CONSTRAINT RANKING THROUGH SYSTEM MODELLING OF THE SUBLEVEL CAVING PRODUCTION CYCLE AT FINSCH DIAMOND MINE

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DECLARATION

I declare that this report is my own, unaided work. Where use has been made of the work of others, it has been duly acknowledged. The work has not been submitted for any degree or other purposes. I have read the University Policy on Plagiarism and hereby confirm that no plagiarism exists in this report. I also confirm that there is no copying, nor is there any copyright infringement. I willingly submit to any investigation in this regard by the School of Mining Engineering, and I undertake to abide by the decision of any such investigation.

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ABSTRACT

Finsch Diamond Mine (FDM) is a sublevel caving (SLC) operation in the Northern Cape province of South Africa and is owned by Petra Diamonds Limited. The mine was experiencing challenges in achieving its planned production throughput of 280 000 tonnes per month. In addition, it was also facing an increase in unit operating costs and low diamond prices. Consequently, the mine carried out two analytical and optimisation studies in 2018 and 2019, and managed to optimise some operational facets. However, the two studies have fallen short in optimising the production cycle of FDM and reaching the planned production throughput. This research study was therefore undertaken to identify and rank the production cycle input parameters that are the most influential constraints prohibiting FDM from reaching its optimal production efficiency. The Theory of Constraints (TOC) was the main approach used during the study to identify, rank and ultimately make suggestions to eliminate the most influential production cycle constraints. The TOC was chosen as it has a five-step systematic approach to identify constraints and improve the efficiency of a system. It was very important to identify the correct constraints successfully, as it helped to focus and prioritise optimisation projects. Optimisation projects can either be extremely expensive or turn out unsuccessful if focus is placed on the wrong constraints.

To solve the problem, the study's objectives included the preparation of data for the use in, and calibration of, a reliable simulation model of the mine. The data was then used in a software programme called Simio where discrete-event simulation experiments on the production cycle input parameters were run, and compared to a baseline simulation value. The TOC was applied by assuming each time that a parameter might be a constraint. This was followed by testing if it is by incrementally decreasing and increasing its utilisation or influence, and measuring the production output during the second and third steps of the evaluation. Some parameters had to be taken to the fourth step where it was elevated by increasing the number of machines for example. The last step of the TOC was to repeat the process and find a new constraint, as was done in the first step. By exploiting, synchronizing or elevating an assumed constrained, it was not only possible to determine if an input parameter can be listed as an identified constraint, but it could also be ranked on the basis of its magnitude of influence on the production output tonnage. The use of simulation was chosen because it is highly representative of reality and the most cost effective way to experiment with a system that consists of multiple objects, actions and parameters. Furthermore, qualitative discussions and an analysis of historical data were also used in the study to identify other constraints that could not be identified through simulation. A preliminary constraint ranking was created from the simulation runs which created an ideal framework to evaluate parameters in more detail by means of adding historical data to support analyses and arguments.

After presenting and discussing the results from the simulation runs, historical data analysis, and qualitative discussions, the following constraint ranking was established (most influential to less):

- Scheduled production time.
- Number of Load, Haul and Dump (LHD) equipment in use.
- Tunnels available for loading.
- LHD load capacity in tonnes.
- LHD tramming speed.
- Number of production days scheduled.
- Number of drill rigs in use.
- Drilling quality.
- Charging and blasting quality.
- Tip availability.

It was apparent after the ranking that the available production time, the number and performance of LHD equipment in use, and the availability of ore are core to a successful SLC production cycle. The ranking may seem relatively obvious; however, a more detailed discussion about each listed constraint is presented in the research project.

The final constraint ranking was followed by concluding remarks and recommendations to improve the simulation model and possible solutions to reduce or eliminate the ranked constraints. The main recommendations were that the approach presented in this study should be used as the precursor for any optimisation study at FDM in the future, and that the constraint ranking should also be core to any optimisation projects to focus and prioritise effort. Other recommendations were focused on improving the simulation model by adding for example, more qualitative logic, including precursory activities and adding the ability to change the time horizon of the model. More focus was placed on recommendations and solutions to reduce or eliminate the ranked constraints and included some of the following:

- Introduction of a 12-hour shift and a 4-day compressed workweek, with a second blasting opportunity.
- Reduction of pre- and post-production delays with the assistance of digital technology.
- Introduction of remote operation capabilities to increase loading and drilling time.
- Utilising tablets and task management/scheduling software to assist in short-term interval control.

- Maintaining the operation of nine LHDs in each shift, and always have swing units and tunnels available on each production level.
- Upgrading the quality of the roadways and introduce mobile rail-mats in each draw point.
- Review the drilling and blasting practice to achieve better blasts.

Some constraints are complex enough that major studies can solely be conducted on them in the future. The ranked constraints and recommendations remain a guideline to improve the production cycle at FDM and assist in future optimisation studies or projects.

ACKNOWLEDGEMENTS

Several people assisted in the successful completion of this project, and their guidance has been invaluable in this regard. I want to sincerely thank the following individuals and organisations for the fundamental roles they played during this research study:

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- Mr F. van Huyssteen (Business Development Director, Process Design and Automation), for the training he gave me on Simio, for designing the FDM Simio model, assisting in the calibration phases of the model and his valuable guidance throughout the simulation process.

- Mr J. Langenhoven (Senior Mine Planner, Finsch Diamond Mine), for guiding me to successfully extract simulation input data from the multiple systems that collect data on the mine and furthermore, for sharing his extensive knowledge about mining and the optimisation of production processes.

- Mr P. Leeuw (Senior Lecturer, University of the Witwatersrand), for co-supervising, guiding and reviewing my research proposal, draft report and final report.

- Prof C. Musingwini (Head of School, University of the Witwatersrand), for his supervision and guidance during the write-up of my research proposal and reviewing the draft chapters of my research report and final report.

DEDICATION

I want to dedicate this research to my late mining supervisor and mentor, Mr Deon Stander (Senior Training Officer: Mining), who sadly passed away during my studies in the middle of 2019 - after 45 years of service at Finsch Diamond Mine. Mr Stander always motivated me to keep going, particularly when times were tough, and the road ahead looked uncertain. He assisted me in turning my dreams into a reality, and I will forever be grateful.

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LIST OF ABBREVIATIONS AND UNITS

Abbreviations

4IR	Fourth Industrial Revolution
ANFO	Ammonium Nitrate Fuel Oil
BC	Block Caving
CAD	Computer-Aided Drawing
FDM	Finsch Diamond Mine
IoT	Internet of Things
IoS	Internet of Services
LHD	Load-Haul-Dump equipment
LiDAR	Light Detection and Ranging
LOM	Life of Mine
PDL	Petra Diamonds Limited
ROM	Run-of-Mine
SCADA	Supervisory control and data acquisition
Simio	Simulation Modelling framework based on Intelligent Objects
SLC	Sublevel Caving
TOC	Theory of Constraints

Units

ct	carats
R	South African Rand
t	tonnes
tpd	tonnes per day
tpm	tonnes per month
US$	United States Dollar

1. INTRODUCTION

1.1 Overview of Chapter 1

Chapter 1 introduces the research topic background, the challenges experienced by Finsch Diamond Mine (FDM), how the problem was identified, and the research study goal. In Section 1.2, background information is given about the research topic, highlighting the challenges experienced at FDM that led to the research topic being pursued. The research problem is stated in Section 1.3, which summarises the problem to be solved. In Section 1.4, the purpose and value in solving the problem are explained. Section 1.5 presents the motivation behind researching the problem, followed by the fundamental research question answered from the study in Section 1.6. Then section 1.7 outlines the aim and objectives, and provides insight into the main focus points that can be expected in the research report. Lastly, the content of the remaining chapters in the report is described in Section 1.8.

1.2 Background information

Finsch Diamond Mine mines a diamondiferous kimberlite deposit and is a sublevel caving (SLC) operation. SLC requires a lot of planning, execution discipline and organisation to ensure strategic objectives are achieved. FDM is a highly mechanised and digitally-enabled mine, but must continuously innovate and optimise all facets of the mine to remain competitive and sustainable.

FDM is owned by Petra Diamonds Limited (PDL), and the company invested a significant amount of funds, financed through debt (US$650 million bond), dating back to 2015 up to the time of this study. The debt was acquired to develop the mines in its portfolio, with the increase in net debt being illustrated in Figure 1.1. To reduce its debt, PDL launched a multi-pronged initiative to increase the efficiency of all its operations, increase production tonnages and reduce costs (Petra Diamonds Limited, 2019).

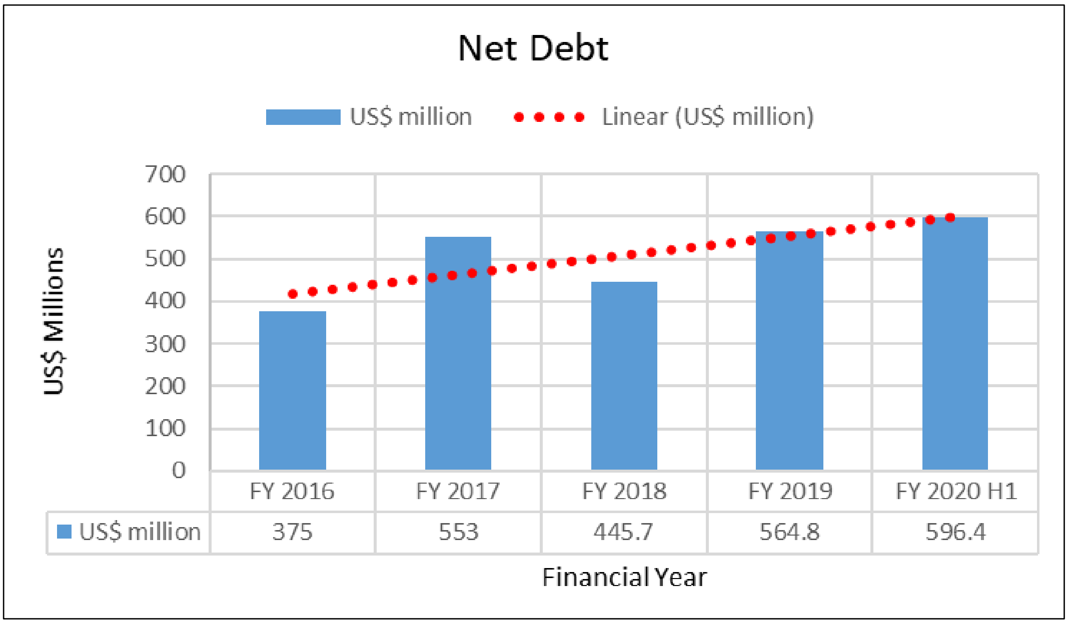

Figure 1.1 An illustration of the increase of net debt at Petra Diamonds Limited from the 2016 to the 2020 financial years (Petra Diamonds Limited, 2020; Petra Diamonds Limited, 2019; Petra Diamonds Limited, 2018; Petra Diamonds Limited, 2017; Petra Diamonds Limited, 2016).

Besides the significant debt challenge, the global decrease in diamond prices is also a major problem for the company (Figure 1.2). Locally, the price of FDM diamonds has fallen from about US$101/ct in 2017, to about US$79/ct in 2020 (Figure 1.3). Furthermore, the mine's unit operating costs increased from about R253/t in 2017 to about R388/t in 2019 (Figure 1.3). The combination of these two financial factors was affecting the mine's ability to add value to PDL's mission to reduce debt and increase value for all stakeholders.

Figure 1.2 Diamond price index from January 2018 to January 2020, showing the significant fall in diamond prices (Index, 2020).

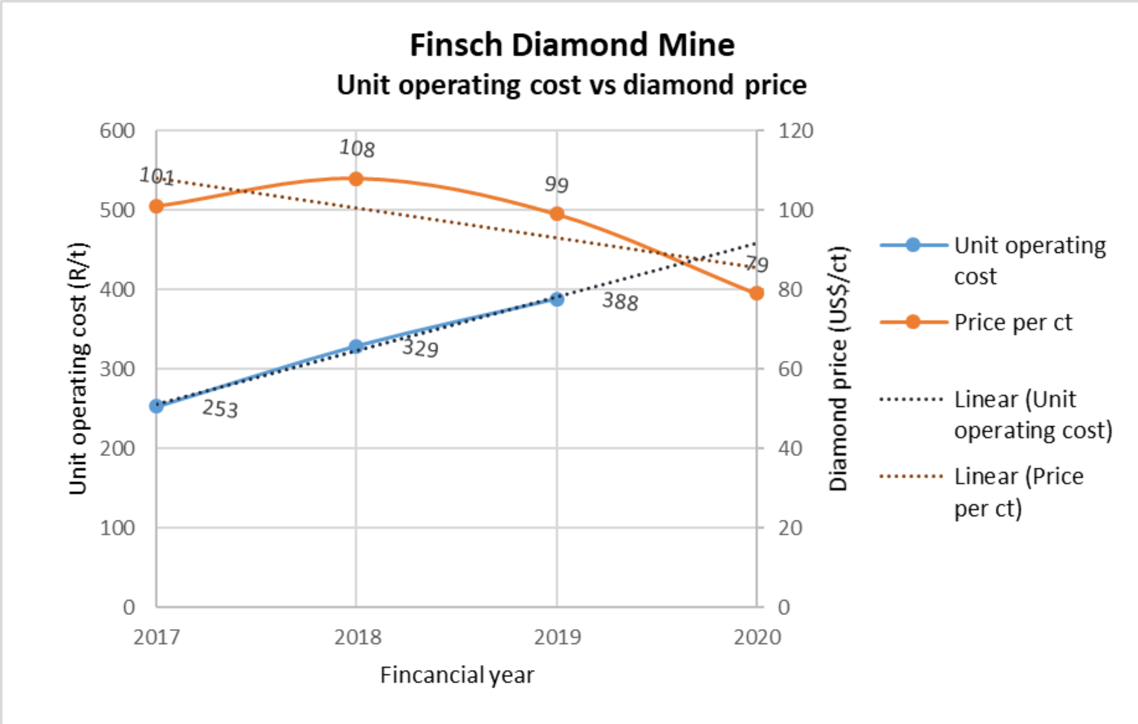

Figure 1.3 An illustration of the increase in unit operating costs versus the decrease in diamond prices at Finsch Diamond Mine (Petra Diamonds Limited, 2020; Petra Diamonds Limited, 2019; Petra Diamonds Limited, 2018; Petra Diamonds Limited, 2017; Petra Diamonds Limited, 2016).

To counteract the challenges mentioned above at FDM, an increase in production to an average of 280 000 run-of-mine (ROM) tonnes a month is required to reach 3.36 million tonnes per annum (Figure 1.4). To address this challenge, the mine undertook an SLC analytical and optimisation study in mid-2018, which had focused on the efficiency of load-haul-dump (LHD) equipment, including the external factors affecting them. During the analytical and optimisation study, real-time data from Sandvik's Optimine system was used. During the analytical and optimisation study, the following problems were identified and quantified:

- A shortage of LHDs in production, where optimally nine active and two standby LHDs are needed each shift to consistently reach production targets.
- Not having enough available production time (facetime) which was due to many factors. However, the main problem was slow shift ramp-ups, poor shift changes and early shift endings.
- Congestion at fuel bays due to not properly scheduling LHDs for refuelling.
- LHDs inflating their tyres at a bay 30 minutes away from the production section, instead of being assisted by a mobile vehicle fitted with a compressor waiting in the section.

- Operators searching for LHDs at the start of a shift because of unknown machine locations due to a lack of reporting their locations or not having a dedicated parking location.

Some of the issues identified in the study were addressed in the months after the study and helped ROM production to increase to an average of 235 000 tpm (October 2018 – September 2019) (Figure 1.4). However, most problems were only addressed when Project 2022 started at the mine in September of 2019. Project 2022 was also an analytical and optimisation study at the mine, but the focus was expanded to assess the entire mine's performance and costs using a value driver tree analytical approach (Petra Diamonds Limited, 2019). The constraints that were addressed by the second study led to an increase in the average ROM production to 250 000 tpm from October 2019 to February 2020 (Figure 1.4).

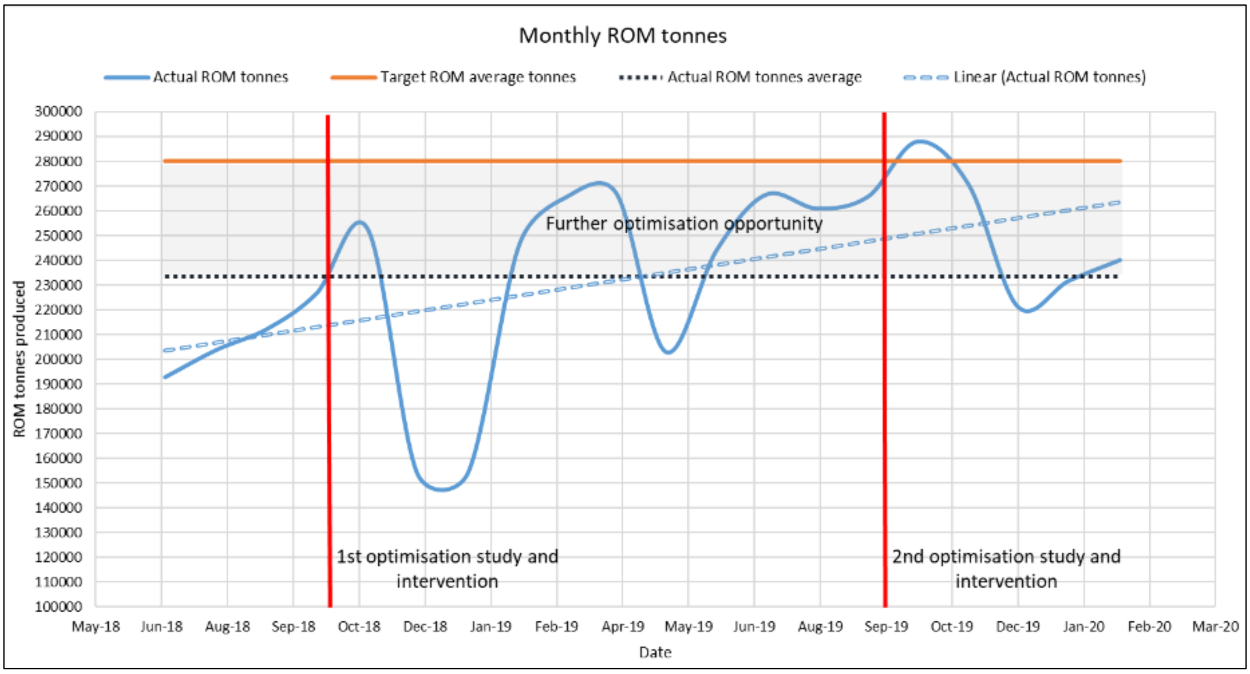

Figure 1.4 Monthly ROM tonnes at Finsch Diamond Mine from June 2018 to February 2020, indicating the optimisation attempts.

The problem with both studies was that they were done using analytical methods with a limited optimisation focus and had no dynamic capability to model the complex interaction and relationships between various processes and the effects they have on each other. Furthermore, the ROM production targets were achieved by working 26 production days per month instead of 20 planned production days per month (because of overtime production on weekends). This overtime significantly added to the increase in unit operating costs of the mine. For 20-day production months to be possible (excluding weekends) and to reach future targets, ROM production should average 14 000 tpd, and this was not feasible. If overtime on weekends are included, only 11 000 tpd is needed. In the six months from September 2019 to February 2020, ROM production averaged 8 350 tpd, as shown in Figure 1.5. Daily ROM production (for example, January and

February) was also inconsistent. This indicated that there might be production input parameters, such as available facetime, machine availability, loader cycle time, tunnel availability and degree of material fragmentation, that significantly affect the output tonnage performance.

