

https://dspace.org/

Technology adoption in mining: a multi-criteria analytical tool for emerging technology selection for surface mines

Dayo-Olupona, Oluwatobi Ifedayo

2020

https://hdl.handle.net/10539/31139

Downloaded from a DSpace repository. https://dspace.org/

Technology Adoption in Mining: A Multi-Criteria Analytical tool for Emerging Technology Selection for Surface Mines

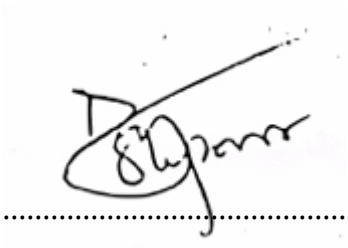
Oluwatobi Ifedayo Dayo-Olupona

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

Johannesburg, 2020

DECLARATION

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



.....

Signature of candidate

On this ..... **16th** ..... day of .....**September**.....

....**2020**.... (year), at .....**Wits University**.....

ABSTRACT

The integration of technologies across the mining value chain is becoming critical because it is recognized as a process enabler. Recent studies have argued for a dire need for a technology roadmap and strategy to help facilitate technology adoption and implementation in order to solve mines' productivity challenges and consequently, contribute to operational cost reduction. Hence, this research aimed to identify the best possible technologies applicable to an operation, based on the chosen criteria. In keeping with this aim, this study focused on investigating adoptable technologies for a mining project, developing a conceptual framework for the analytical process and validating the framework using a hypothetical case study. The case study comprised of a technology decision problem, the result of which consisted of six technology alternatives, four criteria and one decision maker.

The Multi-Criteria Decision Making (MCDM) operation research methodology was used in the process. Of the several MCDM techniques available, the fusion of the analytic hierarchy process (AHP) and preference ranking organisation method of enrichment (PROMETHEE) techniques were employed for this study. This is due to their ability to scientifically solve problems involving quantitative and qualitative analysis. The AHP was used to determine the hierarchal weight of each decision-making criterion and its consistency while the PROMETHEE method was used to carry out the overall process evaluation. Additionally, the fuzzy set theory was infused into the hierarchical structure analysis to evaluate the quantitative economic criterion to curb uncertainty and imprecision.

The results of the analysis show that the technology alternative A3 – Artificial Intelligence (AI) – is the most preferred alternative. This is due to the technology's net flow value of (0.2493) which outranks other comparative technologies. The approach proposed in this study can help provide the basis for any technology adopting mining company to build its technology business case, strategy and or roadmap to achieve the desired outcome.

ACKNOWLEDGEMENTS

Thanks are due to the following individuals and organisation:

My supervisor, Prof. B. Genc (School of Mining Engineering, University of the Witwatersrand) for his academic guidance through all the phases of writing this research report.

Prof C. Musingwini (Head, School of Mining Engineering, University of the Witwatersrand) for making the school's resource available to me to enhance the completion of this research.

Dr Moshood Onifade (University of the Witwatersrand) for his energy and continued push for me to put in my best.

The Wits' Nigerian Community for their willingness to share useful information when needed and for their help in navigating around South Africa.

DEDICATION

To my late Dad (Oludayo Idowu Olupona) who would have been the most joyous to see me complete this postgraduate degree. I just want you to know that I will keep the banner flying high.

To my Mum; Tosin Olupona, thank you for being my biggest cheerleader.

To my Siblings; Toni and Tofunmi, you guys rock.

And to GOD, who has been my chief motivator.

CONTENTS

DECLARATION ..... **i**
ABSTRACT ..... **ii**
ACKNOWLEDGEMENTS ..... **iii**
DEDICATION ..... **iv**
CONTENTS ..... **v**
LIST OF FIGURES ..... **viii**
LIST OF TABLES ..... **x**
LIST OF EQUATIONS ..... **xii**
LIST OF ABBREVIATIONS ..... **xiii**
1 Introduction **1**
1.1 Problem Statement 2
1.2 Aims and Objectives of Research 3
1.3 Research Questions 3
1.4 Research Motivation 4
1.5 Research Scope 4
1.6 Research Outline 5
2 Literature Review **6**
2.1 Technology 6
2.2 Classification and Characteristics 6
2.3 Applicable Technologies in Mining Industry 10
2.4 Criteria Defining the Mining Industry Technology Adoption 11
2.5 Challenges of Technology Adoption within the Mining Industry 12
2.6 Role and Impact of Technology in Mining 13
2.7 Contemporary Company Case Studies 14
2.8 Global Overview of Productivity in Mining. 17
2.9 Chapter Summary 22
3 Research Methodology **23**
3.1 Classification of Multi-Criteria Decision Making (MCDM) Methods ... 24

3.2 General Framework of MCDM 26
3.2.1 Defining phase 26
3.2.2 Processing phase 26
3.2.3 Interpretation and recommendation phase 26
3.3 The Technology Map 27
3.4 The Conceptual Framework 28
3.5 Case Study 30
3.6 MCDM Solution 30
3.7 Analytical Hierarchy Process (AHP) 31
3.8 Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE) 32
3.9 Chapter Summary 34
4 Quantitative Evaluation Procedures 35
4.1 Alternatives. 35
4.2 Criteria 36
4.3 Weights 41
4.3.1 The hierarchical relative weight calculation 42
4.3.2 The judgement consistency step. 44
4.4 Judgment Matrix 45
4.4.1 Fuzzy set theory. 47
4.4.2 Fuzzy economic data 50
4.5 Normalization 55
4.6 Pairwise Comparison 56
4.7 Preference Function 57
4.8 Multicriteria/Aggregated Preference Index 58
4.9 Preference Order 58
4.10 Chapter Summary 59

5 Discussion and Analysis 60
5.1 Results 60
5.2 Analysis 61
5.3 Sensitivity Analysis 62
5.4 The Decision 68
5.5 Chapter Summary 68
6 Conclusions and Recommendations 69
6.1 Conclusions 69
6.2 Recommendations 70
6.3 Limitation of Study and Future Research Work 70
References 72
Appendix 82
APPENDIX A 83
APPENDIX B 86
APPENDIX C 87

LIST OF FIGURES

Figure 2.1: Productivity and Variability Questions across the Mining Value Chain (Ernst & Young, 2017b) 14

Figure 2.2: Impact of Emerging Technologies on Variability and Uncertainty. (Durrant-Whyte et al., 2015) 16

Figure 2.3: Showing declining grade of Copper, Lead, Zinc, Gold, Nickel, Uranium and Diamond Ores (Ernst & Young, 2017a) 18

Figure 2.4: The Average Mining Chilean Labour Productivity from 1978-2015 (Fernandez, 2018) 19

Figure 2.5: Labour Productivity of the South African Gold mining sector in comparison with Average Wage (Deloitte, 2015) 19

Figure 2.6: The Australian, USA, and Canada Mining Industry Labour Productivity; 1995-2013 (Fernandez, 2018) 20

Figure 3.1: General Classification of MCDM methods (Zavadskas, et al., 2014) 24

Figure 3.2: General MCDA process framework 28

Figure 3.3: Schematic framework for technology adoption 29

Figure 4.1: Mining Cycle Framework Highlighting the Procedure for selecting Technology Alternatives from the Technology Map 37

Figure 4.2: MCDA Framework for Technology Selection adapted from Wang & Tu, (2015) 40

Figure 4.3: Triangular Fuzzy Number (Wang & Tu, 2015) 48

Figure 5.1: Complete Ranking of the Technology Alternatives Flow 60

Figure 5.2: The GAIA Plane Analysis of the Decision Problem 61

Figure 5.3: Criterion Weight Variability Graphs 63

Figure 5.4: Results with Original Criteria Weights 65

Figure 5.5: Results with Equal Criteria Weights 66

Figure 5.6: The Action Profile Comparing the Uni-criteria Net Flow Scores of Criteria of the Technology Options 67

LIST OF TABLES

Table 2.1: Characteristics of the 3 Technology Levels (Dessureault, 1999) 8

Table 2.2: Technology Classification and Definition (Jacobs, 2016)..... 9

Table 3.1: MCDM use cases within the Mining Industry..... 25

Table 4.1: Adopted Criteria from (Ordoobadi, 2012; Taha, *et al.*, *2011;* Poulin, *et al.*, 2013; Vujic, *et al*., 2013; Stojanović, *et al.*, 2015)..... 39

Table 4.2: Criteria Selection used in this Study..... 39

Table 4.3: Measurement Scale of Relative Importance (Saaty, 1995)..... 42

Table 4.4: Pairwise Comparing Matrix for Criteria..... 42

Table 4.5: Weight Determination for the Criteria..... 42

Table 4.6: Judgement Consistency Determination for Criteria..... 44

Table 4.7: RCI values for different Order of Matrix (n) (Wang & Tu, 2015)..... 45

Table 4.8: Non-Fuzzy Linguistic Scale for Subjective Criteria..... 46

Table 4.9: Decision Matrix with Filled Subjective Criteria Column..... 47

Table 4.10: Fuzzy Data for the Six Technology Alternatives. 51

Table 4.11: Economic Data of Technology A1, A2, A3, A4, A5, A6..... 53

Table 4.12: Cash Flow Model Showing the Fuzzy and Crisp NPV values for the Technology Alternatives 54

Table 4.13: Normalized Data for the Decision Matrix 55

Table 4.14: Evaluative Deviation of the Technologies with Respect to the Criteria..... 56

Table 4.15: Usual Criterion Preference Function 57

Table 4.16: Aggregated Preference Index Matrix..... 58

Table 4.17: The Leaving and Entering Outranking Flow Values..... 59

Table 4.18: The Net Flow Values of the Technologies 59

Table A1: Technology Map Showing the Mining Cycle and the Technologies that Facilitate Mine Modernization (Jacobs, 2016)..... 83

Table B1: The Preference Functions in PROMETHEE..... 86

LIST OF EQUATIONS

Equation 3.1: PROMETHEE Normalization Function (Abdullah, et al., 2019)... 32

Equation 3.2: PROMETHEE Pairwise Comparision Function (Abdullah, et al., 2019)..... 33

Equation 3.3: PROMETHEE Preference Function (Abdullah, et al., 2019) 33

Equation 3.4: PROMETHEE Aggregated Preference Index (Abdullah, et al., 2019)..... 33

Equation 3.5: PROMETHEE II Net Flow Function (Abdullah, et al., 2019)..... 33

Equation 3.6: PROMETHEE Leaving Flow Function (Yuen & Ting, 2012) 33

Equation 3.7: PROMETHEE Entering Flow Function (Yuen & Ting, 2012)..... 33

Equation 4.1: PROMETHEE Weight Function (Abdullah, et al., 2019)..... 40

Equation 4.2: AHP Geometric Mean Function (Wang & Tu, 2015) 42

Equation 4.3: AHP Weight Normalization Function (Wang & Tu, 2015) 42

Equation 4.4: AHP Consistency Index Function (Wang & Tu, 2015) 43

Equation 4.5: AHP Consistency Ratio Function (Wang & Tu, 2015)..... 44

Equation 4.6: AHP Judgement Matrix Maximum Eigenvalue Function (Wang & Tu, 2015) 44

Equation 4.7: Judgement Matrix Structure (Wang & Tu, 2015) 44

Equation 4.8: Expanded Judgement Matrix Structure 45

Equation 4.9: Fuzzy Net Cash Flow Function (Komolavanij, 1995) 48

Equation 4.10: Fuzzy Net Present Value Function (Komolavanij, 1995) 49

Equation 4.11: Fuzzy Defuzzing Equation Net (Wang & Tu, 2015)..... 55

Equation 4.12: Final Judgement Matrix..... 55

LIST OF ABBREVIATIONS

AA	Advanced Analytics
AI	Artificial Intelligence
AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
AR	Augmented Reality
CAES	Computer-Aided Earth-Moving System
CEO	Chief Executive Officer
CFO	Chief Financial Officer
CIO	Chief Information Officer
CSIRO	Commonwealth Scientific and Industrial Research Organisation
C.U	Currency Unit
ELECTRE	Elimination Et Choix Traduisant la Realité (Elimination and Choice Expressing Reality)
ERP	Enterprise Resource Planning
EY	Ernst & Young
GAIA	Graphical Analysis for Interactive Assistance
GNSS	Global Navigation Satellite System
IBM	International Business Machine
IoE	Internet of Everything
IoT	Internet of Things
IRR	Internal Rate of Return

MADM	Multi Attribute Decision Making
MAUT	Multi Attribute Utility Theory
MCDM	Multi Criteria Decision Making
MET	Mining Equipment, Technology and Services
MIS	Management Information System
MODM	Multi Objective Decision Making
NPV	Net Present Value
OR	Operation Research
PB	Payback Period
PROMETHEE	Preference Ranking Organization Method for Enrichment of Evaluations
PWC	Price Waterhouse Coopers
R&D	Research and Development
ROI	Return on Investment
RPAS	Remotely Piloted Aircraft System
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UAVs	Unmanned Air Vehicles
USA	United States of America
WEF	World Economic Forum
WSM	Weighted Sum Model

1 INTRODUCTION

Mining is dynamic (Runge, 1995) and this makes it an industry to be classified as a complex one. Apart from its dynamism, several other factors contribute to the complexity of the industry. Some of them include fluctuating commodity prices, rising cost of operations, extraction of low ore grades, ageing existing mines as well as longer haul distances, resource scarcity, resource nationalism, increased environmental regulation, and geopolitical instability (Durrant-Whyte *et al.*, 2015; World Economic Forum (WEF), 2017).

The cumulative effect of the identified challenges within the industry represents large-scale value destruction over the last 15 years (Bryant, 2015). To solve this value conundrum, mining companies may need to consider certain resolutions. Some of these resolutions include pushing the boundaries on digital transformation, attracting a truly diverse workforce and re-envisioning corporate strategy. In this research, the focus was on digital transformation aided by technology. Mining companies need to recognize technology as a process enabler and, strategically prioritise technological integration across the mining value chain (Deloitte, 2019).

Upstill & Hall (2006) affirmed that the exploration, mining, processing and environmental licensing phases, as well as processes within an existing or new operation, can be greatly improved by technological innovations. The outcomes of technological innovations and its adoption within the mining industry are captured in the World Economic Forum's (WEF) (2017) report on digitisation in mining and the metal industry. The report states that the value-at-stake over the next 10 years are:

a) Safety record improvement which includes 1,000 lives saved, and 44,000 injuries avoided;
b) Society and environmental cost saving of about $30 billion, this is equivalent to a reduction of 610 million tonnes of CO_2 emissions; and
c) Greater than $320 billion worth of business value to be realised.

Crawford (2018) showcased about 13 mine sites already realising value through operational improvement within its operations by capitalising on these new and

emerging technologies. However, with allusions to recent studies, there is a dire need for a coherent technology roadmap and strategy to help facilitate technology adoption and implementation within the mining industry.

In keeping with this need, this research aimed to develop an analytical algorithm that will help filter through an extensive list of technologies and identify applicable technology and or technologies to an operation based on the chosen criteria. The Multi-Attribute Decision Making (MADM) methodology of operation research would be used as the basis for the analytical procedure. Of the several MADM techniques, the fusion of the analytic hierarchy process (AHP) and preference ranking organisation method of enrichment (PROMETHEE) techniques was employed for this study. In addition, the research outcome will be critical in forming the necessary technology business cases needed for the decision makers.

1.1 Problem Statement

In recent times, the mining industry has been identified as a sector that adopts technologies from other industries. In line with these adoptions, PriceWaterhouseCoopers (PWC) (2015) notes that, within the mineral industry, adopting technologies, especially the smarter and newer ones, can either destroy or transform the business model. Additionally, new technologies can generate a greater level of responsiveness, which will position mining companies for long-term growth (Deloitte, 2015). Moreover, without disregarding the implication of the new cost structure attached to the adoption of new technologies to any operation, it is important to note that complexity exists in acquiring, implementing and maintaining this set of additional infrastructures.

The mining industry's C-level executives (CEO, CIO, CFO, etc.) are today challenged with making technology decisions (Deloitte, 2015). Some of which include:

a) Selecting the right technology;
b) Selecting the technology vendors;
c) Managing the implementation of the identified technology; and

d) Managing the associated adaptation of workforce to the work-cultural change.

Therefore, it was beneficial to develop a well-thought-out plan to make technology and technological services selection in alignment with mining business objectives. Notably, various studies have discussed the likely impact of emerging and 4th industrial revolution technologies on mining operations. However, there has been no clarification on how to suitably identify the best possible technologies, for better value addition to various components across the mining value chain.

1.2 Aims and Objectives of Research

This research aimed to create an analytical algorithm that would be useful in investigating the various technologies listed in Jacobs (2016) technology map to select the most optimal for a mine.

The following objectives were set out to achieve the aim of the study;

a) Investigate the adoptable technologies for the specific mining project;
b) Develop a conceptual framework for the analytical algorithm; and
c) Validating the framework using a hypothetical case study.

1.3 Research Questions

Beyond sorting, the analytical algorithm was useful for refining the number of technologies. It was also useful in identifying technological solutions with the best possible value-add within the mining value chain. Furthermore, the adopting mining company or institution is tasked with some questions. For the purpose of this research, the two questions that were considered are:

a) What existing technologies have the necessary features and competencies needed to meet some of the mining business objectives?
b) Of this list of technologies generated, which of them or what technology mix should be considered appropriate for the mining business operation and its value chain?

1.4 Research Motivation

In addressing the several challenges experienced in the mining industry, Deloitte (2019) advocates that there is a need to prioritise technology as a strategic enabler across the mining value chain. In building a case for technology adoption and implementation in mining, Kumar & Kumar (2016) pointed out that it is expedient to align mining with the current technological age. Furthermore, the researchers argue that special focus should be on the trend moving towards high technology innovation. However, doing this will require:

a) The consideration of all possible and available technology options; and
b) The development of a unique technology strategy/business case/roadmap that complements the mining business model.

