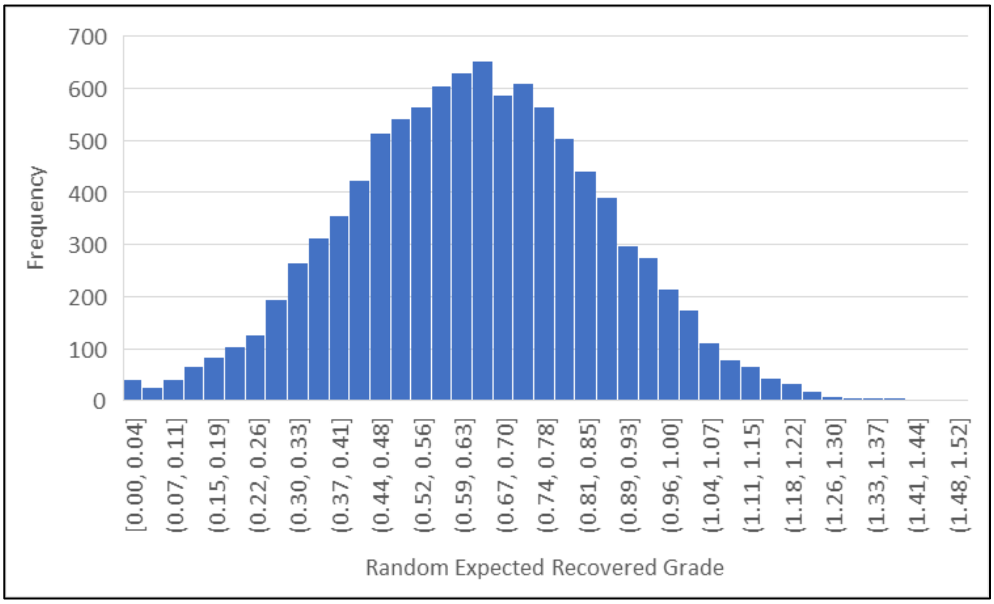

Figure 18: Expected recovered grade probability distribution

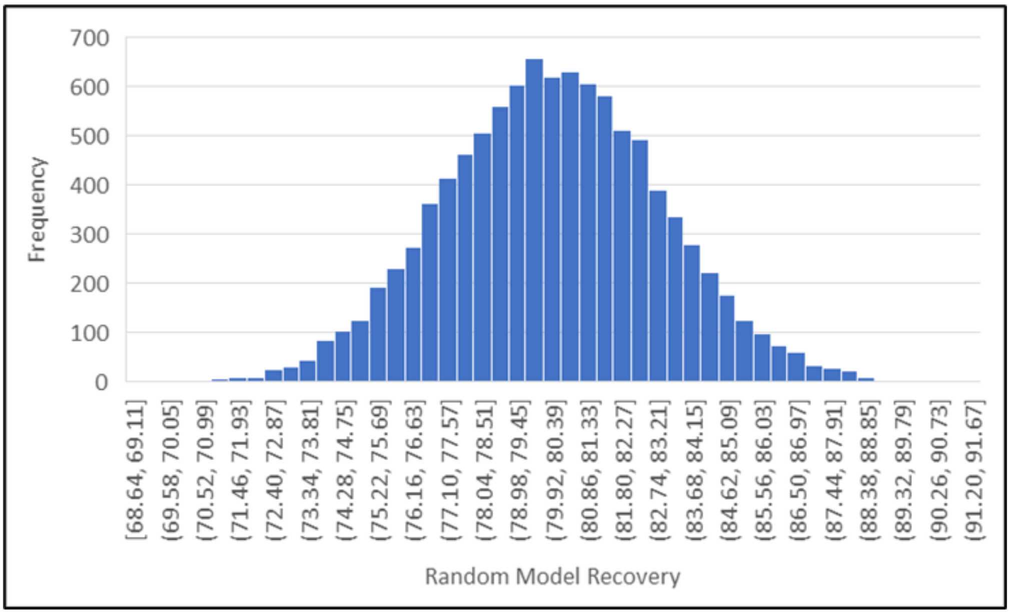

Figure 19: Model recovery probability distribution

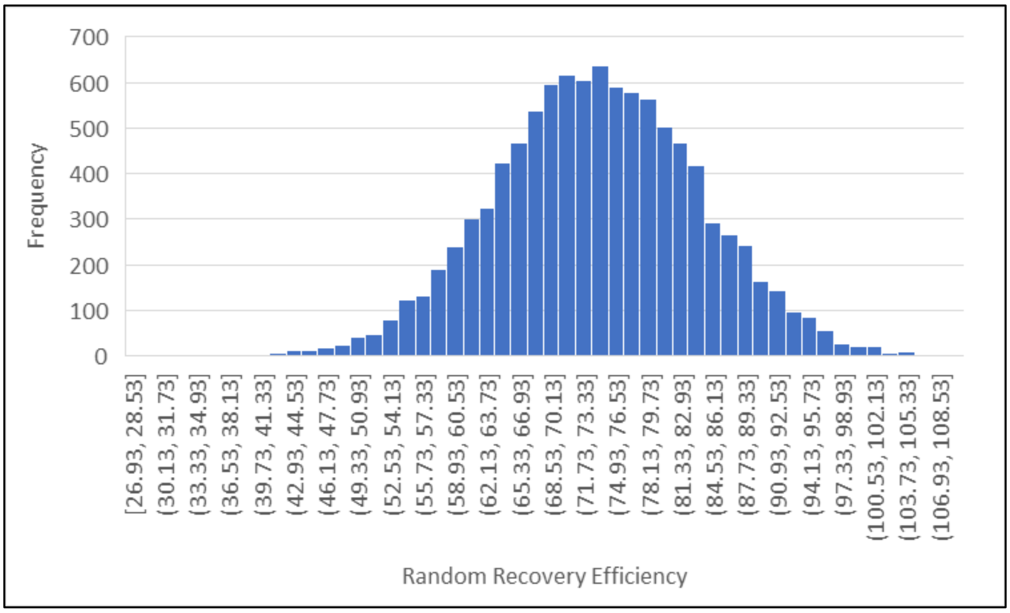

Figure 20: Recovery efficiency probability distribution

To aid interpretability, the statistical characteristics of the histograms are summarised in Table 5 showing the distribution shape, central tendency, variability and key interpretations.

Table 5: Summary of the Current State Histogram Interpretations

Parameter	Shape	Mean	Median	Std Dev	Range (Min–Max)	Key interpretation
Processed Tonnes	Near-normal	875,472 t	873,908 t	123,248 t	445,863 – 1,304,258 t	Throughput generally consistent, though extremes exist at both ends
Feed Grade (cpt)	Slight right-skew	0.81 cpt	0.81 cpt	0.31 cpt	0.00 – 1.97 cpt	Ore quality variable with high-grade spikes and some low-grade outliers
Recovered Carats	Symetrical	517,766 ct	517,207 ct	179,013 ct	0 – 1,355,003 ct	Stable recovery performance; central tendency consistent.
Adjusted Recovered Carats	Wider spread	652,310 ct	652,986 ct	267,242 ct	0 – 1,893,801 ct	Adjustments account for improved recovery but introduce variability.
Recovered Grade (cpt)	Symmetrical	0.58 cpt	0.58 cpt	0.19 cpt	0.00 – 1.24 cpt	Stable and consistent recovery grade with minimal skewness
Adjusted Recovered Grade (cpt)	Slight right-skew	0.73 cpt	0.73 cpt	0.25 cpt	0.00 – 1.65 cpt	Adjusted estimates improve grade but show wider spread
Expected Recovered Grade (cpt)	Symmetrical, balanced	0.64 cpt	0.64 cpt	0.22 cpt	0.00 – 1.45 cpt	Forecasts are stable and reliable, though subject to moderate variability and occasional extremes.
Model Recovery (planned, %)	Near-normal	80.15%	80.15%	2.92%	68.64 – 91.23 %	Consistent planned recovery values, tightly distributed
Recovery Efficiency (actual, %)*	Wide, irregular	73.86%	73.82%	10.10%	26.9% – 109.9 %	Actual recovery shows a much wider spread than planned, indicating operational instability

Most CSM parameters display consistent central tendencies but variability differs significantly across metrics. Processed tonnes follow a near-normal distribution with moderate variability, reflecting stable but not perfectly consistent throughput. Feed grade is right-skewed with a wide range and high standard deviation confirming ore quality inconsistencies and the need for tighter stockpile management. Recovered carats and adjusted recovered carats demonstrate higher variability with wide ranges pointing to operational and geological uncertainty. In contrast, recovered grade is relatively stable with low variability, while recovery efficiency shows a wide spread between 27% and 110%, highlighting significant fluctuations in plant performance. Overall, the histogram summary confirms that feed grade and recovery efficiency are the most unstable factors driving inefficiencies in the current state. These histogram results are further validated by the CDF interpretations in Table 6 which confirm the same patterns of stability and variability across the current state model.

4.2.7 Cumulative Distribution Function Graphs

To complement the histogram analysis, which highlighted variability in feed grade and recovery efficiency, CDFs provide additional insight by showing the cumulative distribution and concentration of values across parameters. This enables clearer interpretation of stability versus variability within the mine-to-mill value chain. Figure 21 to Figure 29 present CDF graphs of simulated key mine-to-mill-parameters. The blue line on the graph represents the empirical CDF, showing the cumulative probability of adjusted metric values while the red dashed lines indicate the 10^{th}, 50^{th} (median), and 90^{th} percentiles, marking key thresholds for performance assessment.