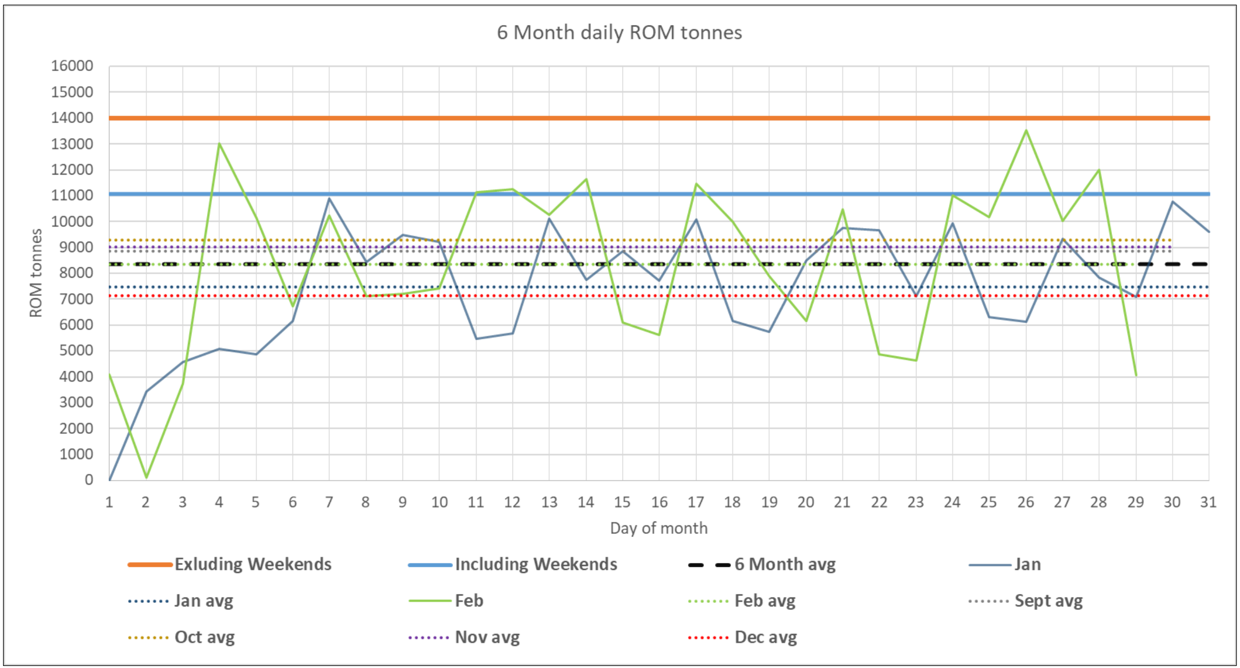

Figure 1.5 Six-month daily ROM performance at FDM.

The above information indicated that there was an opportunity to identify more inefficiencies in the production cycle with the use of other techniques such as computer simulation. Analytical methods were still essential, as some inefficiencies were not identifiable through a computer simulation. By identifying more inefficiencies and eliminating them to optimise the production system, the mine might be able to increase ROM production tonnes and reduce the unit operating cost.

1.3 Problem statement

Due to the complexity of the SLC mining method, constraints are often met that can destroy value by reducing the tonnes produced and increasing production costs. To identify inefficiencies and monitor deviation from best practice in the SLC environment is extremely challenging. SLC activities are not static, and they occur in multiple areas of the deposit's footprint. They must also occur in an orchestrated manner to decrease the probability of bottlenecks forming. Activities consist of multiple input parameters, and in many cases, these input parameters can become constraints. As a result, analysis and optimisation were required to eliminate these constraints. In the past, a static/analytical approach to analysis and optimisation was taken at FDM. The analytical approach used in previous studies at the mine only investigated a specific point or period in production time and the associated activities/input parameters. This approach relies heavily on historical data and is a mostly-backward looking approach. It is suitable for monitoring processes and measuring their performance, but not sufficient to map the complex dynamics existing between processes and how they influence each other.

There was also inadequate knowledge and literature on input parameters that have the largest influence on the production cycle (for example, 1. drilling; 2. charging and blasting; 3. loading, hauling, and dumping) performance of an SLC operation. Without definitively knowing which input parameters might constrain the production cycle performance the most, it is not easy to identify where the most attention needs to be focused during optimisation.

1.4 Purpose of the study

The scope of this research study was the production cycle at FDM (Figure 1.6). The main purpose was to identify and rank the SLC production cycle input parameters that are the most influential constraints prohibiting FDM from reaching optimal production efficiency. The ranked constraints would then be used to identify and recommend current and future optimisation solutions. The optimisation solutions will potentially help to increase FDM's ROM production output tonnes and reduce operating costs by using machines and the workforce more productively during planned production days.

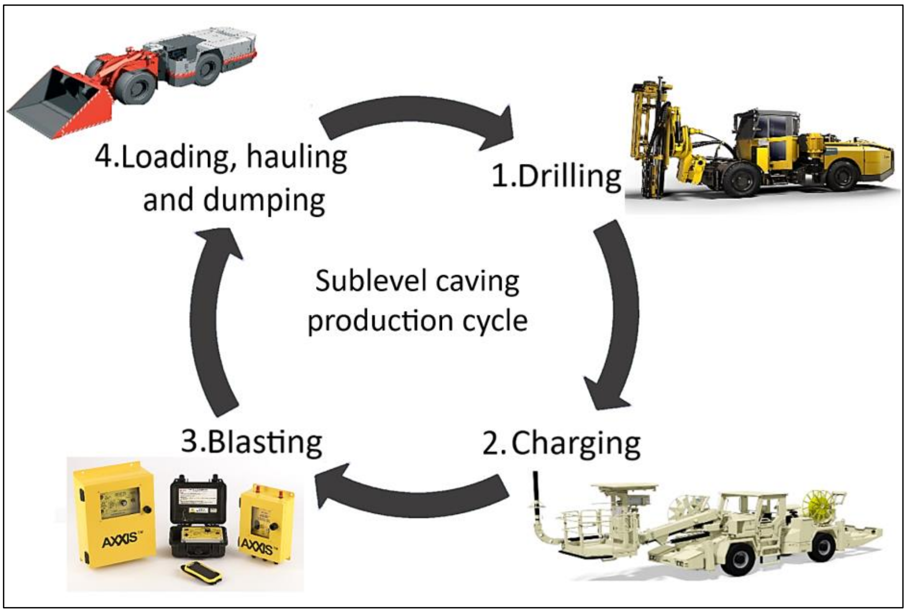

Figure 1.6 Sublevel caving production cycle (Adapted from: Epiroc, 2020; Normet, 2020; Axxis, 2020; Direct Industry, 2020).

1.5 Research motivation

To ensure FDM remains self-sustainable and be able to reach its planned Life of Mine (LOM), the mine must eliminate its inefficiencies to increase ROM production output and reduce costs. Focusing on and addressing these input parameter constraints occurring in the multiple activities in the FDM production cycle, can help the mine unlock more value. There was also a need to investigate an alternative way to identify system constraints at FDM that is more encompassing and dynamic. Constraint identification is important because the formulation of any optimisation model or process requires incorporating constraints inherent in the system. If constraints are not correctly identified, then the subsequent optimisation process will be flawed as incorrect constraints will be incorporated in the model formulation.

1.6 Research question

The core question for this research was**,** *"what production cycle input parameters are the most influential constraints prohibiting Finsch Diamond Mine from reaching its optimal production efficiency?"* This research study investigated the effect, and extent of the sensitivity that various input parameters have on the ROM production tonnage at FDM. The identified and ranked input parameter constraints were then discussed in more detail and used to recommend possible optimisation opportunities or solutions to resolve them. The input parameter constraint ranking can also be used in the future as a reference by FDM to increase production output.

1.7 Aim and objectives

The study aimed to identify and rank production cycle input parameters that are the most influential constraints on the production cycle at FDM. This ranking was then discussed in more detail to identify possible solutions to eliminate the effect of the constraints.

The objectives of the research study included:

- The collection, processing, and validation of production cycle input parameters for modelling.

- The running of discrete-event simulation models in Simio software on the production cycle input parameters by incrementally changing each and then ranking them after a baseline comparison. Simio means simulation modelling framework based on intelligent objects (i.e., Simio).

- Performing analytical calculations on the production cycle input parameters and analysing historical data to identify other constraints unidentifiable by the discrete-event simulations.

- Discussing the identified input parameter constraints to establish why they occur and find optimisation solutions that are currently possible or that may be possible in the future.

1.8 Outline of chapters

Chapter 1 has presented a background to FDM, its SLC operation and challenges experienced in its production environment. The chapter also introduced two previous studies undertaken at FDM to improve performance. Limitations from these two studies were discussed, leading to the formulation of this research study's research question.

Chapter 2 consists of a literature review of the various topics associated with and required to solve the research problem. The first part of the chapter places the research problem in a locational context by giving an overview of FDM. To better understand the dynamic FDM mining environment, a section explaining SLC as a mining method and the specific design and mining cycle is included. The section is followed by an overview of the fourth industrial revolution and how advances in technology, enabled the researcher to simulate and identify system constraints and find innovative solutions to eliminate them. The chapter also discusses optimisation principles and what approach had to be followed to optimise a function or system. Additionally, a section on the Theory of Constraints (TOC) and its use during the constraint identification process is reviewed. Finally, the simulation and modelling principles are reviewed, followed by a short introduction to Simio, the simulation tool used during the research study.

Chapter 3 describes the research methodology used to identify the most influential constraints in the FDM production cycle. The design and functions of the Simio model are discussed which explains the capabilities of the software, its ability and suitability to simulate the FDM production cycle. The chapter continues by giving an overview of the process to collect simulation model input data, which includes the systems from which the data were sourced from and some other traditional methods. The section concludes with a list of the input data that was used in the simulation runs. Furthermore, the chapter describes the process of calibrating and validating the simulation model by assessing the input and output data and comparing it to real-world production data. The application of the TOC during the study is also discussed and explained in detail, which entails how the simulation runs were conducted and different techniques used to rank the constraints. Finally, the chapter includes a section explaining the methodology used to identify constraints, that could not be identified through simulation, using historical data analysis and static mathematical relationships.

Chapter 4 reports on and discusses the results obtained from the simulation runs, historical data analysis, and limitations encountered during the simulation. The first section reports on the summarised simulation output data combined with a discussion on the results in the form of a preliminary constraint ranking. The preliminary constraint ranking is followed by subsections discussing each parameter in more detail. This discussion includes more simulation results, historical data analysis, and qualitative discussions. Constraints that were identified qualitatively are also considered for the final constraint ranking. The section ends with limitations encountered during the simulation process. To conclude the chapter, the final constraint ranking is presented, which considers all the data and arguments presented in the previous section.

Chapter 5 is a summary of the research conducted and concluding remarks and recommendations on how some of the constraints can be eliminated. Finally, the chapter discusses how the constraint ranking can be used in the future as guidance and what potential future research work can still be done on this topic.

2. LITERATURE REVIEW

2.1 Overview of Chapter 2

Chapter 2 summarises the literature used to explore the research topic and the approach taken while solving the problem. In Section 2.2, the research topic’s location is introduced with an overview of FDM and its mining history. To depict the environment of the research topic and the characteristics of the place the research problem occurs in, the theory of SLC is discussed in Section 2.3, and the specific design and characteristics of the FDM SLC are presented in Section 2.4. Section 2.5 summarises the fourth industrial revolution (4IR) concept, as the research methodology and the solution for the research problem also depend on technology and the advancement thereof. Optimisation principles are discussed in Section 2.6 and include the approaches taken in various industries to optimise complex systems consisting of multiple activities, entities, and parameters. A suitable method was required to identify system constraints, and this method is discussed in Section 2.7. The concept of using simulation and modelling as a tool to identify the system constraints is reviewed in Section 2.8, and in Section 2.9, the chosen simulation technique is introduced. Finally, a summary of the chapter is presented in Section 2.10.

2.2 An overview of Finsch Diamond Mine

FDM is located about three kilometres outside the town of Lime Acres and approximately 160 kilometres north-west of Kimberley, the capital of the Northern Cape province in South Africa, as shown in Figure 2.1. The Finsch kimberlite pipe was discovered by A.T. Fincham and E. Schwabel in 1960 while making their way to asbestos mines in the area. It can be inferred that “Finsch” was derived from the first three letters of each of the names of the two discoverers Fincham and Schwabel. Around 1963, De Beers Consolidated Mines acquired the deposit and production started soon after 1966 (Barnett & Preece, 2002).

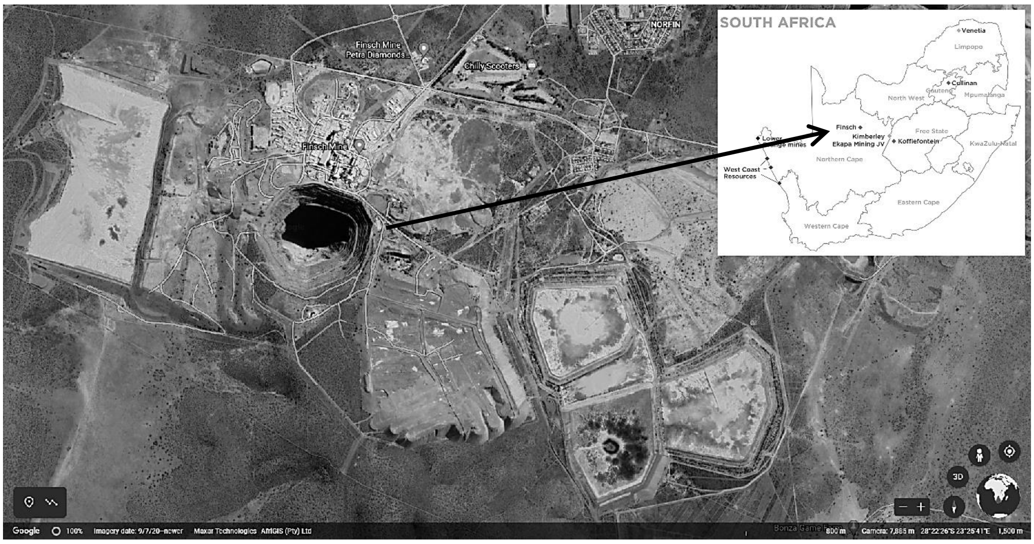

Figure 2.1 Aerial photograph and geographical location of Finsch Diamond Mine (Google, 2020).

The FDM diamondiferous kimberlite pipe is an almost vertical “carrot-shaped” deposit with an intrusion area of about 17.9 hectares on the surface. The FDM pipe forms part of the Finsch kimberlite cluster that consists of three kimberlite pipes, of which FDM is the largest and only economically viable deposit (Khati & Matabane, 2018). The kimberlite pipe intruded into two formations of the Cambell Rand Supergroup, namely the Ghaap Dolomite and Asbestos Hills formations (Preece & Liebenberg, 2007). The FDM kimberlite pipe consists of eight main facies of kimberlite and is named F1 to F8 (Figure 2.2). The largest parts of the kimberlite pipe by volume consists of facies F1 and F8 (Khati & Matabane, 2018).

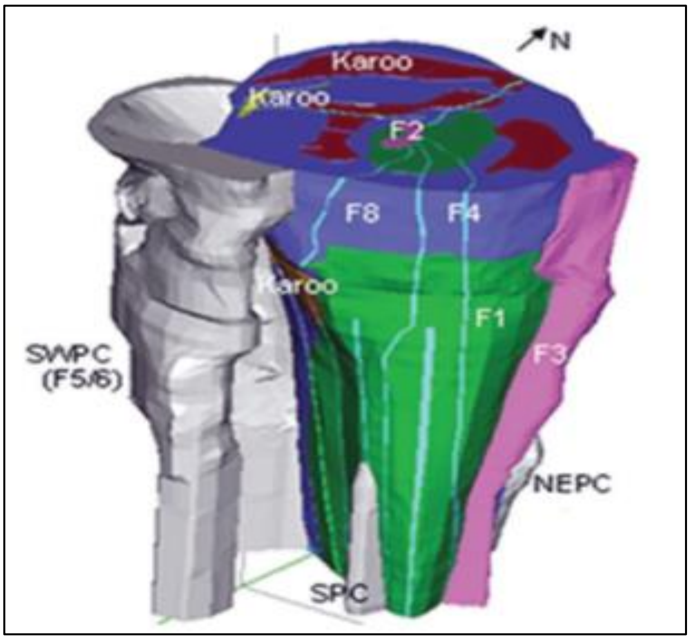

Figure 2.2 Geological model displaying kimberlite facies of Finsch Diamond Mine (Stone, 2015).

The mine was a surface operation until September 1990 when it transitioned into an underground mining operation. In Figure 2.3, the various mining methods used at FDM over the years can be seen in the mining layout. Blast hole open stoping was the first underground mining method used to mine out Block 1 and 2 remnants left behind from the surface operation. In 1996, Block 3 went into production, and blast hole open stoping was again used as the mining method. During the life of mine discussions in 1994, it was decided that block caving (BC) would be used for Block 4 instead of blast hole open stoping. The decision was made due to concerns that a massive pit failure might occur due to pit sidewall instability. A single-sided herringbone BC was implemented on 63 Level and went into production in 2004 (Preece & Liebenberg, 2007). The block was mined out in 2018.

The Block 4 development at FDM transformed the way underground cave mining was done. Using the most sophisticated and state of the art technology proven at the time, FDM became a leading diamond mine for technology and innovation (Fiscor, 2008). The highlight of Block 4 was a fully autonomous ore transportation system that consisted of 50t Torro dump trucks that ran in an enclosed truck haulage loop to transport the ore to a gyratory crusher situated close to the shaft. BC planning and scheduling were done using Geovia's Panel Cave and Block Cave (PCBC) planning software and cave management software (CMS) to provide daily production schedules. A process control system controlled the trucks that were connected to the PCBC, and CMS draw control systems (Preece & Liebenberg, 2007). Since 2004, FDM aspired to be an underground mine that is always leading with technology and innovation in South Africa, and it remains to be so, with the new Block 5 SLC that went into production in 2016. The SLC mining method is reviewed in the next section to provide some insight on the FDM mining environment and challenges experienced.