Drawing from the aforementioned, Jacobs (2016) in agreement with Kumar & Kumar (2016), created a technology map consisting of a comprehensive list of modern technologies that can be adopted along within the mining value chain to create value. Remarkably, Kostoff *et al*. (2004) pointed out that various, already existing planning processes are prominently deficient in recognising the mix of technologies needed to meet and optimise any industries performance objectives.

In this study, the filtering nature of the technology analytical algorithm makes it a multi-utility tool applicable to various processes along the mining value chain. It is also applicable to various types of mining operations across the mining value chain. The general-purpose nature of the analytical procedures also makes it applicable across all mining methods, processes and operations. However, in establishing the context of this research, the focus was on surface mining operations.

1.5 Research Scope

In establishing the purpose of this study and for the design of the analytical algorithm, the focus of this research was on emerging technologies that have been identified to contribute value to the mining industry. A study by Jacobs (2016) has identified and compiled a comprehensive list of technologies that are poised to add value to mining and aid mining modernisation. These technologies were organised into a technology map that covers every phase of the entire mining lifecycle. The

technologies were under 330 value drivers which were used as the inputs into the database from which the Multi Criteria Decision Making (MCDM) analytical algorithm identified the criteria-meeting technologies. Throughout this research, the word ‘technology’ has hence been used interchangeably with ‘digital technology’ and ‘emerging technology’.

1.6 Research Outline

This research project is divided into six chapters. Chapter 1 provides a general introduction explaining the research context, problem statement, research question and objectives. Chapter 2 focuses on a literature review of the various technologies applicable to the mining industry, the current state of technology adoption within the industry and highlights similar research carried out within the mining industry technology space. The 3rd Chapter discusses the operation research methodology used as well as the study’s conceptual framework. Chapter 4 shows the stepwise implementation of the selected method of analysis. The 5th Chapter provides an interpretation for the finding and results for the analysis done in Chapter 4. Lastly, Chapter 6 discusses the conclusions and recommendations of the research.

2 LITERATURE REVIEW

This chapter presents an overview of technologies with a specific focus on mining technologies. In addition, the classifications and characteristics of mining technologies are presented. It also presents the applicability of the new and emerging classified technologies to mining. Finally, the factors that constantly influence the adoption of technologies within the mining industry are identified and described.

2.1 Technology

Technology is broadly defined as the application of knowledge towards providing practical solutions to problems (Gorse *et al.*, 2013). Technology in itself is inclusive and is believed to include physical hardware, operational procedures, organisation structures and management practices (Paterson *et al.*, 2001). For the purpose of this study, technology is defined within the context of mining as it cuts across its value chain. Mining technology is therefore referred to as an accumulation of equipment or machinery that are associated with mining operations (such as loading, hauling and drilling equipment). Mining technology is also explained as the technology that supports mining, such as monitoring, control, communications systems; planning and design tools and services.

2.2 Classification and Characteristics

Based on the similarity of mining technology to that of the manufacturing industry, the level of complexity and integration into newer technologies, are classified into three levels (Dessureault, 1999) namely:

a) Stand-alone technology;
b) Single process integrating technology (linked); and
c) Multiple process integration technology (integrated).

Stand-alone technology, which is otherwise known as a Level 1 technology, is a set of technology often said to increase flexibility and improves performance dynamically. Typical examples of stand-alone technology within the mining operations include shovels, conveyor belts and haul trucks. A purchase of these

items or an additional purchase of one of these items increases capacity and its benefits to any typical mining operations are directly attributable, qualitative and easily quantifiable.

Single process integrating technology, which is also known as a Level 2 technology, integrates activities within one single process. They are believed to mostly impact efficiency and effectiveness. Efficiency is defined as maximising the output obtained per unit of input, while effectiveness is the attainment of the maximum output from a given amount of input (Dessureault & Scoble, 2000). Examples of the Level 2 technology include global navigation satellite system (GNSS), as well as drilling-monitoring.

Multiple processes integrating technology, which is also known as Level 3 technology, is similar to the Level 2 technology. However, instead of integrating activities within a process, this set of Level 3 technology integrates processes with processes.

Table 2.1 summarises the characteristics of the three classes of technologies and an example of the technologies with each classification are given. In contrast to Dessureault (1999), Jacobs (2016) classifies technologies into physical and digital technologies. Table 2.2 shows his verbatim definition of the two classes of technology.

Table 2.1: Characteristics of the 3 Technology Levels (Dessureault, 1999)

Level **1**: Truck (& operator) • Basic tool; does not provide any benefits other than its allocated task. Drill (& operator) • Basic tool, relatively little flexibility in unplanned design change; and • Shovel - important tool, used to determine the size truck fleet, does not provide any benefits other than its allocated task.
Level **2:** Enabling Technologies: GNSS, Drill Monitoring, Organizational Theory GNSS assisted planning & drilling; • Integrates a series of activities, such as planning, map updating, drilling and surveying into a more integrated process; • Provides less human interaction thereby can be more repetitive and hence produce designs with higher quality; • Flexible to unplanned design changes; and • Can take more factors into account during planning thereby increasing quality of design.
Level **3:** Enabling Technologies: GNSS, Computer-Aided Earth-Moving System (CAES), Enterprise Resource Planning (ERP), Management Information System (MIS), Operation Research (OR) Mine-Mill integration: • Integrates many major activities into a single process; • Can take advantage of market changes; • Greatly reduces human interaction thereby is less prone to human error; • Greatly reduces transcribing information; • Reduces repetitive human tasks; and • Produces ore of better quality.

Table 2.2: Technology Classification and Definition (Jacobs, 2016)

Technology Class	**Definition**	**Examples**
Physical Technologies	Any technology that has a physical nature in its use and work output, such as machinery, equipment or the devices necessary to use data & information technologies.	Unmanned Aerial Vehicles (UAV)/Remotely Piloted Aircraft System (RPAS)/Drones. Wearable Technologies. Tracking Technology (e.g. leaky feeder). Cooling technologies (Immersion-cooling technologies). Autonomous and Semi-autonomous Vehicles Advanced Robotics etc.
Digital (Data, information & communication) Technologies	Any technologies relating to the sourcing, analysis and application of data or information. This may include the generation of data from sensors or other sources. It may also include the transfer of information, which may range from statistics and forecasts to communications and instructions. It may further include the analysis and refinement of data to information, to value-adding knowledge or insights. Lastly, any software application will also be classified under this section regardless of what type of role it plays in the usage of either data or information.	Advanced analytics and big data. Data integration & Visualisation. Artificial Intelligence (AI) & Machine Learning. Autonomous Agent and things (e.g. Virtual Personal Assistance,). Augmented Reality & Virtual Reality. Cloud Technology. Communication Technologies (e.g. wearable Translator). Internet of things (IoT), Internet of everything (IoE) and IoT platforms. Mobile Internet, etc.

2.3 Applicable Technologies in Mining Industry

In describing the digital technologies that would shape the future of mining, Ernst & Young (2017b) report highlighted technologies including; big data, IoT, wearable technology, AI, remote centre, advanced analytics, and social media. The study, however, mentioned that the mining industry, to a considerable extent has slowly adopted digitisation and technologies such as mine planning systems, plant automation systems, GNSS, and in recent times, cloud computing. Regardless of the benefits realised from such integration, the report argued for the persistent need to develop a more holistic approach (Ernst & Young, 2017b).

In keeping with a holistic approach, the Commonwealth Scientific and Industrial Research Organisation (CSIRO) (2017) developed a roadmap for the mining and Mining Equipment, Technology and Services (METS) industry in Australia. From the study, five opportunities for growth were identified. Although not exhaustive, they include:

a) Mining automation and robotics;
b) Advanced extraction;
c) Exploration under cover;
d) Data-driven mining decisions; and
e) Social and Environmental sustainability.

Emphasis was placed on the roles of integrating emerging technologies to extract value for these growth areas. Some of these technologies include, but are not limited to;

- Sensors (passive, high precision);
- 3D impact and natural user interface (NUI) sensor;
- Advanced communication and wireless technologies;
- Advanced multi-purpose drilling equipment;
- Data analytics;
- Artificial intelligence;
- Crowdsourcing;
- Cloud-based advanced platforms;

- Equipment and infrastructure mobility;
- Modularity;
- Digital twinning;
- Virtual and augmented reality; and
- Cybersecurity.

Without disregarding the aforementioned findings, Jacobs' (2016) study presented the most comprehensive list of technologies. In the study, a technology map for the mineral industry was created. This map consisted of seven by six matrix which encompasses seven identified value-driving pillars and six mining phases – from exploration to mine closure. A total of 330 value drivers were identified after tabulating and expanding the matrix. Furthermore, technologies deemed fit were added in, under each value driver. A total of 550 technologies or group of technologies were compiled into the map, some of which were included in Table 2.2.

It is important to note that due to the multiple-use nature of technologies, several technologies were applicable in multiple phases of the mining operation. This, therefore, led to a replication of some of these technologies on the technology map.

2.4 Criteria Defining the Mining Industry Technology Adoption

Of the several factors, drivers and perspectives that drive the mining and mineral industry, Steen *et al*. (2018) identified the following three recurring priority areas for innovation and technology:

a) Resource quality improvement;
b) Productivity improvement; and
c) Social and environmental sustainability.

Jacobs & Webber-Youngman (2017) while conceptualizing the mining cycle for the technology map study, identified the following six main driving mining pillars:

a) Mineral Resource Management;
b) Production;
c) Productivity and Asset Efficiency;

d) Socio-Economic Factors;
e) Supply Chain; and
f) Health, Environment, Safety and Legal.

2.5 Challenges of Technology Adoption within the Mining Industry

There is a consensus among several authors (Ernst & Young, 2017a; Jacobs & Webber-Youngman, 2017; Durrant-Whyte *et al.*, 2015; Bryant, 2015) that adopting emerging and digital technologies could be critical and integral for the growth needed in mining. However, there are challenges with deploying these technologies.

Some, as observed by Steen *et al*. (2018) include:

a) Non-virtualised mining industry deliverables – the primary output from the mining industry is not service-oriented, neither is it information-based nor of a virtualised nature;
b) The "moving factory" operational environment – the uncertainty that is a result of the mining industry's dynamic nature makes digitisation a complex endeavour;
c) The statutory regulations and the unforgiving mining environment; and
d) Enterprise lack of end-to-end system-interoperability – fragmentation of the information network occurs due to the industry's mix of legacy and systems and processes.

However, Jordaan & Hendricks' (2009) study on the challenge of technology highlighted the lack of alignment of the technology strategy with the overall business strategy. This lack of alignment was mentioned to be commonplace in the mining industry. The ad hoc manner in which most mining and exploration companies approach technology strategy, planning and road mapping is another stumbling block to the way technological benefits can be fully realised (Jordaan & Hendricks 2009).

Furthermore, the negligence of the human-technology interface (the role of the human element in interacting with technology) is commonplace in the industry. Although currently neglected, this neglect will ultimately determine the successful

application and utilization of the adopted technology component (Jordaan & Hendricks, 2009).

2.6 Role and Impact of Technology in Mining

The mining industry's ability to gain a competitive edge lies in the willingness of its operating mines to adopt product cost-reducing technologies as well as improving process and system innovation. This will involve the adoption of end-product cost-reducing technologies and safety-advancing technologies.

A cross-continental Accenture survey of 201 mining industry's top management executive revealed that 82% of them have prioritised increasing investment in digital technology over a three years period (Callahan & Long, 2017). Furthermore, 28% of them specified that they were ready to infuse large investments into digitization (Callahan & Long, 2017). The imminent value of digital technology transformation is intrinsic in nature and it is evident in the way it enables companies to do things differently compared to how it has been done (Sganzerla *et al*., 2016). This in turn affects several processes along the value chain, some of which include:

a) Reduced operations variability;
b) Integrated turnaround management;
c) System performance management; and
d) Predicted & condition-based asset management.

When mining, energy and information technology are integrated, these technologies would assist companies to increase their mining intensity, while also reducing labour, capital and energy intensity. Reduced operating cost, improved safety standards and optimised energy mix can also be achieved if these groups of technologies can be innovatively combined and included in the process design of a mine (Deloitte & Touche, 2014)

2.7 Contemporary Company Case Studies

In this section, questions 1 through 5 in Figure 2.1 were addressed with case scenarios of companies who have adopted emerging technologies.

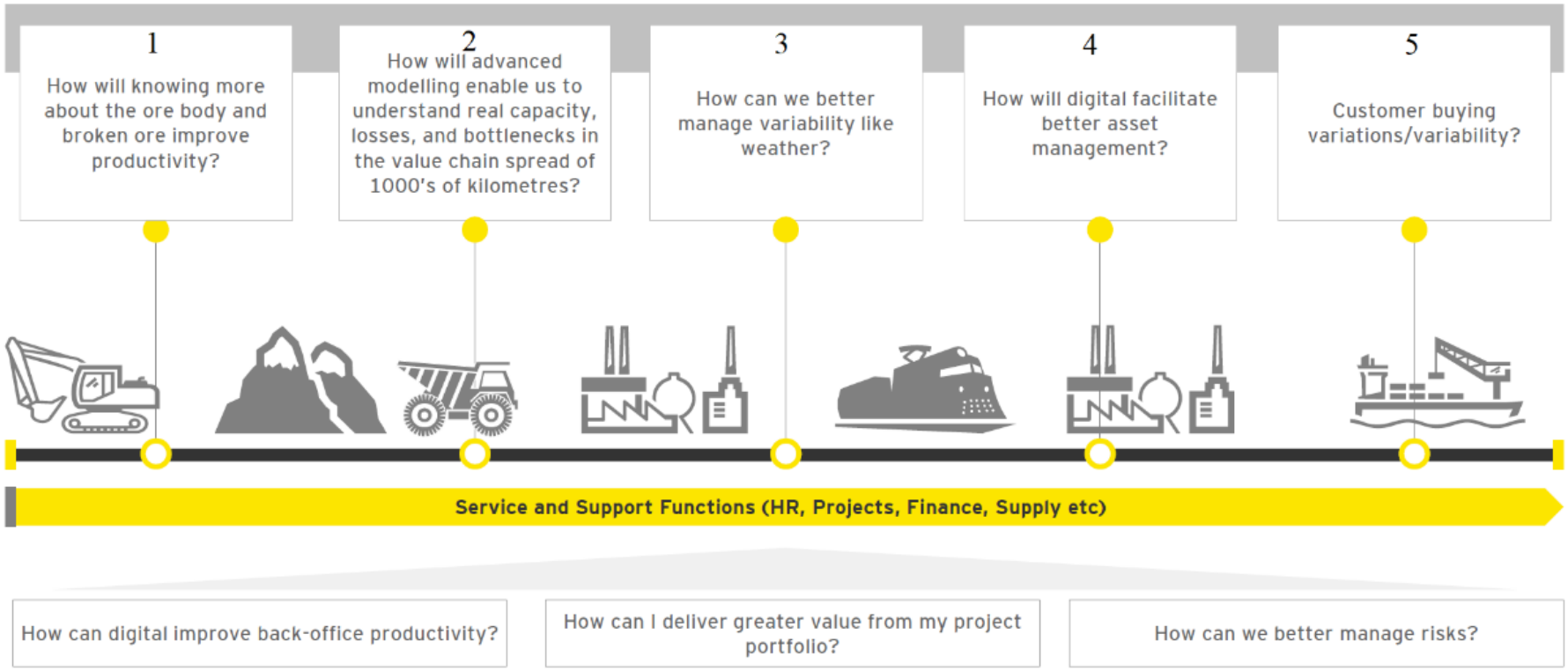


Figure 2.1: Productivity and Variability Questions across the Mining Value Chain (Ernst & Young, 2017b)

1) Goldcorp (now NewmontGoldcorp) and International Business Machine (IBM) Canada in 2018 co-authored an innovative approach by using artificial intelligence (AI) to improve the predictability of gold mineralization. After IBM's Watson was trained with 80 years' worth of Goldcorp's Red lake data, Watson's cognitive technology (spatial analysis, machine learning, predictive model) helps explorers make geological extrapolations and propose new drill targets. 97% efficiency in data processing has already been recorded. (International Business Machine (IBM), 2018; Quash, 2018)
2) Exarro's Belfast coal mine adopted the digital twin technology for its Mpumalanga mine. The digital twin technology can best be described as a time machine. Looking back, it helps discover how the best performance of an operation was achieved. Projecting forward, it allows operations to simulate ideal situations by experimenting with your choice of parameters. At present, this almost high-fidelity digital representation of a real-time operation can run parallel what-if scenarios on its simulators. Other mines that have adopted this digital twin include, OceanaGold's Haile mine, South 32, and Anglo America's Los Bronces mine (Collins, 2018; Exarro, 2018; Moore, 2018; Stewart & Pokracic, 2018)

3) To deal with uncertainty as a result of variability, Rio Tinto introduced mine of the future initiative. This is an innovative reinvention that started in 2008 and it is aimed at leveraging automation technology. In line with this, Rio Tinto has expanded its fleet to include automated drilling rigs and haul trains. This has in return improved precision and equipment utilization. When precision is increased, variability is reduced and as a result, uncertainty is equally reduced and more manageable. Figure 2.2 shows how digital technology reduces uncertainty.