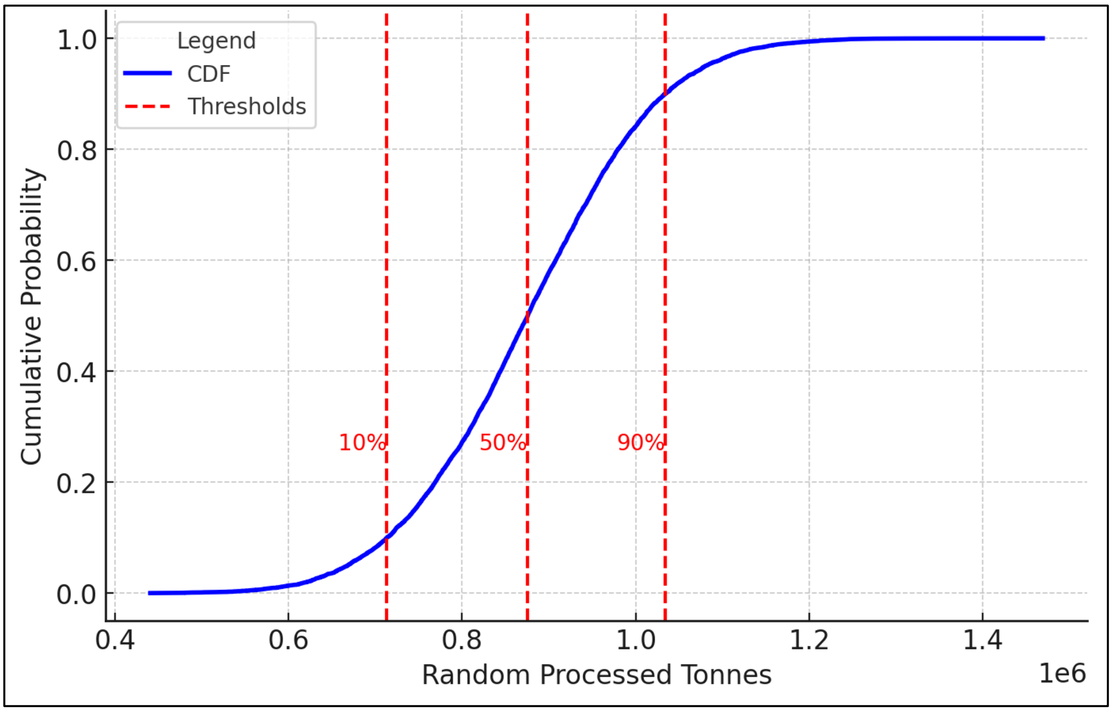

Figure 21: CDF of processed tonnes

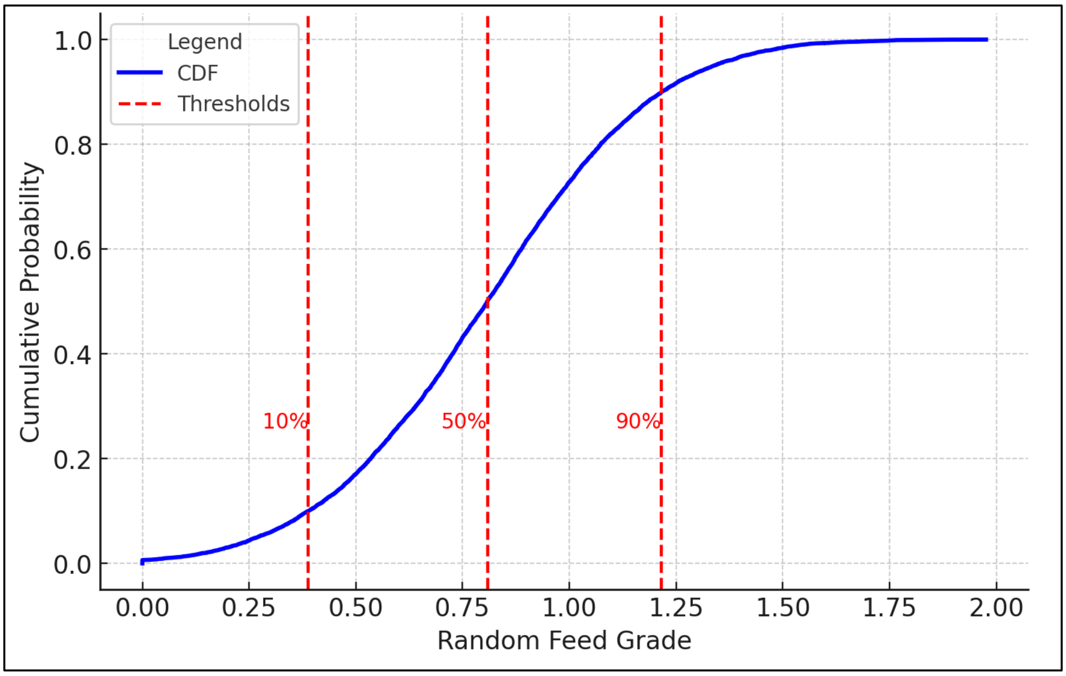

Figure 22: CDF of feed grade

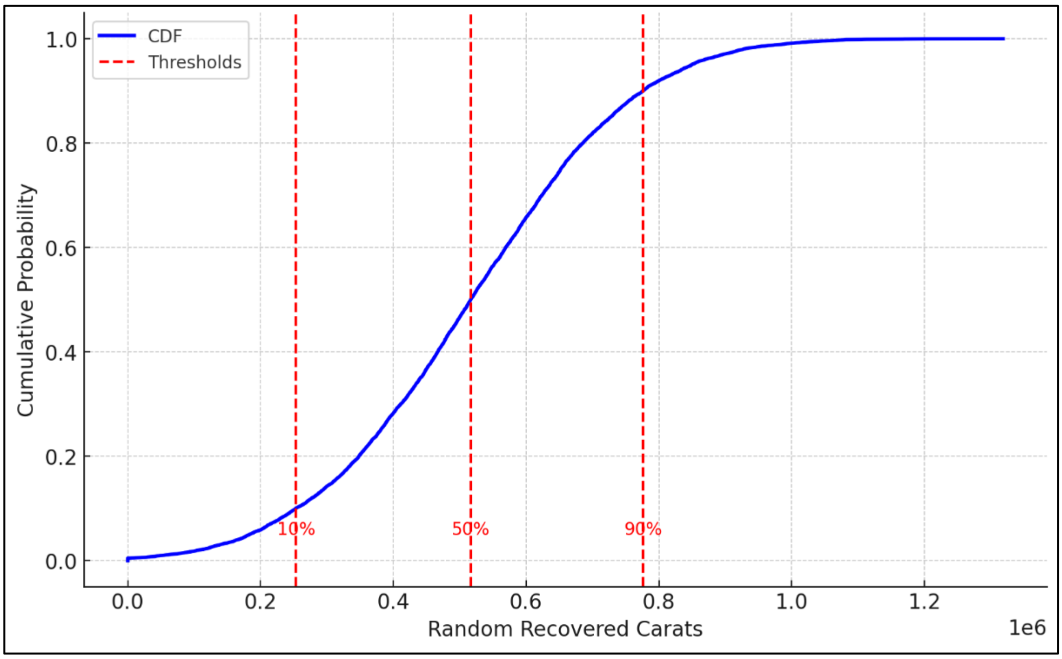

Figure 23: CDF of recovered carats

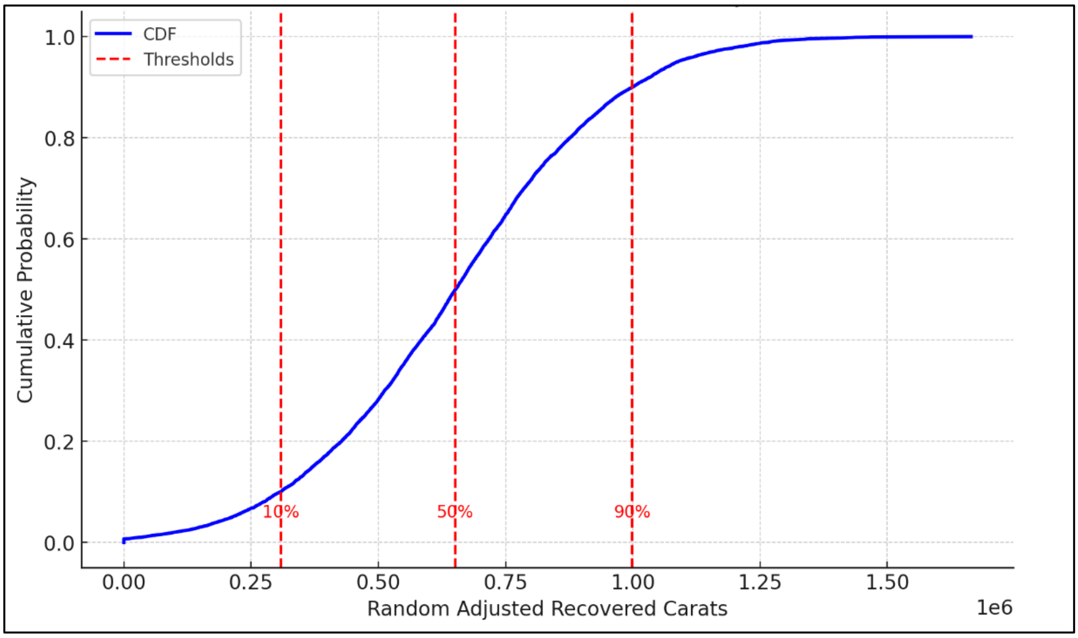

Figure 24: CDF of adjusted recovered carats

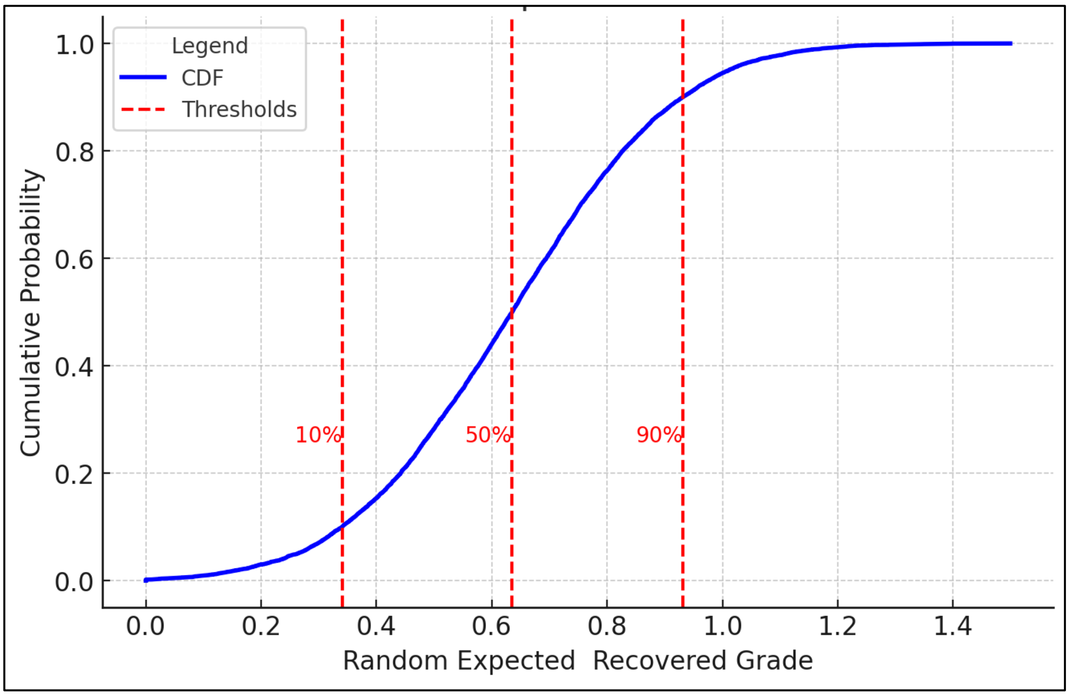

Figure 25: CDF of expected recovered grade

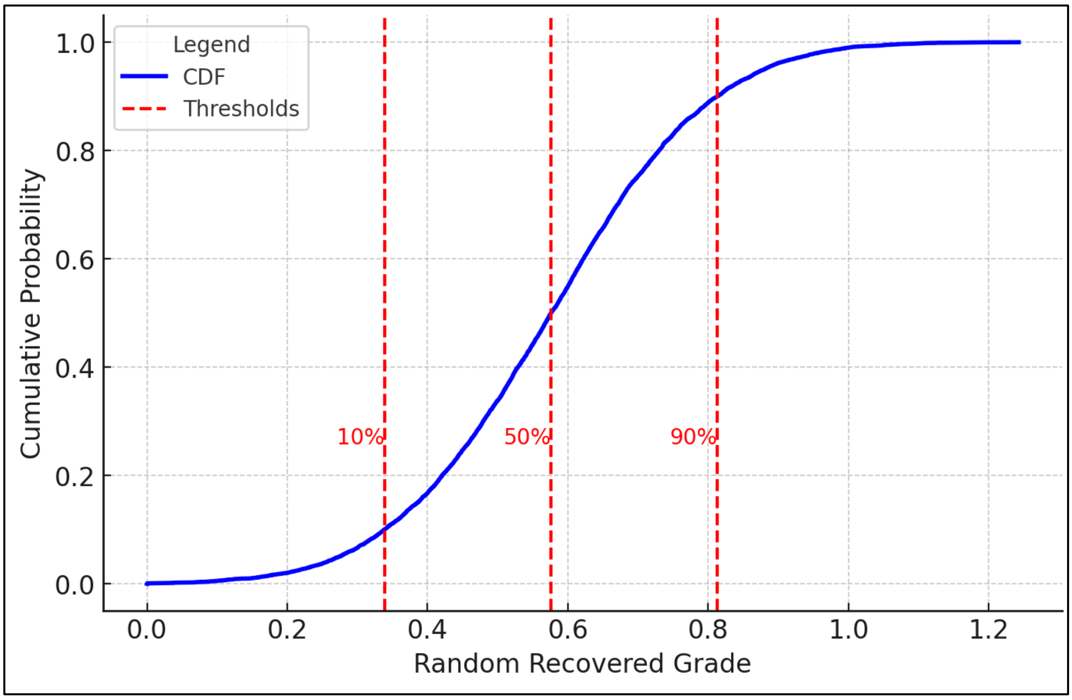

Figure 26: CDF of recovered grade

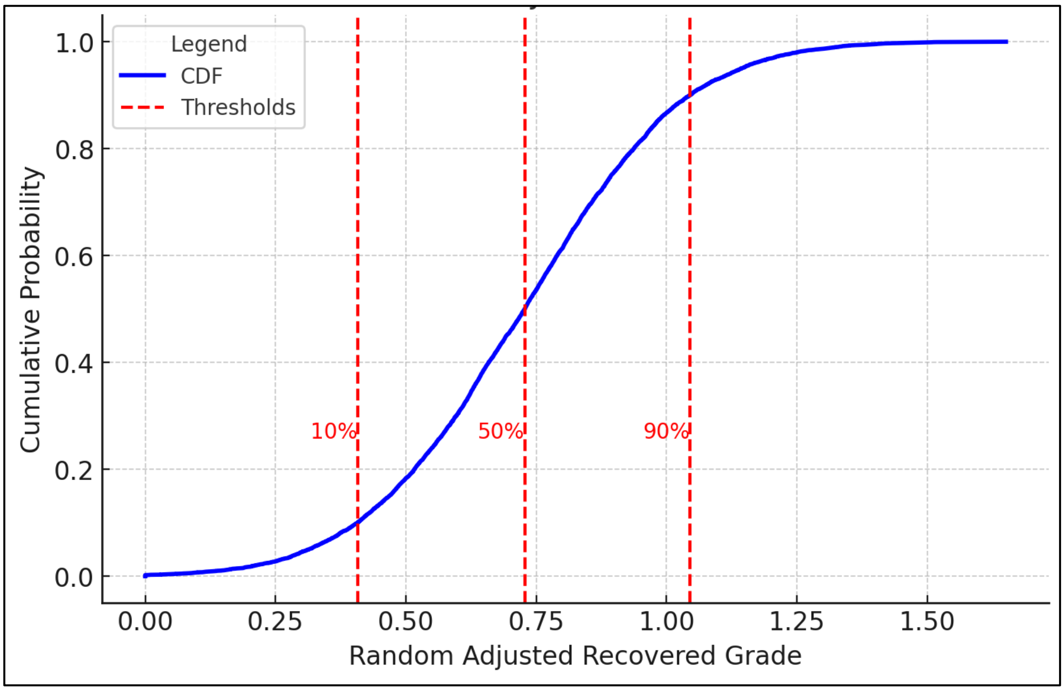

Figure 27: CDF of adjusted recovered grade

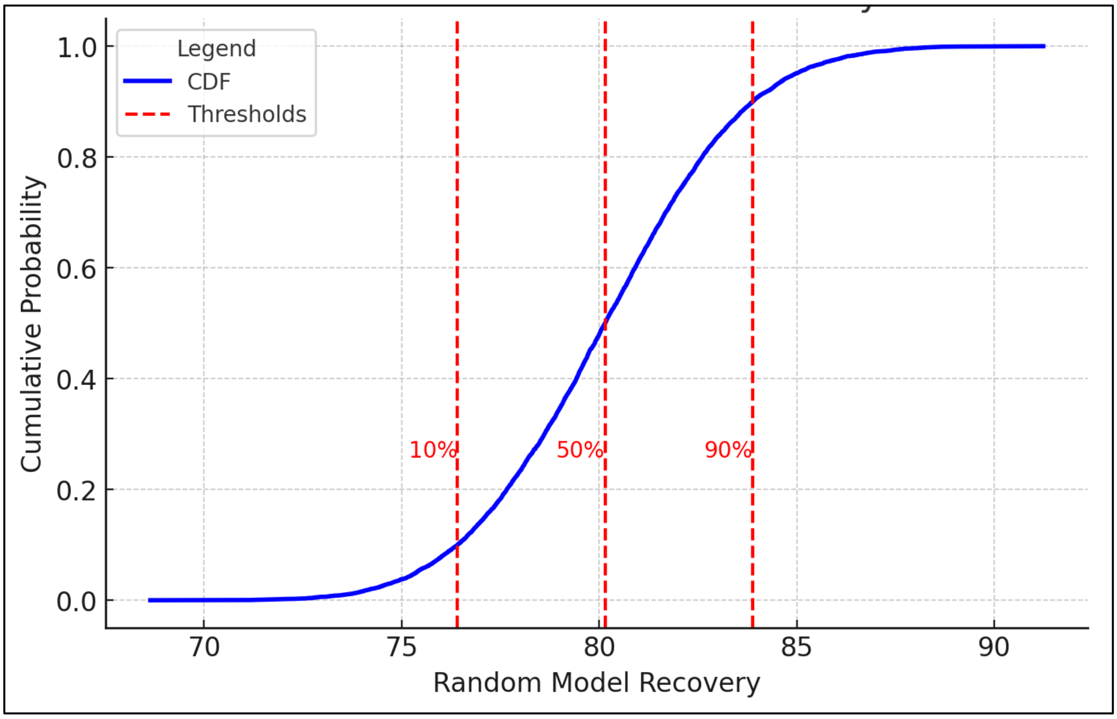

Figure 28: CDF of model recovery

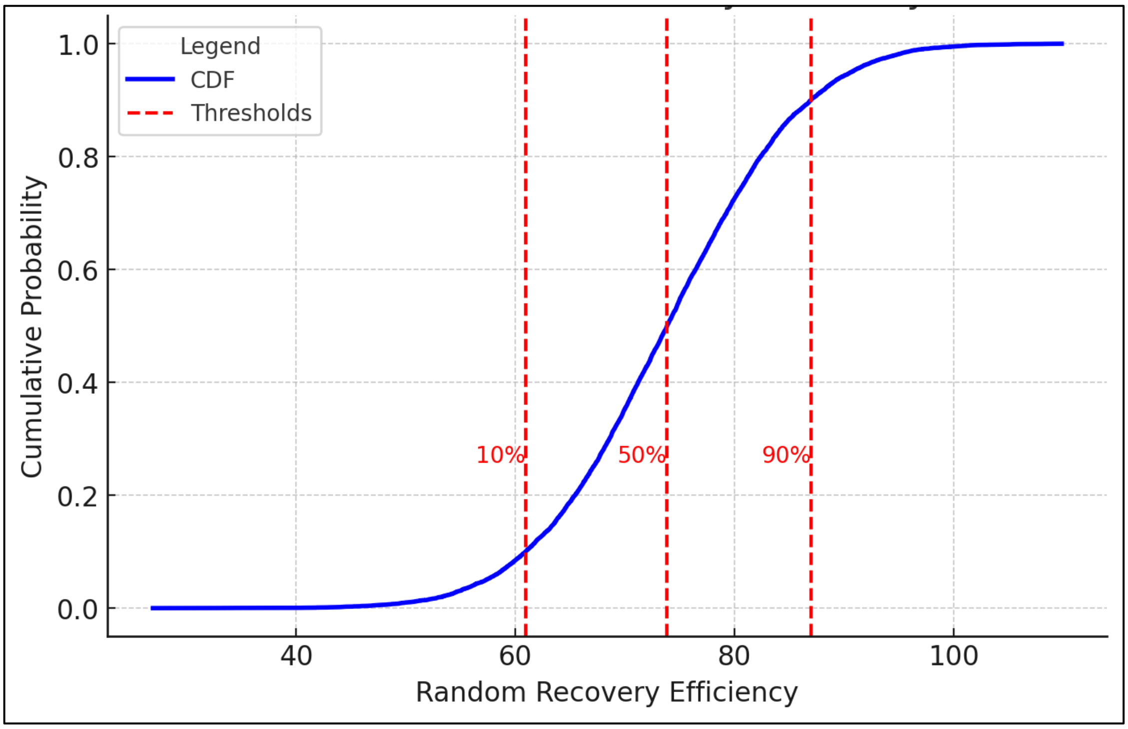

Figure 29: CDF of recovery efficiency

Table 6 summarises the slope and interpretation of each CDF for ease of readability.

Table 6: Summary of the Current State CDF Interpretations

Parameter	Slope / Shape	Interpretation
Processed tonnes	Moderately steep around median	Consistent throughput, values tightly clustered within a narrow range.
Feed grade	Gradual slope, wide spread	High variability with bias to lower grades, matches histogram's high stdev.
Recovered carats	Steep, concentrated	Stable recovery, carat values closely grouped.
Adjusted recovered carats	Flatter, more dispersed	Adjustments add variability to carat estimates.
Expected recovered grade	Gradual start, then steep rise	Moderate variation initially, stabilises at higher values.
Recovered grade	Smooth, slight skew to lower grades	Mostly consistent recovery, occasional low-grade outliers reflect inefficiencies.
Adjusted recovered grade	Very steep, highly concentrated	Stable adjusted recovery with minimal variation.
Model recovery	Very steep, narrow distribution	Reliable and consistent modelled recovery.
Recovery efficiency	Broad range, flatter slope	Greater variability, some cases over- or under-perform expectations.

The CDF results in Table 6 reinforce the histogram observations in Figure 12 to Figure 20 and summarised in Table 5. For processed tonnes, both analyses show moderate but consistent throughput, with a near-normal histogram distribution mirrored by a moderately steep CDF slope. Recovered carats are similarly stable, with a symmetrical histogram confirmed by a steep CDF curve tightly clustered around the median. However, adjusted recovered carats display greater variability in both tables, as reflected in the wider histogram spread and more dispersed CDF slope. Recovered grade and adjusted recovered grade show strong consistency, with low histogram standard deviations corresponding to steep, concentrated CDFs. By contrast, feed grade and recovery efficiency exhibit the widest spreads: right-skewed histograms with high standard deviations are matched by gradual, widely dispersed CDFs, confirming significant variability in ore quality and plant performance. Taken together, the consistency in Table 5 and Table 6 strengthens the conclusion that while throughput and grade recovery are generally stable, controlling ore quality and improving recovery efficiency remain the primary levers for reducing variability and optimising mine-to-mill performance.

4.2.8 Qualitative Results

This section presents a qualitative analysis of the impact of operational inefficiencies identified within the mine-to-mill value chain, based on insights gathered through interviews with key personnel. The interviews, conducted with engineers, operators, and supervisors across mining and processing functions, provided context-rich observations about how delays, equipment downtimes, poor fragmentation, stockpile mismanagement, and unstable plant operations affect overall performance. These firsthand accounts not only validated the quantitative findings but also revealed the underlying causes of inefficiencies, such as communication gaps, inadequate maintenance planning, and challenges in adhering to standard operating procedures (SOPs). The qualitative data helped highlight the practical implications of these inefficiencies on throughput, recovery rates, and resource utilisation, offering a deeper understanding of process disruptions and their impact on daily operations.

This subsection presents results of the interviews conducted. The interviews were focused on respondents' roles in operations, their insights into inefficiencies and bottlenecks, and their suggestions for improving productivity along the value chain. They also explored their familiarity with VSM and MCS for process optimisation. The results are presented based on the general theme of the interview question that were asked. The detailed question-by-question responses have been tabulated in Appendix E for reference.