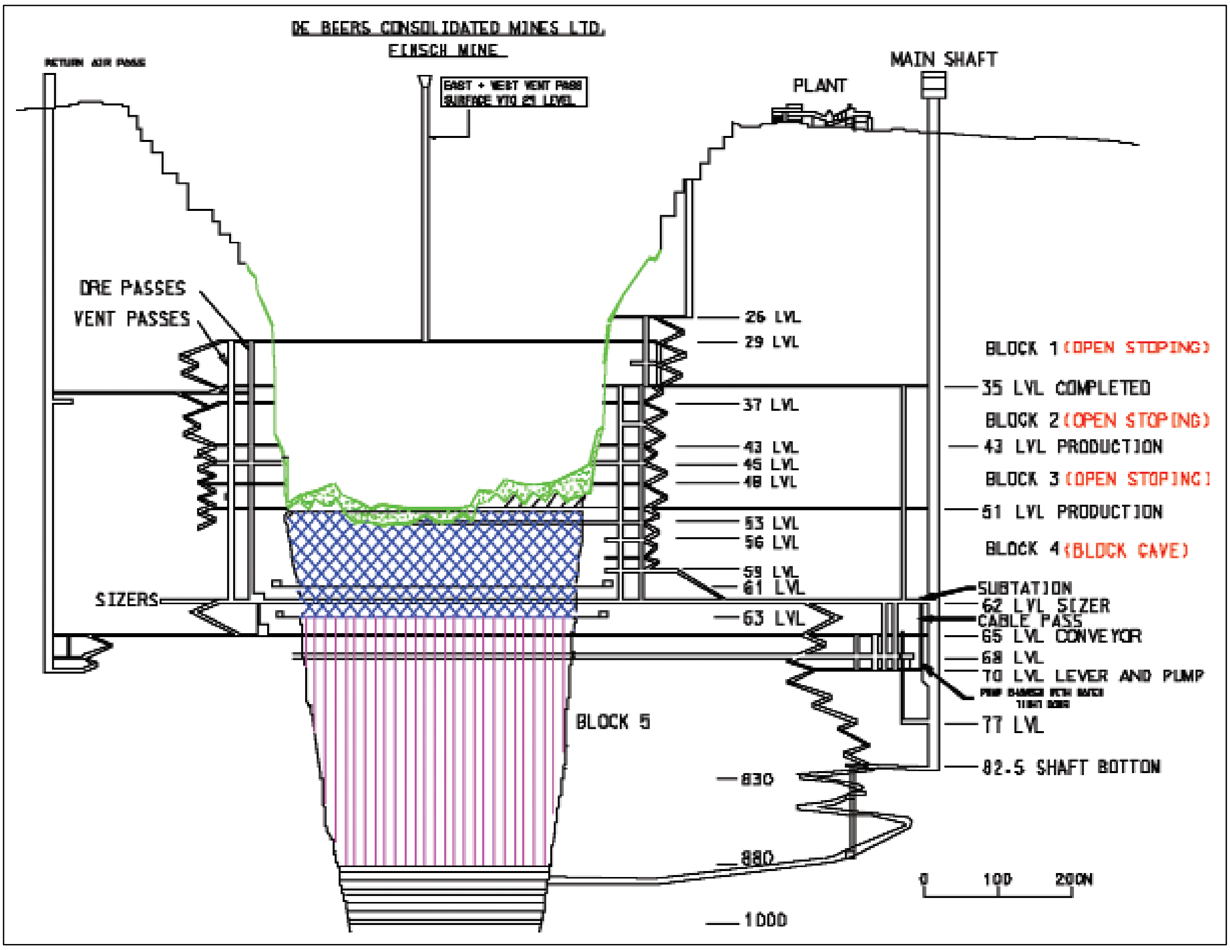

Figure 2.3 Section view through Finsch Diamond Mine, illustrating its mining layout of pre-2015 mining activities (Preece & Liebenberg, 2007).

2.3 Sublevel caving

SLC is mostly used in large deposits that are sub-vertical or vertical. Throughout the orebody, sublevels are developed, consisting of multiple parallel drifts, and either cut across or run along the orebody's footprint (Figure 2.4). Fan holes (vertical long-holes) are drilled from the drift of a lower sublevel to in-between drifts of a sublevel above. After the drilling and charging of fan holes, the ore between sublevels is predominately broken up by blasting. Crown pillars left between blocks will reach a hydraulic radius at some point; resulting in the rock to fracture and eventually collapse under gravity. The broken rock flows out of an opening in the drift called a draw point (Hartman & Mutmansky, 2002). As the ore is extracted from level to level, workings are established downwards through the orebody (Villa & Diering, 2010). Careful planning, accurate development and production execution ensure that sublevels and drifts within sublevels interact with each other. As the ore is loaded from the draw points, caving starts to occur in the mined-out upper levels of the orebody as well as subsidence of the surface (Hartman & Mutmansky, 2002). A controlled fracturing of the orebody and host rock is necessary to establish a successful and safe caving operation (Fernberg & Smith, 2007).

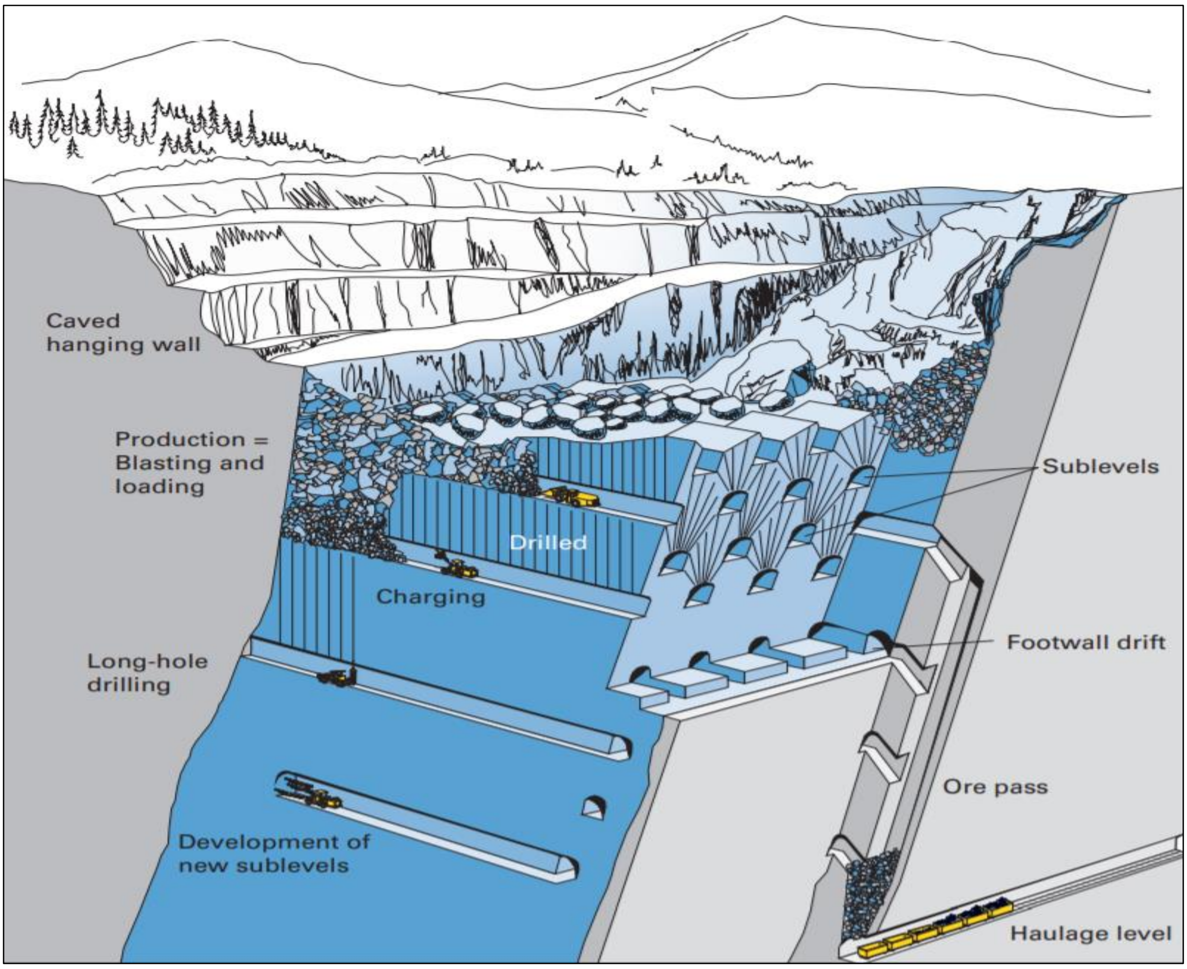

Figure 2.4 Schematic layout of sublevel caving (Fernberg & Smith, 2007).

When comparing SLC to other mining methods, it requires considerably more pre-development to establish access to the orebody (Hartman & Mutmansky, 2002). Caving mechanics of the orebody and the availability of technology control the parameters (size of drifts, sublevel heights and drift spacing) used during the SLC design (Hustrulid & Kvapil, 2008). Table 2.1 and Figure 2.5 show how SLC design parameters have changed over the years.

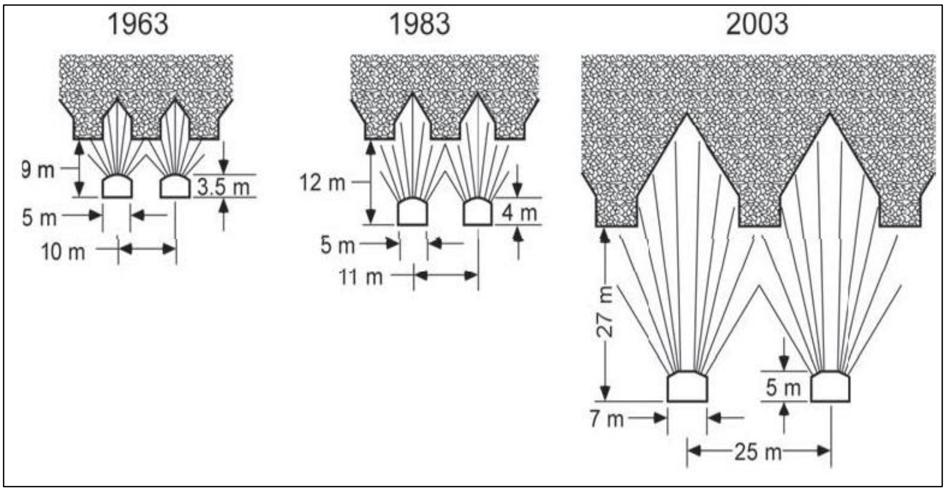

Figure 2.5 Illustration of the sublevel cave design parameters since 1963 (Hustrulid & Kvapil, 2008)

Table 2.1 Sublevel cave design parameters since 1963 (Hustrulid & Kvapil, 2008).

	Year		
Parameter	1963	1983	2003
Drift width (m)	5	5	7
Drift height (m)	3.5	4	5
Sublevel height (m)	9	12	27
Sublevel drift spacing (m)	10	11	25
Blast hole diameter (mm)	45	57-76	115
Burden (m)	1.6	1.8	3
Holes/ring	9	9	10
Tons/ring (t)	660	1080	9300
Tons/meter of drift (t/m)	400	600	3100

As mentioned above, significant development is required in SLC before production can take place. During development, only 15% to 20% of production takes place. Development mostly occurs in the form of drifts, crosscuts, ore passes and access ramps. At the end of each drift, a slot is blasted to facilitate the fragmentation and flow of ore (Hartman & Mutmansky, 2002).

SLC follows a conventional production cycle (drilling, charging, blasting, and loading) and is highly mechanised. Drilling is conducted by using surveying techniques to align drill holes correctly. It has become a standard in most mines to use intelligent drill rigs. Long-hole charging rigs with intelligent capabilities are also used to ensure holes are accurately charged according to the charge plan designed by the drill and blast engineer. Loading of material is done with load-haul-dump (LHD) equipment, and is common for mines to use remote-controlled or semi-autonomous LHD equipment (Hartman & Mutmansky, 2002). Table 2.2 is a summary of machines and material typically used in a SLC development/production cycle.

Table 2.2 Summary of equipment and material used in production cycle operations (Hartman & Mutmansky, 2002).

Operation	Equipment and material
Drilling	Long-hole fan drill rigs; Double- or three boomed jumbo drill rigs.
Blasting	Ammonium nitrate and fuel oil (ANFO); Slurries; Emulsion; Firing electrically, electronically or by detonating fuses.
Secondary Breaking	Single boom rigs; Hang-up rigs; Explosives used are auto-stem, cone packs or Penetrating Cone Fracture (PCF); Impact hammer.
Loading	LHD.
Haulage	LHD; Trucks; Railway; Conveyors.

At FDM, there is a strong focus on draw control to ensure successful interaction between sublevels and drifts. Draw control and planning adherence is also crucial for achieving and maintaining the correct face shape and lead-lags between sublevels to reduce mining-induced stresses, and to control the grade of material flowing from the cave. To ensure safe and consistent production at FDM is a big challenge, as it operates in a challenging mining environment with several activities occurring at once. The probability of inefficiencies is higher with an increase in mining complexity and the number of tasks that need to occur in a specific order and time. The next section gives an overview of the SLC design at FDM, as well as the processes and machines used in the various activities.

2.4 The sublevel caving design at Finsch Diamond Mine

FDM consists of a four-level SLC (70 Level, 73 Level, 75 Level and 78 Level), with 11 parallel production drifts running from the south-west to the north-east and are known as the Eastern Kimberlite Tunnels (EKT) (Figure 2.6). Another seven, shorter parallel production drifts, which are perpendicular to the EKT's and run from the north-west to the south-east are known as the Northern Kimberlite Tunnels (NKT).

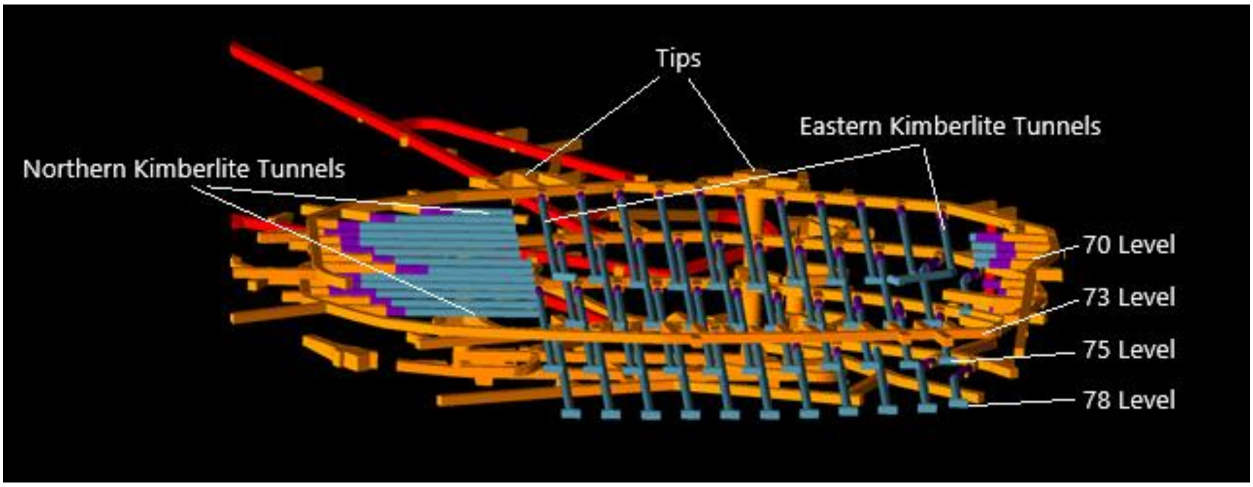

Figure 2.6 Schematic of the Finsch Diamond Mine sublevel caving layout (Source: MineRP Analyser).

On the north, to the north-eastern side of the deposit, the ground handling infrastructure is installed to support the whole Block 5. This infrastructure consists of four ore passes connecting the levels, of which the longest ore pass runs from 63 Level to 81 Level where two jaw crushers are located. Each level has two separate ore pass tips, fitted with 600 mm aperture grizzlies and a rock breaker. On each level, a rim tunnel connects the EKT - NKT tunnels to the ore pass tips. In Table 2.3, the basic design parameters of the FDM SLC are summarised. In Figure 2.7, a schematic of the levels and rings can be seen.

Table 2.3 Summary of the design parameters of the Finsch Diamond Mine sublevel caving operation.

Parameter	Value
Drift width (m)	4 - 4.5
Drift height (m)	4 - 4.5
Sublevel height (m)	25
Sublevel drift spacing (m)	21
Blast hole diameter (mm)	89 - 102
Burden (m)	2
Holes/ring	17
Metres/ring	400
70 Level – 78 Level tonnes/ring (incl. caving tonnes)(t)	2500 - 9100

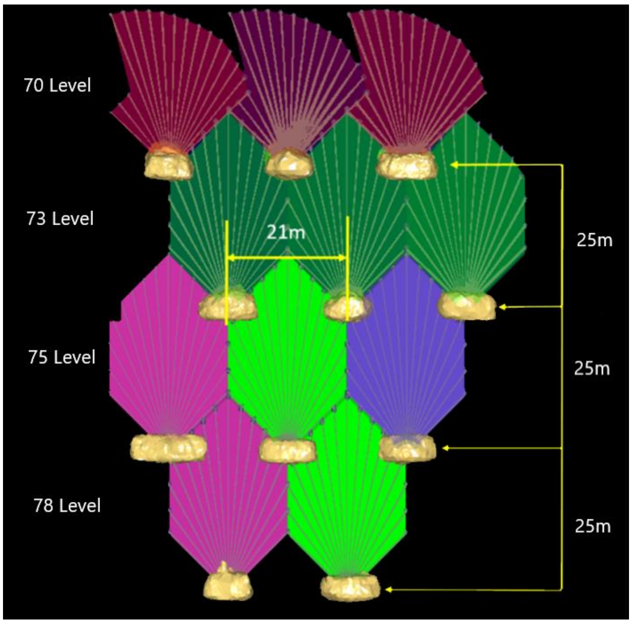

Figure 2.7 Schematic of the dimensions and ring designs of the Finsch Diamond Mine sublevel caving layout (Source: MineRP Analyser).

After the production drifts have been developed across the footprint of the deposit, the mining thereof can start by retreating backwards in the production drifts by blasting rings. This is done by first establishing a slot at the start of the production drift, to the level above, through blind boring and long-hole fan drilling (Figure 2.8).

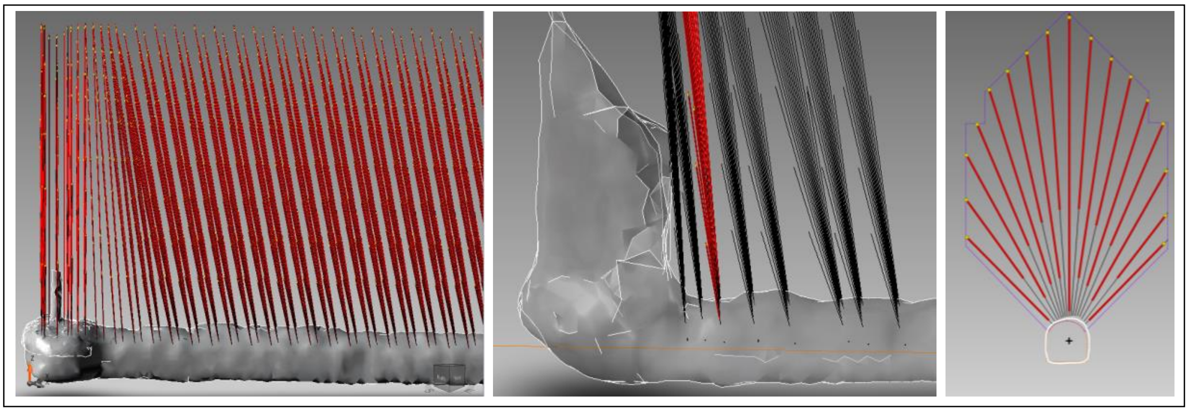

Figure 2.8 Illustration of a production drift ring set, a scan of an established slot and a ring design at Finsch Diamond Mine (Source: Aegis).

Long-hole fan drilling at FDM is done with Epiroc Simba M4C and ME7C drill rigs (Figure 2.9). A single ring usually consists of 400 metres of drilling. After the drilling has been completed, the 17 shot holes are charged with an AARD-BME modified charge rig (Figure 2.10), BME Viper Boosters, Axxis GII electronic detonators and two tonnes of BME Innovex UG pumpable emulsion. Blasting is done from the surface with the use of an Axxis Centralised Blasting System. After blasting, the fragmented ore is loaded with Sandvik LH410 LHDs (Figure 2.11) and trammed to the ore pass tips situated on the outside of the rim tunnel. The blasting of rings in the various production drifts is dependent on accurate designs and planning to ensure compliance with FDM's draw control strategy.

Figure 2.9 Epiroc Simba M4C and ME7C drill rigs used for long-hole drilling (Epiroc, 2020).

Figure 2.10 AARD-BME long-hole charging rig (Source: On-site picture).

Figure 2.11 Sandvik LH410 load-haul-dump (LHD) machine (Sandvik, 2020).