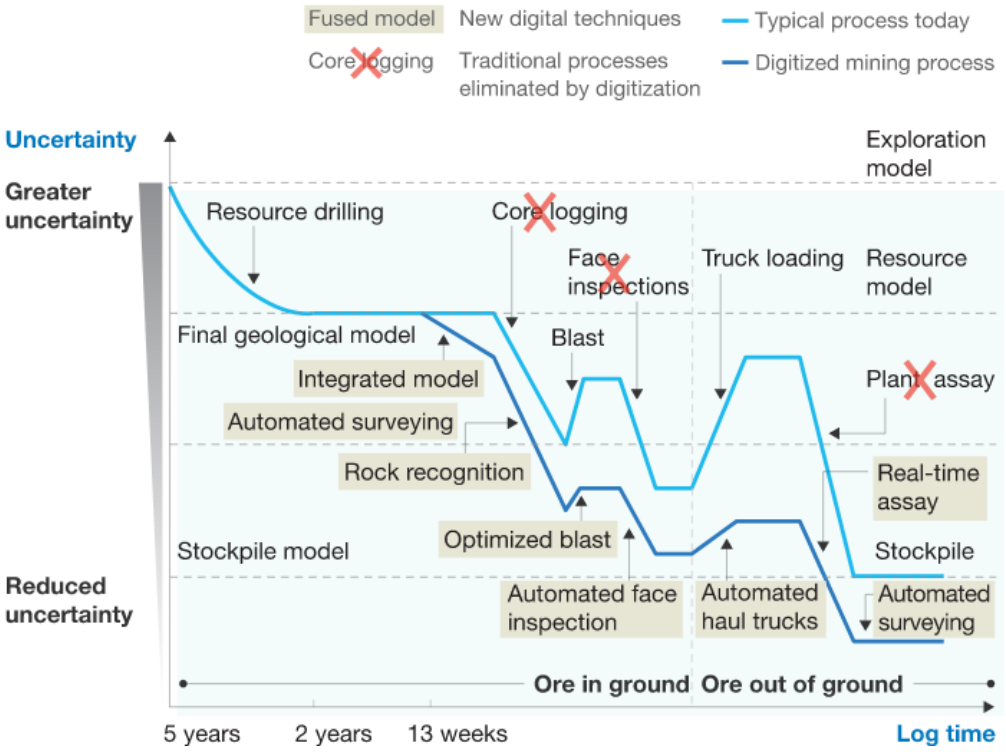


Figure 2.2: Impact of Emerging Technologies on Variability and Uncertainty. (Durrant-Whyte et al., 2015)

4) Newcrest, in collaboration with unearthed solutions, used crowdsourcing and hackathons to develop an innovative solution to several complex mining business problems. Some of the asset-improvement based projects aimed at;
    a. Predicting surge events in the SAG (ore crushing) mill:
    b. Predicting tailings density to reduce water usage in gold processing;
    c. Predicting maintenance for cyclone feed pumps; and
    d. Improving pre-start check at crushing and floatation plants.

On implementation of the solution of the first challenge, the asset located in Newcrest's Cadia Mine has not had any significant surge events (Unearthed, 2018; Dyson, 2018).

5) Lucara Diamond's Clara is an online e-commerce diamond trading platform that leverages on the blockchain technology. This trading platform aims to improve the age-long complexity associated with the customer's buying variation and, the variability within the supply chain of the diamond industry. The blockchain technology backed tool allows customers to purchase a diamond, based on specific preferences as opposed to, purchasing a bucket of diamonds just to sort out those that fit the buying criteria and, resell the rest (Lucara Diamond Corp, 2018; Hoikkala & Rolander, 2019).

2.8 Global Overview of Productivity in Mining.

According to Bartos (2007), an economist's measure of increased technology-use in any space is usually closely linked to an increase in productivity. This section discusses the productivity trend in mining and its relationship with technology.

Accenture's (2011) study on the balance of demand and supply revealed that in the long term, the mineral demand for most commodities is healthy but the means to meet the supply might not be available. This is not because of the lack of commodities around the world, but the scarcity of deposits in high concentration. Moreover, declining ore grade across the industry plays a contributory role in the inability of supply to meet demand (Ernst & Young, 2017a).

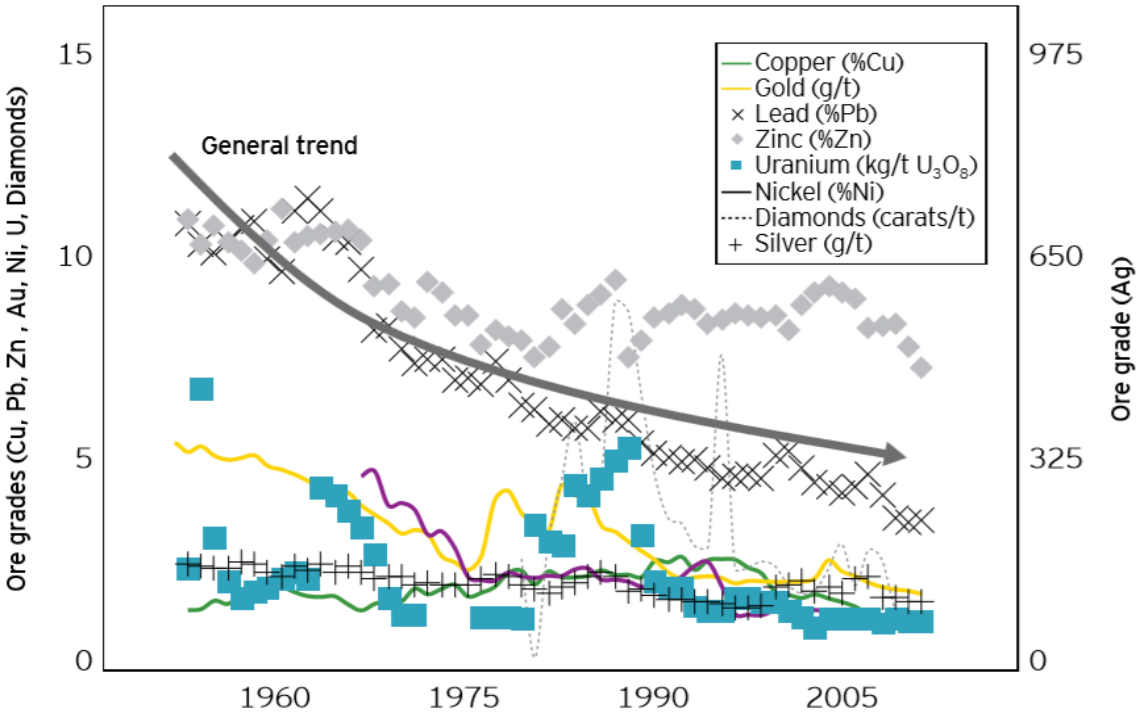


Figure 2.3: Showing declining grade of Copper, Lead, Zinc, Gold, Nickel, Uranium and Diamond Ores (Ernst & Young, 2017a)

A quick comparison of the ore grades of commodities in Figure 2.3 highlights the fact that the general trend in the mineral industry has indeed declined over the past 4 to 6 decades. However, for the commodity ore grades of diamond and gold, there were noticeable spikes around 1975 to 1980, and 1990, respectively. In contrast to other industries, the mining industry is not characterized by product differentiation because a commodity produced in one mining company is the same commodity in another. This leaves the companies within the industry with efficiency and productivity as paths to differentiate itself from the others. The capacity to triumph amongst other things, however, depends on reducing the aligning production cost (Poulton *et al.*, 2013).

Even though efficiency and productivity differ from one mining company to another and, from one commodity to another, an overall view of the global industry indicates that productivity has continually been declining. Mining operations have declined on an annual average of 3.2% from the year 2004 to 2013 and an overall of about 28% during the same decade (Durrant-Whyte *et al.*, 2015).

Tilton (2003) investigated the Chilean and USA's copper industry productivity. Fernandez (2018) also conducted a similar study featuring the Australian, Canadian and USA's mining industry. Although the Chilean mining industry was primarily investigated, productivity comparison within the industry was made. Similarly, South Africa's productivity data was captured in the Deloitte (2015) report. The finding of all of the above-described studies is summarized in Figures 2.4 through 2.6.

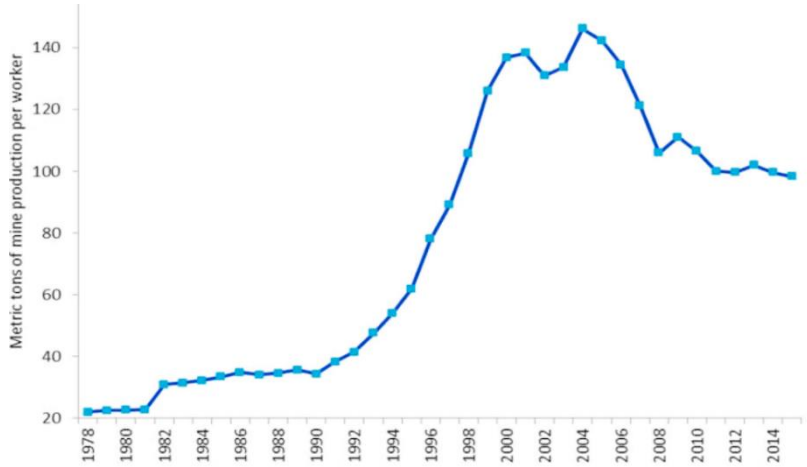


Figure 2.4: The Average Mining Chilean Labour Productivity from 1978-2015 (Fernandez, 2018)

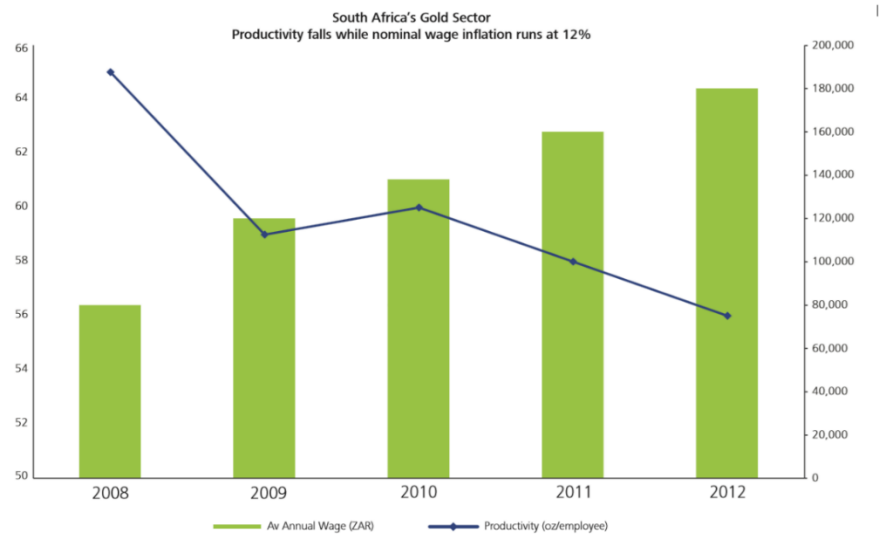


Figure 2.5: Labour Productivity of the South African Gold mining sector in comparison with Average Wage (Deloitte, 2015)

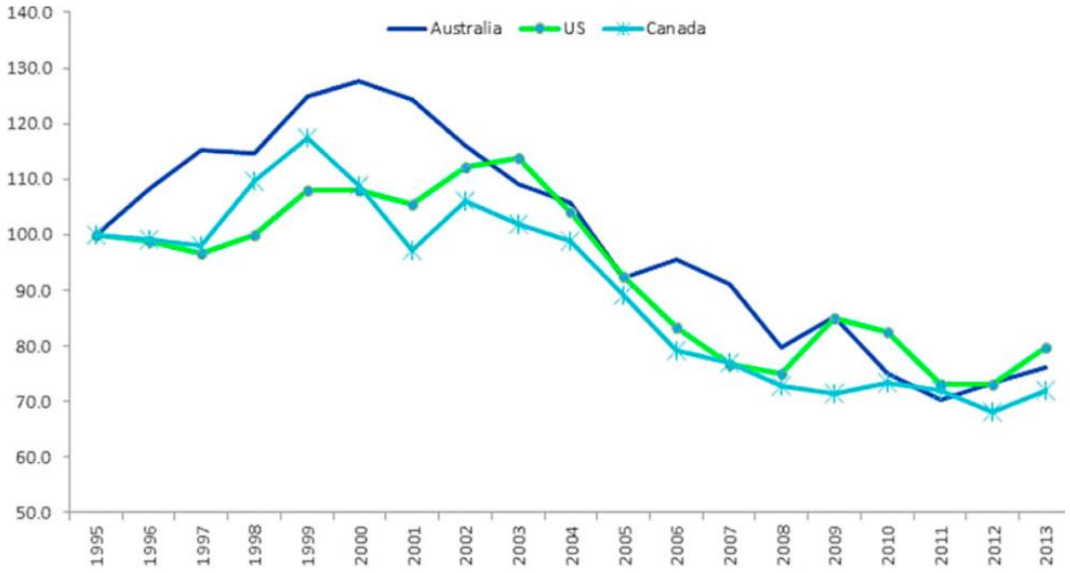


Figure 2.6: The Australian, USA, and Canada Mining Industry Labour Productivity; 1995-2013 (Fernandez, 2018)

The general trend from Figure 2.4 through 2.6 shows that there is a steady decline in productivity in the mining industry across various countries, especially since the beginning of the millennium. All the productivity decline shows that there is a need for a reverse in this course. Several studies have however identified technology and innovation as the tools needed to make this a step closer to reality (Simpson *et al*., 2014; Runge, 1995; Willis, 2000; World Economic Forum (WEF), 2017; Kumar & Kumar, 2016; Steen *et al*., 2018).

It is important to note that, at present, most of the world's mineral production is carried out using surface mining methods. Current statistics show that about 95% of all non-metallic minerals, 90% of metallic minerals, and about 60% of all coal production are mined by surface methods (Ramani, 2012). Therefore, even though surface mines are not directly mentioned in this chapter, it can be inferred that they are the major contributor to the global output of the mining industry.

In recent times, this has been proven to be beneficial as mines have relied on the use of GNSS tracking systems to efficiently deploy and dispatch various mining equipment. The continuous swell in the capacity of dump trucks, as well as the

shovel sizes, has helped to compensate for the increasing cost and the decreasing grades experienced by the industry (Kumar & Kumar, 2016; Poulton *et al*., 2013).

Poulton *et al*., (2013) further support the possibility of approaching the end of the era with productivity growth as a result of increased machinery and equipment size. Deloitte (2019) substantiated this by pointing out that this underlining conceptual strategy of low-cost operation rather than shifting of cost base only lead to an upsurge of debt incurred by the companies.

Neingo (2014) confirmed that some underground operations are worth being mechanized and automated. However, some current underground conditions do not provide a suitable working condition for the machinery (Neingo, (2014). Thus Neingo (2014) recommends a better understanding of the orebody for further optimization. On the other hand, it can be argued that technology would also be needed to help further the understanding of the ore body. Such technologies include those described in Table 2.2.

Notably, Bartos (2007) identified that the rate of investment in research and development within the mining industry compared to other industries is constantly declining. The various productivity increases experienced within the industry has originated from the adoption or transfer of technology from other industries. The study states that an economist's measure of increased technology-use in any space is usually closely linked to the increase in productivity. This can be substantiated with the example of the increased productivity recorded within the Chilean copper industry when the SX-EW processing technology was introduced. The era of a continuous increase in the bucket capacity of the haul truck also reinforces this. However, just as new and emerging technologies are already defining how other industries such as aerospace and manufacturing are run, the mining industry would continually need these technologies and innovations.

In the search for extant literature, it seemed that only two studies within the mining industry employed the use of either of the MCDM techniques and methods to adopt one form of technology or the other. The first was Stojanović, *et al*., (2015) study on selecting optimal technology for surface mining. The second was Vujic, *et al* ., (2013) study on a selecting technological system at an open-pit mine in the Republic

of Siberia. Vujic, *et al*., (2013a) used the PROMETHEE II MCDM technique in comparing the mode of machinery arrangement. Similarly, Stojanović, *et al*., (2015) used the Combined AHP and Elimination Et Choix Traduisant la Realité (ELECTRE) method in selecting the machinery operation method choice.

Due to the limited number of literature addressing the application and adoption of technology, this research has contributed to literature within the mining industry. References are made to literature from manufacturing, aerospace, information technology and the health industry. This is to glean from the methodologies and systems these industries have instituted to technologically advance their operations.

2.9 Chapter Summary

This chapter discussed technology, its classification and, its application as well as its role within the mining industry. Contemporary case studies of some mining companies that have adopted emerging technologies to solve several challenges along the mining value chain were also identified. The state of productivity within the industry was also explored. This chapter concluded on the note of, comparing the rate of adoption of technology within the mining industry to other industries. Lastly, a discussion about studies similar to this was also included. The next chapter discusses the operation research methodology used in this study as well as the study's conceptual framework.

3 RESEARCH METHODOLOGY

This study focused on developing an analytical process that can be used to systematically filter and reduce the number of technologies applicable to a typical mining project. The MCDM operation research method was used in this process. MCDM is also known as Multi-Criteria Decision Analysis (MCDA). The MCDM is broadly classified into Multi Attribute Decision Making (MADM) and Multi Objective Decision Making (MODM) (Sabaei, et al., 2015). Of the several MADM techniques, the fusion of AHP and PROMETHEE techniques were employed in this study. The AHP was used to determine the hierarchal weight and its consistency, while the PROMETHEE method was used to carry out the overall process evaluation.

The complexity of operations within the mining industry makes it important to take a multifaceted approach to solve the managerial, technical and technological problems. Solving these problems, however, involves the use of multidisciplinary knowledge which crisscrosses economics, environments, politics, policies and social aspects (Sitorus *et al.*, 2019). One of the ways the mining industry has engaged with such is by generating several possible solutions for such problems, thereafter, selecting the most suitable one.

The MCDM tools are the most preferred tools to assist in this situation. The tool is often used in operational research because of its ability to scientifically solve problems that involve both quantitative and qualitative analysis (Sitorus, et al., 2019). In addition, the scientific process allows the possibility to consider complex and conflicting multiple uncertainties and criteria. Such scenarios would leave the decision maker with only experience and intuition as a guide.

MCDM's features enable it to carry out qualitative and quantitative analysis, making it a tool that is applicable in scenarios that are either certain or uncertain (Sitorus *et al.*, 2019). In various industries, the methodologies utilised by practitioners are mostly different from the ones defined by academics. This disparity is usually as a result of the non-applicability of the models defined by the academics (Jacobs & Webber-Youngman, 2017). However, the involvement of

both parties in the defining, processing and the interpretation phases of the analytical model, allows for the possible increased use of the method. The identified role for the practitioners involves the use of experienced-based scoring to identify weights for the alternatives, while the roles of the academics involve carrying out the statistical analysis.