The respondents outlined their roles within the mine-to-mill value chain, which encompass managing and overseeing the crushing plant, haulage and dispatch, blasting for optimal fragmentation, DMS, operating recovery equipment, and stockpile management and blending. Each of these functions plays a critical role in ensuring efficient material flow, optimised recovery, and overall process efficiency.

All respondents, based on their perceptions and observations, unanimously acknowledged significant inefficiencies within the mine-to-mill value chain, negatively impacting overall productivity. In loading and hauling operations, major challenges identified included low availability of haulage trucks and congestion on haul roads. Specifically, IR 1 noted frequent truck downtime due to delayed maintenance, disrupting ore movement. IR 6 further highlighted that congestion and delays were exacerbated during peak operation periods, particularly during shift changes and blasting re-entry times.

Blasting and crushing were also identified as critical areas with significant challenges. IR 2 reported that blasting frequently resulted in oversized material, slowing loading operations and reducing crushing efficiency. Additionally, IR 3 noted that improper boundary marking during blasting caused dilution of ore with waste material, negatively impacting downstream processing stages. At the DMS stage, IR 4 emphasised its sensitivity to fluctuations in density and pressure, resulting in significant diamond losses when not adequately controlled. Furthermore, IR 5 highlighted recovery-stage inefficiencies, particularly regarding delays caused by prolonged lead times for obtaining spare parts for X-ray sorting equipment. The delivery of essential recovery plant components could take several weeks, substantially affecting overall recovery rates.

The respondents exhibited varying levels of familiarity with VSM and MCS but collectively acknowledged their potential to enhance the mine-to-mill value chain. IR 7 emphasised that VSM could provide a clear visualisation of inefficiencies and aid in identifying areas of value loss. However, IR 3 noted that while VSM holds promise, its practical application has been limited so far. Regarding MCS, IR 4 highlighted its ability to offer insights into variability and recovery scenarios, while IR 5 underscored its usefulness in assessing the impact of operational changes. For example, operator concerns regarding haulage delays were validated by CDF results showing variability in processed tonnes, while interview insights on grade control aligned with histogram evidence of high feed grade spread.

4.2.9 Proposed Future State Map

Arbitrary 5% improvement on the mean was used and 15% on variability reduction. Variability reduction was based on findings from studies such as Adel et al. (2006b), who demonstrated that refining blasting practices and implementing process optimisation techniques in mine-to-mill initiatives can reduce performance variability by up to 20%. The 15% in overall operational efficiency was based on process enhancements that require no additional capital expenditure. Table 7 presents the current mean and standard deviation with the calculated future means and standard deviations.

Table 7: Optimised simulation input data

Metric	Current Mean	Future Mean (5%)	Current STDEV	Future STDEV (15%)
Processed Tonnes	875464	919237	123181	104704
Feed Grade	0.80	0.84	0.32	0.27
Recovered Carats	517169	543027	201546	171314
Recovered Grade	0.58	0.61	0.19	0.16

The future mean and future standard deviation figures in Table 7 were used in MCS. These were calculated using Equation 1 and Equation 2. Table 8 shows the standard deviations and means from simulated data. `

Table 8: Optimised data

	Optimised Random Tonnes	Optimised Feed Grade	Optimised Recovered Carats	Optimised Recovered Grade
Mean	918,669	0.84	545,524.70	0.61
STDEV	104,257	0.27	172,418.38	0.16
10th Percentile	785,573	0.49	321,185.77	0.39
50th Percentile	918,566	0.85	545,262.19	0.61
90th Percentile	1,161,008	1.47	948,052.63	0.98

From Table 8, the means and standard deviations of the parameters in the future state and their various percentiles are higher than those of the current state. Figure 30 to Figure 33 show proposed FSM histograms. The histograms were created using simulated data generated from Table 7.