Every machine used in the production cycle has intelligent system capabilities and communicates real-time data over an underground Wi-Fi network to monitoring systems. The intelligent system and Wi-Fi network ensure the successful execution and tracking of the primary cycle activities. For each of the main cycle activities to be executed, multiple smaller activities must occur beforehand. Examples of these smaller activities include tunnel safe declarations, the fixing or retreat of ventilation, roadway maintenance, the rehabilitation of tunnel support, surveying, safety net installation, waste sampling, draw point inspections and ring charging preparation. In the following section, an overview of the 4IR is given. The overview gives background to how solutions of the 4IR enable FDM to run a complex, intelligently connected mine and how technology assists in constraint analysis and optimisation research.

2.5 The fourth industrial revolution

Since the start of the first industrial revolution in 1760, with the invention of the steam engine, the world has gone through three industrial revolutions and is currently in the fourth (Figure 2.12).

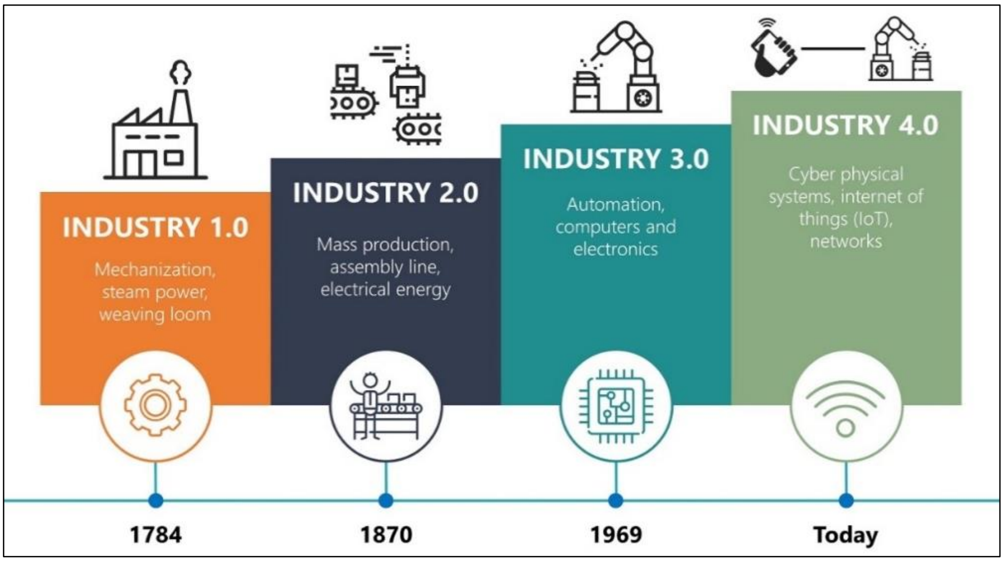

Figure 2.12. Highlights of each industrial revolution (DataPoint, 2018).

The fourth and current industrial revolution (4IR) started in 2011 in Germany as a high-tech strategy to reform German economic policies (Roblek *et al.*, 2016). Industry 4.0 is based on technology and concepts that comprise of the Internet of Things (IoT), cyber-physical systems, the Internet of Services (IoS), big data and analytics, simulation, robotics, three-dimensional printing, augmented reality, and autonomous robots (Roblek *et al.*, 2016; Xu *et al.*, 2018). The revolution is primarily driven by the concept that constant network communication is no longer limited to human-to-human or human-to-machine communication, but also consists of communication between the machines themselves. Large amounts of data are transferred in real-time from machines, over a wireless/wired network, where it is received and analysed by computers running intelligent software which responds automatically to the machine based on the received data (Xu *et al.*, 2018).

For the mining industry, the various industrial revolutions helped to increase mining productivity, lower costs, and make the working environment safer. The focus of this research fell on mine optimisation and more explicitly mining productivity. To determine if production cycles are executed optimally, data is needed. Data assists the mining industry to do a comprehensive long-term analysis of the driving parameters that influence mining productivity. To model and simulate the parameters' influence on the production cycle in the future, a mine needs to look at how the parameters influenced it in the past. Constraint analysis is also made possible by having large amounts of data that can be used to identify trends in parameter constraints within a production cycle. By also looking at the performance data of machines, steps can be taken to increase the size and quality of these machines, which makes bigger mines possible. By using larger and more productive machines, unit operating costs are reduced because of economies of scale. It is unlikely that 4IR will have as large an effect on mining productivity as the second industrial revolution, but it will change the way mining is done (Humphreys, 2019). Mines will become entities that are interconnected and highly optimised because of 4IR.

The research study conducted at FDM was highly dependent on 4IR technology. The data that was used during analytical and dynamic simulations were collected from real-time generated machine data. The data was very reliable and of high quality, as there is very low human interference. To identify and rank production input parameter constraints, 4IR technology such as computer simulation, was mainly used. When optimisation solutions were recommended, the author focused a great deal on 4IR technology to eliminate or reduce the effects of production input parameter constraints. The next section discusses the principles of optimisation and what the process of optimisation entails.

2.6 Optimisation principles

Optimisation comes from the word "optimal", which means "best". When something is optimised, an attempt is made to make it the best. In theory, optimisation is the attempt to attain results that are, under the circumstances, the best possible outcome (Astolfi, 2006). A process is followed in optimisation to either maximise benefit or minimise the effort in a specific function (Astolfi, 2006; Muzychka, 2006). Trade-off calculations are carried out to ascertain the most optimal operating point (Muzychka, 2006).

The approach to follow during the process of optimising a function is as follows (Muzychka, 2006):

- Define all the parameters and specific characteristics of a system or process through analysis.
- Establish the optimisation reasons and identify the objective function in regard to the defined parameters.
- A mathematical model should be developed for the system or process with identified input parameters to generate output parameters in the form of known empirical relationships and physical principles.
- Break the problem up into smaller parts or simplify the model and the objective if it is too complicated to optimise.
- A suitable optimisation technique should be applied.
- Answers should be checked, and the sensitivity to variation in assumptions and coefficients should be examined.

Identifying parameters/variables that constrain systems can be done in multiple ways (Astolfi, 2006). Modern-day approaches make use of computer modelling and simulation to identify these constraints. Data diagnostics plays a significant role in defining the input parameters for the modelling and simulation process. After the constraints have been identified, the next step is to begin researching and generating ideas to improve them to better optimise the system. The last step is to implement and manage the ideas and make continuous improvement part of the mining culture.

As mentioned, due to the complexity of the SLC mining production cycle at FDM, it consists of multiple system entities that continuously interact with each other. Each entity has its defining input parameters that influence its outcomes, or the collective outcome of the system based on a set of logic (empirical relationships and physical principles). To experiment with these system entities, their defining input parameters and interaction logic, an agile, inexpensive approach was needed to realistically imitate the real-world production cycle of FDM. The selected approach had to allow the experimentation and evaluation of a real-world imitation. The best tool available for this purpose was a computer simulation that experiments on a model that is representing reality.

However, having a simulation tool was only one part of the research approach. A method was still needed to use the tool to identify possible system constraints effectively. The chosen approach had to be systematic and focus the experiments on priority areas. The study aimed to identify system constraints, and it was assumed that one of the system entities, their defining input parameters, or the way they interact with each other was going to be a constraint. For this reason, the TOC was the best method to apply during the identification process of constraints when running computer simulations. In the next sections, the TOC and principles of simulation and modelling are discussed in more detail.

2.7 The Theory of Constraints in mining

The TOC is a five-step systematic method of improving the efficiency of a system (Morrison *et al.*, 2018). In the manufacturing industry, it was extensively used as a methodology that aimed at resolving constraints through continuous improvement and optimisation (Elkington & Finch, 2016). The TOC improves complex systems scientifically, by assuming that within multiple linked activities that make up the system, one will be the biggest constraint on the system. The TOC approach consists of identifying and eliminating constraints, applying multiple processes to analyse and resolve problems and ends with throughput tracking to calculate the performance of efforts. At FDM, a software solution called PiPware is used to track the throughput and performance of efforts. The TOC assists in focusing on current constraints and helps to increase the focus on priority processes that need immediate improvement (Morrison *et al.*, 2018). The five focusing steps of the TOC are (Şimşit et al., 2014):

1. Identify the main constraint in the system.
2. Exploit the identified system constraint by increasing its utilisation.
3. Synchronize the rest of the system to match the constraint's output.
4. Elevate the constraint by investing in additional equipment, people or work space.
5. If a constraint is resolved or reaches its optimisation limit in any of the previous steps, return to step number one and repeat the process.

It is critical that for the TOC to be applied successfully, constraints are correctly identified and ranked before they can be resolved in the system. Applying the TOC, will help to focus on the most significant constraint at a time that will make the biggest difference to the system (Elkington & Finch, 2016). Therefore, it is important to not only identify the constraints but also rank them. The focus will increase production by improving system capacity when eliminating constraints and attain a faster production rate by reducing lead times, ultimately increasing profit (Morrison *et al.*, 2018). Equally, if time is spent on parameters that are non-constraints, it will most likely improve the system very little or not at all (Elkington & Finch, 2016). A concept that is often used in industry is the value-ease matrix. The main idea behind the matrix is to identify optimisation opportunities that will be the easiest to implement and add the most value.

System constraints can prohibit any mining operation from generating more cash, and therefore an essential step in the TOC is to identify and classify constraints (Elkington & Finch, 2016). In a mining production system, three types of constraints can have an effect; and these are natural constraints, activity constraints and process constraints. Natural constraints are factors like rock stress, humidity, heat and the characteristics of the orebody. An example of natural constraints is that shallow mines will have fewer problems with heat and humidity, and deeper mines will have significantly more. It is sometimes impossible or very expensive to mitigate some of these natural constraints (Morrison *et al.*, 2018).

Activity constraints are related to the characteristics and execution of the activities. Activities during the mining process can sometimes be very complex and require considerable intervention from humans. This creates a problem for reducing costs since labour costs are sometimes the largest single expenditure in mining. Examples of activity constraints are performance-related measures, such as rate of advance, drilling rate, rock-cutting rate, and speed of loading and tramming material. The TOC will address these measures by optimising them to operate as a collaborative system. This will endeavour to reduce the production loss because of the sequential nature of activities whose rates may not be optimally matched. Mismatches between sequential activities create activity constraints. Process constraints are related to activities that must be completed before another can continue. Examples of this are mines that require backfilling before the rest of the production cycle can continue. A way to minimise this constraint is to ensure that enough production ends are available to allow other activities to continue (Morrison *et al.*, 2018). At FDM, production end availability is one of the major issues and the source of the problem is process constraints in the system.

After identifying the system constraints, finding the solutions for them is generally straightforward (Elkington & Finch, 2016). Activity and process constraints were the primary focus when assessing FDM's production cycle. Applying the first step of the TOC with the assistance of 4IR technology helped to effectively identify and rank the production input parameter constraints influencing production throughput and FDM unit costs. It also assisted in directing research and idea generation to find solutions and recommendations to eliminate the constraints. Furthermore, the use of the TOC to reduce the risk of spending time and money on non-constraints will be extremely beneficial to the mine in the future. The approach taken to identify constraints during the research study is discussed in the next section, and the principles of simulation and modelling are also discussed.

2.8 Principles of simulation and modelling

Simulation is a technique of imitating the entities of real-world processes/activities using computers and software. The collective of these entities of real-world processes is referred to as a system. System entities can be machines or people that interact and act collectively to achieve a logical end. When doing a scientific study of a system, it is required to assume various aspects of how it works. These assumptions are usually in the form of logical or mathematical relationships, and collectively they create a model. Models are used to investigate how the related system behaves (Law, 2015). Simulation is an important method used to help solve problems in the real world. It helps individuals to understand a system's behaviour to improve the design of a system in the real-world (Banks, 1998).

Systems can be studied in different ways, depending on the pursued objective and outcome (Figure 2.13). Studying systems aims to predict system performance under new or different conditions or to ascertain the relationships among the various entities comprising the system. It is always best to do experiments with the actual system, however, due to high costs and the risk of disrupting the system it is best to experiment with a model of the system (Law, 2015). Simulations are done on models that represent the characteristics of the existing system (Banks, 1998). Models can be divided into physical (for example, item in a wind tunnel, aeroplane simulation cockpits) or mathematical models (logical and quantitative relationship representation of a system) (Law, 2015). Due to the complexity, costs associated, and impracticality of studying the FDM's production cycle through a physical model, a mathematical model was found to be more appropriate. It was also easier to evaluate and measure the logical and quantitative relationships during experimentation.

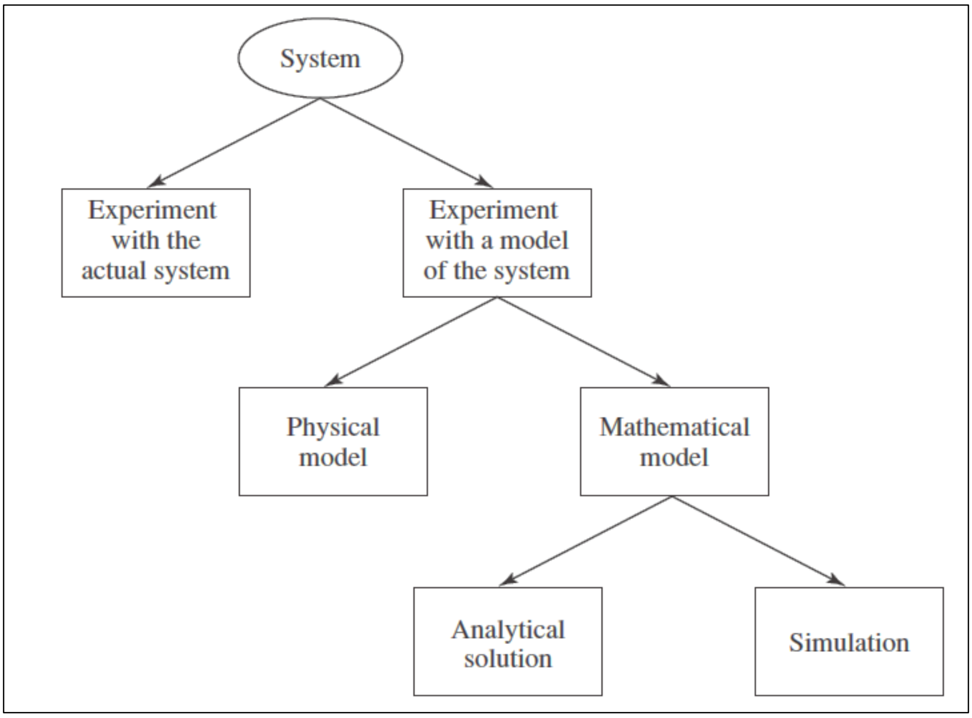

Figure 2.13 A schematic illustration of the different ways a system can be studied (Law, 2015).

If the relationships of a mathematical model are straightforward, an analytical solution can be pursued with the use of mathematical methods, such as calculus and algebra, to obtain an exact answer. However, an analytical solution approach is insufficient to analyse a complex, non-linear, and realistic model of a real-world system. Simulation is needed to study these complex models. Simulation can be described as the process of changing the input parameters of a system to calculate and observe how they influence the output performance of the system. In a simulation, the model evaluation is done numerically with a computer or many computers working concurrently together (Law, 2015).

Simulation models can be classified based on their input parameters. A simulation model that is not dependent on time, and represents a system at one specific point in time, is regarded as a static simulation model. A system that constantly changes over time is regarded as a dynamic simulation model. A model is deterministic if it does not contain any random parameters, and it is stochastic if it does (Law, 2015). When the logic of processes and events are represented in detail and simulated over time, it is regarded as a discrete-event simulation. A discrete-event simulation model consists of parameters or state variables that only change at a discrete point in time on the occurrence of certain events (Banks, 1998). A discrete-event simulation model was used in this study, due to the complexity, specific activity sequences and occasional changes in the production environment over time. The next section introduces the discrete-event simulation model used in the study.

2.9 Simio: Scheduling and simulation tool

Simulation modelling framework based on intelligent objects (Simio) is a software package designed to simulate complex systems. It is completely object-orientated by graphically defining objects and processes and therefore, does not need detailed end-user programming (Figure 2.14). Simio can help to optimise the use of critical resources, simulate the impact of changes to processes and help increase the performance of processes. The software can virtually represent all the entities comprising a system by creating a Digital Twin. It can model production processes as well as optimise schedules. It uses complex algorithms and analysis techniques to run different scenarios of processes and systems to identify the best throughput options (Simio, 2020).

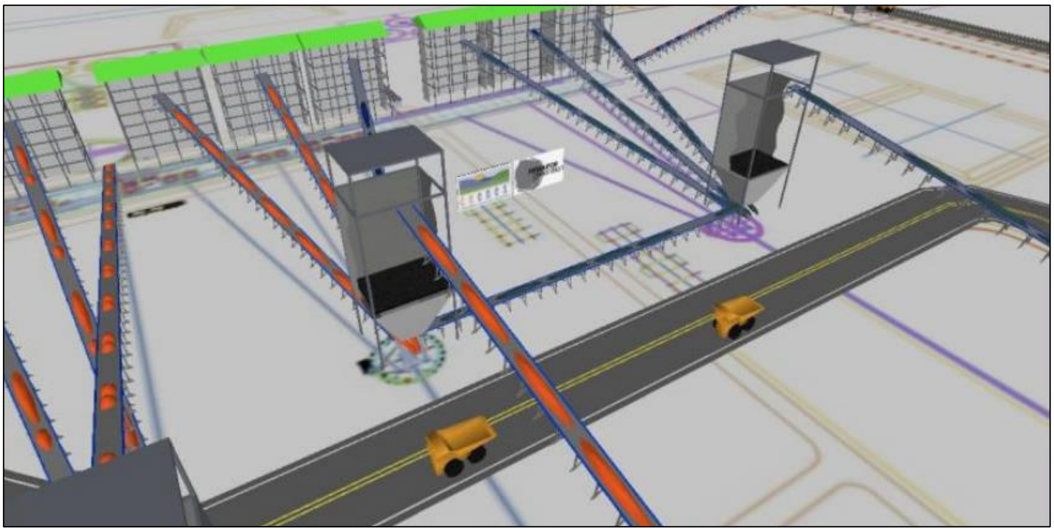

Figure 2.14 Simio model of a coal processing plant (Simio, 2020).

FDM contracted Process Design and Automation (PDA) in 2016 to build a Simio simulation model of the mine's SLC operation. It took more than four years to develop and calibrate the Simio model of the FDM SLC. During this research study, the model was used to run various production input parameter scenarios because it has the most reliable, logical and quantitative representation of the FDM SLC production cycle. In the past, the model has also been used in LOM planning projects, and its representation of reality has been proven highly reliable in those projects.

2.10 Summary of Chapter 2

Chapter 2 presented a review of the literature that gave guidance to the research context and develop a better depiction of the research problem. The chapter also gave an overview of the various methods that can be used to solve the research problem and finally introduced the chosen methodology used during the study. The chapter started by giving an overview of FDM and where it is situated geographically in South Africa. The chapter continued by explaining SLC as a mining method and how complex and dynamic the SLC mining environment is. This was followed by an

FDM SLC design overview, which included a descriptive and visual presentation of the mine design and equipment used during the production cycle.

The success of the research was dependent on high-quality data and the use of a computer simulation tool. This was only possible due to the advances in technology that the fourth industrial revolution has introduced to the mining industry. An overview was given on the fourth industrial revolution and how technology enabled the research that was conducted. After identifying constraints in a system, the system will need some form of optimisation. To explain the concept of optimisation better, the principles of optimisation were discussed.

Additionally, a section on the TOC and its use during the constraint identification process was reviewed. Finally, the simulation and modelling principles were reviewed, followed by a short introduction to the simulation tool used during the research. The next chapter, Chapter 3, builds on from the literature review by presenting the methodology followed based on some of the principles identified during the literature review.