This operation research method's ability to solve critical operational and non-hypothetical real-life problems within the mining industry and other industries make it an analytic tool of choice. Table 3.1 outlines some of its applicability within mining industry technical areas. Some of the other industries where MCDM has been used are Real Estate, Information, Communication and Technology (ICT), Finance, Manufacturing, Economics, Management, and Environment.

3.1 Classification of Multi-Criteria Decision Making (MCDM) Methods

There are many ways MCDM methods can be classified, Kahraman (2008) and Triantaphyllou (2000) suggested that MCDM methods can be classified by the type of data that is used. These classifications include: Fuzzy, Crisp, Stochastic and Deterministic MCDM methods. Triantaphyllou (2000) also classified MCDM by the number of decision makers that were engaged in the course of making the decision. Therefore, there is a single decision-maker MCDM and group decision makers.

According to Zavadskas *et al*., (2014) and Hwang & Yoon (1981), MCDM is also broadly classified into two categories. These categories are discrete MADM and continuous MODM. Figure 3.1 depicts the two categories.

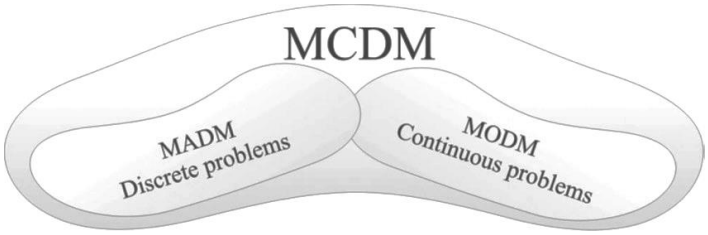


Figure 3.1: General Classification of MCDM methods (Zavadskas, et al., 2014)

Table 3.1: MCDM use cases within the Mining Industry

Technical Areas	Sources	Problem addressed
Mining and mineral processing equipment selection	(Bazzazi, et al., 2009)	The development of a combined AHP, entropy, and FTOPSIS for selection of the method most suitable ore transportation system.
Mining method selection	(Musingwini & Minnitt, 2008)	Ranking the efficiency of selected platinum mining methods using the AHP.
Mining site selection	(Dey & Ramcharan, 2008)	AHP helps select site for limestone quarry expansion in Barbados.
Mining technology selection	(Dessureault & Scoble, 2000; Stojanović, et al., 2015; Vujic, et al., 2013)	Capital investment appraisal for advanced mining technology: case studies in GPS and information-based surface mining technology.
Mineral processing plant and equipment selection	(Owusu-Mensah & Musingwini, 2011)	Evaluation of ore transport options from Kwesi Mensah Shaft to the mill at the Obuasi mine.
Mineral processing method selection	(Montazeri & Taji, 2016)	Ranking and comparing of traditional and industrial coke making by TOPSIS technique in Shahrood Simin Coke Company.
Mine planning	(Mahase, et al., 2016)	A survey of applications of multi-criteria decision analysis methods in mine planning and related case studies.

Regarding the MADM, it is usually applicable in cases where the set problems have a finite or limited number of alternatives. With this method, the decision space is discrete. On the other hand, the MODM; is associated with problems where alternatives are infinite or not predetermined. This method is generally used in planning and design and with this method the decision space is continuous.

3.2 General Framework of MCDM

Generally, MCDM methods consist of three-macro phases and they are the defining; the processing and; the interpretation and recommendation phase. (Haddad & Sanders, 2018; Vujic, *et al.*, 2013; Sitorus, *et al*., 2019).

3.2.1 Defining phase

This is usually the first phase, and in this phase, the problem is evaluated, clearly defined and thereafter, the evaluation matrix is constructed. This evaluation matrix is always based on the continuous selection of alternatives, criteria, sub-criteria (their weightings inclusive). An understanding of their assessment indicators is very critical (Vujic, *et al*., 2013).

3.2.2 Processing phase

The second phase is the data processing phase. The weightage scoring of alternatives is calculated. The evaluation matrix is also solved in order to score all alternatives with respect to their evaluating criteria. The computation in this phase usually differ from one problem to the other and this is dependent on how the MCDM method is used to attain the set objectives (Sitorus, *et al*., 2019).

3.2.3 Interpretation and recommendation phase

In this phase, the overall score for all the alternatives will be noted as the ranking and sorting would be done using the score. Depending on the decision maker's goal and the MCDM method used, the best alternatives, preferably a mix of alternatives, were identified.

In addition to addressing the research objectives one and two, Chapter 3 and Chapter 4 focus on the defining and processing phase respectively, while Chapter 5 will discuss the interpretation and recommendation phase.

3.3 The Technology Map

The technology map as seen in the appendix A (Table A1) was adopted from Jacobs (2016). Jacobs used the created technology map to address the need for a platform that provides technology-related information which specifically addresses and or represents the various phases of a mining cycle. This map firstly addresses the six mining phases, thereafter, each was further expanded to capture value drivers that impact a mine operation. The six mining phases are; exploration; project evaluation and planning; mine design and construction; operations; decommissioning/closure; and post closure. The seven main value-driving pillars under which other value drivers were categorized include: production, supply chain, profitability and cost control, productivity and asset efficiency, mineral resource management, socio-economic factors, and health, environment, safety and legal.

The six by seven matrix was then fitted with numerous physical and digital technologies that meet a set of five qualifying factors. These factors tested the ability to:

a) Increase efficiency (efficiency that adds value to the organization and not directly impacting production *e.g.* a more efficient payroll system);
b) Increase production (ability to measure effectiveness, e.g. tonnes/ounces extracted);
c) Increase productivity (ability to measure efficiency, e.g. time or money used in extracting an amount of tonnage);
d) Improve safety (its ability to reduce likelihood and severity of harm/accidents); and
e) Decrease risk of human error (its ability to reduce the likelihood of mishap or blunders)

However, for this study, a slight modification was made. The modification includes the addition to the technologies options to further populate the map.

3.4 The Conceptual Framework

For this study, the procedures depicted in Figure 3.2 shows a summary of the process undertaken to achieve the goal of sorting and selecting the most preferred technology suitable to meet the mining company's organisational goal.

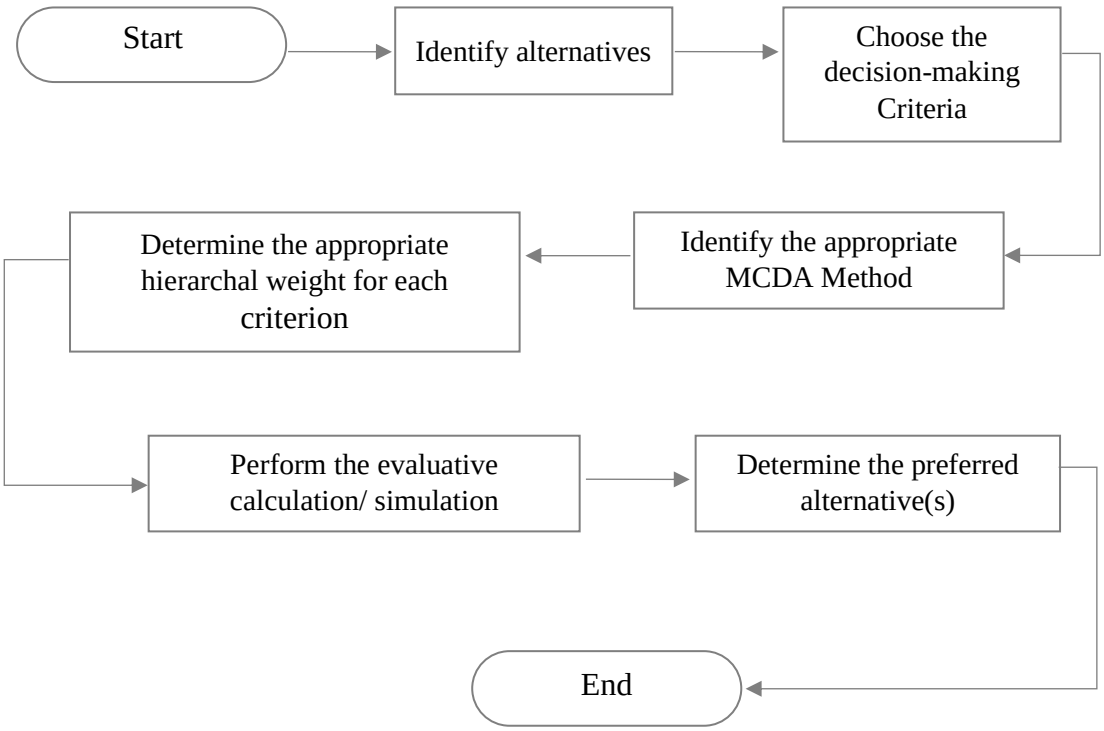


Figure 3.2: General MCDA process framework

As outlined in the three process steps identified in Section 3.2, the flowchart in Figure 3.2 further breaks down the general steps needed in the MCDA process computation. Stemming out from this, the appropriate framework to be used to solve the decision problem in this research is drawn and shown as outlined in Figure 3.3. In Figure 3.3, box A is the expansion of the 4^{th} step in Figure 3.2 and it shows the process and method by which the weights of the decision-making criteria were obtained. Here, the AHP MCDM method is used. Similarly, Box B is an expansion of the 5^{th} step in Figure 3.2 and it showed the process and methods used in the computational evaluation of the judgement matrix. The PROMETHEE II was used to make the calculation. In addition, fuzzy set theory was used to calculate the evaluative values for the objective criteria.

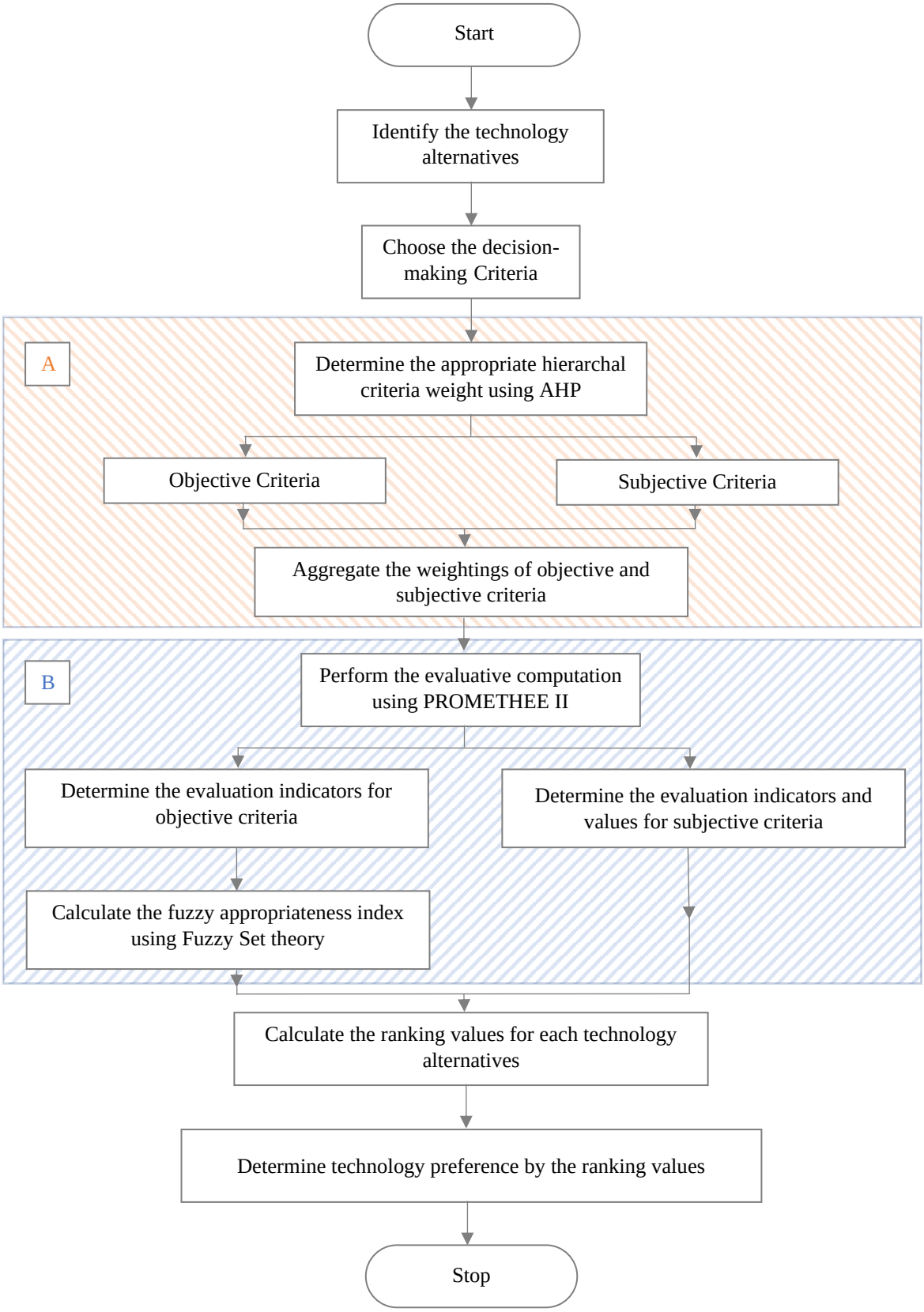


Figure 3.3: Schematic framework for technology adoption

3.5 Case Study

In this study, a hypothetical case study is used to further substantiate the conceptual model created in section 3.4. A single decision maker will decide on behalf of the company to select the best technology to adopt to improve its overall mining operation, while also keeping in alignment the strategic goal of the company.

Scenario Description

Mining company A mines iron ore through the open pit mining method and has in the past been faced with safety challenges. In its previous financial years, the management has decided to opt for adopting technologies to help improve this.

The main goal for management is to ensure that the hazards and risks in open pit mining are better managed and anticipated to ensure maximum safety. By adopting the select optimal technology for a surface mine of body, the aim is to reduce the occurrence of life-threatening happenings by 50% in 3 years specifically through hazard identification.

The budget for this technical upgrade is about 60,000 currency units (C.U).

3.6 MCDM Solution

According to Vujic, *et al*., (2013), the quality of a decision depends on the quality of the criteria and the alternatives and to a certain extent the selection method. Furthermore, selecting the appropriate mathematical-model approach hinges on the problem type and structure, and the decision maker's proficiency. In the following sections, the structure, alternatives and criteria for the multi-criteria decision problem are addressed.

The techniques of MCDM to be used in this study to solve this problem is a fusion of AHP and PROMETHEE. Generally, the AHP, PROMETHEE and ELECTRE are some of the most frequently used MCDM techniques (Sitorus, *et al*., 2019). As noted by Sitorus, *et al*., (2019), these three techniques have unique characteristics needed to tackle different types of challenges. The AHP is used to solve the choice challenge, the PROMETHEE to solve the ranking challenge and ELECTRE has the

ability to both the ranking and sorting challenges. Some of the other generally used MCDM techniques include Weighted Sum Model (WSM), Analytic Network Process (ANP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Multi-Attribute Utility Theory (MAUT).

In the following sections, the stepwise procedures of the operation are described.

3.7 Analytical Hierarchy Process (AHP)

AHP is an MCDA method proposed by Thomas L. Saaty, an operation research scientist in 1977 (Koksalan, *et al.*, 2011). It focuses on structuring complex multi-criteria decision problems into a multi-dimensional hierarchical model. The AHP techniques usually entail the following three steps:

a) The Hierarchical Judgment Matrix Design;
b) The Hierarchical Relative Weight calculation; and
c) The Judgement Consistency Step.

AHP has found application across several industries and area of specialization. Over the past three decades, its methodology has been modified to overcome some of its limitations. The limitations are in the areas of: weight synthesis; group decisions; problem modelling; and sensitivity analysis (Sitorus, et al., 2019). The decision to include AHP as one of the two techniques used in this study was based on three reasons:

1. AHP method detects inconsistency judgements and supplies an estimated degree of inconsistency (Musingwini & Minnitt, 2008);
2. The AHP is one of the most prominently used MCDA methods, Also, its application in the mining industry is becoming pre-eminent (Musingwini & Minnitt, 2008); and
3. The AHP is categorized as one of the techniques that are best used to solve decision problems (Haddad & Sanders, 2018; Stojanović, *et al*., 2015).

3.8 Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE)

The PROMETHEE method was proposed by Jean-Pierre Brans in the 1980s (Koksalan, *et al*., 2011). It is a method that is particularly skilled in outranking results of the multicriteria problem. Using the decision makers criteria and preferences, the outranking methods do not eliminate any alternatives in the pairwise comparison; rather, it arranges the results in order. In addition, PROMETHEE is very suitable for problems with a finite number of alternatives.

Evaluation Matrix for the PROMETHEE method

Abdullah, *et al*. (2019) summarized the computational procedure of PROMETHEE into seven steps. These steps were adopted for the computation of the data in this study. However, they were modified and expanded to make a total of nine steps.

Step 1: Determine the set of possible alternatives in the decision problem.

Step 2: Determine the criteria

Step 3: Determine the weights for each of the criteria

Step 4: Construct the decision matrix

Step 5: Normalize the decision matrix ensuring that X_{ij} ranges from 0 to 1 using:

$$R_{ij} = \frac{|[X_{ij} - \max(X_{ij})]|}{[\max(X_{ij}) - \min(X_{ij})]} (i = 1,2,\dots,m; j = 1,2,\dots,n) \quad 3.1$$

where X_{ij} is the evaluation value either calculated or provided by the decision maker. $i = 1,2,\dots,m$ and numbers of criteria $j = 1,2,\dots,n$. R_{ij} is the normalized value for each X_{ij} variable.

Step 6: Determination of deviation using pairwise comparison.

$$d_j(a,b) = g_j(a) - g_j(b) \quad 3.2$$

$d_j(a,b)$ signifies that the difference between the evaluations of a and b on each criterion. $g_j(a)$ and $g_j(b)$ represents the normalized criteria values for each technology alternative.