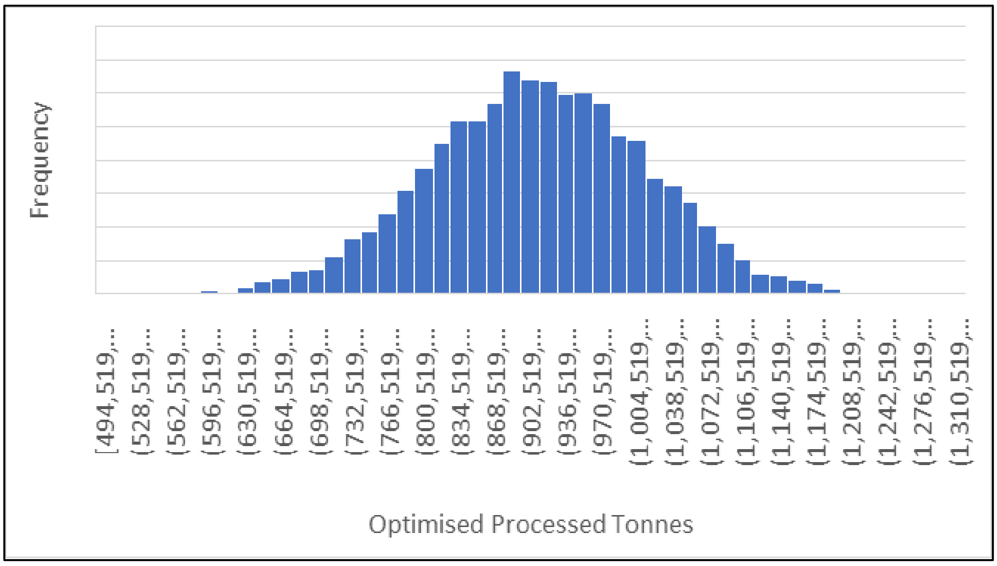

Figure 30: Optimised processed tonnes probability distribution

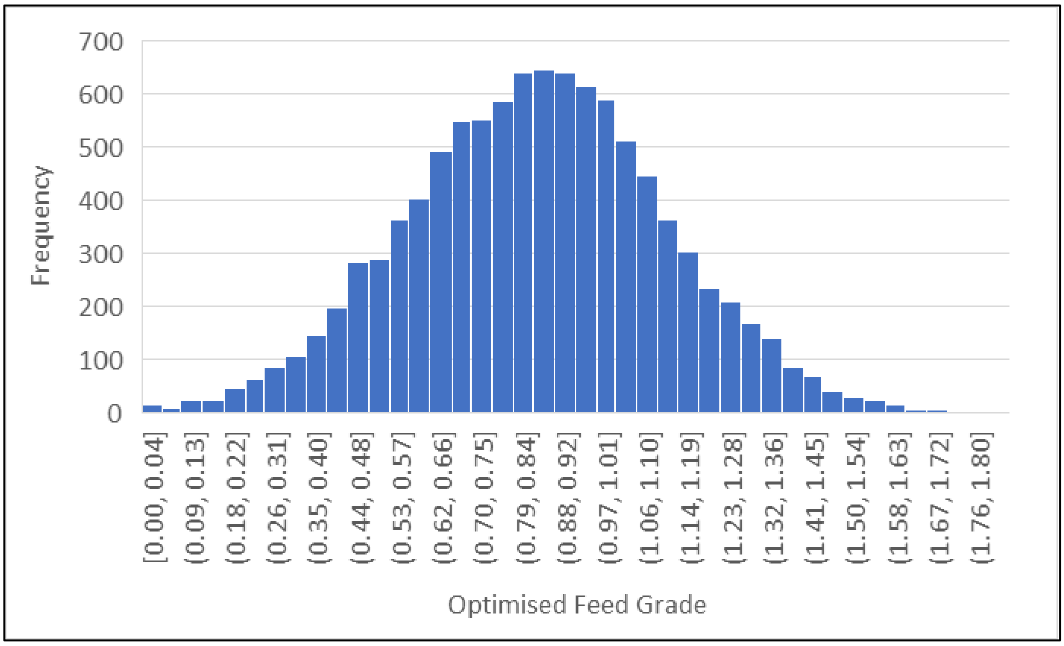

Figure 31: Optimised feed grade probability distribution

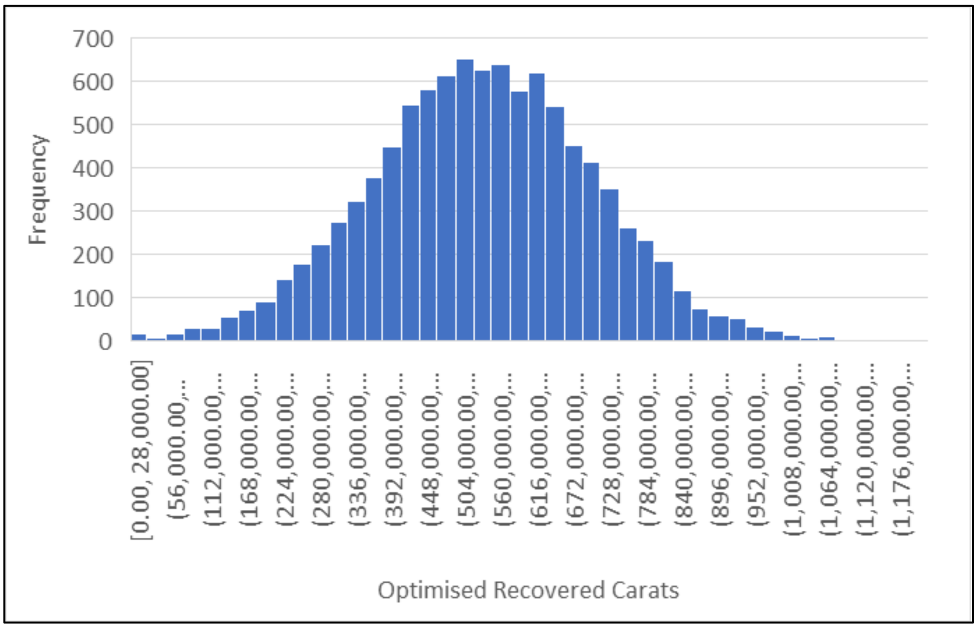

Figure 32: Optimised recovered carats probability distribution

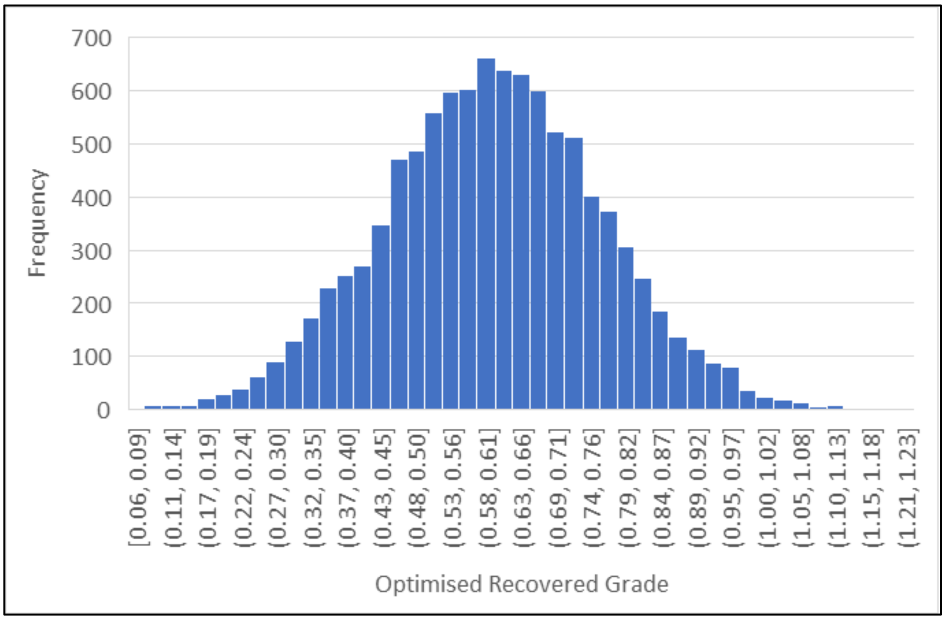

Figure 33: Optimised recovered grade probability distribution

Table 9 summarises the distribution patterns, central tendency, variability and key operational interpretations of the simulated outputs.

Table 9: Summary of the Future State Histogram Interpretations

Parameter	Slope / Shape	Mean	Median	Stdev	Range	Interpretation
Processed tonnes (t)	Symmetrical, steep around median	918,669 t	918,566 t	104,262 t	494,519 – 1,316,296 t	Balanced throughput with moderate variability, overall consistent production.
Feed grade (cpt)	Symmetrical, moderate spread	0.84 cpt	0.85 cpt	0.27 cpt	0.00 – 1.81 cpt	Even distribution around mean, noticeable variability with occasional extremes.
Recovered carats (ct)	Nearly symmetrical, dispersed	545,564 ct	545,262 ct	172,294 ct	0 – 1,212,080 ct	Central values consistent, wide spread highlights operational/geological variability.
Recovered grade (cpt)	Near-normal, steep	0.61 cpt	0.61 cpt	0.16 cpt	0.06 – 1.23 cpt	Stable and predictable recovery, minimal outliers confirm efficient performance.

From Table 9, the FSM histograms confirm that mine-to-mill performance improves in both stability and predictability compared to the CSM. Processed tonnes and feed grade show balanced, symmetrical distributions with means closely aligned to medians, indicating reduced bias and moderate variability. Recovered carats remain broadly consistent but still reflect some spread due to geological and operational factors though the mean and median values are tightly matched. Recovered grade demonstrates the strongest stability with minimal standard deviation and a narrow range confirming reliable plant performance. Overall, the FSM analysis shows more consistent throughput, better grade control, and stable recovery outcomes. These histogram results are further validated by the CDF interpretations in Table 10, which confirm the reduced variability and improved stability of the future state model. Figure 34 to Figure 37 present the future state CDF graphs.