3. RESEARCH METHODOLOGY

3.1 Overview of Chapter 3

The research methodology was a mixture of qualitative and quantitative approaches and is discussed in the next sections. In Section 3.2, the design and functions of the FDM Simio model are described and how it can simulate the real-world environment. As the model requires data for the input parameters and comparable output data for calibration, data had to be collected from various sources. Section 3.3 explains how most of the data were collected through real-time data collection systems on the mine and processed for use as input parameters. The section furthermore explains how some facets of the research study used primary data collected through formal discussions with individuals responsible for their respective sections. The section concludes by summarising the input data and comparable output data used during the simulation experiments as well as the historical data analysis and static mathematical relationship calculations. To ensure the accuracy of the simulation results, the FDM model had to be calibrated to match real-world results, and this process is discussed in Section 3.4. The TOC was the main approach used in identifying and ranking the most influential constraints and the five focusing steps and their use during the simulation runs are explained in Section 3.5. In Section 3.6, the methodology used to identify and rank system constraints in Simio through simulation is explained. The analysis of historical data and static mathematical relationship calculations used to identify constraints that could not be simulated are discussed in Section 3.7. Section 3.8 is a summary of salient points from Chapter 3.

3.2 Design and functions of the Simio model

The layout of the FDM SLC in the Simio model is spatially representative of reality. A computer-aided design (CAD) drawing was imported into the model and scaled to the correct size (Figure 3.1). The map was then fitted with various static and moveable objects representing the ore body, machines and infrastructure of the mine (Van Huyssteen, 2019).

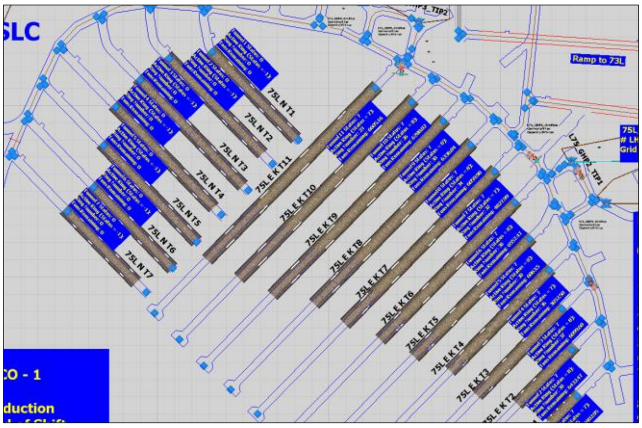

Figure 3.1 Illustration of the 75 Level layout fitted with objects and the remaining rings to be extracted (brown bars).

Static objects include nodes (start point or endpoint), links (paths) and tanks (ore passes) and moveable objects include LHDs, drill rigs and charging rigs (Figures 3.1 and 3.2). Each object has different parameters that can be changed and will be discussed later in this section.

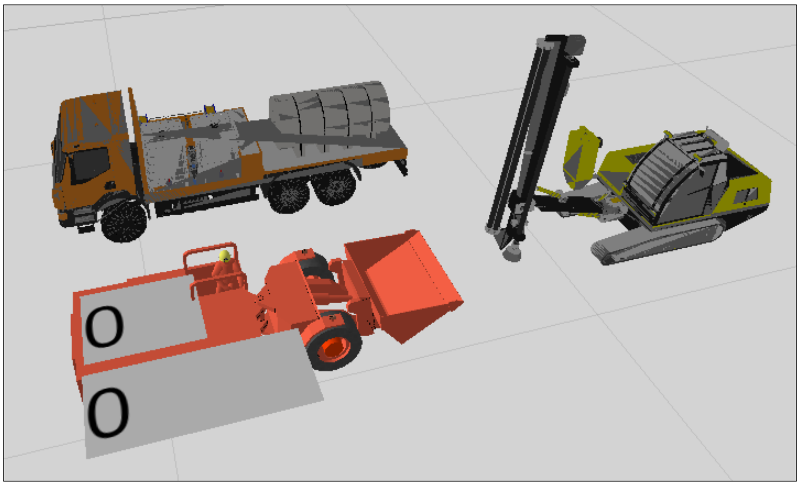

Figure 3.2 Moveable objects (LHD, charging rig and drill rig).

Another set of data that was critical to the model is the production plan which defines the Mineral Reserves to be mined. The production plan is done with an in-house developed extraction planning software called VenterFactor. VenterFactor takes account of the various draw control rules and strategies applicable to SLC's when planning the extraction sequence of rings. The data that was imported to the Simio model from VenterFactor included the level number, tunnel number, ring number, tonnes to be extracted, drill date, blast date, extraction end-date, and finally a sequence number that logically sorts the extraction of each ring. Simio uses this data to assign various tasks at the correct date and time in a logical order. When the model runs, it will show a brown bar in each tunnel representing the rings that still need to be extracted.

After the primary data was imported into the model, and the layout was fitted with objects, some of these objects had to be defined with input parameters. Input parameters can either be a property or a state. A property is an input parameter that is static and will not change during the simulation. Properties include inputs such as tipping time, LHD fleet size, refuelling time and charge time. A state is an input parameter that is dynamic and can change during the simulation. Examples of state input parameters include buckets per hour, tonnes tipped and ring tonnes remaining (Van Huyssteen, 2019).

For the objects to act and interact, a process logic was designed for each of them. The process logic is a set of actions that an object will complete to achieve a specific outcome. In this case, the set of actions were that a ring is drilled, blasted, loaded and tipped into the ground handling infrastructure. Actions can include checking if the fuel tank is full, if it is the correct time in the shift to start drilling, deciding where to load and if there is material to load and starting or stopping the movement of an object. The process logic enables the simulation model to replicate the logical relationships that occur between objects in reality as accurately as possible. Some process logic statements also require input data of which actions are dependent on. There are 40 tables of input data in the model, and examples include shift patterns, maximum LHDs allowed per level, ring information and the skip schedule.

Finally, after the model design was completed, the simulation runs could be done. Simulation runs can be done in two ways, of which the first method consists of selecting a time period then visually observing and tracking the simulation as it runs in the facility (layout) window. Data is then displayed in various statistical formats and critical data such as LHD cycle time, machine utilisation, tonnes loaded per area and total tonnes tipped are measured. This method works best when testing/calibrating the logic and interaction of the various objects within the model. The second method is to use an experimental environment where scenarios can be created. Each scenario can then be run with multiple replications (to account for randomness within the model) to get output averages that are statistically more representative of reality. Model input parameters can also be changed for each scenario, for example, to see the tonnage difference when using different LHD fleet sizes. The experimental method was used during this study to see the effects of changing various input parameters on the monthly output tonnage. In the following section, the collection of data and processing thereof is discussed.

3.3 Data collection and processing

Since 2016, the model has been changed and refined a few times due to mining conditions that change over time, and the model had to be adapted accordingly. Hence, data collection is a part of every project conducted to ensure that the most recent and accurate data is used. Therefore, most of the data collected during this study were used to update and calibrate the model to the most recently available data and mining conditions.

The data collected for the calibration of the simulation model was divided into three categories, namely input parameter (Table 3.1), output parameter and historical production data. The input parameter data was used to define object properties. The output parameter data was used to determine if the model is correctly calibrated by comparing it to object states after simulation runs were completed. Historical production data was also used in the calibration process of the model as a reference point for calibration. This helped to ensure the model as a whole represents reality from input parameter and model logic perspectives.

Table 3.1 Baseline input parameters used during the model calibration and simulations.

Baseline Parameter	Value			Unit
Production	**Minimum**	**Average**	**Maximum**	
Scheduled production time		16.5		Hours
Overtime weekends		3		Weekends
Drill rigs in use	-	4	-	Machines
Drilling time (per ring)	18	-	24	Hours
Drill rig tramming speed		1.5		Km/h
Charging rigs in use	-	3	-	Machines
Charging rig setup time	20	25	30	Minutes
Charging time per ring	1	1.5	2	Hours
Charging rig tramming speed	-	3	-	Km/h
Loader, Hauler Dumper (LHD) in use	-	8	-	Machines
Allowed LHD - 70 Level		2		Machines
Allowed LHD - 73 Level		4		Machines
Allowed LHD - 75 Level		5		Machines
Allowed LHD - 78 Level		3		Machines
LHD load size (fill factor)	6	8.5	12	Tonne
LHD tramming speed (empty)		9		Km/h
LHD tramming speed (full)		6		Km/h
LHD fuel capacity	50	-	350	Litres
Probability of grid being unavailable		1 out of 15		Tips
Grid clean time	5		10	Minutes
Fixed rock breaker availability		85		Percent
The ground handling system's parameters will remain fixed during the study as it has the capacity to crush and convey up to 18 00 tonnes per day.				

Data were collected in two ways, the first being machine/equipment log data. Almost all machines and equipment at FDM are fitted with sensors. These sensors either communicate to a data collection unit on the machine and then over the network to servers, or directly from the sensors to the servers. The mine makes use of manufacturer-provided software or third party software to analyse the collected data. Drill rig data were extracted using Epiroc Certiq, and examples of data available include drill hours/day, drill speed, drill rig utilisation and metres/hour (drilling and retraction). LHD data were extracted using Sandvik OptiMine, and the data available include loading timestamps, number of LHDs in use, load size, cycle times and average tramming speed. Even though the material handling section of the mine was not part of this study, as it is nearly autonomous and has sufficient throughput, it was still necessary to collect data to calibrate that part of the model. Material handling data is extracted from a supervisory control and data acquisition (SCADA) system, and the data available include conveyor belt speed, crushing rates, hoisting speed and tonnes hoisted and ore pass levels. Breakdown data was extracted from Ampla where all breakdowns are manually booked and include breakdown start and end times and reoccurrences to calculate the probability of a breakdown occurring.

The second data collection method, or mostly data verification, included formal discussions with the individuals responsible for the respective sections. Data extracted from the various systems were discussed and confirmed with supervisors during joint sessions. The supervisors provided any data that could not be collected digitally from an experience standpoint. Furthermore, data that could not be attained by the above methods were collected and verified with underground time-studies, but it was minimally the case during the study. Examples include charging rig set-up time, ring charging time, LHD tipping waiting time and time to clear big rocks on a tip using a rock breaker. The logic of the objects and processes was also discussed and verified by the respective section supervisors. The next section discusses the process of validating all the data and logic, and finally calibrating the model.

3.4 Calibration and validation of the simulation model

To ensure input parameter data and the logic of the model was accurate and correct, the model had to be calibrated against an actual month. The best month is where the planned VenterFactor tonnes, which is used in the model, and the actual tonnes achieved are about the same. Furthermore, it should also be a good production month to ensure the modelled answers will have the probability of reaching targets of historically good production months. After all the input parameters and logic matched the real-world data, 15 replications of the model were run (simulating a month for 15 times). Running multiple replications allows the simulation to test a range of scenarios as a result of randomness in the assigned input parameters and process logic of the model. The simulation then calculates the minimum, average and maximum output values from the 15 datasets. Fifteen replications were done as the standard deviation is minimal between the output data of 15 replications and the output data of more than 15 replications (Figure 3.3). In other words, the total moving average of replication tonnes becomes relatively constant after 15 replications.

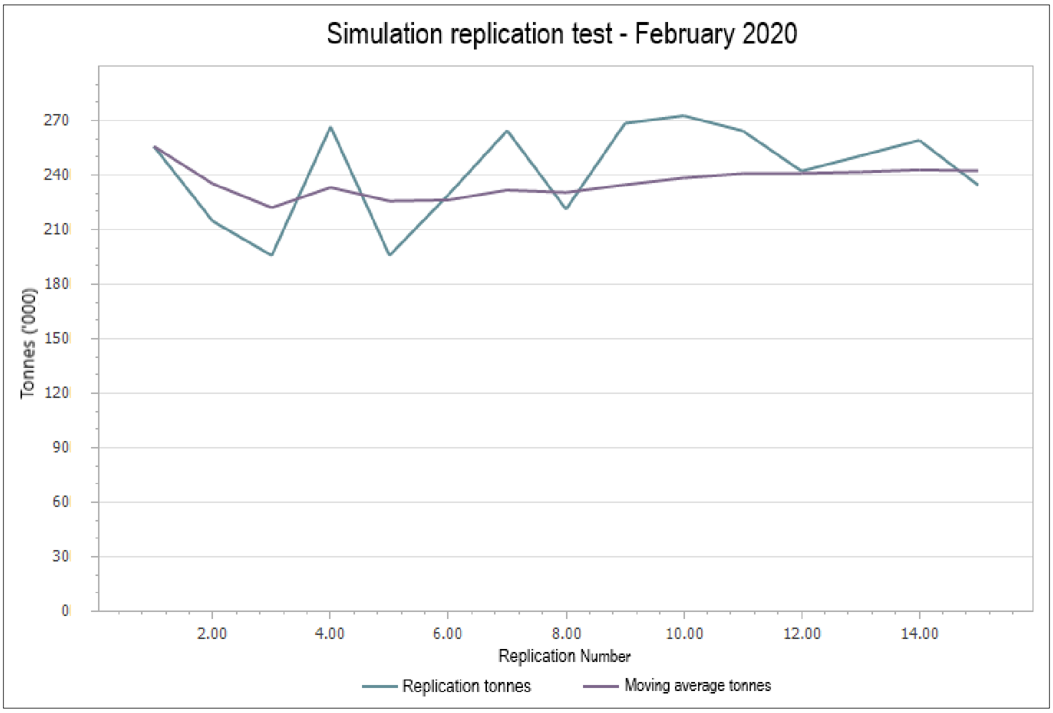

Figure 3.3 Graph illustrating the tonnes for a specific simulation replication and the moving average tonnes of all replications.

After the model was run, the output data were compared and analysed against actual production data to identify any variances. If an output parameter varied more than 10% with reality, the whole process was restarted to identify which input parameter or logic might be differing from reality. Table 3.2 contains the planned and actual tonnages produced on the mine for December 2019 to March 2020. February had actual figures that were relatively close to the planned tonnages from that month and those used in Simio (from VenterFactor).

Table 3.2 Planned versus actual production tonnes from December 2019 to March 2020.

Month	Planned tonnes	Actual tonnes
December 2019	176 378	220 684
January 2020	223 053	265 196
February 2020	**241 585**	**258 204**
March 2020	270 017	202 450

Simulation runs were done on the model for February, and the model calculated an average tonnage of 245 929 (after 15 replications) which differed -4.75% from the actual tonnage for that month (Figure 3.4). The average tonnage was ideal for the simulation, as the calibration of the model should be slightly conservative compared to reality. Other output parameters were also compared to reality, such as average LHD cycle time, load size, tonnes produced daily and tip availability, and it compared in range with reality. After the model was successfully calibrated, the simulation runs to identify and rank the constraints could be done, and this is discussed in the next section.

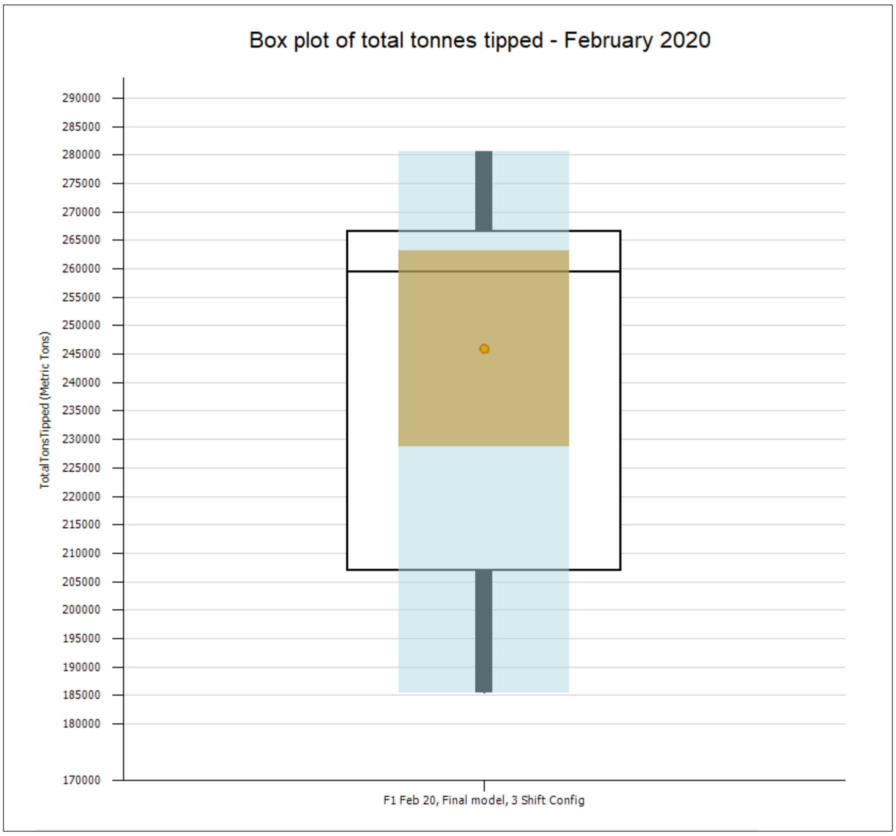

Figure 3.4 Box plot of the output tonnage for the February 2020 simulation run.

3.5 Applying the Theory of Constraints

The main idea of the TOC is to identify the most influential constraint, optimise or resolve it and move on to the next constraint. As for this study, the aim was to identify and rank all the constraints that can influence the FDM production cycle, and also recommend possible reasons or solutions for the constraint. The approach in applying the five focusing steps of the TOC was more selective during this study. This is only possible because a simulation model of reality is used and nothing in real life was changed which made it possible to apply the fourth TOC step and test the effect of, for instance, adding additional equipment. The approach of assuming what the main constraint in the system might be, by testing all the parameters as possible main constraints, are easier and more accurate in simulation. The five focusing steps of the TOC can be used again in real life after a ranking of the most influential constraints have been established.

To create a ranking of the most influential constraints, the five focusing steps of the TOC were applied as follows:

- An assumption was made that all input parameters were an individual constraint in the system, this way each of them could be taken to step two, exploiting the constraint.

- Each input parameter's utilisation/influence was incrementally changed to see if it will have any effect on the output production tonnage. A parameter can also sometimes become a constraint by being over-exploited or elevated, it was useful to take each parameter through an amended approach of the third TOC step.

- An amended approach to the third TOC step was taken by incrementally reducing the number or size of an individual input parameter, rather than synchronising all other parameters to the constraint, to see if it will have a positive or negative effect on the output tonnage. Step three is more focused on the idea of reducing the effort in achieving a certain output, than maximising the output of a parameter like in step two. Most input parameters could be identified and ranked with just applying steps two and three, however, some had to be taken to step four.

- Step four is applied when no change in the output is seen by just optimising a parameter’s utilisation. Therefore, the number of machines used like LHDs, drill rigs and charge rigs were also incrementally changed.

- By exploiting, synchronising or elevating an assumed constrained, it was not only possible to determine if an input parameter can be listed as an identified constraint, but it could also be ranked on the basis of its magnitude of influence on the production output tonnage.

In the next section, Section 3.6, a better explanation is given on the approach taken during the simulation runs. The section explains how the runs were done, and ultimately the methodology used can be tied back to the explanation given above as to how the TOC was used to identify and rank the most influential constraints within the FDM production cycle.

3.6 Simulation runs and constraint ranking

All simulation runs were done after the model was calibrated and the baseline tonnage used to compare all the simulation results, was the 245 929 tonnes achieved in February 2020. During the simulation runs, each production cycle activity's input parameter (Table 3.1) was individually increased and decreased by a 10% interval, for example, -30% -20%, -10%, +10%, +20% and +30%. Where an input parameter could only be changed using integer increments, as in the case of vehicles or number of overtime weekends, such increase or decrease was applied, and normalised to a percent increase. When an activity parameter was changed, all other parameters were set to the baseline parameter values.