Step 7: Define the preference function

$$P_j(a,b) = F[d_j(a,b)] \quad 3.3$$

$P_j(a,b)$ is the function of the difference of evaluating the technology alternative a in regard to technology alternative b. Each of the criteria is converted to values ranging between 0 to 1.

Step 8: Determination of the multicriteria/aggregated preference index.

$$\pi(a,b) = \sum_{j=1}^{k} P(a,b)w_j \quad 3.4$$

w_j are the weights for each of the criterion, $\pi(a,b)$ indicates that the degree preference of a to b for all criteria, when $\pi(a,b) \approx 1$ implies the preference of a over b is Strong, $\pi(a,b;) \approx 0$ implies the preference of a over b is Weak.

Step 9: Determination of the preference order

Here the choice is usually made between the PROMETHEE I and the PROMETHEE II. This is done to determine if the result would be ranked partially or completely. PROMETHEE I rank the resulting alternatives partially, while PROMETHEE II ranks them completely. For this study, the complete ranking of PROMETHEE II is employed and equation 3.5 is used;

$$\varphi(a) = \varphi^+(a) - \varphi^-(a) \quad 3.5$$

$$\varphi^+ = \frac{1}{m-1}\sum_{b=1}^{m} \pi\,(a,b) \quad 3.6$$

$$\varphi^- = \frac{1}{m-1}\sum_{b=1}^{m} \pi\,(b,a) \quad 3.7$$

where

$\varphi(a)$ represents the net outranking flow for each alternative, $\varphi^+(a)$ means positive outranking flow or leaving flow. This also means how a dominates other

alternatives. $\varphi^{-}(a)$ means the negative outranking flow or entering flow. This also shows how a is been dominated by other alternatives.

The following also shows reference relations of the alternatives.

$$a\ outranks\ of\ b\ \left(aP^{(II)}b\right)\ i\ ff\ \varphi(a) > \varphi(b), \qquad \forall a, b \in A$$
$$a\ outranks\ of\ b\ \left(aP^{(II)}b\right)\ i\ ff\ \varphi(a) = \varphi(b), \qquad \forall a, b \in A$$

Thus, based on the $\varphi(a)$ values of each alternative, all alternatives can be compared. The alternatives with the highest $\varphi(a)$ values represent the most preferred.

3.9 Chapter Summary

This chapter focused on the methodology employed in this study. The MCDM methods used include AHP and PROMETHEE. Two of the three objectives were also discussed in this chapter. Further discussion was carried out on the application of the method in the mining industry. The decision problem that was proffered with a solution in this study was also defined. The source of technology alternative, which was evaluated, and the conceptual framework of the evaluation process was discussed. The next chapter outlines the detailed calculations supporting the above-listed evaluation steps.

4 QUANTITATIVE EVALUATION PROCEDURES

This chapter outlines the detailed calculations supporting the evaluation steps listed in section 3.8. In addition, critical background and scoping terms have been explained.

4.1 Alternatives.

Step 1: Determine the set of possible alternatives in the decision problem.

According to Triantaphyllou (2000), alternatives are the choices of action made available to a decision maker. For this study, the set of alternatives which are technology options are finite and are screened, prioritized and eventually ranked.

Figure 4.1 shows the pictorial representation of how the alternatives for this study were collated. This process is described below.

After taking note of the objectives of the mining company facing the problem (as described in Section 3.5) and noting the keywords used in describing the state and situation of their operation, the following steps were taken to select the alternatives for this analysis:

a) From the technology map (as shown in appendix A), select the phase on the value chain in which the technology upgrade is targeted at. This is easily recognisable at the header along the horizontal axis.
b) Select the main value-driving pillars of the application, along the left vertical axis. In this case Health, Safety and Environments is the major value driver of choice.
c) Select the target sub-divisional theme. This is at the intersection of the chosen value chain process and the chosen value driver. In this case its Hazard Identification (highlighted in red fonts in Figure 4.1).

The results of the above-described procedure generate six technologies and they are;

[AR, AA, AI, UAVs, IoT and IoE]

a) Augmented Reality (AR) $\boldsymbol{A_1}$;

b) Advanced analytics (AA) A_2;
c) Artificial Intelligence (AI) A_3;
d) Unmanned Air Vehicles (UAVs) A_4;
e) Internet of Things (IoT) A_5; and
f) Internet of Everything (IoE) A_6.

4.2 Criteria

Step 2: Determine the criteria

Criteria are sometimes known as "goals" or "decision criteria" or "attributes". They can be described as a measure of effectiveness and they form the basis on which the evaluation is made (Hwang & Yoon, 1981).

Being a desktop study, this research extracted its decision-making criteria from five journal papers across four industries. The industries involved are aerospace, manufacturing, technology and mining. (Ordoobadi, 2012; Taha, *et al*., 2011; Poulin, *et al*., 2013; Vujic, *et al*., 2013; Stojanović, *et al.*, 2015). The decision to select from these industries was based on Bartos (2007) study that compared the mining industry's rate of technology adoption to manufacturing, and semiconductor (technology) industry. As a result, a total of 29 criteria were compiled and categorized in a hierarchal structure and it is displayed in Table 4.1. The major criteria categories are economic, technical and ergonomic factors. The criteria were further subdivided into sub-criteria such as cost, economic analysis, strategic fit, human resources and social.

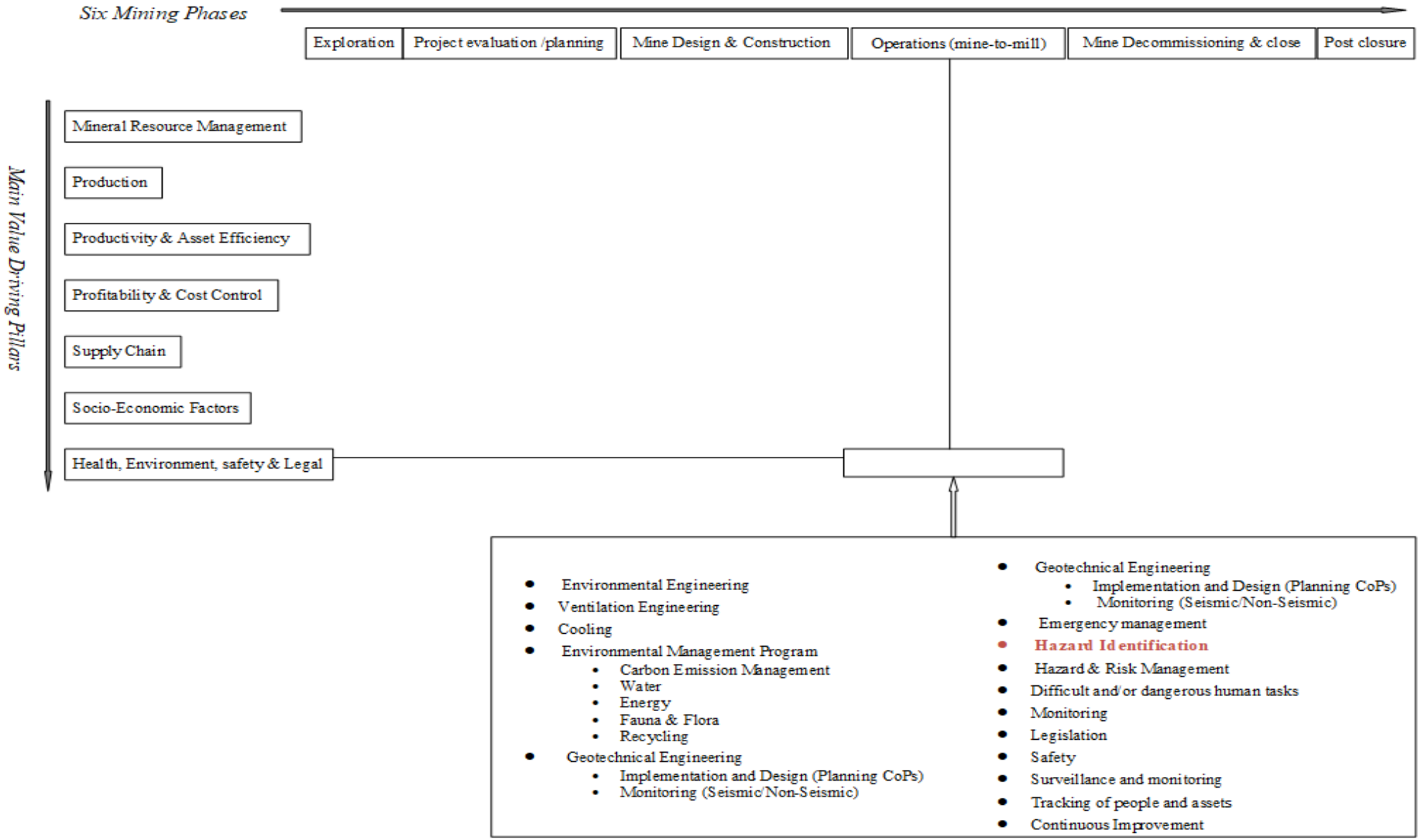


Figure 4.1: Mining Cycle Framework Highlighting the Procedure for selecting Technology Alternatives from the Technology Map

Drake, *et al*, (2017) notably stated that there is no rule governing the number of criteria to be included in analysis. Furthermore, the higher the number of criteria, the higher the complexity and cognitive effort needed for the decision maker to fill out the judgment matrix. Based on this, the decision maker streamlined the 29 aggregated criteria to four criteria (as displayed in Table 4.2) with a minimum of one from each of the major categories. For this study, the four chosen criteria are;

a) Economic analysis;
b) Suitability;
c) Strategic fit; and
d) Operational safety.

The economics analysis criterion was chosen for the list of economic factors in Figure 4.1. Similarly, the suitability, strategic and operational safety were criteria chosen from the list of technical and ergonomic factors in Table 4.1. As shown in Figure 4.2, the economic analysis criterion was an objective criterion while the other three were the subjective criteria.

Table 4.1: Adopted Criteria from (Ordoobadi, 2012; Taha, *et al., 2011;* Poulin, *et al.*, 2013; Vujic, *et al*., 2013; Stojanović, *et al.*, 2015)

Economic Factors	**Technical Factors**	**Ergonomic Factors**
Cost	Efficiency	Strategic fit
Investment cost	Suitability	Finance position
Wages/labour	Productivity	Government policy
Maintenance	Reliability	Market position
	Sustainability/Utility	Competition
Economic analysis	Quality	Management interaction
	Technical maturity	R&D activities
	Automation level	
	Knowledge and Training	Human resources impact
	Geological Properties	Employee morale/motivation
		Manpower planning
		Employee and Working relationships
		Higher level of skill
		labour intensity
		Social
		Community development
		Ecology/Environmental Protection
		Responsiveness
		Customer satisfaction
		Operational safety
	-	

Table 4.2: Criteria Selection used in this Study

Economic Factors	**Technical Factors**	**Ergonomic Factors**
Economic analysis	Suitability	Strategic fit
		Operational safety

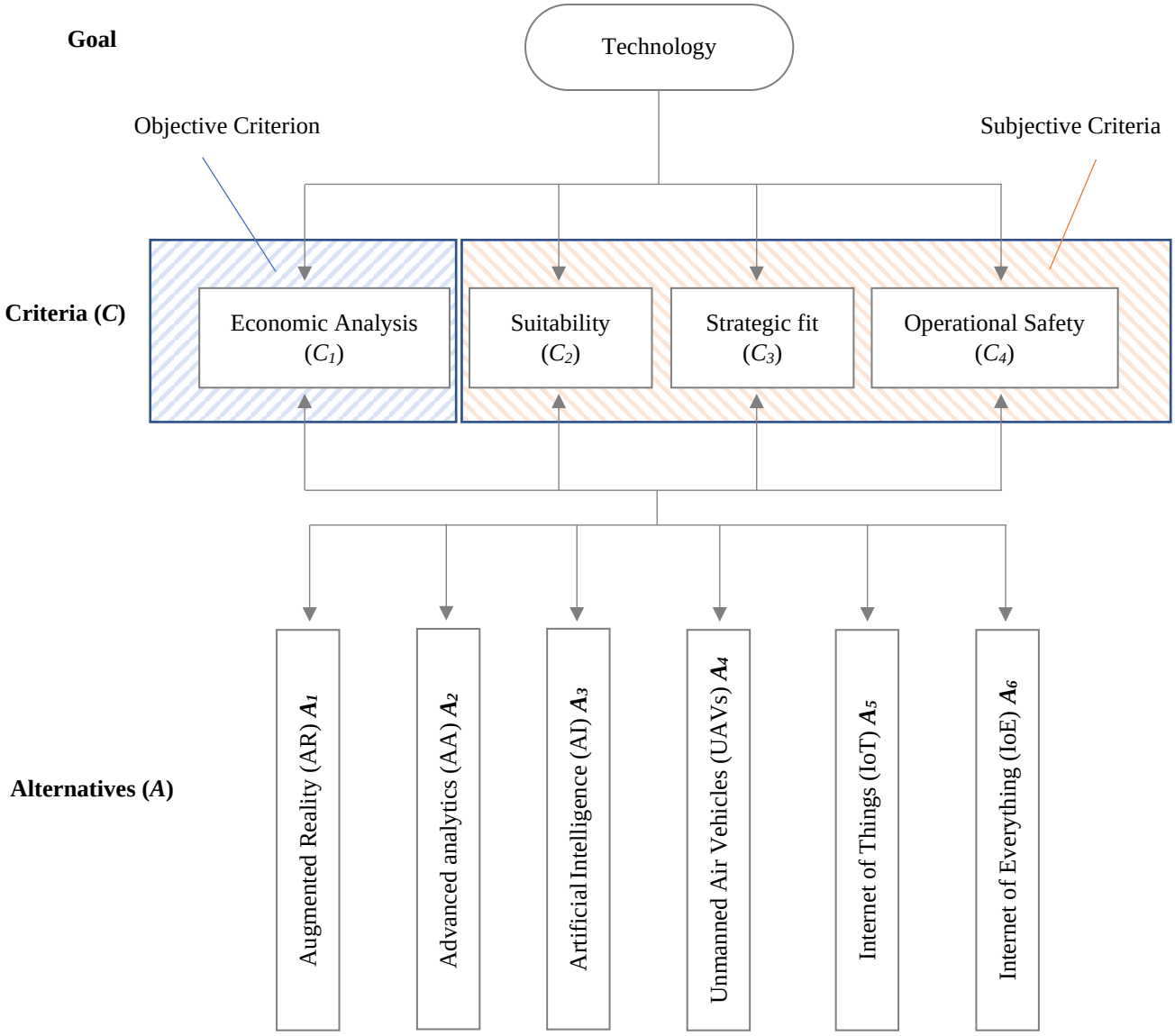


Figure 4.2: MCDA Framework for Technology Selection adapted from Wang & Tu, (2015)

Figure 4.2 shows the hierarchal structure of the technology decision problem that was computed in this research. This gives a pictorial view of all the highlighted criteria and alternatives highlighted in Sections 4.1 and 4.2 and its relation to the overall goal of the decision maker. The framework shows the goal of the decision problem, which is to select the most optimal technology for the Iron ore mine. It also shows the four subjective and objective criteria and the six technology alternatives ($\boldsymbol{A_1 - A_6}$) from which the decision would be made.

4.3 Weights

Step 3: Determine the weights for each of the criteria

Weights are assigned to each criterion to measure its individual importance in relation to the general objectives of the decision problem. The weight of a criterion is usually denoted by the symbol W_j where $W_j > 0$ and always within a set of real numbers (Triantaphyllou, 2000). These weights are normalized, to sum up to one. The equation 4.1 shows it (Abdullah, *et al.*, 2019)

$$\sum_{j=1}^{n} \mathrm{W}_j = 1 \qquad 4.1$$

For this study, the weights were arrived at by procedure 1 to 3 of AHP technique described in Section 3.5 comparing the criteria with each other in a pairwise comparison matrix. Filling up the matrix required the decision maker to answer questions such as "with the goal of selecting the most optimum technology, what is the relative importance of the economic factors to strategic fit"? As shown in Table 4.4, the decision maker answered by stating that the economic factor is strongly more important than the strategic fit. This is allocated the number 5 in the first row, third column or (1,3). Conversely, the reciprocal value is entered into the (3, 1) position indicating that strategic fit criteria is strongly less important when compared to the economic factor. Similarly, the results of other comparisons are shown in Table 4.4 and this formed the hierarchical judgement matric for the criteria.

The scale used here to make this subjective pairwise comparison is recommended by Saaty (1995). Saaty (1995) referred to it as "the fundamental scale of the AHP with absolute values of 1 to 9". Table 4.3 shows the table of scale. Each number corresponds to the preference strength of one variable or element over another. "1" shows that the elements to be compared are of equal importance while "9" show that one of the elements is extremely more important than the other. In situations where a compromise is needed between both the elements to be compared, the intermediate values of 2, 4, 6 and 8 would be used.

Table 4.3: Measurement Scale of Relative Importance (Saaty, 1995)

Verbal judgement or preference	Numerical rating
Equally Important	1
Moderately Important	3
Strongly Important	5
Very Strongly Important	7
Extremely Important	9
Intermediate values between two adjacent Judgment (when compromise is needed)	2, 4, 6, and 8

Table 4.4: Pairwise Comparing Matrix for Criteria

	Economic	Efficiency	Strategic Fit	Operational safety
Economic	1	5	5	1
Efficiency	1/5	1	1/3	1/3
Strategic Fit	1/5	3	1	1/5
Operational safety	1	3	5	1

4.3.1 The hierarchical relative weight calculation

In order to meet the precision requirement for calculating the relative weight using the AHP technique, the approximate calculation was done using the square root method.