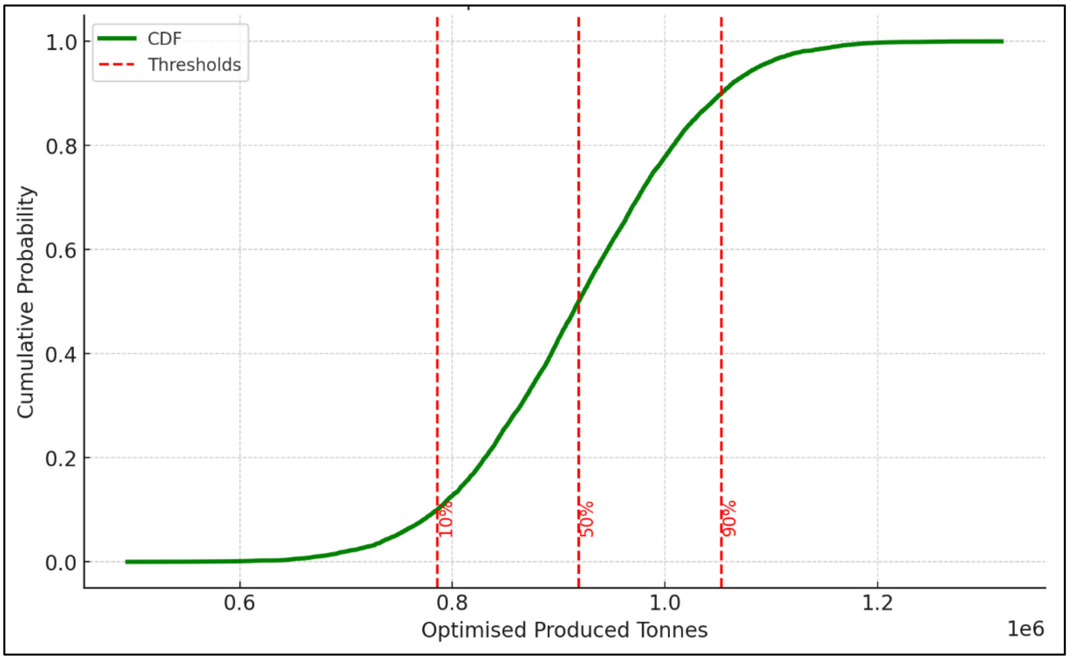

Figure 34: CDF of future state processed tonnes

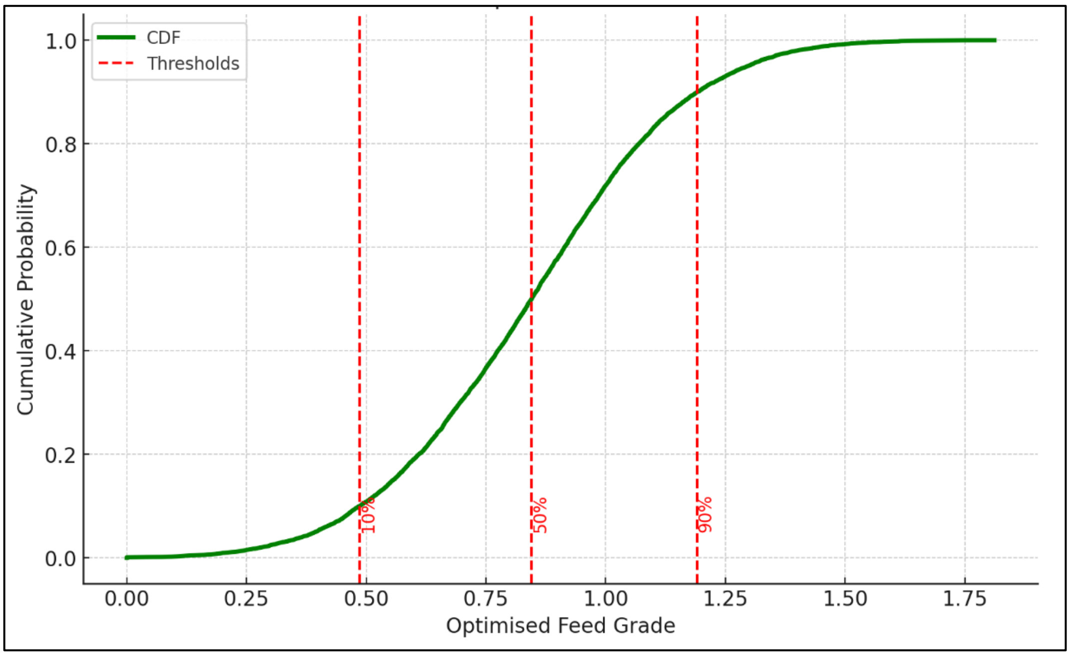

Figure 35: CDF of future state feed grade

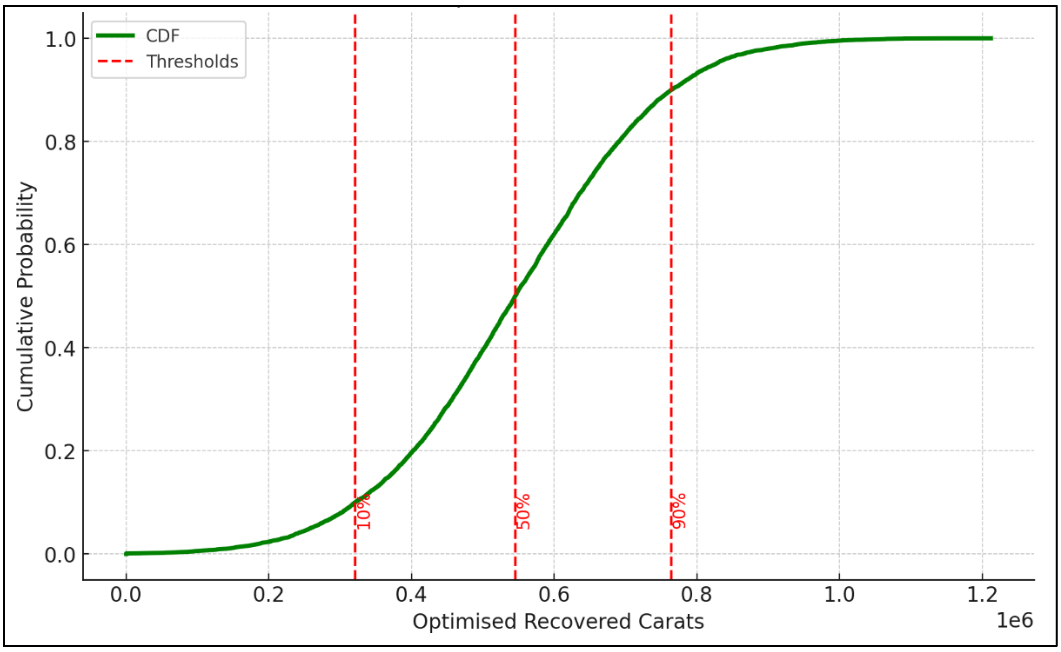

Figure 36: CDF of future state recovered carats

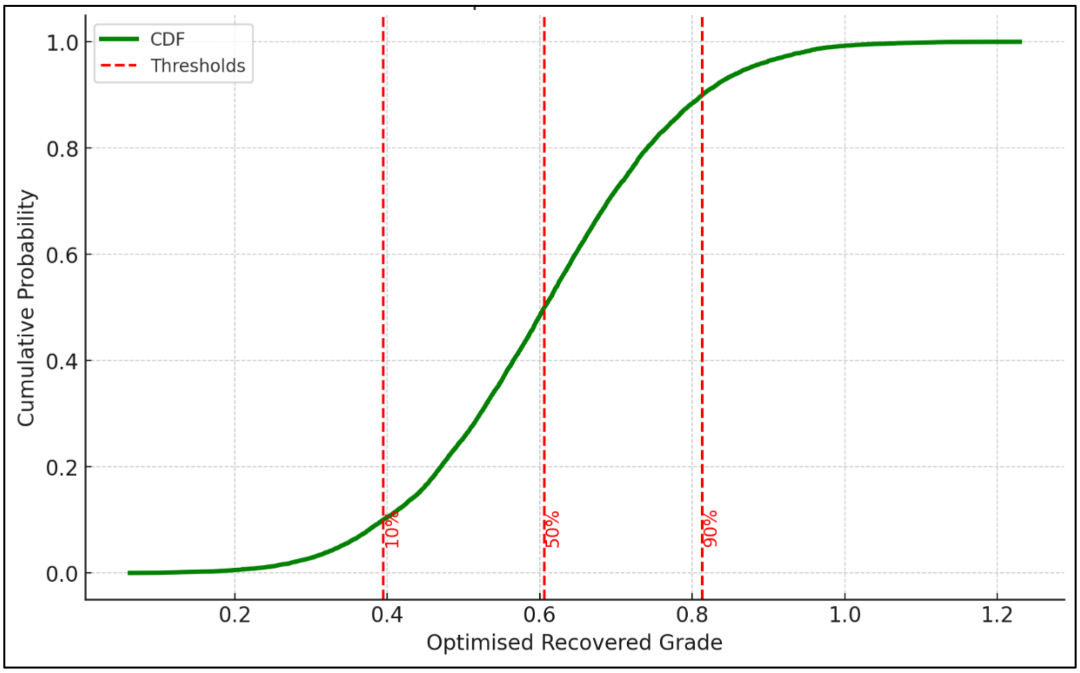

Figure 37: CDF of future state recovered grade

Future state CDF graphs interpretation is summarised in Table 10.

Table 10: Summary of the Future State CDF Interpretations

Parameter	Slope / Shape	Interpretation
Processed tonnes	Moderately steep, clustered	Values tightly grouped around the median showing consistent throughput and lower variability
Feed grade	Gradual slope, wide spread	Significant variability in grades highlighting less predictability ans inefficiencies in grade control
Recovered carats	Moderate steepness, dispersed	median recovery stable but wide spread shows substancial variability from external or geological factors
Recovered grade	Moderate steepness	Generally considtant recovery perfomance with occasional deviations at the extremes

The CDF results shown in Figure 30 to Figure 33 and summarised in Table 10 reinforce the histogram observations in Table 9. For processed tonnes, the symmetrical histogram with moderate variability aligns with a steep, tightly clustered CDF slope, confirming more consistent throughput in the FSM. Feed grade shows moderate variability in both tables. The histogram indicates a balanced distribution around the mean, while the CDF reveals a gradual slope and wider spread, highlighting ongoing uncertainty in grade control. Recovered carats demonstrate consistency across both analyses, with a near-symmetrical histogram supported by a moderately steep CDF centred on the median, although both highlight some external variability. Recovered grade shows strong stability, with low histogram standard deviation corresponding to a steep CDF slope, reflecting predictable performance. Overall, the alignment between Table 9 and Table 10 confirms that future state improvements are not only visible in higher mean values (like throughput and recovery) but also in reduced variability, thereby ensuring more reliable and predictable mine-to-mill performance. The difference between the current state and future state means and standard deviations is shown in Table 11.

Table 11: Changes between current and future state metrics

	Current State Mean	Future State Mean	Mean % Change	Current State Std Dev	Future State Std Dev	Std Dev % Change	Current State Median	Future State Median	Median % Change
Processed Tonnes	875,449.12	918,668.55	4.94	123,265.78	104,256.75	- 15.42	874,869.07	918,566.06	4.99
Feed Grade	0.80	0.84	5.43	0.31	0.27	- 13.32	0.79	0.85	6.62
Recovered Carats	516,327.17	545,564.21	5.66	196,520.86	172,294.35	- 12.33	516,653.64	545,262.19	5.54
Recovered Grade	0.57	0.61	5.84	0.19	0.16	- 12.59	0.57	0.61	5.87

Table 11 compares the current and future state models by analysing the percentage changes in mean, standard deviation, and median for processed tonnes, feed grade, recovered carats, and recovered grade. The increase in mean and median values across all parameters indicates an overall improvement in process efficiency. Meanwhile, the reduction in standard deviation suggests that operational variability has decreased, leading to greater stability and predictability. Processed tonnes and feed grade show the most significant improvements, highlighting the effectiveness of mine-to-mill optimisation strategies in enhancing throughput and ore quality. Figure 38 to Figure 41 show overlays between the current and future state CDF graphs for comparison.