With each simulation run where the parameter was adjusted, a monthly ROM tonnage throughput was calculated and noted against that parameter in a matrix table. After calculating the percentage difference between the baseline and the increased/decreased input parameter ROM tonnage results of the various discrete-event simulation model runs, the input parameters were then ranked according to their level of influence on the ROM tonnage. Not all parameters and logic could be modelled during the study. Therefore, historical data and qualitative discussions had to be relied upon to identify other constraints, and the next section discusses the methodology followed.

3.7 Historical data analysis

As some activities and parameters such as inflating a tyre, searching for machines, treating big rocks or hang-ups, installing a safety net, filling a slumped footwall, fixing roadways and ventilation pipes and rehabilitating tunnel support could not be modelled and simulated, an analytical approach was taken. This was done to identify other possible constraints by looking at historical production delay data. The systems used to extract the data included Sandvik Optimine (loading), Epiroc Certiq (drilling), Ampla (breakdowns and delays) and odd data collected manually by system operation controllers (SOC) in the central control room (CCR) of the mine. Some constraints are not necessarily measurable or quantifiable, such as communication and short-term interval control, but are known to affect activities which in turn affect the ROM tonnage. These constraints will also be mentioned and how they affect activities and how they can be resolved.

3.8 Summary of Chapter 3

Chapter 3 outlined the methodology used to research the production constraints and focused primarily on simulation and modelling in Simio. The chapter gave an overview of the design and functions of the Simio model. The introduction explained how the model is visually represented with a CAD drawing of the mine workings and then fitted with static and moveable objects to represent the ore body, infrastructure, and equipment. An overview was then given on the data and logic assigned to the various objects to make them representative of reality. This was followed by the methodology used to collect data for the model, as the use of accurate data and logic is critical to a simulation model. A table summarising the baseline parameters used in the model is included, as it is also the parameters that were simulated individually to create a constraint ranking. A section explaining the calibration and validation of the Simio model followed after that to describe the steps taken to ensure the model is as representative of reality as possible. This is followed by a section explaining the application of the TOC during the simulation runs. The chapter is concluded with an overview of the simulation runs and constraint ranking methodology and how historical data analysis was used to identify constraints that could not be simulated. The next chapter (Chapter 4) discusses the results obtained from applying the methodology presented in Chapter 3.

4. RESULTS AND DISCUSSION

4.1 Overview of Chapter 4

Chapter 4 presents the research results and the results of experiments conducted in line with the methodology discussed in Chapter 3. In Section 4.2, the simulation results on the various production input parameters in Simio are ranked and tabled. The section discusses the results in more detail by expanding on the aspects that influence the outcome of some parameters. This includes graphs created from the simulation data, as well as examples from historical data analysis. To organise the constraints better a brief categorisation of the constraints are discussed. Some limitations were also discovered during the simulation runs, and they are briefly discussed. After considering the simulation results, historical data analysis and qualitative discussions, the final constraint ranking is presented in Section 4.3. The chapter is summarised in Section 4.4.

4.2 Constraint ranking through system modelling and historical data analysis

After the model was successfully calibrated, and the output results corresponded with the actual production data, the experiments on the multiple production input parameters could be conducted. This resulted in numerous scenarios being run, which amounted to thousands of replications of the February 2020 production month. Simio provides results in various formats, but the focus was on the monthly output ROM tonnage. Each input parameter's monthly output ROM tonnage was tabled and then converted to a percentage variation from the baseline tonnage, and this can be seen in Table 4.1. It should be noted that this is only a preliminary ranking of the most influential parameters on FDM's production output and that the final ranking will be given in Section 4.3 after other findings were taken into consideration.

The ranking in Table 4.1 took account of an input parameter's positive and negative impact on the output ROM tonnage. With some parameters, it can be observed that only a negative impact is resultant and no positive impact. In this case, the parameter has already reached its most optimised state and can only influence the output ROM tonnage if its state worsens. Other observations will be discussed in the subsections that follow.

Table 4.1 Preliminary input parameter ranking of the most influential constraints on the FDM production cycle.

Input Parameter	Unit	Value						
		Worsen			Baseline	Improve		
		30%	20%	10%		10%	20%	30%
Scheduled production time	Hours	-28.73	-20.62	-14.27	0.00	4.94	19.34	34.46
Load-haul-dump (LHD) units in use	Machines	-30.70	-21.26	-11.31	0.00	10.61	18.05	25.61
Tunnels available for loading	Tunnels	-30.70	-21.26	-11.31	0.00	10.61	18.05	25.61
LHD load size	Tonne	-29.51	-18.93	-10.55	0.00	7.72	11.97	28.32
LHD tramming speed (full)	Km/h	-23.06	-11.04	-14.53	0.00	1.13	9.89	8.17
LHD tramming speed (empty)	Km/h	-14.68	-9.39	-8.03	0.00	2.28	3.67	1.95
Overtime weekends	Weekends	-7.86	-5.24	-2.62	0.00	1.16	2.33	3.49
Drill rigs in use	Machines	-4.32	-2.88	-1.44	0.00	1.44	2.88	4.32
Charging rig tramming speed	Km/h	-3.95	-5.21	-1.66	0.00	-4.62	0.21	-3.58
Probability of grid being available	After # Tips	0.30	-5.35	-7.58	0.00	-0.21	2.63	-1.19
Grid clean time	Minutes	-2.10	-4.17	-3.58	0.00	2.84	-2.02	-2.77
Drill rig tramming speed	Km/h	0.92	0.30	-5.57	0.00	0.49	-6.52	-1.04
Allowed LHD - 70 Level (2)	Machines	-2.79	-1.86	-0.93	0.00	0.54	1.07	1.61
Allowed LHD - 73 Level (4)	Machines	0.35	-1.69	-0.84	0.00	-0.97	-1.95	-3.68
Charging rig setup time	Minutes	-5.84	3.54	-2.78	0.00	-5.05	1.67	0.16
Charging time per ring	Hours	-0.78	-2.47	0.69	0.00	2.77	-8.16	0.89
Charging rigs in use	Machines	1.99	1.33	0.66	0.00	-0.55	-1.11	-1.00
Allowed LHD - 78 Level (3)	Machines	2.85	1.90	0.95	0.00	0.00	0.00	0.00
Allowed LHD - 75 Level (5)	Machines	-0.48	0.35	0.17	0.00	-0.21	-0.42	-0.64
Drilling time (per ring)	Hours	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LHD fuel capacity	Litres	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fixed rock breaker availability	Percent	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Percentage change in production output

4.2.1 Scheduled production time and overtime weekends

As seen in Table 4.1, scheduled production time is the most influential input parameter at this moment. The fractional increase of production time will almost result in the same fractional increase in the output ROM tonnage. The reasoning for this might be that it is the single parameter that influences all the other parameters, and will have the most significant impact on the output ROM tonnage. Currently, 16.5 production hours are possible with a three-shift configuration. This is due to the morning shift start-up, morning-afternoon and afternoon-night shift changeover and night shift-end. Almost eight hours of production time gets lost during these four pre-, mid- and post-shift events that can sometimes take up two hours. The delay is due to personnel that need to travel via shaft conveyance underground, which has a limit of 100 people at a time. Furthermore, they have to travel from the shaft to the designated waiting places where the start-of-shift meetings are conducted before they travel to their respective workplaces. When reaching their workplaces, another series of activities like receiving instructions based on the tunnel or draw point condition, tunnel safe declarations and vehicle pre-start inspections need to be conducted. In Figure 4.1, a typical morning shift start-up of the loading section is illustrated. The shift starts at 6:00, but it takes about two hours before most of the LHD machines have loaded their first bucket of the shift. As mentioned previously, this delay is due to the travelling time from the shaft to the section, start-of-shift toolbox talks and general arrangements, pre-starting of machines and the safe declaration of the tunnels to be loaded.

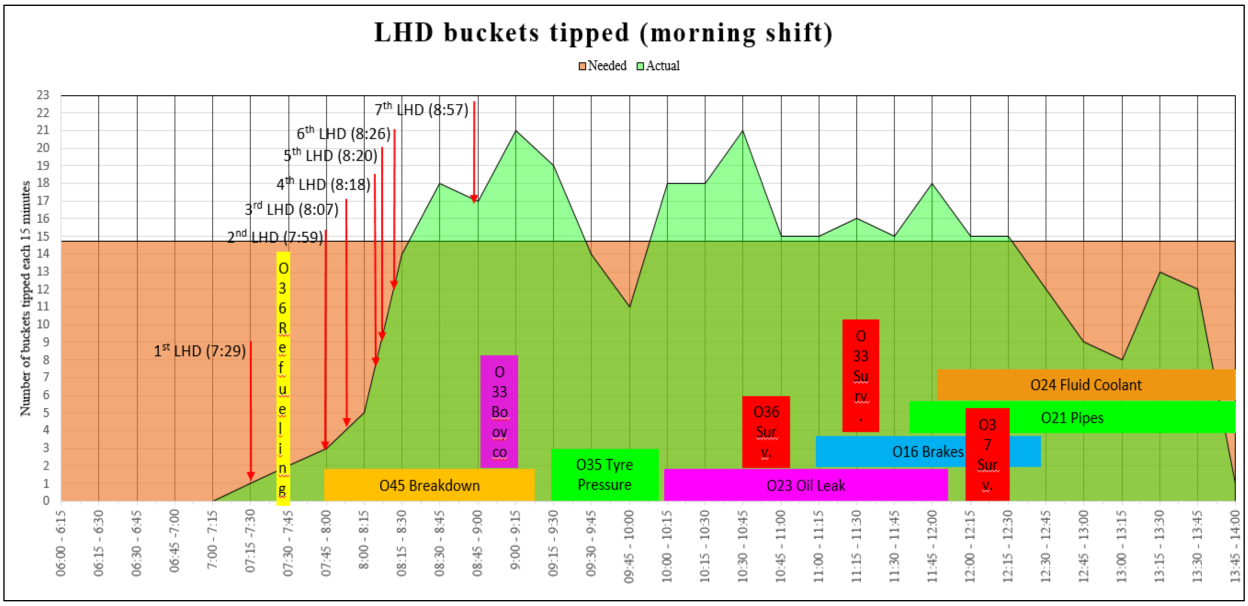

Figure 4.1 Typical morning shift production profile graph combined with machine activity data.

The inter-shift delays are an occurrence every day in a week, as shown in Figure 4.2. The biggest delay is between 4:00 and 8:00 (due to blasting at 5:00) and then minor delays during the day at 13:00 (morning - afternoon shift changeover) and 21:00 (afternoon - night shift changeover). Inter-shift delays are not the only factor reducing the available production time; delays within shifts are also a factor. These delays occur in starting activities late, waiting for another activity to occur or finish, or taking longer than it should to complete the activities.

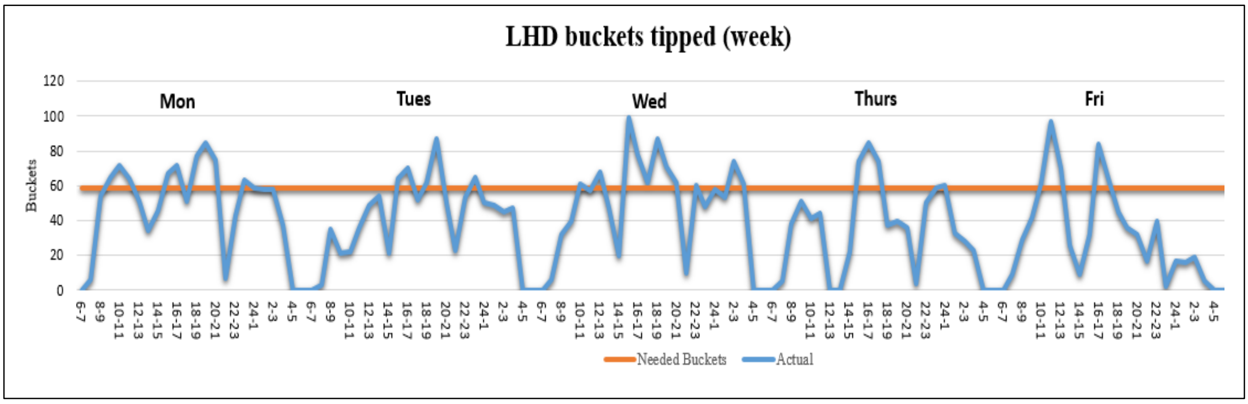

Figure 4.2 Five-day production profile illustrating the production delay between shifts.

There are many ways the available production time can be increased, and they consist of reducing the length of pre- or post-shift delays or cutting out a shift changeover by adopting a two-shift configuration consisting of twelve-hour shifts, instead of nine-hour shifts in a three-shift configuration. Almost two hours, previously lost to changing over from one shift to the next, can be gained by cutting out a shift and extending the remaining two. A two-hour increase in production time can add almost 20 000 tonnes a month. However, caution should be taken that this might influence the work performance of personnel as fatigue can set in after nine hours. As a result, personnel can become less efficient in the last three hours compared to if it was a nine hour, three-shift configuration. Another way to increase or be more efficient with production time is to implement a short-term interval control system that automatically schedules and tracks activities. The system should notify owners of the activity that it is upcoming and will notify them and their supervisors if their activity started late. It should also track their progress over time and notify them if the activity takes longer than usual.

Overtime weekends are also a way to increase the total available production time during a month, as this adds more days, and therefore more production time. It is a costly option, though, as people earn overtime at a rate of 1.5 to 2 times their normal salary rate for conducting work over a weekend. The mine’s original plan was to have a five-day production week and use weekends to conduct essential maintenance or schedule additional production activities if there was a significant delay during the week. Unfortunately, it resulted in low production performance during the week, as personnel realised that the mine would be forced to schedule production over the weekends to reach the monthly production target. This behaviour resulted in labour and other operational costs ballooning due to working overtime over weekends and having poor monthly production performance. Production tonnes lost during the week could not always be recovered over the weekends. The system is put under too much strain and then overwhelmed by trying to produce the lost tonnes in such a short time over a weekend.

The only solution to this specific problem is to enforce a policy that no production will be scheduled over weekends if the week’s production performance was not as planned, or by adopting a continuous operation approach. A continuous operation approach will consist of 12-hour shifts and a compressed four-day cycle arrangement (as per the labour law) where after the 4^{th} day, a new cycle starts for another group. This increases the total available production time during a month by having less shift changeover delays and more production days. Labour costs will also be lower and more constant, as overtime work will not be needed anymore and a fixed continuous operation incentive can be paid. This is also an excellent opportunity to add a second blasting time at 18:00 to blast rings, hang-ups and compacted draw points. This will increase the number of tunnels available to load from and will be discussed in more detail later in the section. Having sufficient production time is critical, but getting the ore from the cave into the ground handling system is just as important. The next subsection discusses LHD parameters and the influence it has on the output ROM tonnage.

4.2.2 LHD parameters

The second biggest influence on the output ROM tonnage is the number of LHDs in use (Table 4.1). Consequently, parameters affecting the performance of each LHD in use, also rank relatively high in the matrix. Each parameter will be discussed in more detail later in this subsection. LHDs are practically the only transfer connection between the broken ore and the rock handling system. The output ROM tonnage is thus highly sensitive to any changes in the number of LHDs in use, or any change to the LHDs parameters. As illustrated in Figure 4.3, it can be seen that adding or removing an LHD has a profound effect on the potential production output provided ore is available to load. This can be seen with real-world results in Figure 4.1. Whenever an LHD stops producing in the section for example, when LHDs O35 and O36 stopped, an immediate decline in the production output can be seen. The magnitude of the decline in production output is also highly dependent on the area being loaded (distance from tip, fragmentation and roadway conditions) and the skill of the individual who is doing the loading.

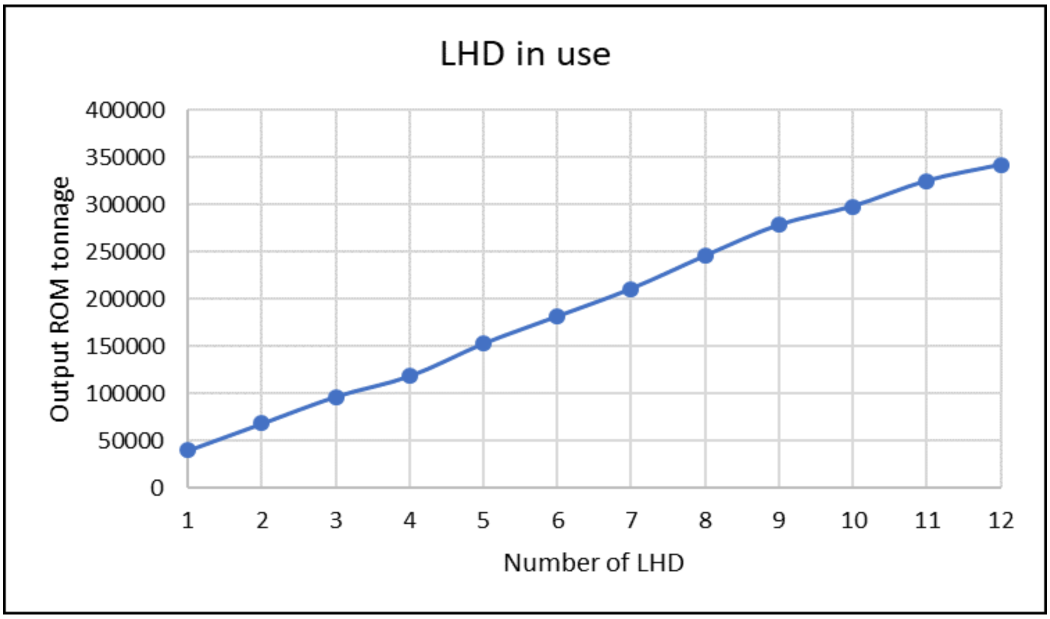

Figure 4.3 LHDs in use versus output ROM tonnage per month.

The biggest increase in ROM tonnage can be seen up to nine LHDs, where after the effect of adding an LHD starts diminishing. Cognisance should be taken that increasing the number of LHDs will not necessarily result in an increase in tonnage. The number of LHD to be used should have the same amount of tunnels available to load from i.e. available broken ore. Other parameters can also constrain the positive effect of adding LHDs such as material fragmentation, roadway conditions and distance from the tips. However, it has been established in previous studies that the ideal number of LHDs for the FDM mining footprint is nine. With more than nine LHDs, the congestion in the various levels becomes too much, and tunnel availability also becomes a constraint. Adding more than nine LHD will still assist in increasing the ROM tonnage, but the significance of the return is less than the effort, and there are other ways to optimise the system. The best approach is to have nine LHDs always running and two on standby to immediately replace an LHD that breaks down.

The other LHD parameter that has a significant effect on the output ROM tonnage is the load size, or weight of each bucket loaded. The Sandvik LH410s at FDM are fitted with a 10-tonne bucket capacity but can manage to load larger loads by weight. In some instances, because of overloading or loading material with higher density, up to 20 tonnes have been recorded. The weight of each load can be influenced by:

- The penetration and breakout forces of the machine used.
- The bucket capacity.
- Fragmentation of the material (bucket fill factor).
- The specific gravity of material loaded (waste has a higher specific gravity than ore at FDM).
- The loading skills of an operator (the ability to load fuller buckets).
- Footwall conditions (traction of wheels when mucking and solidity of the pivot point between the bucket and the footwall).
- Time taken with each load (making sure the bucket is completely full by “shaking and re-dipping” the bucket a few times).