Table 4.5: Weight Determination for the Criteria

	A1				A2	A3
	Economic	Efficiency	Strategic Fit	Operational safety	ϖ	Weights (ω)
Economic	1	5	5	1	2,2361	0,432
Efficiency	1/5	1	1/3	1/3	0,3861	0,075
Strategic Fit	1/5	3	1	1/5	0,5886	0,114
Operational safety	1	3	5	1	1,9680	0,380
				$\Sigma\varpi$	**5,1787**	**1**

To calculate the geometric means of the varying elements on each row of the Judgement matrix (A1 column of Table 4.5), equation 4.2 was used.

$$\varpi_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}}, \; i = 1,2, \dots, n, \tag{4.2}$$

where a_{ij} stands for the elements of the judgment matrix, and $\varpi = (\varpi_i, \varpi_2, \dots, \varpi_n)$ (Wang & Tu, 2015).

The calculated geometric mean ϖ are shown in column A2 of Table 4.5

Thereafter ϖ_i is normalized to give the weight vector ω, the normalization was done using the equation 4.3 (Wang & Tu, 2015);

$$\omega = \frac{\varpi_i}{\sum_{i=1}^{n} \varpi_i}, i = 1,2, \dots, n, \tag{4.3}$$

The weight vector $\omega = (\omega_1, \omega_2, \dots, \omega_n)$ obtained is shown in the A3 column of Table 4.5 and Table 4.6. Therefore, the relative weights of each criterion with respect to the goal is shown as follows:

$$\omega = (0.432, 0.075, 0.114, 0.380)$$

The "Economics" criterion held the largest weight with the value of 0.432, this is closely followed by the "Operational Safety" criterion weighing at 0.380. The "Strategic fit" and "Efficiency" criteria respectively have the values of 0.114 and 0.075.

4.3.2 The judgement consistency step.

The checking of consistency in judgment matrices is usually done to measure its credibility. According to Saaty (1995), a pairwise comparison in an evaluation matrix is said to be consistent when the consistency ratio is smaller than 10%. This was calculated by first computing the consistency index (equation 4.4) (Wang & Tu, 2015). Next, the consistency index value was divided by the correction value know as random consistency index (RCI) to get the consistency ratio (equation 4.5) (Wang & Tu, 2015).

As shown in Table 4.6 the consistency ratio of the AHP matrix is 0.09645, which is less than the 0.1 (10%) standard. This translates to the fact that the AHP judgement matrix is consistent.

Table 4.6: Judgement Consistency Determination for Criteria

A3	A4		A5		
	A1*A3		A4/A3		
Weights				Consistency Index	Consistency Ratio
0,432	1,7528		4,0595	0,08681	**0,09645**
0,075	0,3255		4,3655		
0,114	0,4997		4,3966		
0,380	1,6037		4,2201		
1		Avg.	**4,2604**		

Consistency Index (CI)

$$= \frac{\lambda_{max} - n}{n-1} \qquad 4.4$$

Consistency Ratio (CR)

$$= \frac{1}{RCI} \times CI$$

$$= \frac{1}{RCI} \times \frac{\lambda_{max} - n}{n-1} \qquad 4.5$$

where, RCI is the correction value and is known as the Random Consistency Index (Table 4.7), depending on the dimensions of the matrices; λ_{max} represents the maximum eigenvalue (equation 4.6) (Wang & Tu, 2015).

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(R\varpi)_i}{n\varpi_i} \quad 4.6$$

where R is the judgment matrix and $(R\varpi)_i$ is the i^{th} element of the matrix $(R\varpi)_i$

Table 4.7: RCI values for different Order of Matrix (n) (Wang & Tu, 2015)

Order of Matrix (n)	1	2	3	4	5	6	7	8	9
RCI value	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

The RCI value for the order of the matrix table shown in Table 4.7 is a table of standard randomized vales that are used while making AHP calculations.

4.4 Judgment Matrix

Step 4: Construct the decision matrix.

For all MCDM methods, a decision matrix, otherwise known as judgement matrix or decision table forms the base structure from which a pairwise comparison is made. It is illustrated as follows (equation 4.7):

Suppose a problem has m alternatives with a set of alternatives $a = [A_1, A_2, \dots, A_m]$ and n number of decision criteria with the set of criteria $X = [x_1, x_2, \dots, x_n]$.

x_{ij} $(i = 1,2, \dots, m; \quad j = 1,2, \dots, n)$ are the elements of the matrix which denotes the performance value of the i^{th} alternative A_i in terms of the j^{th} criterion (Wang & Tu, 2015).

$$R = (X_{ij})_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad 4.7$$

After including the alternatives and criteria, the judgment matrix looks as follows (equation 4.8);

$$R = (X_{ij})_{m\times n}$$

$$= \begin{bmatrix} & Economic & Efficieny & Strategic\ Fit & Operational\ Safety \\ AR & x_{11} & x_{12} & x_{13} & x_{14} \\ AA & x_{21} & x_{22} & x_{23} & x_{24} \\ AI & x_{31} & x_{32} & x_{33} & x_{31} \\ UAVs & x_{41} & x_{42} & x_{43} & x_{53} \\ IoT & x_{51} & x_{52} & x_{53} & x_{54} \\ IoE & x_{61} & x_{62} & x_{63} & x_{64} \end{bmatrix} \quad 4.8$$

As shown in the matrix 4.8, alternatives $a = [A_{1,}A_{2,} \dots, A_m]$ are

$$[AR, AA, AI, UAVs, IoT, IoE]$$

while criteria $X = [x_1, x_2, \dots, x_n]$ are

$$[Economic, Efficency, Strategic\ Fit, Operational\ Safety].$$

For this study, the subjective criteria such as suitability, strategic fit and operational safety criteria are qualitative and were described by linguistic assessments. On the other hand, the objective criterion - the economic analysis - is quantitative and was appraised in monetary terms.

Table 4.8: Linguistic Scale for Subjective Criteria

	Linguistic Scale	Numeric Scale
Very High	VH	5
High	H	4
Medium	M	3
Low	L	2
Very Low	VL	1

For the subjective criteria, filling in the decision matrix was based on the linguistic numeric scale as presented in Table 4.8. Based on the subjective knowledge of a decision maker, the decision maker described, in linguistic terms, how one technology alternative meets the subjective criteria.

Filling up the matrix, required the decision maker to answer questions such as. “how much value will UAVs add to the operational safety of the mining project”? As shown in Table 4.9, the decision maker answered by stating that the potential value add for UAVs to operational safety is high. This is assigned the number 4 in the fourth row, fourth column or (4,4). Notably, “efficiency” and “strategic fit” criteria approached the maximum, while the “operation safety” criterion approached the minimum.

For the objective criteria, the fuzzy set theory would be used to get the crisp quantitative net present value (NPV) values to be used in the judgment matrix and it approached the maximum.

Table 4.9: Decision Matrix with Filled Subjective Criteria Column

	Economic	**Efficiency**	**Strategic Fit**	**Operational safety**
AR	x_{11}	1	5	3
AA	x_{21}	3	3	3
AI	x_{31}	3	3	2
UAVs	x_{41}	4	4	4
IoT	x_{51}	3	4	3
IoE	x_{61}	3	4	3

4.4.1 Fuzzy set theory.

Chan, *et al*. (2000) highlighted that in order to evaluate the economic factor for technology selection several researchers have adopted precision-based methods. Some of them include; return on investment (ROI), net present value (NPV), payback period (PB) and the internal rate of return (IRR). However, the crisp nature of the data required for factors such as investment cost, interest rate, salvage value, gross income, depreciation, is quite difficult to quantify.

In such circumstances, decision makers usually give assessment based on practical knowledge, and subjective judgement. In a bid to convey estimations, linguistic

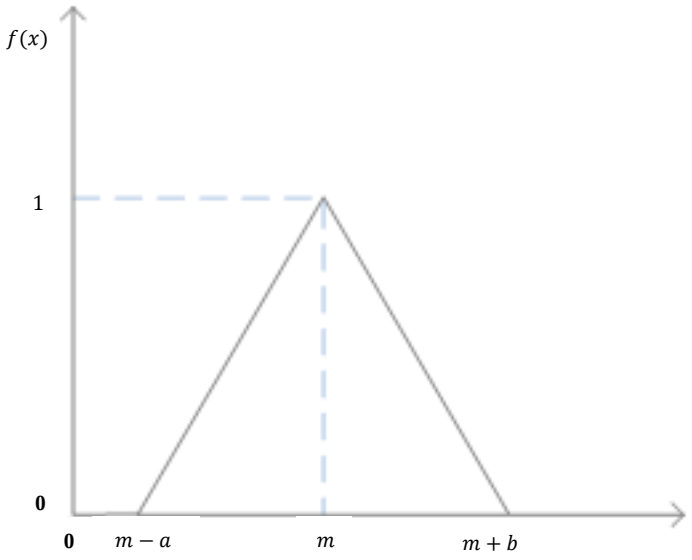


Figure 4.3: Triangular Fuzzy Number (Wang & Tu, 2015)

terms such as “about $10,000”, “high”, “approximately between $100,000 and $250,000”, “around 25%”, “very low” are used by decision makers. Chan, *et al.* (2000), however, introduces the fuzzy set theory to deal with the vagueness of human thought. Tackling these ambiguities associated with the linguistic estimations involves converting these linguistic terms to fuzzy numbers.

From the triangular fuzzy number model illustrated in Figure 4.3, $f(x)$ is the membership function of fuzzy number x,

where $x = (m, a, b)$ i.e. $m - a, < x < m + b$ and $f(x) \in [0,1]$.

Within the scope $(m - a, m), f(x)$ is a linear increasing monotone function, while for $(m, m + b), f(x)$ is a linear monotone decreasing function (Chan, *et al.*, 2000) where, $m - a$ will serve as the lower boundary and $m + b$ will be the upper boundary. Therefore, $(m, a, b) = (m - a, m, m + b)$.

In this study, the economics analysis criteria of the multicriteria problem could not be quantified accurately, therefore, the fuzzy set theory was introduced to help

quantify the criterion. It was calculated by the fuzzy cash flow model proposed by Komolavanij (1995). The operations of a fuzzy number can also further be obtained from (Komolavanij, 1995).

The proposed equation was;

$$X_{mj} = \left(G_{mj} - C_{mj}\right) - \left(G_{mj} - C_{mj} - D_{mj}\right) \times T_m - K_m + L_{mj} + V_{mj} \quad 4.9$$

where,

X_{mj} is the net total cash flow of the technology m at the end of year j;

G_{mj} is the turnover of the technology m at the end of year j;

C_{mj} is the operating expenses of the technology m; at the end of the year j;

D_{mj} is the depreciation amount of technology m in year j;

T_m is the tax rate of the technology m;

K_m is the investment cost of the technology m;

L_{mj} is the salvage value received in year j;

V_{mj} is the incremental tax credit of the technology m in year j.

Thereafter, the NPV of m technologies will be calculated using equation 4.10.

$$NPV_m = \sum_{n=0}^{j} \frac{X_{mj}}{(1+i)^n} \quad 4.10$$

where

NPV_m is the net present value of technology m;

i is the discount rate; and

j is the life of a project.

4.4.2 Fuzzy economic data

The following hypothetical economic data and assumptions structured after the Komolavanij's (1995) format was used for the economic fuzzy NPV calculations:

- The budget for this technical upgrade is about 60,000 currency units (C.U);
- The gross income/turn over (G_{mj}) is assumed to be about 50% of the yearly investment cost;
- Operating expenses (C_{mj}) are assumed to be about 20% of the investment cost;
- Tax rate (T_m) of technology is assumed to be 40% based on Komolavanij (1995);
- The depreciation (D_{mj}) amount of technology is assumed to be about 33.3% based on (Ernst & Young, 2018) Discount rates (i) are variable and presented in Table 4.10;
- L_{mj} = 0 (Komolavanij, 1995); and
- V_{mj} = 0 (Komolavanij, 1995);

Lastly, the decision maker's assumed fuzziness is said to be within the 7% range due to the uncertainty in the data. Based on the information provided above Table 4.10 was generated, providing hypothetical fuzzy values for each of the technology options. This data provided in Table 4.10 was further expanded in Table 4.11 providing the basis to carry out the fuzzy calculations to evaluate the annual cash flow for each of the technology options.

Table 4.10: Fuzzy Data for the Six Technology Alternatives.

	Technology A_1			Technology A_2			Technology A_3		
	AR			AA			AI		
	Pessimistic Value	Possible Value	Optimistic Value	Pessimistic Value	Possible Value	Optimistic Value	Pessimistic Value	Possible Value	Optimistic Value
K	9 300.0	10 000.0	10 700.0	12 090.0	13 000.0	13 910.0	19 530.0	21 000.0	22 470.0
G	7 905.0	8 500.0	9 095.0	10 276.5	11 050.0	11 823.5	16 600.5	17 850.0	19 099.5
C	1 860.0	2 000.0	2 140.0	2 418.0	2 600.0	2 782.0	3 906.0	4 200.0	4 494.0
T	0%	40%	0%	0%	40%	0%	0%	40%	0%
D	3 100.0	3 333.3	3 566.7	4030.0	4 333.3	4 636.7	65 10.0	7 000.0	7 490.0
i	0%	12%	0%	12%	12%	12%	8%	10%	12%

	Technology A_4			Technology A_5			Technology A_6		
	UAVs			IoT			IoE		
	Pessimistic Value	Possible Value	Optimistic Value	Pessimistic Value	Possible Value	Optimistic Value	Pessimistic Value	Possible Value	Optimistic Value
K	22 320.0	24 000.0	25 680.0	14 880.0	16 000.0	17 120.0	14 880.0	16 000.0	17 120.0
G	18 972.0	20 400.0	21 828.0	12 648.0	13 600.0	14 552.0	12 648.0	13 600.0	14 552.0
C	4 464.0	4 800.0	5 136.0	2 976.0	3 200.0	3 424.0	2 976.0	3 200.0	3 424.0
T	0%	40%	0%	0%	40%	0%	0%	40%	0%
D	7 440.0	8 000.0	8 560.0	4 960.0	5 333.3	5 706.7	4 960.0	5 333.3	5 706.7
i	6%	9%	11%	8%	10%	12%	8%	10%	12%

From the data presented in Table 4.10, it is observed that technology ***A₄*** has the highest investment cost with the cost ranging from 22,320 to 25,680 C.U. This is closely followed by technology ***A₃***. Technology ***A₁*** was the cheapest cost-wise. Similarly, the operating expenses and turnover values from adopting are highest in technology ***A₄*** and lowest in technology option ***A₁***.

All the variables present in equations 4.9 and 4.10 were specified as a triangular fuzzy number. They represent, "the possible value", "the pessimistic value" and "the optimistic value". In evaluating the objective criterion, the decision-maker analysed the fuzzy cash flow analogous to the technology alternatives ***A₁, A₂, A₃, A₄, A₅,*** and ***A₆*** to calculate the fuzzy NPV.

It is important to note that Table 4.11 is an expanded version of Table 4.10. From Table 4.11, it is noticeable that year 0 is the investment year and the subsequent years are the years where returns were derived from the investment. For each of the technology options, the net cash flow value (X_{mj}) for the technology were calculated for year 0 and the subsequent three-year period. This cash flow values were presented in the fuzzy pessimistic, possible and optimistic value on Table 4.12. Subsequently, the NPV values were calculated.

After calculation, the resulting fuzzy NPV provides economic data that is used in combination with other data for further analysis. This calculated Fuzzy NPVs are presented in Table 4.12. The in-line calculative procedures are displayed in the fuzzy calculation section (Section 8.3) of Appendix C, where the annual cash flow and NPV for each technology were determined using Equations 4.9 and 4.10 respectively.

However, the fuzzy economic values cannot be used directly in the decision matrix. Goumas & Lygerou (2000) proposed the use of the Yanger index function (Equation 4.11) to "defuzz" the fuzzy numbers to get crisp (non-fuzzy) numbers that can be used in the decision matrix.