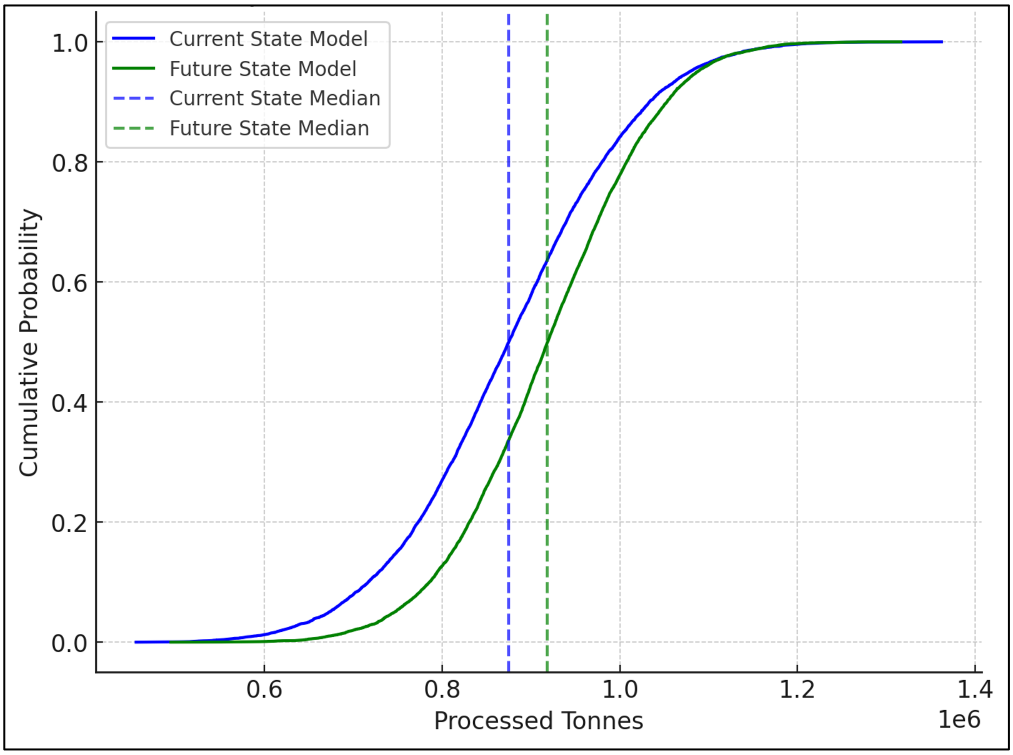

Figure 38: Overlay CDF of random processed tonnes

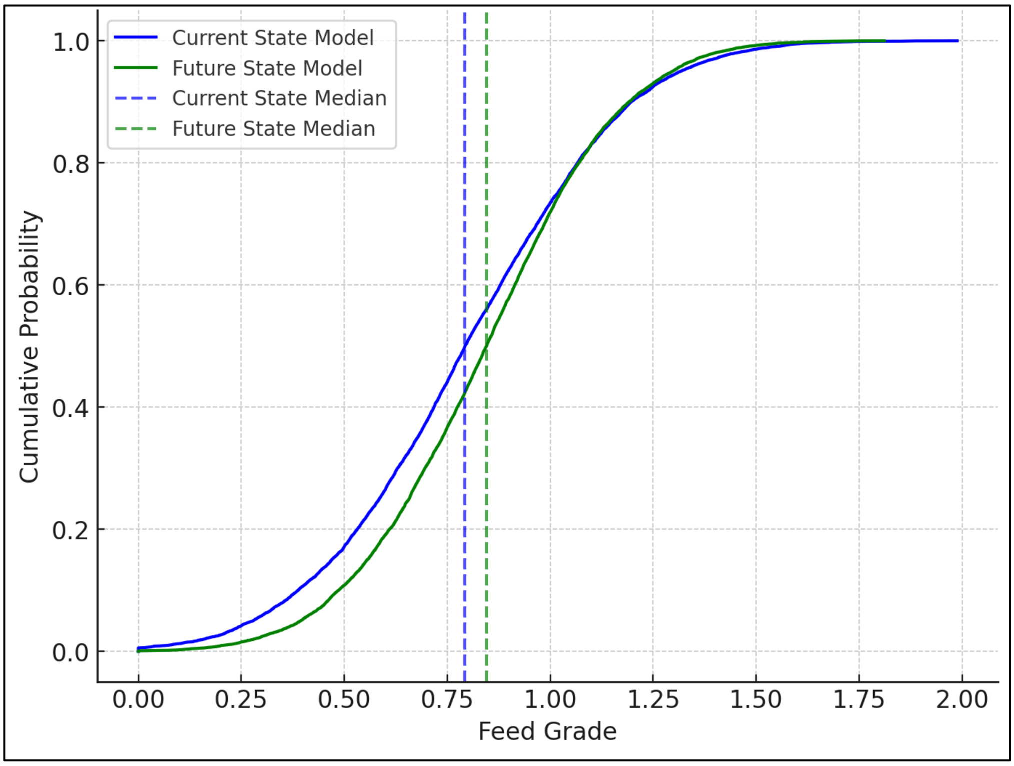

Figure 39: Overlay CDF of random feed grade

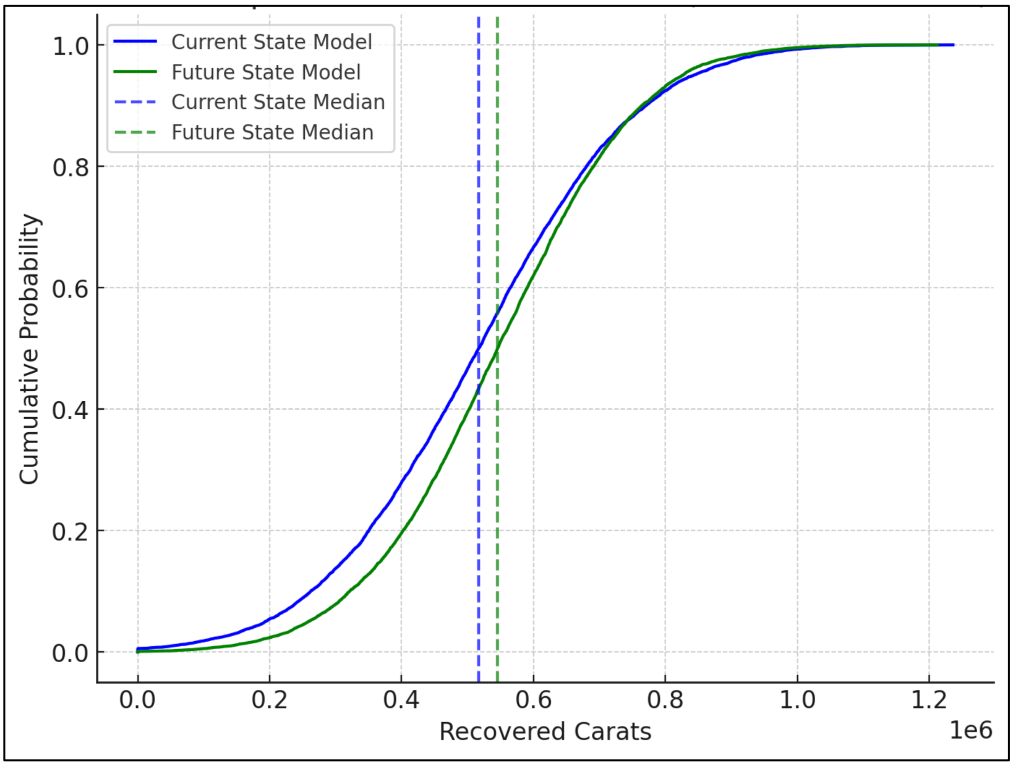

Figure 40: Overlay CDF of recovered carats

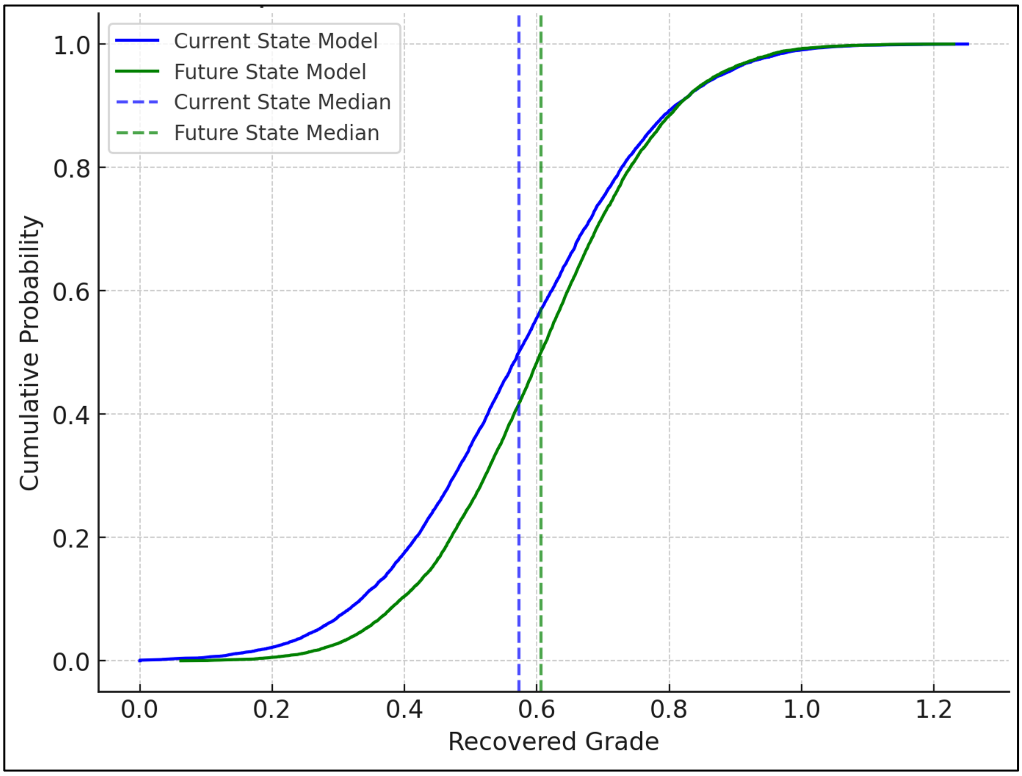

Figure 41: Overlay CDF of recovered grade

The CDF analysis comparing the current and future state models highlights notable improvements across key operational parameters, including processed tonnes, feed grade, recovered carats, and recovered grade. The future state model is consistently on the right, indicating increased throughput, higher feed grade, and improved recovery performance. Additionally, the steeper CDF slopes in the future state suggest reduced variability, ensuring more stable and predictable operations. The processed tonnes CDF (Figure 38) shows a clear increase in throughput in the future state model, with a higher median value confirming sustained improvements in processing capacity. The steeper curve suggests reduced variability, indicating that the optimised system achieves more consistent production levels. This improvement is likely due to enhanced haulage, crushing, and screening efficiency, ensuring better material flow through the mine-to-mill process. The feed grade CDF (Figure 39) demonstrates an increase in the quality of ore being fed into the system. The rightward shift indicates that improved ore selection and stockpile blending have resulted in higher average feed grades. The steeper slope further suggests that feed grade variability has been minimised, allowing for more consistent plant performance. This improvement enhances both crushing efficiency and DMS performance, leading to better recovery outcomes.

The recovered carats CDF (Figure 40) highlights an increase in the total number of recovered carats in the future state model, confirming the effectiveness of process optimisations. A higher median value indicates sustained improvements, while the reduced spread suggests greater consistency in recovery. These trends point to enhanced DMS separation efficiency, better recovery equipment performance, and reduced losses in the sorting process. The recovered grade CDF (Figure 41) also exhibits significant improvement, with a rightward shift confirming higher recovered grades. The future state model shows a steeper distribution, indicating reduced variability and more controlled recovery rates. These improvements suggest better liberation of diamonds, improved sorting efficiency, and more stable process conditions, leading to lower fluctuations in recovery performance.

Overall, the analysis indicates that mine-to-mill optimisation strategies, such as improved blasting fragmentation, stockpile management, and process control enhancements can lead to increased production efficiency, higher recovery rates, and greater operational stability. These conclusions are drawn from the observed bulk sample and validated through simulation. However, they should be interpreted as indicative rather than definitive. Confirmation across multiple blasts and extended datasets would be required to generalise these improvements to the entire operation. The proposed FSM is illustrated in Figure 42.

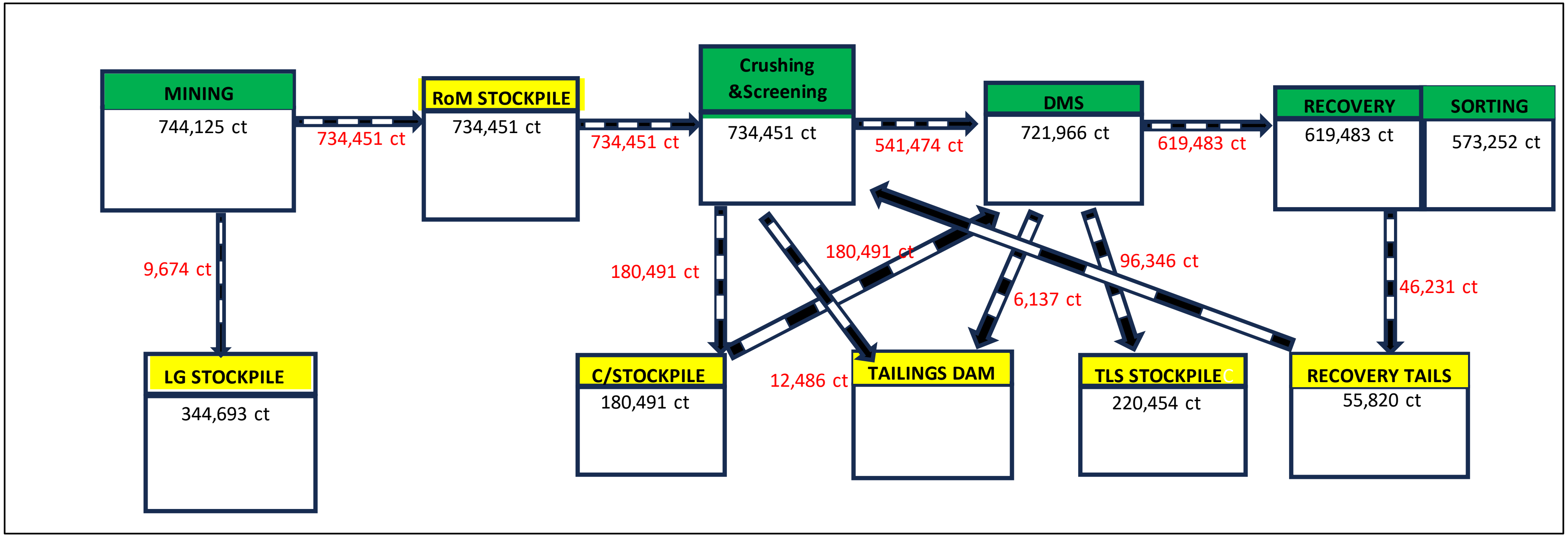

Figure 42: Proposed future state map carats flow

Figure 42 presents the FSM, illustrating an optimised mine-to-mill value chain with improved carat flow and streamlined operational performance. Compared to the historical data CSM, FSM dilution improved from 6% to 5.1% thereby increasing the diamonds sent to the processing plant. Carats lost to the tailings dam (fines), tailings stockpile and recon stockpile were all reduced. Annual average recovered grade improved from 0.59 cpt to 0.66 cpt and the recovery efficiency improved from 74% to 78%. To further evaluate the robustness of the PVSM outputs, a sensitivity analysis was performed on key parameters, including feed grade, recovery efficiency, and processed tonnes. The results, shown in Figure 43, illustrate the change in recovered carats when these parameters were varied by ±10%.

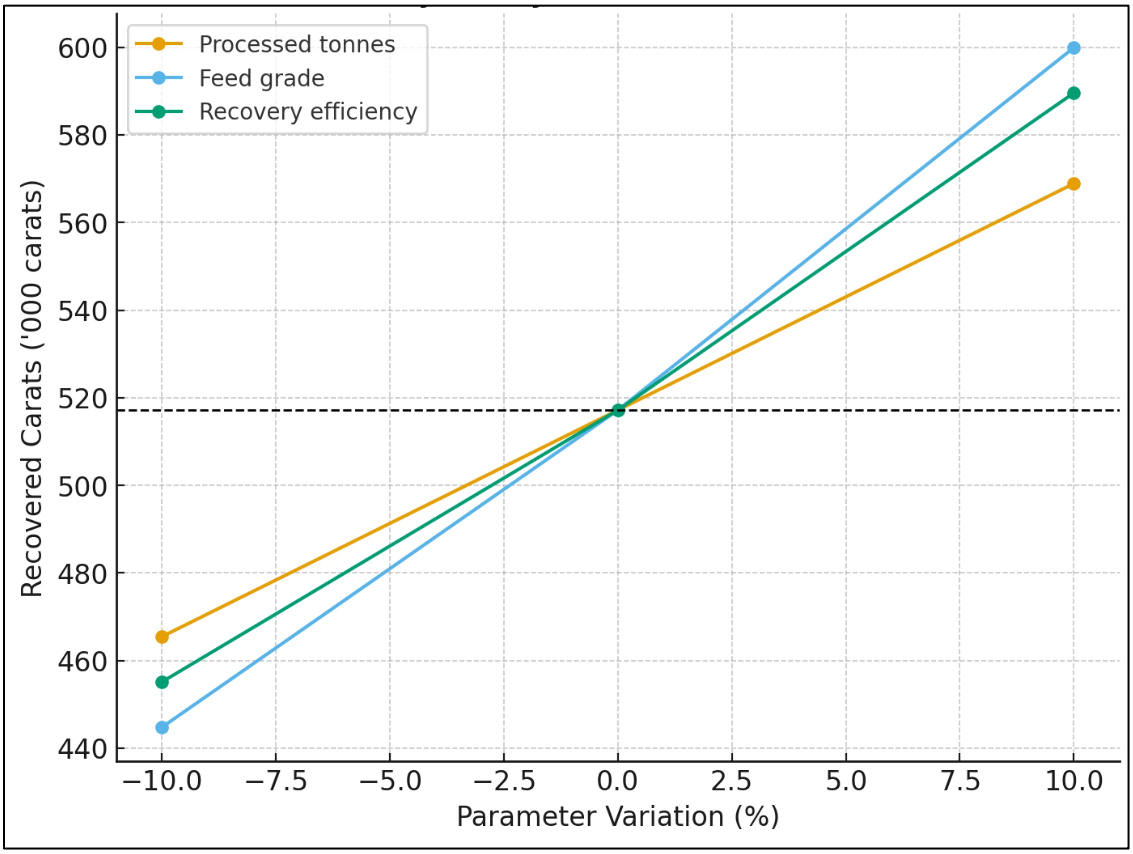

Figure 43: Sensitivity of Recovered Carats to Key Parameters

The sensitivity analysis shown on Figure 43 confirms that feed grade has the strongest influence on recovered carats, with a ±10% variation translating into a change of approximately ±83,000 carats. Recovery efficiency follows closely, where a ±10% change results in about ±72,000 carats difference. In contrast, processed tonnes have a comparatively smaller effect, with a ±10% variation yielding a shift of around ±52,000 carats. These results align with the histogram observations in Table 5, which showed high standard deviations for feed grade and recovery efficiency, and with the CDF results in Table 6 that revealed wide spreads for these parameters. Together, the findings confirm that controlling ore quality and stabilising plant recovery efficiency are the most critical levers for improving mine-to-mill performance, while throughput plays a secondary role.The numerical results of the sensitivity analysis are summarised in Table 12, which presents the percentage change in recovered carats when each parameter was varied by ±10%.

Table 12: Sensitivity of Recovered Carats to Key Parameters

Parameter Tested	Baseline	–10%	Effect on Recovered Carats	+10%	Effect on Recovered Carats
Processed tonnes (t)	875,469	787,922	–10% (–51,717 ct)	963,016	+10% (+51,717 ct)
Feed grade (cpt)	0.8	0.72	–14% (–72,403 ct)	0.88	+16% (+82,747 ct)
Recovery efficiency (%)	74%	66.60%	–12% (–62,060 ct)	81.40%	+14% (+72,403 ct)

Building on the sensitivity analysis findings, which identified feed grade and recovery efficiency as the most critical drivers of variability, the key improvements proposed focus on strengthening grade control, optimising recovery processes, and stabilising throughput. Enhanced blasting and stockpile management are recommended to reduce dilution and ensure consistent feed quality, while advanced process controls in the DMS plant will help stabilise recovery efficiency. In addition, predictive maintenance and improved equipment utilisation are expected to minimise downtime and support consistent material flow.

The deployment of advanced sorting technologies, such as XRT sorters, supported by AI-driven predictive analytics, offers further opportunities for improvement by enabling real-time adjustments. These include recalibrating sorter thresholds to match changing ore characteristics, optimising conveyor feed rates, and dynamically refining recovery cut-off points, thereby reducing losses and stabilising plant performance. Collectively, these measures address the primary inefficiencies identified in the current system and form the foundation of the proposed FSM for optimising mine-to-mill performance. While these technical improvements demonstrate clear potential to enhance throughput, grade consistency, and recovery, their economic viability is assessed separately in Section 4.3 through a detailed cost–benefit analysis..

4.3 Proposed Probabilistic Value Stream Mapping Strategy and Implementation Plans

The study utilised Lewin's Change Management Model to formulate a structured framework that aligns well with the implementation plan of PVSM outlined in the study, ensuring that the transition is effectively managed and sustainable. The three stages of the model which are: unfreeze, change, and refreeze, were proposed to guide the mine through the transformative process.

The unfreeze stage prepares employees for change by creating awareness and addressing resistance. In this context, training is anchored on PVSM, which highlights inefficiencies and variability in mine-to-mill processes. Practical sessions focus on drilling and charging accuracy to improve blast outcomes, ore–waste differentiation to reduce dilution, and material handling protocols to enhance loading, hauling, and stockpile management. By linking these skills to PVSM analysis, the workforce develops both awareness and competence, laying the foundation for effective implementation of change.

The change stage focuses on turning awareness into action by applying insights from PVSM to address bottlenecks in the mine-to-mill chain. Employees participate in workshops and collaborative sessions that not only diagnose inefficiencies but also promote ownership of solutions. A pilot test programme forms the core of this stage, targeting critical areas such as haul truck cycle times, crusher utilisation and choke management, DMS stability, stockpile blending, and recovery efficiency. Implementing improvements on a pilot scale allows processes to be refined and challenges resolved before full adoption. This emphasis on controlled testing and iterative learning reduces risk, encourages collaboration and ensures that employees are actively engaged in shaping the changes which increases the likelihood of long-term success.