Close attention should be paid to the above points as it can increase the output ROM tonnage or significantly reduce the effort needed to produce the target tonnage. The last LHD parameter that has a considerable influence on the output ROM tonnage is the tramming speed. The following conditions can influence the tramming speed:

- Roadway conditions (wet, uneven, undulating and rutted roadways).
- Congestion in section (LHD, other trackless mobile machines or pedestrians).
- Tunnel width (the production drifts are more narrow than the rim tunnels).
- Operator skill and confidence.
- Fragmentation of material (big rocks can fall off the buckets and therefore the bigger the rocks get, the slower the tramming speed becomes).

The number of LHDs allowed per level can also affect the output ROM tonnage. If too many LHDs are on a level, it can cause congestion in travelling ways and tipping points and the ventilation will potentially have to be increased. Assigning the wrong number of LHDs per level can congest one level and take away more efficient loading opportunities from another. As seen in Table 4.1, the number of LHDs allowed in 70 Level is suboptimal, and the level can benefit slightly by adding one extra machine if there are any available. Regarding 73 Level and 75 Level, the number of LHDs allowed at the moment are optimal and removing or adding one will be detrimental to the production output of the levels. It can also happen that too many LHDs are allowed per level, as seen with 78 Level. In this case, it would be beneficial to reduce the allowed LHDs on the level by one machine.

There are two main factors that are beneficial to 73 Level and 75 Level to handle more LHDs, the first being that the production tunnels are still relatively long, especially 75 Level, and both levels have a northern side to load from. This factor makes the tramming time from the draw point to the tip much longer, which means less congestion overall as the machines are more widely spread out. The second factor is the ore pass capacity, as both levels are 60-80 metres above the 81 Level crushing infrastructure. Having more ore pass capacity creates a buffer zone for any delays at the crushers. On 78 Level, there is limited ore pass capacity (buffer capacity) as the level is 20 metres above the 81 Level crushing infrastructure. Consequently, if there is an interruption or breakdown at the 81 Level crushers, it does not take long before the passes fill up to 78 Level and tipping has to be stopped. For this reason, a mineral sizer, with its own ore pass down to 81 Level, has been planned for 78 Level. This will add more tipping flexibility, enable more LHDs to run on the level and reduce the burden on the current rock handling infrastructure. The management, availability and performance of LHDs are critical but with none, or not enough tunnels to load from can also have a major impact on the output ROM tonnage. In Section 4.2.3, the importance of having tunnels available for loading is discussed.

4.2.3 Tunnels available for loading (tunnel availability)

The number of tunnels available for loading is just as significant as the number of LHDs available for loading. The effect on the output ROM tonnage that the number of tunnels available for loading has is directly proportional to the number of LHDs available, and much work needs to be done to ensure that a sufficient number of tunnels are available for loading. There are currently between 31 and 34 production tunnels available for activities to occur in at any time during the current mining phase of the block. However, the tunnels available for loading are much less, and can sometimes vary from one tunnel to 15 tunnels available.

The conditions or activities that prohibit tunnels from being loaded include the following:

- The draw point is hanging up, compacted or empty.
- Big rocks are present in the draw point.
- High waste ingress is reported.
- Part of the tunnel has to be re-supported due to blasting or loading damage.
- The footwall requires maintenance or has to filled up because of slumping.
- Water has to be pumped out from the tunnel.
- Ventilation infrastructure needs to be fixed, extended or retreated.
- The tunnel is being prepared for drilling (safety net installation, footwall filling, safety berm has to be constructed, surveying fixed points have to be installed, electrical/drill rig boxes have to be fixed or installed and Wi-Fi infrastructure has to be fixed).
- Inventory rings are being drilled or re-drilled in the tunnel.
- The tunnel is being prepared for charging (ramp and/or safety berm at draw point needs to be constructed, support mesh covering the shot hole collars of the ring to be charged has to be cut open, hanging wall has to be barred and made safe, and shot holes have to be opened and measured with cane rods).
- A ring in the tunnel is being charged.

Some activities are essential to increase the tunnels available for loading, such as drilling, charging and blasting. However, some of the other activities are detrimental to the number of tunnels available for loading and should not occur unnecessarily or take too much time to resolve. Examples of these activities include the fixing of ventilation, tunnel rehabilitation, re-drilling of rings, roadway maintenance, pumping of water, and blasting of hang-ups or big rocks. The main goal is to keep the mining cycle in the tunnel as short as possible and the tonnes extracted per blast as close as possible to the mining plan. Figure 4.4 shows that the typical tunnel mining cycle is around 17 days for 73 Level and 20 days for 75 Level. The main reason for this is that 75 Level has more tonnes per blast that need to be loaded, and the tunnels are longer.

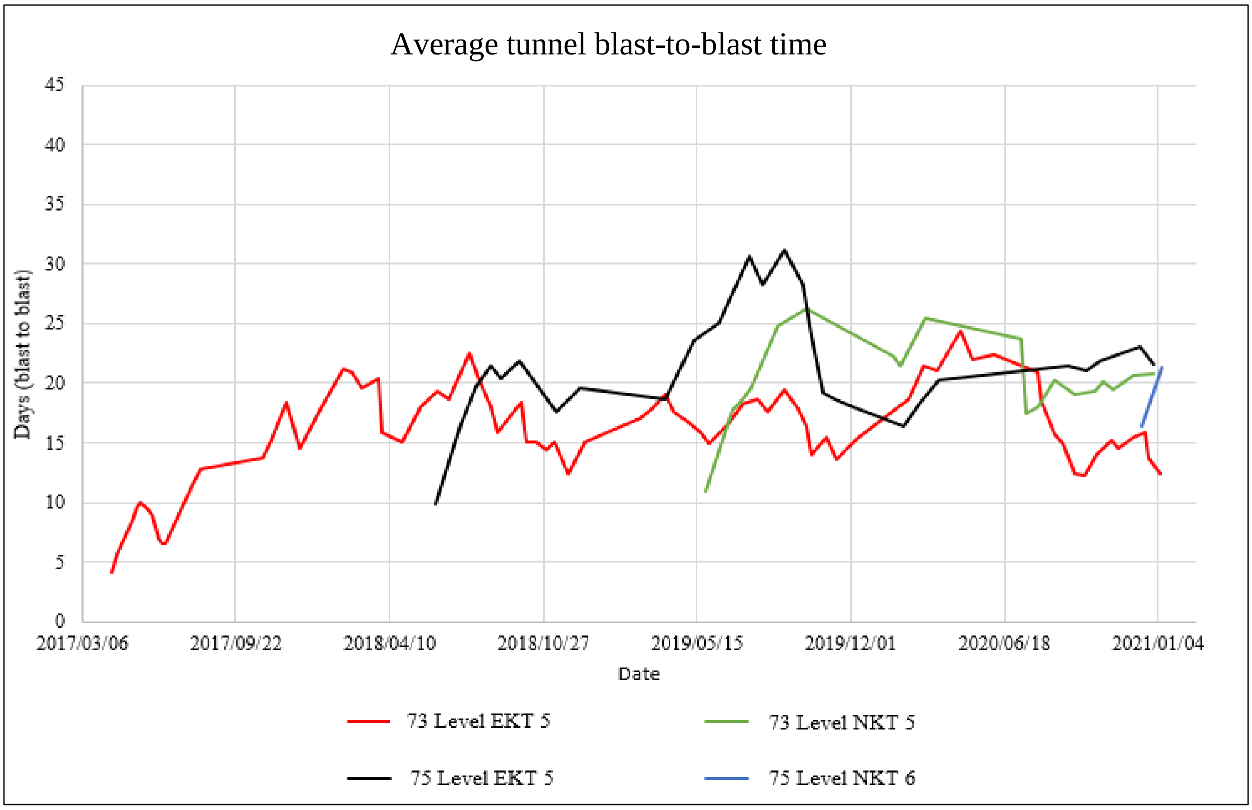

Figure 4.4 Graph of the average tunnel blast-to-blast time on 73 and 75 Level.

To load out the blasted tonnes from a tunnel can take anywhere from four to 10 days, depending on the flow of rock from the draw point. After that, all the other activities, and sometimes delays, occur before the tunnel can be blasted and loaded again. It is a major challenge to get through the delays and ore creating activities to make enough tunnels available for loading and meet the production plan. Resolving the delays and executing the ore creating activities must be well planned and scheduled to ensure no bottlenecks form in the system. However, as mentioned before, a significant amount of time is sometimes lost during this phase as the planning and scheduling of everything is highly complex and situational. Changes in the production environment sometimes occur by the hour, which requires instant re-planning and scheduling. To continue the discussion on ore creating activities, the next subsection discusses drill rig parameters and the constraints that occur in drilling.

4.2.4 Drill rig parameters

The effect of changing drill rig parameters is not fully realised with the simulation model because inventories of four to six rings are drilled per tunnel before the month it is blasted in. The rings blasted within a chosen month were already drilled a month, and up to 3 months in advance. Any changes to the drill rig parameters will only be realised in the following month, or the month thereafter. The model can thus not predict the effect of changing drill rig parameters in the chosen month a simulation is run in. The simulation runs indicated that increasing/decreasing the number of drill rigs or tramming speed will affect the output ROM tonnage, but as explained, it is not a reliable measurement. For this reason, the following historical analyses and calculations were used to better evaluate the effects of drill rig parameters. The production plan requires 18 000 metres to 22 000 metres per month to be drilled. For this to be achieved, four drill rigs need to drill per day in a 20-day production month (Table 4.2). It is possible to drill the same or more metres per month with just three drill rigs if the production schedule is continuous and/or consist of 30 production days (Table 4.3).

Table 4.2 Average drill rig performance parameters (Source: Epiroc Certiq Software).

Penetration rate (metres/hour)	Percussion hours/day	Drill metres/hour	Average utilisation hours/day	Average metres/day
67.44 (1.12 m/min.)	3.09	36.52	6.5	237.38

Table 4.3 Number of drill rigs vs metres per month.

Number of drill rigs	Metres/day	Metres/20-day month	Metres/30-day month
1	237.38	4 747.60	7 121.40
2	474.76	9 495.20	14 242.80
3	712.14	14 242.80	21 364.20
4	949.52	18 990.40	28 485.60
5	1186.9	23 738.00	35 607.00

The number of drill rigs needed to reach the planned production drilling target can also be reduced by improving the average utilisation of each rig per day (Table 4.4). Many factors influence the utilisation of each rig; however, the following factors have a significant influence:

- Available production time.
- Availability of drill rig specialists (operators).
- Breakdowns (boom, hydraulic system and electrical issues).
- Time spent setting-up the drill rig (navigating, connecting to the Wi-Fi and receiving drill plans)
- Moving the drill rig to another tunnel/ring, lining up, and collaring a new hole.

Table 4.4 Average utilisation of drill rigs vs metres per month.

Average utilisation hours/day	Drill metres/hour	Average metres/day	Metres/month (3 Drill rigs used)	Metres/month (4 Drill rigs used)
6.5	36.52	237.38	14 242.80	18 990.40
7.15 (+10%)	36.52	261.12	15 667.20	20 889.60
7.8 (+20%)	36.52	284.86	17 091.60	22 788.80
8.45 (+30%)	36.52	308.59	18 515.40	24 687.20

A limitation during the study was to simulate the effects of poor drilling quality on the production output. Drilling a ring in SLC does not only create a means to produce *in-situ* blasted tonnes, but it also creates an opening for caving material to flow into the draw point. For this to take place, the blasted ring needs to break wide enough on the shoulders to break into the adjacent tunnels and reach the designed height at the apex to break into the upper level. If the shoulders do not break well the interaction with adjacent tunnels will be poor, and if height is lost, the flow from above within the draw cone zone will not take place as planned.

Poor drilling quality can also be detrimental to the production output by delaying a blast due to crushed holes. If a ring is not drilled at the designed 10 degrees (80 degrees from horizontal) but backwards, towards the next ring in the inventory, the resultant blast can crush the back ring's holes and will require re-drilling. Other drilling practices, like drilling a smaller burden or twisting the ring's orientation, can also result in inventory rings being crushed after a blast. The opposite can also occur during drilling, where a ring is drilled at a flatter angle of 10 degrees plus (less than 80 degrees). This practice will increase the toe burden of a ring and result in either big rocks or pillars forming in the hanging wall. The practice mentioned above can be seen in Figure 4.5, which illustrates the difference between the design of a ring set and how the rings were drilled underground.

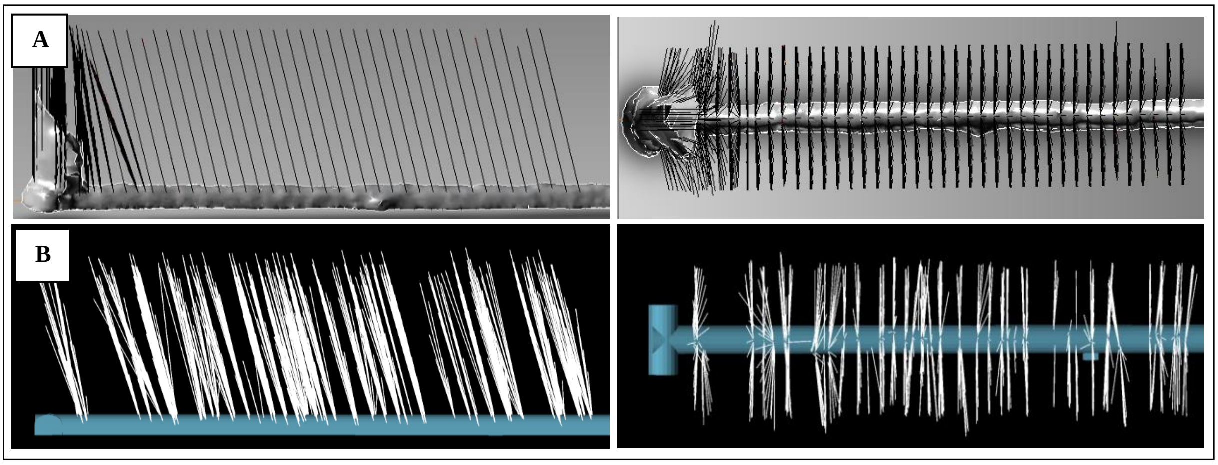

Figure 4.5 Planned versus actual drilled rings, 75 Level EKT 6. (A): Side- and top-view of designed rings sent from Aegis. (B): Side- and top-view of actual drill holes recorded by the Epiroc Simba drill rigs (Source: MineRP Analyser).

Good drilling performance and quality is not the only part of having a successful blast and high producing draw point. The charging process at FDM also plays a significant role in maintaining and increasing the output ROM tonnage, and the next subsection will discuss the parameters surrounding the charging of rings and how it affects production output.

4.2.5 Charging rig parameters

As with the drill rig parameters, not all the parameters of the charging rigs could be simulated. For that reason, the discussion will be more qualitative, as the effect of the parameters on the output ROM tonnage is difficult to quantify. The simulation runs indicated that using fewer charging rigs is beneficial to the production output (Table 4.1) because occupying too many tunnels at a time with a charging rig takes away the opportunity to load the area. The rigs are also slow, which causes some congestion in the section. Charging a 16-hole ring with 1.8 tonnes of emulsion takes around an hour and a half, therefore only using one to two charge rigs is sufficient in the section.

What the simulation does not include is the time it takes to prepare a ring for charging. For a ring to be charged, it needs to be exposed in the tunnel with sufficient vertical space to access it with a basket attached to a telehandler. It also has to be safe, which involves the draw point not being open to the cave with a big void, have large unstable rocks inside and the ring needs to be accessible from a supported area. It occasionally happens where a ring is covered by the muckpile and can sometimes require days of loading until the draw point hangs up and stops flowing. A breakdown of activities and their duration that need to occur before a ring can be charged is summarised in Table 4.5.

Table 4.5 Pre-ring charging activities and their duration.

Activity	Duration
Repairing of the footwall	30 minutes – 2 hours
Building a safety berm	15 minutes – 30 minutes
Installing a safety net	15 minutes
Cutting of support and barring loose rocks to expose the hole collars of a ring	30 minutes – 1.5 hours
Unblocking and measuring the length of holes with cane rods	20 minutes – 2 hours
Charging plan preparation	15 minutes – 30 minutes

The time it takes to prepare and charge a ring is not the only factor influencing the output ROM tonnage. The quality of the charging and blasting can also influence the production output by having the following adverse effects:

- Coarse fragmentation and big rocks.
- Compaction of material in the draw point.
- Poor breakthrough on the shoulders and apex of the ring (no interaction with adjacent tunnels or level above).
- Damage to the brow and support.
- Crushing of the inventory rings.

Multiple factors can influence the quality and success of a blast to ensure the extraction of the planned tonnes from a ring are achieved. Therefore, it is imperative to ensure that each blasting parameter is optimised to ensure the highest probability that the blast will be successful. The parameters that can be looked at include the following:

- Length of blast holes, and compliance to design.
- The diameter of blast holes.
- Ring burden.
- Toe spacing.
- Tilt of ring.
- Powder factor.
- Timing of detonators.

- Adherence to charging instructions (giving the emulsion enough gassing time, charging the correct lengths, kilograms and using the suggested timing of detonators).
- Status of draw point (does it have a void, is it full with material and are there big rocks pressing against the ring to be blasted).

Having a successful blast and loading the material are essential activities. However, the material still needs to get into the rock handling system for further processing, and this is done by tipping into ore passes. The next subsection will report on, and discuss the results obtained from the simulation runs with regards to tipping and the influencing parameters.

4.2.6 Tipping parameters

After the ore is loaded from draw points, the LHDs tram to tips situated at two different locations on each level. The material has to pass through 600 mm aperture grizzlies to enter the ore passes that lead to the 81 Level crushers. If the material is oversized and does not fit through the aperture of the grizzly, it has to be broken up by a rock breaker. The size of the tips is large enough to facilitate a surge in big rocks being tipped, but then time is taken to clear the tip again. Big rocks are not the only constraint that can occur during tipping. Other constraints include removing pieces of steel from the tip, and rock breaker breakdowns.

It can be seen in Table 4.1 that if the probability of the tip being unavailable or the time taken to clean the grid from big rocks or steel increases, it will have an adverse effect on the output ROM tonnage. Improving on these two parameters does not have a significant positive effect on the output ROM tonnage and is thus close to being optimised. All tips have two access points, which can facilitate two LHDs approaching the tip at the same time. Furthermore, if a tip does become unavailable due to a long delay, a switch can be made to the other tip on the level. This will have to be done on all other levels as well, as multi-level tipping arrangements on the same ore pass are not possible due to ventilation constraints with regards to dust control. As mentioned before, the only long-term constraint on tipping is on 78 Level, where the buffer capacity of the ore passes is limited. The previous sections gave an in-depth view on the various constraints that can occur within a system, and in Section 4.2.7, these can be divided into three categories to make them more organized and simple to approach.

4.2.7 Categorisation of constraints

As mentioned in Section 2.7, mining constraints can be organised into three categories which are natural constraints, activity constraints, and process constraints. It was not immediately apparent during the research study but natural constraints do occur and have an influence on the production cycle of FDM. These constraints are predominately geological and geotechnical. Waste ingress is one natural constraint and has to be managed by means of proper draw control rules and strategies. Waste ingress can result in a draw point being stopped from further loading, long before the planned tonnes have been extracted. It is however controllable, unlike gravity forces and rock stresses which are less controllable.

When preparing a ring for charging or drilling, the muck pile should be stabilised at a certain distance from the brow. This becomes a major challenge sometimes when caved material does not want to stop flowing from the draw point. On the contrary, if a draw point has been overdrawn and the draw point opens up to the cave, it becomes a major safety risk as material can suddenly cave, or a big rock can roll out from the cave and injure personnel. These conditions require significantly more preparation work to make it safe for personnel to work in the area, which can severely delay the execution of critical tasks like drilling or charging. Rock stresses can also influence the production cycle when a block of ground shifts and cuts off drill holes, or the holes get crushed. This will require re-drilling which takes away planned resources from other tunnels and the availability of the tunnel to blasted and loaded. Rocks stresses are manageable by ensuring proper lead and lags between tunnels, and levels, to evenly distribute the stresses. It should be noted that the abovementioned natural constraints have not been a major influence on the FDM production cycle thus far but can become in the future if not properly managed.