Table 4.11: Economic Data of Technology A1, A2, A3, A4, A5, A6

	Technology A_1 AR			**Technology A_2 AA**			**Technology A_3 AI**			**Technology A_4 UAV**			**Technology A_5 IoT**			**Technology A_6 IoE**		
	Pessimistic Value	**Possible Value**	**Optimistic Value**	**Pessimistic Value**	**Possible Value**	**Optimistic Value**	**Pessimistic Value**	**Possible Value**	**Optimistic Value**	**Pessimistic Value**	**Possible Value**	**Optimistic Value**	**Pessimistic Value**	**Possible Value**	**Optimistic Value**	**Pessimistic Value**	**Possible Value**	**Optimistic Value**
At the end of year 0																		
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%
K	9300.0	10000.0	10700.0	12090.0	13000.0	13910.0	19530.0	21000.0	22470.0	22320.0	24000.0	25680.0	14880.0	16000.0	17120.0	14880.0	16000.0	17120.0
L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i	12%	12%	12%	11.5%	11.5%	11.5%	8%	10%	12%	6%	8.5%	11%	8%	10%	12%	8%	10%	12%
At the end of year 1																		
G	7905.0	8500.0	9095.0	10276.5	11050.0	11823.5	16600.5	17850.0	19099.5	18972.0	20400.0	21828.0	12648.0	13600.0	14552.0	12648.0	13600.0	14552.0
C	1860.0	2000.0	2140.0	2418.0	2600.0	2782.0	3906.0	4200.0	4494.0	4464.0	4800.0	5136.0	2976.0	3200.0	3424.0	2976.0	3200.0	3424.0
D	3100.0	3333.3	3566.7	4030.0	4333.3	4636.7	6510.0	7000.0	7490.0	7440.0	8000.0	8560.0	4960.0	5333.3	5706.7	4960.0	5333.3	5706.7
T	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%
K	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i	12%	12%	12%	11.5%	11.5%	11.5%	8%	10%	12%	6%	8.5%	11%	8%	10%	12%	8%	10%	12%
At the end of year 2																		
G	7905.00	8500.0	9095.0	10276.5	11050.0	11823.5	16600.5	17850.0	19099.5	18972.0	20400.0	21828.0	12648.0	13600.0	14552.0	12648.0	13600.0	14552.0
C	1860.0	2000.0	2140.0	2418.0	2600.0	2782.0	3906.0	4200.0	4494.0	4464.0	4800.0	5136.0	2976.0	3200.0	3424.0	2976.0	3200.0	3424.0
D	3100.0	3333.3	3566.7	4030.0	4333.3	4636.7	6510.0	7000.0	7490.0	7440.0	8000.0	8560.0	4960.0	5333.3	5706.7	4960.0	5333.3	5706.7
T	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%
K	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i	12%	12%	12%	11.5%	11.5%	11.5%	8%	10%	12%	6%	8.5%	11%	8%	10%	12%	8%	10%	12%
At the end of year 3																		
G	7905.0	8500.0	9095.0	10276.5	11050.0	11823.5	16600.5	17850.0	19099.5	18972.0	20400.0	21828.0	12648.0	13600.0	14552.0	12648.0	13600.0	14552.0
C	1860.0	2000.0	2140.0	2418.0	2600.0	2782.0	3906.0	4200.0	4494.0	4464.0	4800.0	5136.0	2976.0	3200.0	3424.0	2976.0	3200.0	3424.0
D	3100.0	3333.3	3566.7	4030.0	4333.3	4636.7	6510.0	7000.0	7490.0	7440.0	8000.0	8560.0	4960.0	5333.3	5706.7	4960.0	5333.3	5706.7
T	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%	40%
K	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i	12%	12%	12%	11.5%	11.5%	11.5%	8%	10%	12%	6%	8.5%	11%	8%	10%	12%	8%	10%	12%

Table 4.12: Cash Flow Model Showing the Fuzzy and Crisp NPV values for the Technology Alternatives

	Technology A1			Techonology A2			Technology A3			Technology A4			Technology A5			Technology A6		
	AR			AA			AI			UAVs			IoT			IoE		
	Pessimistic Value	Possible Value	Optimistic Value	Pessimistic Value	Possible Value	Optimistic Value	Pessimistic Value	Possible Value	Optimistic Value	Pessimistic Value	Possible Value	Optimistic Value	Pessimistic Value	Possible Value	Optimistic Value	Pessimistic Value	Possible Value	Optimistic Value
Year 0	-10700.0	-10000.0	-9300.0	-13910.0	-13000.0	-12090.0	-22470.0	-21000.0	-19530.0	-25680.0	-24000.0	-22320.0	-17120.0	-16000.0	-14880.0	-17120.0	-16000.0	-14880.0
Year 1	4699.0	5233.3	5767.7	6108.7	6803.3	7498.0	9867.9	10990.0	12112.1	11277.6	12560.0	13842.4	7518.4	8373.3	9228.3	7518.4	8373.3	9228.3
Year 2	4699.0	5233.3	5767.7	6108.7	6803.3	7498.0	9867.9	10990.0	12112.1	11277.6	12560.0	13842.4	7518.4	8373.3	9228.3	7518.4	8373.3	9228.3
Year 3	4699.0	5233.3	5767.7	6108.7	6803.3	7498.0	9867.9	10990.0	12112.1	11277.6	12560.0	13842.4	7518.4	8373.3	9228.3	7518.4	8373.3	9228.3
Fuzzy Net Present Value	586.21	2569.58	4552.96	889.06	3481.89	6074.72	1231.03	6330.50	11684.06	1879.24	8078.52	14680.90	937.93	4823.24	8902.14	937.93	4823.24	8902.14
	AR			AA			AI			UAVs			IoT			IoE		
Crisp Net Present Value	2569.58			3481.89			6415.20			8212.89			4887.77			4887.77		

In this case, the fuzzy NPV values (shown in Table 4.12) were "defuzzied" and inputted in the matrix shown in Equation 4.12. This was done by using the Equation as follows (Wang & Tu, 2015);

$$f(x) = F(m, a, b) = \frac{(3m - a + b)}{3} \qquad 4.11$$

The resultant crisp NPV values are shown in Table 4.12. Thereafter, these values were inserted in the decision matrix and the decision matrix is presented as follows:

$$R = (X_{ij})_{m\times n} = \begin{array}{c} \\ AR \\ AA \\ AI \\ UAVs \\ IoT \\ IoE \end{array} \begin{array}{c} \begin{array}{cccc} \textbf{\textit{Economical}} & \textbf{\textit{Efficiency}} & \textbf{\textit{Strategic fit}} & \textbf{\textit{Operational safety}} \end{array} \\ \begin{bmatrix} 2569.58 & 1 & 5 & 3 \\ 3481.89 & 3 & 3 & 3 \\ 6415.20 & 3 & 3 & 2 \\ 8212.89 & 4 & 4 & 4 \\ 4887.77 & 3 & 4 & 3 \\ 4887.77 & 3 & 4 & 3 \end{bmatrix} \end{array} \qquad 4.12$$

4.5 Normalization

Step 5: Normalize the decision matrix.

Using Equation 3.1 the elements of the decision matrix are normalized to fall within the range of 0 and 1. The result of the normalization is shown in Table 4.13

Table 4.13: Normalized Data for the Decision Matrix

	Economic	**Efficiency**	**Strategic Fit**	**Operational safety**
AR	0.00	0.00	1.00	0.50
AA	0.16	0.67	0.00	0.50
AI	0.68	0.67	0.00	0.00
UAVs	1.00	1.00	0.50	1.00
IoT	0.41	0.67	0.50	0.50
IoE	0.41	0.67	0.50	0.50

On normalizing the matrix, the biggest number in a matrix column becomes one and the lowest becomes zero. For instance, on applying equation 4.12, the economic value of 8212.89 for UAV becomes 1.00 in Table 4.13. Similarly, the operational safety value of 2.00 for AI becomes 0.00 in Table 4.13.

4.6 Pairwise Comparison

Step 6: Determination of deviation using pairwise comparison.

Here, the evaluative difference of criteria values of each technology alternative with respect to other technology alternatives is calculated. This was done using Equation 3.2. A summary of the results is presented in Table 4.14.

Table 4.14: Evaluative Deviation of the Technologies with Respect to the Criteria

	Economical	Efficiency	Strategic Fit	Operational Safety
D(AR - AA)	-0.16	-0.67	1.00	0.00
D(AR - AI)	-0.68	-0.67	1.00	-0.50
D(AR - UAVs)	-1.00	-1.00	0.50	0.50
D(AR - IoT)	-0.41	-0.67	0.50	0.00
D(AR - IoE)	-0.41	-0.67	0.50	0.00
D(AA-AR)	0.16	0.67	-1.00	0.00
D(AA-AI)	-0.52	0.00	0.00	-0.50
D(AA-UAVs)	-0.84	-0.33	-0.50	0.50
D(AA-IoTs)	-0.25	0.00	-0.50	0.00
D(AA-IoE)	-0.25	0.00	-0.50	0.00
D(AI-AR)	0.68	0.67	-1.00	0.50
D(AI - AA)	0.52	0.00	0.00	0.50
D(AI - UAVs)	-0.32	-0.33	-0.50	1.00
D(AI - IoT)	0.27	0.00	-0.50	0.50
D(AI - IoE)	0.27	0.00	-0.50	0.50
D(UAVs - AR)	1.00	1.00	-0.50	-0.50
D(UAVs - AA)	0.84	0.33	0.50	-0.50
D(UAVs - AI)	0.32	0.33	0.50	-1.00
D(UAVs - IoT)	0.59	0.33	0.00	-0.50
D(UAVs - IoE)	0.59	0.33	0.00	-0.50
D(IOT - AR)	0.41	0.67	-0.50	0.00
D(IOT - AA)	0.25	0.00	0.50	0.00
D(IOT - AI)	-0.27	0.00	0.50	-0.50
D(IOT - UAVs)	-0.59	-0.33	0.00	0.50
D(IOT - IoE)	0.00	0.00	0.00	0.00
D(IOE - AR)	0.41	0.67	-0.50	0.00
D(IOE - AA)	0.25	0.00	0.50	0.00
D(IOE - AI)	-0.27	0.00	0.50	-0.50
D(IOE - UAVs)	-0.59	-0.33	0.00	0.50
D(IOE - IoT)	0.00	0.00	0.00	0.00

4.7 Preference Function

In applying the PROMETHEE method, a preference function is used to define deviations between alternatives for each criterion. Of the several preference functions, the usual criterion preference function as seen in Equation 3.7 was used. A summary of the deviations using the usual function is shown in Table 4.15

Table 4.15: Usual Criterion Preference Function

	Economical	**Efficiency**	**Strategic Fit**	**Operational Safety**
P(AR - AA)	0.00	0.00	1.00	0.00
P(AR - AI)	0.00	0.00	1.00	0.00
P(AR - UAVs)	0.00	0.00	0.50	0.50
P(AR - IoT)	0.00	0.00	0.50	0.00
p(AR - IoE)	0.00	0.00	0.50	0.00
P(AA-AR)	0.16	0.67	0.00	0.00
P(AA-AI)	0.00	0.00	0.00	0.00
P(AA-UAVs)	0.00	0.00	0.00	0.50
P(AA-IoTs)	0.00	0.00	0.00	0.00
P(AA-IoE)	0.00	0.00	0.00	0.00
P(AI-AR)	0.68	0.67	0.00	0.50
P(AI - AA)	0.52	0.00	0.00	0.50
P(AI - UAVs)	0.00	0.00	0.00	1.00
P(AI - IoT)	0.27	0.00	0.00	0.50
P(AI - IoE)	0.27	0.00	0.00	0.50
P(UAVs - AR)	1.00	1.00	0.00	0.00
P(UAVs - AA)	0.84	0.33	0.50	0.00
P(UAVs - AI)	0.32	0.33	0.50	0.00
P(UAVs - IoT)	0.59	0.33	0.00	0.00
P(UAVs - IoE)	0.59	0.33	0.00	0.00
P(IOT - AR)	0.41	0.67	0.00	0.00
P(IOT - AA)	0.25	0.00	0.50	0.00
P(IOT - AI)	0.00	0.00	0.50	0.00
P(IOT - UAVs)	0.00	0.00	0.00	0.50
P(IOT - IoE)	0.00	0.00	0.00	0.00
P(IOE - AR)	0.41	0.67	0.00	0.00
P(IOE - AA)	0.25	0.00	0.50	0.00
P(IOE - AI)	0.00	0.00	0.50	0.00
P(IOE - UAVs)	0.00	0.00	0.00	0.50
P(IOE - IoT)	0.00	0.00	0.00	0.00

4.8 Multicriteria/Aggregated Preference Index

The preference order is also known as the preference index. The values show the degree of preference of one technology over another. The preference index takes into account the criteria weight while calculating. Equation 3.4 was used to calculate the index and the results are presented in Table 4.16.

Table 4.16: Aggregated Preference Index Matrix

	AR	AA	AI	UAVs	IoT	IoE
AR	0	0.1137	0.1137	0.2468	0.0568	0.0568
AA	0.1195	0	0	0.1900	0.0000	0.0000
AI	0.5339	0.4144	0	0.3800	0.3069	0.3069
UAVs	0.5063	0.4437	0.2192	0	0.2793	0.2793
IoT	0.2271	0.1644	0.0568	0.1900	0	0
IoE	0.2271	0.1644	0.0568	0.1900	0	0

4.9 Preference Order

Step 9: Determination of the preference order

Determining the preference order requires that the leaving and the entering outranking flows values of each technology option was calculated. Thereafter, their net outranking flow was computed. Equation 3.6 and 3.7 was used to calculate the leaving and entering outranking flows; the results are presented in Table 4.17. Equation 3.5 was also used to calculate the net outranking flow; the resulting values are shown in Table 4.18.

Table 4.17: The Leaving and Entering Outranking Flow Values

	$\phi^+(a)$	$\phi^-(a)$
AR	0.0980	0.2690
AA	0.0516	0.2168
AI	0.3237	0.0744
UAVs	0.2880	0.1995
IoT	0.1064	0.1072
IoE	0.1064	0.1072

Table 4.18: The Net Flow Values of the Technologies

	Φ	**Rank**
AR	-0.1710	6
AA	-0.1652	5
AI	0.2493	1
UAVs	0.0885	2
IoT	-0.0008	3
IoE	-0.0008	3

The net outranking flow values are obtained by subtracting the individual leaving flow values from its corresponding entering flow values. The computed values are shown in the rank column of Table 4.18. AI has the highest net flow value of 0.2493 and AR having the lowest net flow value of -0.1710. After ranking these net flow values from highest to lowest, AI was rated the first and AR the last. Notably, IoT and IoE have the same net flow values, and this makes both technologies rank equally.

4.10 Chapter Summary

The MCDM approach discussed in Chapter 3 was implemented in this chapter to solve the decision problem. AHP was used to calculate the hierarchal weights of the decision-making criteria. The use of fuzzy set theorem and PROMETHEE II were adopted to carry out the rest of the evaluative computation. To further explain the aforementioned, Chapter 5 discusses the results as well as the analysis of the result obtained in this current chapter.

5 DISCUSSION AND ANALYSIS

5.1 Results

The results of the case study considered in this study are represented in Table 4.18 and Figure 5.1. Table 4.18 shows the net flow values of each of the technology alternatives and the respective ranks when arranged from the highest (best option) to the lowest (worse option). Figure 5.1 shows the pictorial hierarchical order of the results shown in Table 4.18 as generated from the PROMETHEE-GAIA (graphical analysis for interactive assistance) software. In summary, this indicates that AI (***A₃***) is the best technology fit for this mining project in comparison with the other five technology options. In order of preference, the technology can be represented as follows;

$$A_3, > A_4 > (A_5 = A_6) > A_2 > A_1$$

where '>' means 'is more preferred' and '=' means is 'equally preferred to'.

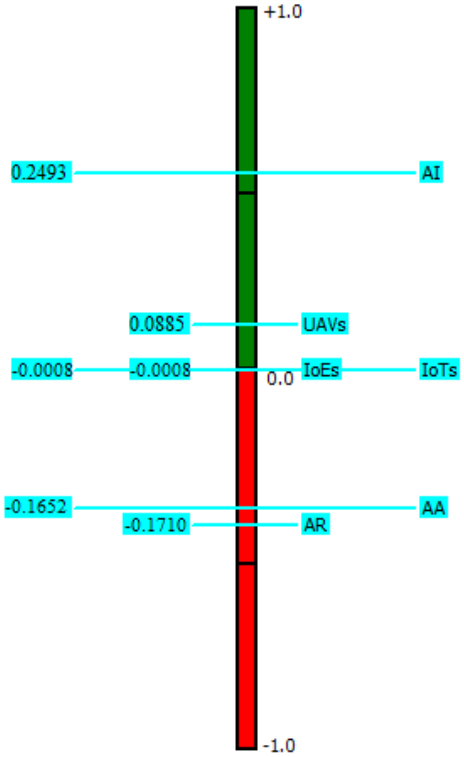
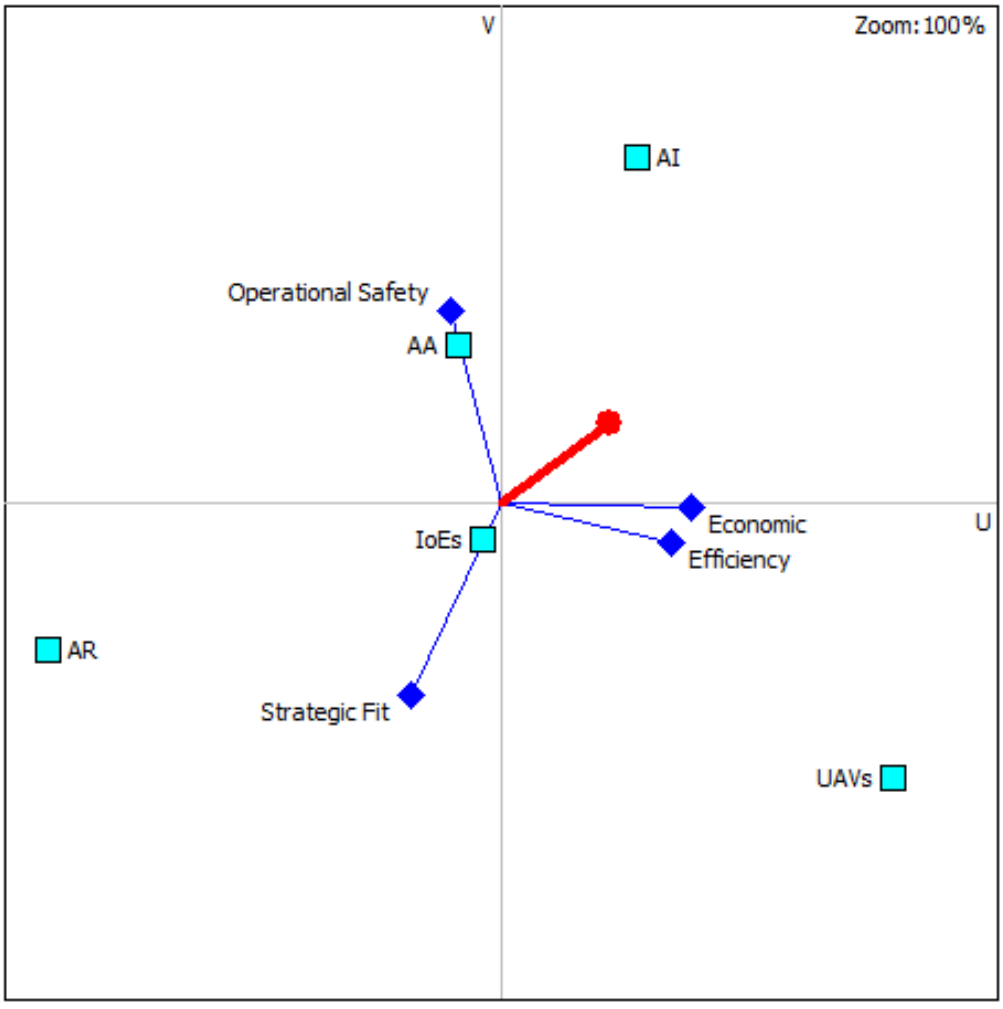


Figure 5.1: Complete Ranking of the Technology Alternatives Flow

5.2 Analysis

Figure 5.2 shows the GAIA plane analysis for the decision problem modelled in this study. The figure shows and helps to understand the relationships between criteria and the technology alternatives. In figure 5.2, the electric-blue square boxes are the technology alternatives, while the vectors with blue lines and rhombuses are the criteria.