Full-scale implementation of PVSM corresponds to the refreeze stage, where changes are institutionalised and the organisation stabilises into the new way of working. Scaling PVSM across the mine-to-mill value chain embeds improvements into operational culture by updating SOPs integrating key performance indicators (KPIs) such as throughput, dilution, equipment and plant utilisation and recovery efficiency into dashboards and embedding accountability in departmental performance reviews. The stage is reinforced through continuous monitoring and evaluation which track performance, highlight further improvement opportunities and mitigate the risk of reverting to old practices. Regular feedback sessions with employees strengthen commitment to the new processes and ensure that operational efficiency is sustained as part of the mine's culture.

In addition to the structured application of Lewin's model, the success of PVSM implementation depends heavily on stakeholder engagement and organisational alignment. The adoption of new practices such as predictive maintenance, advanced sorting, and AI and machine learning (ML), integration can encounter resistance if not supported by training, clear KPIs, and visible leadership sponsorship. Active involvement of supervisors, operators, and technical teams is therefore essential to ensure ownership of the changes, reduce resistance, and maintain momentum. Embedding feedback loops and recognition mechanisms further strengthens employee buy-in, ensuring that the transition is not only technically feasible but also organisationally sustainable.

4.4 Cost Benefit Analysis

In addition to technical feasibility, it was essential to assess the economic viability of the proposed optimisations. To evaluate the economic feasibility of the proposed interventions, a cost–benefit analysis was undertaken using the increase in recovered carats projected under the FSM relative to the CSM. Table 13 presents the results of this analysis, detailing the additional revenue expected from the recovered carats uplift, estimated implementation costs, and the resulting net benefit and payback period.

Table 13: Cost–benefit analysis of proposed FSM interventions

Item	Estimate (US$)	Notes
Additional recovered carats (FSM – CSM)	28,356 carats	Based on FSM vs CSM comparison (545,525 – 517,169)
Average selling price	120/ct	Case study mine management (2022 data)
Additional annual revenue (US$)	3,402,720	28,356 × US$120/ct
Implementation costs (Base Case) (US$)	2,880,000	XRT sorter upgrade (US$2.5M), AI/ML integration (US$300k), training
Net benefit (Year 1) (US$)	522,720	After deducting base-case implementation costs
Payback period	1 year	Revenue uplift covers investment within the first year

The cost–benefit analysis in Table 13 confirms that the proposed optimisations are economically viable. An additional 28,356 recovered carats translate into approximately US$3.4 million in revenue per year. After accounting for indicative implementation costs of approximately US$2.9 million, covering XRT sorter upgrades, AI and ML predictive analytics integration, automation enhancements, and training, the project will deliver a first-year net benefit of approximately US$0.5 million, achieving payback within the first year. From year two onwards, the optimisation provides sustained annual benefits of US$3.4 million, validating both the technical and economic feasibility of PVSM implementation. These financial gains reflect the impact of proposed actions such as improved blasting fragmentation, enhanced stockpile blending, and advanced process controls, which collectively reduce dilution, stabilise feed grade, and close the grade–recovery gap.

Overall, the FSM found that over 28,000 additional recovered carats per year (+5.5%), 7% higher recovery efficiency, and an 8% throughput improvement, can be realised translating into consistent long-term performance gains. The magnitude of these improvements is consistent with efficiency gains reported in other PVSM applications, such as platinum operations in South Africa (12–14% efficiency improvement) and iron ore operations in Australia (17% reduction in haulage cycle variability), suggesting that the approach is transferable across commodities. Finally, the inclusion of AI and ML integration within the implementation costs underscores their role in stabilising throughput, optimising ore blending, and enhancing recovery efficiency. AI-driven predictive analytics enable real-time detection of operational anomalies and adjustment of parameters such as sorter thresholds and DMS cut-points, while ML models improve feed grade consistency through smarter stockpile blending and predict equipment failures before downtime occurs. This not only supports the projected US$3.4 million annual benefit but also aligns the mine with global smart mining practices.

4.5 Chapter Summary

This chapter provided findings and analysis of the study on the optimisation of a diamonds mine's mine-to-mill value chain using value stream mapping. The findings revealed significant declines in production metrics between 2018 and 2022, including reductions in processed tonnes, feed grade, and recovery rates. Key inefficiencies were identified in load and haul, crushing, and DMS stages with bottlenecks caused by truck unavailability, road congestion, and ineffective stockpile management. These challenges were further exacerbated by poor fragmentation, oversized material, dilution, and inconsistent density control in the DMS plant leading to recovery losses and reduced throughput. Using PVSM, which integrates VSM with MCS, the study categorised activities into VA, NVA, and NNVA to provide a targeted framework for waste reduction while simultaneously capturing variability in operational performance. The CDF analyses revealed significant fluctuations in recovery efficiency and feed grade consistency, reinforcing the need for tighter operational controls. Respondent insights emphasised training, process standardisation, and advanced technologies like real-time tracking and X-ray sorting to address inefficiencies.

The sensitivity analysis confirmed that feed grade and recovery efficiency exert the greatest influence on recovered carats, highlighting them as critical levers for improving performance, while throughput played a secondary role. The cost–benefit analysis further demonstrated that the proposed optimisations are economically viable, with additional recovered carats translating into approximately US$3.4 million in annual revenue after implementation. The FSM focused on flow optimisation, process integration, and recovery efficiency incorporating optimised crusher settings, refined blasting parameters, predictive maintenance strategies, and enhanced fleet tracking. These improvements were guided by Lewin's change management model through training, bottleneck identification, pilot programmes, full scale implementation, and continuous monitoring offering a comprehensive roadmap for sustainable operational excellence.

5 CONCLUSION AND RECOMMENDATIONS

5.1 Overview of Chapter 5

This chapter consolidates the key findings, conclusions, and practical recommendations derived from the study, focusing on the optimisation of the mine-to-mill value chain at the case study diamond mine using PVSM. Additionally, recommendations for future research are provided to further expand on the methodologies and findings of this study.

5.2 Summary of Findings

This study identified several critical inefficiencies across the mine-to-mill value chain at the case study mine. The quantitative analyses, using PVSM highlighted that while processed tonnes remained relatively stable, substantial variability in ore grades and recovery rates contributed significantly to an average production shortfall of approximately 26% from 2017 to 2022. Historical data (2018–2022) further revealed notable fluctuations in feed grade and recovery efficiency, underscoring the necessity for tighter operational controls. In addition, if the block model used to forecast grades was inaccurate, this would further compound the observed variability, highlighting the importance of integrating robust grade control and reconciliation practices alongside operational controls.

The CSM process exposed multiple operational bottlenecks, including excessive material handling, poor stockpile management, inadequate haul road maintenance, and inconsistent availability of haulage trucks. Qualitative insights from semi-structured interviews and ethnographic observations complemented these quantitative findings, highlighting significant issues such as delays caused by truck downtime during maintenance, congestion during peak operational periods, and fragmentation challenges resulting from suboptimal blasting practices.

At the DMS stage, respondents consistently reported that fluctuations in medium density and pressure negatively impacted diamond recovery, resulting in frequent operational disruptions and significant diamond losses. Recovery stage efficiency was further compromised by delays in spare parts procurement for X-ray sorting equipment, substantially affecting overall diamond yield. These efficiency gains are broadly consistent with PVSM improvements reported in other commodities, such as 12% in South African platinum operations and 17% in Australian iron ore mines, confirming the transferability of the approach.

5.3 Conclusions

PVSM provides a robust framework for diagnosing operational inefficiencies, quantifying variability, and developing effective process optimisation strategies. Feed grade variability at the mining and stockpiling stages, equipment downtime across hauling and processing units, and inadequate stockpile management at the plant feed point emerged as significant contributors to operational inefficiencies. The analysis reinforced that standardising blasting practices, implementing advanced predictive maintenance, and adopting innovative digital technologies are essential for achieving sustainable operational excellence.

5.4 Limitations of research findings

While the study provides valuable insights into optimising the mine-to-mill value chain using PVSM, several limitations should be acknowledged. The following limitations highlight opportunities for future research:

1. Short observation period: Field observations were limited to 11 days, which, although covering both day and night shifts, may not fully capture the seasonal or long-term variability in mine operations.
2. Reliance on mine-generated data: The analysis depended on archival datasets from OpsData, survey reports, and geological block models. Any inaccuracies or biases in these sources would directly affect feed grade and recovery estimates.
3. Single bulk sample calibration: The FSM–CSM comparison was based on one bulk sample coupled with Monte Carlo simulations, which introduces the risk that results may not fully represent broader operational conditions.
4. Lack of pilot validation: No pilot validation programme was carried out to test simulated improvements in practice, limiting the extent to which the FSM results can be generalised with certainty.
5. Small interview sample size: Only seven respondents were interviewed out of fifteen invited, which, while providing meaningful insights, restricts the diversity of perspectives across all departments.
6. Conceptual technology assessment: Proposed enhancements such as AI-driven analytics and advanced XRT sorting were evaluated at a conceptual level only, without field validation, leaving their practical impact untested.
7. Challenges of probabilistic modelling: While PVSM provided robust insights into variability, its application in dynamic mining environments is constrained by computational demands and the need for advanced technical expertise. In this study,

these challenges were mitigated through structured sampling and iterative validation, but they remain a barrier for large-scale operational deployment.

5.5 Recommendations

To address the identified inefficiencies and enhance operational efficiency, the following recommendations are provided for the case study mine:

1. Standardise blasting practices to improve fragmentation, reduce oversized material, and minimise ore dilution. Improved blast quality will enhance downstream crushing and screening efficiencies, leading to more stable throughput.
2. Implement predictive maintenance and Internet of Things enabled real-time monitoring of equipment to proactively manage equipment health and reduce downtime. This will improve equipment availability and utilisation, particularly for critical haulage and processing units.
3. Upgrade and calibrate advanced sorting technologies like X-ray sorting and RFID tracking to enhance ore classification accuracy. Improved ore–waste separation will reduce dilution, improve feed grade, and ultimately raise recovery rates.
4. Deploy automated, real-time density and pressure control systems in the DMS plant to stabilise recovery rates. Enhanced process control will reduce fluctuations in diamond recovery efficiency and minimise carat losses.
5. Reconcentrate tails should be crushed and reintroduced into the processing circuit, enhancing recovery efficiency. This measure ensures that diamonds remaining in tails are recovered, thereby reducing waste and improving overall yield.
6. Foster a culture of continuous improvement through comprehensive training programmes in PVSM and TOC methodologies. Training in PVSM will equip employees to map processes, identify VA, NVA, and NNVA activities, and evaluate variability in throughput and recovery, while TOC will strengthen skills in identifying and managing bottlenecks. Together, these programmes will promote data-driven decision-making and sustained efficiency improvements.
7. Establish KPIs and regular feedback mechanisms to sustain improvements and maintain process stability. Clear KPIs, linked to throughput, dilution, recovery efficiency, and utilisation, will provide ongoing accountability and support continuous improvement.
8. Apply the Lewin's Change Management Model to successfully implement PVSM. This will ensure that employees are prepared for change (unfreeze), actively engaged in

process improvements (change), and supported to embed these practices into routine operations (refreeze).

9. Future work should include a structured pilot validation programme to test the FSM improvements under real operational conditions. Running a pilot on selected blocks or circuits would provide empirical evidence to confirm the accuracy of the simulated results, while also allowing adjustments to be made before full-scale implementation.

These integrated improvements will address identified inefficiencies holistically, significantly enhancing operational resilience and consistency across the mine-to-mill value chain. Future research should focus on:

- Evaluating the long-term impacts of PVSM and TOC methodologies on operational efficiency and profitability.
- Exploring the integration of AI-driven predictive analytics with PVSM models to dynamically optimise mining operations.
- Conducting comparative analyses across various mining contexts to assess the scalability and general applicability of PVSM and TOC approaches.
- Investigating environmental and sustainability outcomes associated with lean and probabilistic methodologies in mining.