Activity constraints have the biggest influence on the production cycle at FDM as they are the characteristics or parameters of activities. Since they mostly consist of performance related parameters such as tramming speed, drilling rate and load size they can almost be found in every part of the production cycle. A more comprehensive list can be seen in Table 4.6, but the most influential activity constraints are available production time, LHDs in use, LHD load size, LHD tramming speed and drill rigs in use. The constraints themselves are much more complicated and were discussed in previous sections.

Process constraints on the other hand co-occur with natural and activity constraints if one activity is not able to continue as a result of a preceding one being incomplete. Since mining production consists of a cycle, one task's start will always depend on the completion of the previous task. However, as per the definition in the literature review, it mostly consists of the odd tasks that need to be completed before one of main activities can continue. To mitigate this effect, it is useful to have sufficient production ends available as tunnel availability is the third most influential constraint in the FDM production cycle. Some process constraints that can occur at FDM are roadway maintenance, the fixing of slumping at draw points, ventilation repair or stripping, and safety net or berm installation. This section gave a general classification of the different system constraints identified during the study but with all research there are always limitations. The next section, Section 4.4, discusses the limitations encountered during the simulation runs.

4.4 Limitations of simulation runs

The Simio model of FDM is relatively comprehensive and remains an extremely powerful tool to simulate the mathematical and logical relationship between various parameters and activities. However, it does lack the option to simulate the more detailed parameters at this moment. Some of the previously highlighted parameters and activities in this chapter can be built into the model over time and will be further mentioned in the recommendations. The main limitations of the simulation runs include the following:

- Exclusion of precursory activities that can be constraints such as safety net installation, void scanning, ring preparation for charging, fixing of ventilation infrastructure, secondary blasting and roadway maintenance.

- The ability to only simulate one month at a time restricts the process of determining the full effect of changing drilling parameters due to rings being drilled months in advance.

- The model remains highly quantitative and does not include much logic on qualitative aspects such as, poor drilling quality or not breaking through to adjacent tunnels/level above after a blast.

Some of the above-mentioned limitations can be added to the model in the future as parameters, activities or additional logic. After considering all of the above limitations and the previous discussions in this chapter, the next section, Section 4.4, presents the final constraint ranking.

4.4 Final constraint ranking

After preliminary ranking of the constraints, discussing and expanding on each one and investigating historical data, the final ranking of parameters that can be influential constraints on the FDM production cycle can be seen in Table 4.6. The combination of using the simulation model, historical data analysis, and qualitative discussions to establish which parameters will be most influential turned out to be a good combination. The parameters that are ranked have more depth to them and are discussed earlier in the chapter. The ranking can either be used to increase the production throughput to achieve the planned production target, help decrease the effort needed to reach a set target or reduce the operational costs of the mine.

Table 4.6 Final constraint ranking of the most influential input parameters on the FDM production cycle.

Ranking	Parameter	Details
1	Scheduled production time	The hours available per day to run production.
2	LHDs in use	The average number of LHDs that have to run during production.
3	Tunnels available for loading	The number of tunnels that need to be available to load ore from.
4	LHD load size	The tonnage of each bucket loaded.
5	LHD tramming speed	The average speed at which the LHD needs to run between the draw points and tips.
6	Production days scheduled	The number of days available in a month to run production.
7	Drill rigs in use	The number of drill rigs needed to drill the planned production rings and re-drill damaged rings.
8	Drilling quality	The quality at which rings need to be drilled to facilitate ore flow between sub-levels and adjacent tunnels successfully.
9	Charging and blasting quality	To ensure the charging and blasting practice is such to successfully facilitate ore flow between sub-levels and adjacent tunnels, and to achieve optimal fragmentation.
10	Tip availability	The availability of a tip when an LHD wants to tip or multiple LHDs want to tip consecutively.

As seen in Table 4.6, the available production time remains the largest influence on the FDM production cycle. However, as explained in the TOC section, after optimising a parameter, another parameter will become the largest constraint in the system. Optimisation is a continuous process, and constraints will always remain in an environment such as an SLC mine where changes continuously occur. It is beneficial to have a map that can point optimisation projects in the right direction. This will assist in first optimising the parameters that are the easiest to improve, and which will unlock the most value at the lowest cost. Most of the parameters can already be optimised to a certain extent. This can be done by just changing the behavioural aspect, and improving on the general practice conducted in some activities, for example, ensuring better drilling quality. Other parameters, like the available production time, will require some bigger shifts and changes within the system.

It will be possible for FDM to potentially reach 280 000 ROM tonnes a month, if the ranking of constraints is core to optimisation projects, and the improvements are continuously followed up on. This is where PiPware becomes a critical tool in tracking the throughput of optimisation projects. Some of the parameters ranked and discussed in this chapter have already received attention in the past few months during the study, and the results can already be seen. Optimisation, like safety, is equivalent to sweeping water uphill, and a mine will never stop sweeping. The success in optimising the constraints within the FDM production cycle will be dependent on how it is treated, such as a once-off event, or a continuous process that forms part of the mine's daily operational culture.

4.4 Summary of Chapter 4

Chapter 4 presented and discussed the results from the simulation runs, historical data analysis, and qualitative discussions. The chapter started with a preliminary input parameter ranking of the most influential constraints on the FDM production cycle. The ranking was established through the simulation runs, and each parameter was subsequently discussed thereafter in more detail.

The parameters discussed ranged from scheduled production time to tipping parameters. The discussions consisted of the general understanding of the results, presenting historical data to support arguments, lists on what might influence a particular parameter and qualitative discussions, where applicable. To better organise the constraints, a subsection on the categorisation of the various constraints was included. As with any study, there are limitations, and this was briefly listed and discussed. Chapter 4 concluded with a final constraint ranking of the production cycle input parameters that are the most influential constraints prohibiting FDM from reaching its optimal production efficiency. The next chapter, Chapter 5, concludes the study with final statements. This is followed by a list of recommendations for future studies and suggestions to prevent parameters from becoming constraints or eliminate those that are already constraints.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Overview of Chapter 5

Chapter 5 concludes the research that was conducted to identify the production cycle input parameters that are the most influential constraints prohibiting FDM from reaching its optimal production efficiency. A summary of the research conducted and concluding remarks are given in Section 5.2. This is followed by recommendations on how to approach the findings of the research, in Section 5.3, to ensure the most value is unlocked towards increasing the production output of FDM or decreasing the effort applied or costs to achieve the current output. Section 5.4 presents opportunities for future research work.

5.2 Conclusion

The aim of the study was to identify and rank the production cycle input parameters that are the most influential constraints prohibiting FDM from reaching its optimal production efficiency. To achieve this goal, various topics had to be researched during the literature review to better understand the problem and find a suitable technique to identify and rank system constraints. The chosen approach was to utilise computer simulation in a programme called Simio. A highly reliable simulation model of the mine was already available and was consequently used during the study.

Various objectives were also achieved during the study of which the first was to collect, process and validate production input parameters for the aforementioned simulation model. The model was calibrated to match the real-world as accurately as possible and then only, discrete-event simulations were run on the production input parameters. This was done by incrementally changing each input parameter and then ranking their results against a baseline simulation value. Even though the simulation model and the powerful Simio software were proven highly useful, limitations were still met. Some activities and parameters that can have an influence on FDM's production output could not be modelled and simulated. In this case, historical data and qualitative discussions were used to highlight activities and parameters that can also be influential. The combination of these approaches resulted in a comprehensive discussion on the parameters that can influence FDM's production performance.

By achieving the above-mentioned objectives of the study, the research question could be answered. After a preliminary ranking of the constraints, discussing and expanding on each one and investigating historical data, the final ranking of parameters that can be the most influential constraints on the FDM production cycle was listed. It was found that available production time is the parameter that can be most influential constraint, followed by the number of LHDs used and the number of tunnels available to load from. Each parameter was also discussed in more detail and can provide further guidance during future optimisation efforts. There are other parameters ranked as well which will be a good focus point for more optimisation projects.

Using the final production cycle constraint ranking as guidance to where attention should be focused, FDM can significantly improve the mine’s production performance and reduce operational costs. As mentioned during the literature review, determining what the constraints are, is usually the most difficult part and finding solutions tends to be relatively straightforward. It is crucial though that any solutions and improvements are continuously tracked and optimised to ensure the most value is unlocked out of the effort.

5.3 Recommendations

The study successfully created a ranking of the production cycle input parameters that are the most influential constraints prohibiting FDM from reaching its most optimal production efficiency. With any study, there are recommendations on how to improve on the methodology used and recommend the next steps to be taken to unlock the most value from the research. The following actions are recommended:

- In future, the approach presented in this study should be used as the precursor for any optimisation study at FDM.
- The mentioned parameters and activities that were not included or well represented in the simulation model, should be built into the model to ensure future simulation runs are even more comprehensive and reliable.
- The time horizon format of the simulation model should be changed from a monthly time horizon to a user-defined time horizon to account for periods longer or shorter than a month.
- To increase the available production time, a 12-hour shift and a 4-day compressed workweek should be implemented with blasting twice a day.
- Pre-production delays should be reduced by implementing digital technology to shorten the time taken to conduct start-of-shift meetings, safe declarations and vehicle pre-start inspections. Post-production delays can be reduced by removing non-essential production personnel first from underground and essential production personnel last.
- Production loading and drilling time can be increased by implementing remote operation capabilities or introducing semi-autonomous vehicles. This way, personnel can operate the

LHDs and drill rigs from the surface, and therefore start significantly earlier. This way they will not be delayed by the blasting re-entry period and time taken to travel underground to their respective machines.

- Eight to nine production LHDs should always be running and it is recommended that two additional swing units are available to be utilised if an LHD in the section breaks down.
- To increase the average bucket load size, training should be conducted to transfer loading skills from top operators to the less experienced operators.
- Mobile rail-mats should be placed in each of the draw points to reduce footwall slumping and improve the loading pivot point.
- To increase the tramming speed, roadways should be better maintained. This can potentially be done by implementing an intelligent roadway monitoring system. The system could utilise a LiDAR (Light Detection and Ranging) scanner that scans all the roadways each day, and automatically report and rank areas that show the most deterioration. A study could aslo be conducted on the feasibility and benefit of upgrading the roadways to a more competent material than just gravel, such as concreting, paving or tarring.
- LHD buckets that are larger in volume should be considered to increase the load size without overloading the LHDs due to the effect of the swell factor.
- Production drifts should be made wider in the future to reduce sidewall damage from the machines and increase the tramming speed.
- Autonomous drones fitted with a camera and LiDAR scanner should be utilised to scan draw points during, and at the end of each shift to get a more reliable report on the status of draw points. This can also assist engineers on the surface to recommend solutions to alleviate problems in draw points to make them available for loading again. The approach can be made autonomous in the future by introducing artificial intelligence that automatically establishes where in the draw point an issue lies, and then suggest the most optimal secondary-blasting explosives placement.
- Semi-rigid polymer ventilation ducting can be used instead of galvanized ducting. It is less prone to being damaged by blasts or when a machine bumps it, and is also easier and quicker to install. This will help that tunnels are less unavailable due to ventilation issues.

- The feasibility of ring preparation and pre-charging immediately after a fresh blast should be investigated with the use of Orica's new in-hole wireless primers. These primers utilise magnetic induction waves of low frequency to communicate and initiate. This approach will reduce the high amount of time spent to get to a ring to blast it, and it is also much safer for personnel to work in front of a closed brow.
- The average utilisation of drill rigs per day should be increased, and the number of rigs used decreased. This can be done by determining the most common breakdowns experienced and eliminating or engineering them out. Focus should also be placed on reducing the amount of time it takes to set-up a rig before it can start drilling and packing it up and moving it to a new location.
- The effect of quality drilling on the production tonnage should be thoroughly researched and quantified. The importance of drilling quality should also be highlighted and tracked better, by reducing the number of rings that need to be re-drilled, due to being damaged from blasting a previous ring drilled at poor quality and accuracy.
- The blasting practice currently followed should be reviewed, to reduce backbreaking into inventory rings, compacting the ground in the draw points and ensuring better breakthrough to the adjacent tunnel and level above. Fragmentation analysis should also be done more frequently to move to a more optimal rock fragmentation. LiDAR scanning should also be utilised more before a blast to have a more situational approach to the blast than a generic approach. This is especially important where breakthrough was not achieved, and the draw point is filled with compacted material or big rocks. Currently, the approach to blasting a place is relatively blind, and it would be helpful to visualise and quantify the void that is being blasted into.

5.4 Potential future research work

The research study was a comprehensive approach to identify and address some of the constraints experienced at FDM, however, it did uncover that there are issues that will require more investigation and research. By using this research study as a roadmap, even more value can potentially be unlocked in optimising the production cycle at FDM. Based on the conclusions and recommendations, and some limitations that were met in the research study, the following research work can potentially be conducted in the future:

- Expansion of the FDM Simio model to include more parameters regarding the quality of drilling and blasting practices. These parameters can include probabilities and variability in fragmentation (load sizes), total tonnes extracted from a ring, probability of hang-ups and big rocks, and time taken to load at a draw point.

- Inclusion of precursory activities such as void scanning, ring preparation for charging and drilling, safety net installation, fixing of ventilation infrastructure, roadway maintenance and secondary blasting. These precursory activities can be built in as activities that should occur at a certain probability and take a variable amount of time to complete.

- Research into alternative road building techniques and materials for underground roadways.

- An investigation into different shift configurations can be conducted to determine the advantages and disadvantages of various configurations, and which will fit the FDM operation the best.

- A comprehensive study should be done on the feasibility of, and capabilities needed in, tablets/mobile device usage underground. This should include the practicality of such devices, safety risks, rigidity, communication capabilities and task management ability.

- The various benefits of using an autonomous drone fitted with a LiDAR scanner and video camera.

REFERENCES

Astolfi, A., 2006. *Optimization - An Introduction.* 2nd ed. London: Imperial College, London.

Axxis, 2020. *Axxis Underground.* [Online] Available at: http://www.axxis.co.za/the-system/underground [Accessed 9 March 2020].

Banks, J., 1998. *Handbook of Simulation: Principles, Methodology, Advances, Applications and Practice.* 1st ed. Atlanta: John Wiley and Sons, INC.

Barnett, W. & Preece, C., 2002. Expanding the Geological Model for Finsch Mine. *South African Journal of Geology,* 1 (105), pp. 375-396.

DataPoint, 2018. *Industry 4.0: Importance of Data and Signals and Triggers.* [Online] Available at: https://www.presentationpoint.com/blog/data-signals-triggers-industry-4-0/ [Accessed 22 January 2020].

Direct Industry, 2020. *Sandvik Mining and Technology.* [Online] Available at: https://www.directindustry.com/prod/sandvik-mining-rock-technology/product-40142 644235.html [Accessed 9 March 2020].

Elkington, T. & Finch, A., 2016. *Can the theory of constraints guide the next wave of mining productivity improvement?.* [Online] Available at: https://www.ausimmbulletin.com/feature/can -the-theory-of-constraints-guide-the-next-wave-of-mining-productivity-improvement/ [Accessed March 16 2020].

Epiroc, 2020. *Simba M4.* [Online] Available at: https://www.epiroc.com/en-in/products/drill-rigs/production-drill-rigs/simba-m4 [Accessed 9 March 2020].

Epiroc, 2020. *Simba ME7C.* [Online] Available at: https://www.epiroc.com/en-me/products/drill-rigs/production-drill-rigs/simba-e7 [Accessed 5 September 2020].

Fernberg, H. & Smith, M., 2007. *Underground Mining Methods,* Orebro: Atlas Copco.

Fiscor, S., 2008. *Finsch Automates Diamond Mining.* [Online] Available at: http://www.womp-int.com/story/2008vol1/story025.htm

Google, 2020. *Google Maps.* [Online] Available at: https://www.google.co.za/maps [Accessed 20 January 2020].

Hartman, H. L. & Mutmansky, J. M., 2002. *Introductory Mining Engineering.* California: John Wiley & Sons Inc..

Humphreys, D., 2019. Mining productivity and the fourth industrial revolution. *Mineral Economics,* pp. 1-11.

Hustrulid, W. & Kvapil, R., 2008. *Sublevel caving – past and future.* Luleå, Luleå University of Technology, pp. 107-132.

Index, 2020. *Diamond Prices.* [Online] Available at: http://www.idexonline.com/diamond_prices_index [Accessed 10 March 2020].

Khati, T. & Matabane, M., 2018. Kimberlite-country rock contact delineation at Finsch Diamond Mine. *Diamonds - Source to Use 2018 Conference, 11–13 June 2018, Birchwood Hotel and OR*

Tambo Conference Centre, JetPark, Johannesburg, South Africa. The Southern African Institute of Mining and Metallurgy, pp. 9-28.

Law, A. M., 2015. *Simulation Modeling and Analysis.* 5th ed. Tucson: McGraw Hill Education.

Morrison, D., Drylie, V. & Labrecque, P., 2018. *A systems approach to mining innovation.* Perth, Australian Centre for Geomechanics, pp. 511-518.

Muzychka, Y.S., 2006. Mechanical Systems. In *Mechanical Equipment and Systems*. Labrador: Memorial University, pp.123-137.

Normet, 2020. *Charmec MC 605 D(V).* [Online] Available at: https://www.normet.com/product/charmec-mc-605-dv/ [Accessed 9 March 2020].

Petra Diamonds Limited, 2016. *Annual Report and Accounts,* London: Design Portfolio.

Petra Diamonds Limited, 2017. *Annual Report and Accounts,* London: Design Portfolio.

Petra Diamonds Limited, 2018. *Annual Report and Accounts,* London: Design Portfolio.

Petra Diamonds Limited, 2019. *Annual Report and Accounts,* London: Design Portfolio.

Petra Diamonds Limited, 2020. *Interim results for the six months to 31 December 2019,* London: Petra Diamonds Limited.

Preece, C. & Liebenberg, B., 2007. Cave management at Finsch Mine. *The Journal of The Southern African Institute of Mining and Metallurgy*, 107 (12), pp. 775-781.

Roblek, V., Meško, M. & Krapež, A., 2016. A Complex View of Industry 4.0. *SAGE Open,* pp. 1-11.

Sandvik, 2020. *Sandvik LH410.* [Online] Available at: https://www.rocktechnology.sandvik/globalassets/products/underground-loaders-and-trucks/pdf/lh410-specification-sheet-english.pdf [Accessed 4 September 2020].

Simio, 2020. *Simio.* [Online] Available at: https://www.simio.com/about-simio/ [Accessed 26 January 2020].

Şimşit, Z. T., Günay, N. S. & Vayvayc, Ö., 2014. Theory of Constraints: A Literature Review. *Procedia - Social and Behavioral Sciences,* Volume 150, pp. 930 - 936.

Stone, T., 2015. A world-class operation. In: *Inside Mining.* Johannesburg: 3S Media, pp. 17-21.

Van Huyssteen, F., 2019. *Finsch Mine Simulation Model User Manual,* Johannesburg: Process Design and Automation.

Villa, D. & Diering, T., 2010. *A new mine planning tool for sublevel caving mines.* Perth, Australian Centre for Geomechanics, pp. 237-252.

Xu, M., David, J. M. & Kim, S. H., 2018. The Fourth Industrial Revolution: Opportunities and Challenges. *International Journal of Financial Research*, 9 (2), pp. 90-95.