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Appendix A: Simulated Data

Iteration	Random Tonnes	Random Feed Grade	Random Recovered Grade	Random Adjusted Recovered Grade	Random Expected Recovered Grade	Random Model Recovery	Random Recovery Efficiency
1	814,356	1.07	0.40	0.71	0.26	79.54	66.87
2	899,113	0.91	0.78	0.63	0.55	79.07	63.71
3	933,899	1.27	0.43	0.48	0.98	79.18	60.38
4	1,107,436	0.78	0.63	0.75	0.60	77.62	91.95
5	671,452	0.83	0.62	0.72	0.38	75.08	58.70
6	853,876	0.61	0.53	0.97	0.81	82.27	84.42
7	875,973	0.79	0.79	0.69	0.70	81.53	83.93
8	969,724	0.80	1.04	1.05	0.45	80.73	55.10
9	694,438	0.33	0.67	0.73	0.48	81.81	67.81
10	896,108	0.60	0.41	0.79	0.89	75.15	63.54
11	889,492	0.83	0.62	0.53	0.56	88.21	78.84
12	770,212	0.66	0.63	0.76	0.51	83.98	86.69
13	849,723	0.85	0.40	0.75	0.73	82.63	75.13
14	856,121	1.22	0.62	0.65	0.90	78.84	80.25
15	999,671	1.24	0.40	0.84	0.55	84.72	65.47
16	741,632	0.74	0.47	0.85	0.30	80.74	86.33
17	760,848	0.91	0.83	0.69	0.83	79.38	71.12
18	976,205	0.39	0.57	0.41	0.61	78.97	78.47
19	746,594	0.88	0.59	1.04	0.78	84.06	60.53
20	790,358	0.87	0.62	0.53	0.53	86.68	80.56
21	703,929	0.91	0.81	0.80	0.57	78.25	73.66
22	1,033,910	0.97	0.10	0.37	0.27	79.15	76.89
23	1,018,982	0.85	0.57	0.41	0.79	74.93	50.15
24	825,367	0.42	0.48	0.44	0.63	82.06	103.09
25	823,059	1.18	0.51	0.86	0.68	76.63	71.52
26	908,568	0.06	0.64	0.85	0.87	74.12	69.71
27	981,605	0.61	0.68	0.83	0.24	82.05	62.51
28	937,473	0.84	0.60	0.70	0.81	75.45	76.25
29	705,576	0.99	0.41	1.03	0.73	79.60	69.37
30	704,743	1.29	0.72	0.21	0.79	81.49	81.00
31	870,662	1.32	0.54	0.72	0.68	75.89	91.77
32	916,725	0.79	0.85	0.59	0.88	81.46	66.16
33	833,334	0.28	0.52	0.65	0.20	84.39	64.49
34	835,838	0.47	0.72	1.23	0.33	77.33	80.73
35	778,684	0.55	0.77	1.01	0.80	82.17	74.33
36	973,167	0.55	0.84	1.03	0.40	84.84	72.02
37	956,971	1.01	0.57	0.71	0.49	82.19	75.82
38	1,018,987	0.90	0.44	0.87	0.52	81.64	83.19
39	818,093	0.97	0.32	0.66	0.88	78.12	77.21
40	819,977	0.79	0.75	0.16	0.24	79.05	93.78
41	993,359	0.36	0.90	0.40	0.68	79.87	83.31
42	943,680	0.75	0.68	1.05	0.63	80.53	85.21
43	942,617	1.39	1.08	1.09	0.81	79.42	61.33
44	891,125	0.62	0.63	0.84	0.56	79.69	69.99
45	852,615	1.10	0.27	0.37	0.55	80.84	69.04
46	891,576	0.67	0.47	0.96	0.58	80.88	69.41

Appendix B: Optimised Simulated Data

Iteration	Optimised Random Processed Tonnes	Optimised Random Feed Grade	Optimised Random Recovered Grade
1	829,587	0.61	0.44
2	923,758	0.71	0.55
3	734,593	0.94	0.54
4	735,603	0.61	0.73
5	910,313	1.13	0.48
6	860,323	0.45	0.26
7	749,013	0.56	0.44
8	836,171	1.30	0.70
9	848,523	1.14	0.29
10	845,547	1.26	0.49
11	959,833	1.16	0.54
12	925,534	0.69	0.68
13	957,799	0.62	0.82
14	987,761	1.16	0.66
15	857,904	0.63	0.50
16	1,076,930	0.70	0.57
17	964,312	0.85	0.44
18	838,606	0.94	0.70
19	709,643	0.81	0.79
20	815,156	0.40	0.47
21	906,884	1.41	0.47
22	754,873	0.81	0.37
23	900,818	0.99	0.78
24	728,042	1.04	0.39
25	822,094	0.39	0.41
26	800,664	1.22	0.41
27	819,834	0.81	0.24
28	865,281	1.20	0.64
29	1,029,625	0.53	0.56
30	935,779	0.29	0.56
31	729,969	0.58	0.43
32	851,144	0.45	0.50
33	763,986	1.05	0.60
34	872,723	1.06	0.59
35	986,272	0.52	0.57
36	987,719	0.55	0.55
37	761,750	1.23	0.59
38	732,034	0.67	0.63
39	940,163	1.19	0.38
40	732,371	0.94	0.46
41	790,680	0.84	0.42
42	853,821	0.83	0.61
43	956,972	0.61	0.82
44	808,312	0.98	0.28
45	906,672	0.44	0.73
46	752,188	0.47	0.74

Appendix C: Interview Questions

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INTERVIEW GUIDE

DEAR PARTICIPANT,

I am carrying out a study on optimisation of a diamonds mine mine-to-mill value chain using Value Stream Mapping. All this information will be used solely for academic purposes. You are expected to remain anonymous and all your responses will be treated with highest confidentiality throughout the research process and after. In responding to this interview, I request you to be very objective and truthful in all your assessments. This interview guide has 4 sections (Section A to D) and you are required to answer all questions and your participation remains optional. I would like to thank you in advance for your positive contributions to the success of the project by your participation in completing this interview.

SECTION A: YOUR ROLE AND THE CURRENT MINE-TO-MILL PROCESS

1. Can you briefly describe your role at the mine.
2. In your view, how efficient is the current process of moving ore from the pit to the recovery plant? Where are the inefficiencies?
3. Which stage do you think is the most critical to the overall productivity of the mine's mine-to-mill value chain (drill and blast, load and haul, crushing, DMS, recovery)? Why?
4. What are the main bottlenecks you've observed in the value chain?

SECTION B: PROCESS LOSSES

1. From your experience, how consistent is the diamonds grade from the mining face to the mill?
2. What factors do you think lead to variations in the expected grade and the recovered grade during the process?
3. At which points in the process where do you notice a significant grade or tonnage loss or discrepancies? How do you think these issues can be solved?
4. Are there any current practices to manage optimize the grade or tonnage in the value chain?

SECTION C: VALUE STREAM MAPPING AT MINE X

1. How familiar are you with using Value Stream Mapping (VSM) as a tool for optimising processes?
2. Has Value Stream Mapping been applied at this mine? If so, how has it helped improve the mine-to-mill process?
3. What types of waste can you identify in the value chain? How can these be eliminated?
4. In your opinion, how could Value Stream Mapping further improve the efficiency in the value chain and the accuracy in reconciliation?

SECTION D: RECOMMENDATIONS FOR IMPROVEMENT

Based on your experience, what recommendations would you give to improve the overall efficiency and reduce losses in the mine-to-mill value chain

Thank you for your cooperation and support!!

Appendix D: Qualitative Data Collated Questionnaire Responses

	Interview Question	Coded Respondent	Response
	In your view, how efficient is the current process of moving ore from the pit to the recovery plant? Where are the inefficiencies?	IR 1	Not very efficient because of frequent mobile equipment breakdowns due to poor maintained practices of the equipment
		IR 2	The process is efficient. The only se back is the hauling capacity which is constrained by the haulage road width.
		IR 3	The current process is efficient to some extent. Inefficiencies are: i. Blasting (dilution), ii. Incorrect hauling to stockpiles, iii. Pulverising at crushing, iv. Incorrect DMS parameters, v. X-Ray inefficiencies.
		IR 4	The current process is marred by inefficiencies due to the low availability (%) of haulage trucks... most of them spent long hours in the workshop due to unavailability of spares.
		IR 5	We try by all means to efficiently haul ore from the pit to the ROM pad. However, the process solely depends on human monitoring. And humans tend to make some errors. From the loading of ore and waste, number of hooters are used by the excavator operator to signal the truck operator of the stockpile to haul the material to. One hooter means ROM pad, two means low grade and three means waste dump. If the truck operator isn't attentive, he might send wrong material to the wrong stockpile. We sometimes see waste or low-grade loads at the ROM pad. This affects the feed grade and consequently the recovered grade. The mined blocks have different block grades; thus, the material is to stockpiled separately. Mixing up the ores affects blending ratios and subsequently the reconciliation process.
		IR 6	The efficiency of moving ore from the pit to the recovery plant depends on factors like equipment reliability, ore blending practices, and logistics coordination. Some common inefficiencies include: • Fragmentation issues: Inconsistent blasting practices can lead to oversize material that slows down crushing and screening. • Truck cycle times: Congestion or delays in haul roads, loading points, or stockpile management can disrupt the flow of ore. • Stockpile management: Ineffective blending at stockpiles can lead to feed variability, affecting plant performance and diamond recovery. Communication gaps: Misalignment between mining and plant teams can result in suboptimal feed delivery schedules, causing downtime or underutilization of equipment.
		IR 7	The current process is not very efficient. This is so as it involves the use of trucks that in turn have their own efficiency issues... Use of a conveyor would be most suited.
	Which stage do you think is the most critical to the overall productivity of the mine's mine-to-mill value chain (drill and blast, load and haul, crushing, DMS, recovery)? Why?	IR 1	I think it is the drill and blast because you have to get the right fragmentation for your loading and hauling capabilities and also your primary crushers. If you fail to get the right fragmentation it will mean secondary blasting which will be an extra cost to the business and delay as well.
		IR 2	Drill and blast are the most critical. The product of the blast (Fragmentation) determines the cost of the following activities. Good fragmentations ensure good digging and hauling, minimises crushing or lowers crushing cost.
		IR 3	All stages are critical... I would say the DMS is slightly more critical. If parameters are not met, you either get less sinks thereby recovering less diamonds in turn losing the diamonds to the tailings.
		IR 4	The Drill and Blast stage is the most critical... If we optimise this process, for example blast the section with high grade ore, we have the capacity to improve the whole value stream.
		IR 5	All processes are interlinked and have a role to play in the Value Chain. However, I think the most critical stage is in the plant, both the liberation and separation processes. No matter the effort put in the pits, if we do not liberate the diamonds and properly separate them from the gangue material then productivity is affected because final product is the diamonds (carats)

Appendix E: Primary Results of a Bulk Sample Run

Process	Activity	Tonnage (t)	Grade (cpt)	Material Description
Mining	Blasted ore plan	14,560	0.51	Blasted ore material in the pit
	Blasted ore actual	15,462	0.48	
	Loading and Hauling to RoM stockpile	13,687	0.51	Blasted ore material extracted and hauled to the the RoM stockpile
	Loading and Hauling to low-grade stockpile	1,775	0.25	Blasted ore transported to the low grade stockpile
	RoM stockpile Opening Balance	7,863	0.44	Material already on the stockpile
	RoM stockpile Closing Balance	6,600	0.44	Material remaining in the stockpile after plant feed
	Low Grade Stockpile Opening Balance	1,521,934	0.22	Low grade ore stockpile composing of P1 and P2 material
	Low Grade Stockpile Closing Balance	1,523,709	0.22	
Processing	**Crushing and Screening**	14,950	0.50	Size reduction for plant feed
	Crushing and Screening Fines	2,990	0.05	Very fine material from the crushing circuit flushed to the tailings dam
	DMS direct feed	9,180	0.62	Material from crushing and screening, fed direct to the DMS using conveyors
	Crushed Stockpile	2,780	0.62	Materail from the crushing and screening plant which could not go straight to DMS due to DMS capacity
	DMS	11,960	0.62	Crushed material from the crushing and screening plant
	Tails Stockpile	10,046	0.12	Diamond bearing material with low density awaiting further processing
	Tailings Dam	1,794	0.05	Slurry from the DMS plant
	Reconcentration	120	51.30	Concentrated material sent to the 10 tonne DMS
	Tails Stockpile Opening Balance	970,265	0.12	
	Tails Stockpile Closing Balance	980,311	0.12	
	Recovery	120	51.30	DMS concentrates
	Recon Tails	120	14.30	Coated diamonds that are not fluoroscent enough to pass as diamonds
	Recon Tails Opening Balance	2,312	16.40	Tailings from the 10t DMS and the recovery plant
	Recon Tails Balance Balance	2,432	16.30	
	Sorting	4416 carats		Hand sorting and cleaning of diamonds

Appendix F: January 2018 to June 2021 Monthly Production Figures

Monthly Production Figures						
Month	Processed Tonnes	Model Grade	Recovered Grade	% of Carats delivered to plant per ore domain		Adjusted Recovered Grade
				P1 %	P2 %	
Jan-18	85,700	1.32	0.7	0	100	0.93
Feb-18	68,420	1.2	0.58	0	100	0.77
Mar-18	90,286	1.27	0.54	16	84	0.72
Apr-18	79,403	1.32	0.57	0	100	0.76
May-18	97,000	1.32	0.73	0	100	0.97
Jun-18	97,137	1.25	0.75	0	100	1.00
Jul-18	107,554	1.06	0.71	0	100	0.95
Aug-18	97,687	1.27	0.42	0	100	0.56
Sep-18	64,784	1.3	0.48	0	100	0.64
Oct-18	72,853	1.31	1.1	0	100	1.47
Nov-18	76,948	1.31	1.09	0	100	1.45
Dec-18	77,318	1.29	1.04	0	100	1.38
Jan-19	75,731	1.44	0.88	0	100	1.18
Feb-19	62,821	1.37	0.96	0	100	1.28
Mar-19	71,892	1.33	0.95	0	100	1.27
Apr-19	78,036	1.39	0.83	0	100	1.11
May-19	55,370	1.39	0.96	0	100	1.28
Jun-19	68,582	1.39	0.96	0	100	1.28
Jul-19	90,011	0.75	0.71	96.2	3.8	0.86
Aug-19	82,473	0.84	0.67	100	0	0.81
Sep-19	64,595	0.75	0.68	100	0	0.82
Oct-19	68,179	0.76	0.65	100	0	0.78
Nov-19	70,004	0.76	0.64	100	0	0.77
Dec-19	70,697	0.75	0.65	99.5	0.5	0.78
Jan-20	70,050	0.77	0.65	53	47	0.82
Feb-20	71,352	0.61	0.57	100	0	0.69
Mar-20	80,696	0.64	0.5	100	0	0.6
Apr-20	82,681	0.47	0.42	94	0	0.51
May-20	92,105	0.63	0.52	81.2	18.8	0.64
Jun-20	82,559	0.68	0.51	76	24	0.63
Jul-20	85,882	0.91	0.58	59	41	0.73
Aug-20	82,527	0.71	0.67	100	0	0.81
Sep-20	81,883	0.99	0.74	100	0	0.89
Oct-20	84,726	0.75	0.71	100	0	0.86
Nov-20	67,902	0.71	0.66	100	0	0.8
Dec-20	63,747	0.69	0.73	100	0	0.88
Jan-21	52,370	0.67	0.56	100	0	0.67
Feb-21	65,777	0.48	0.61	99.3	0.7	0.74
Mar-21	78,279	0.79	0.65	78	22	0.8
Apr-21	79,315	0.8	0.76	69	31	0.94
May-21	64,888	0.75	0.48	77	23	0.59
Jun-21	78,590	0.83	0.44	61	39	0.55