The orientation of these criteria vectors shows how closely related or conflicting one criterion is to another. From Figure 5.2, the "Economic" and "Efficiency" criteria are closely related. This means technologies with high economic values also



have

Figure 5.2: The GAIA Plane Analysis of the Decision Problem

high-efficiency rates, while “Operational Safety” and “Strategic Fit” are relatively conflicting with themselves and other criteria. The decision vector is the thick red axis with a big dot. Its orientation indicates the degree of alignment of each criterion with the PROMETHEE ranking. The decision axis is opposite to strategic fit; therefore, it is expected to find technologies with higher economic NPVs and higher efficiency at the top of the PROMETHEE rankings.

The degree of closeness of each technology to a criterion indicates how much such technology is good at exhibiting the characteristic of the nearby criterion. For instance, the technology AR, IoEs and IoTs (***A*$_1$**, ***A*$_5$, *A*$_6$**) are situated close to the “Strategic Fit” criteria. This means that these technologies have the best strategic fit for the mining project. For the “Operational Safety” criteria, Technology AA (***A*$_2$**) has the best fit. Similarly, UAVs (***A*$_4$**) is independently the most efficient and it also has a significant economic value.

In the same way, technology alternatives with similar profiles are situated close to each other, as in the case of IoEs and IoTs (***A*$_5$, *A*$_6$**). Their profiles are similar to the extent where they literary overlap. On the other hand, in the same Figure 5.2 UAVs and AA (***A*$_5$, *A*$_2$**) tend to have different profiles because they are situated very far from each other.

5.3 Sensitivity Analysis

Sensitivity analysis in this study aims to find out how much the output of the model used to solve the decision problem is affected by the uncertainty in the input variable. This is carried out to identify any close competition to the most preferred alternative. The validation process involves analysing the effect of weight modification for each criterion on the technology choice for the mine. Figure 5.3 was generated using the visual stability intervals feature of the PROMETHEE-GAIA software. Graphs in Figure 5.3 show the effect of criteria weight.

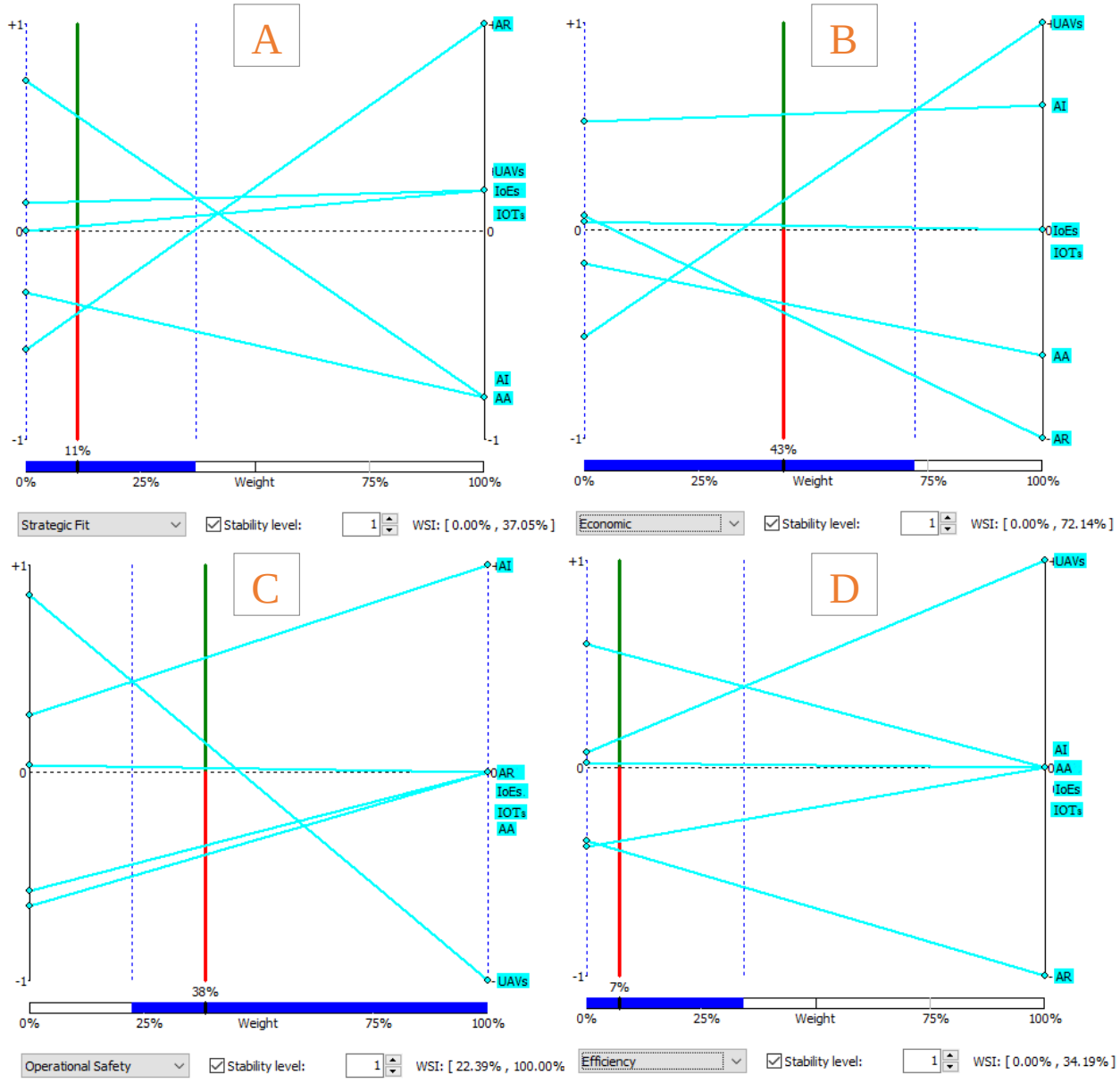


Figure 5.3: Criterion Weight Variability Graphs

For each of the Graphs (A-D) in Figure 5.3, the vertical axis is the net flow axis while the horizontal axis is the criterion weight axis labelled from 0% to 100%. Each of the electric blue lines shows how each of the technology alternatives changes with a modification of the criterion weight.

It is important to note that the green and red vertical lines make it easy to identify the technology alternative ranking at the weight assigned in this study for the criteria considered in the graph. For instance, the AI ($\boldsymbol{A_3}$) is ranked at the top for the

11% weight for the strategic fit criteria (Graph A), 43% weight for economic criteria (Graph B), 38% weight for operational safety criteria (Graph C), and 7% weight for efficiency criteria (Graph D).

In Graph D, the efficiency criterion is considered, and for the criterion weight lesser than or equal to 34.19% (0.34), the AI (A_3) technology option is ranked at the top of the alternatives. However, for the efficiency criterion weight greater than 34.19%, UAVs (A_4) is ranked the first.

In Graph C, the operational safety criterion is considered and for criterion weights lesser than or equal to 22.39% (0.22) UAVs is ranked the first choice among all the technology alternatives. However, for operational criterion weight greater than 22.39%, AI (A_3) is ranked first.

In Graph B, the economic criterion is considered and for weights lesser than or equal to 72.14% (0.72), AI (A_3) is ranked at the top, However, if weight value higher than 72.14% was assigned to the economic criterion, UAVs (A_4) became the first on rank.

In Graph A, the strategic fit criterion is considered and for weights lesser than or equal to 37.05% (0.37), AI (A_3) is ranked in the first place. For the efficiency criterion weight between 37.05% and 47.05%, UAVs (A_4) is ranked in the first place. If the weight value was greater than 47.05% and was assigned to the same criterion, AR (A_1) is ranked in the first place.

Similarly, using the walking weights interactive feature of the PROMETHEE-GAIA software, the sensitivity of the result to variability in the criterion weighing is tested. Figure 5.4 and Figure 5.5 show the weightings and the result. The originally calculated criteria-weights assigned by the decision maker for technology decision problem considered in this study is depicted by the deep-blue bars in Figure 5.4. The six bars highlighted in electric blue colour in Figure 5.4 show the technology alternatives, arranging them from the most preferred to the least suitable (moving from left to right).

To test for sensitivity, all the weights were set equal and the results displayed by the electric-blue bar charts in the upper portion of Figure 5.5 show that UAVs (A_4)

was the most preferred and AA (A_2) was the least preferred. These noted variances show that the applied model used in this study is moderately stable as it is sensitive. An extremely stable model would not have generated a different alternative rank or result even when the criteria are varied or set equal. The expected reasons why this problem model is sensitive are listed below;

1. The presence of more subjective criteria than objective criteria;
2. A single decision maker was used in this study, making it not the perfect representation for a decision-making situation in a mine; and
3. The hypothetical nature of the case study.

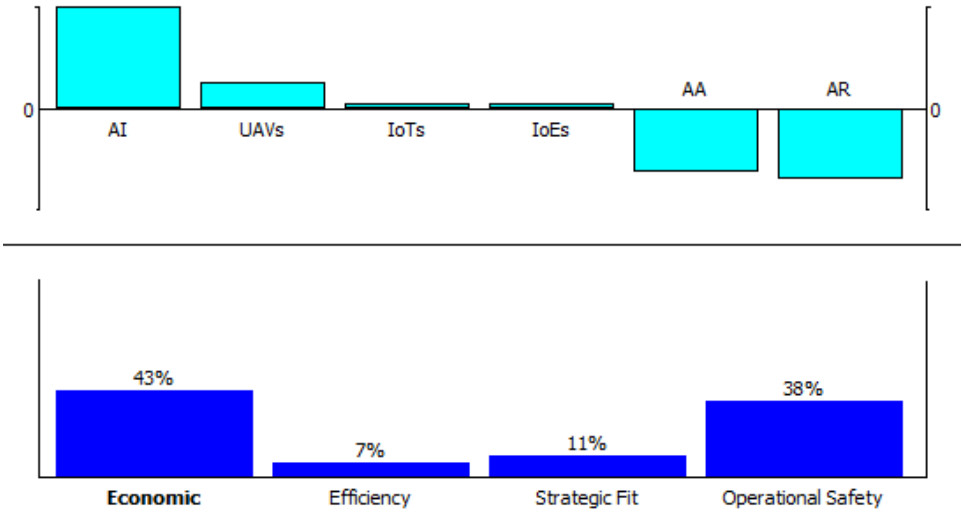


Figure 5.4: Results with Original Criteria Weights

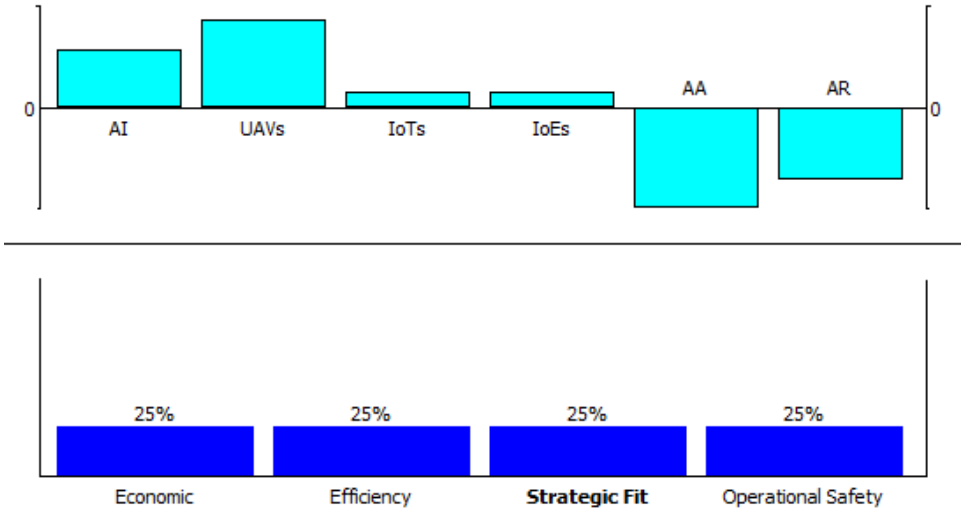
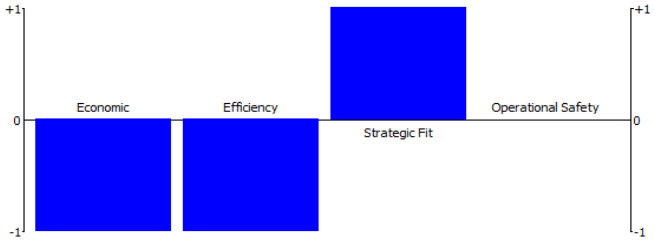


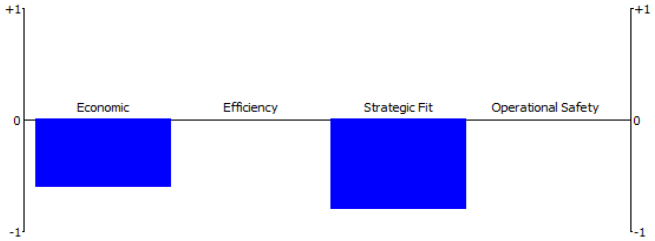
Figure 5.5: Results with Equal Criteria Weights

Figure 5.6 generated using Visual PROMETHEE-GAIA software is an action profile that shows the individual strengths and weaknesses of the technology alternatives based on their corresponding criteria net flow scores (1 being the highly preferred and -1 the least preferred).

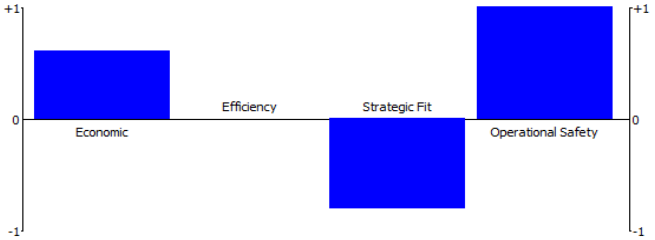
Concerning the decision making-criterion, the action profile shows that the technology options A_3 and A_4 performed better, followed by technology options A_1, A_5, A_6, and A_2. From Figure 5.6, it is observed that only technology alternative A_3 has positive "Operational Safety" values. This indicates that compared to other technology alternatives, "A_3" has the best operational safety capability. Similarly, technology options A_1, A_4, A_5 and A_6 all fit into the strategic digitization goals of the mining company, however, individually, A_1 has the best strategic fit.



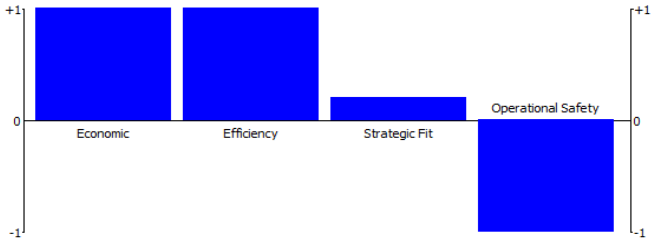
(***A₁***); Augmented Reality (AR)



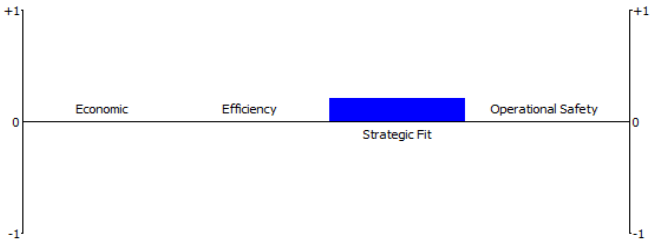
(***A₂***); Advanced Analytics (**AA**)



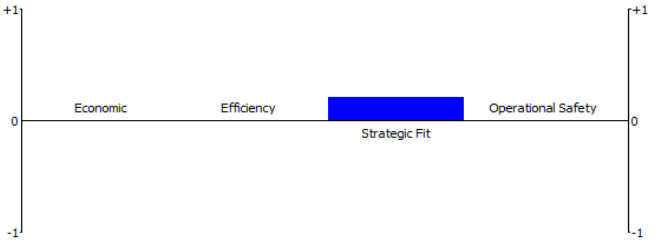
(***A₃***); Artificial Intelligence (**AI**)



(***A₄***); Unmanned Air Vehicles (**UAVs**)



(***A₅***); Internet of Things (**IoT**)



(***A₆***); Internet of Everything (**IoE)**

Figure 5.6: The Action Profile Comparing the Uni-criteria Net Flow Scores of Criteria of the Technology Options

5.4 The Decision

Based on the need of the company, the most preferred technology would be AI (A_3). The maximum capital expenditure for this technology option is 22,470 C.U making this decision would in turn lead to a company savings of at least 37,530 C.U. Considering the budget of 60,000 C.U set aside by the mining company, an additional technology (A_4) – UAVs – can be adopted in addition to A_3. This is because, as indicated in the overall ranking (shown in Figure 5.1), UAVs are the next preferred option and, the investment and operational cost for both technology options range from 50,220 to 57,780.

5.5 Chapter Summary

The results computed in the previous chapters were explained and analytically discussed in this chapter, followed by the decision on the selection of the most suitable technology. The following chapter concludes by giving an overview and discussing the findings made during the study.

6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This study has demonstrated the application of two MCDA methods in evaluating emerging technologies for the selection of a single or group of preferred technologies for any adopting mining company. The structure of the decision problem resolved by the MCDA method consisted of six technology alternatives – AR, AA, AI, UAVs, IoEs and IoTs – from a cumulative of about 550 that were assessed against four criteria. This evaluation procedure used the AHP method to determine the hierarchal weight of each decision-making criterion and its consistency while the PROMETHEE method was used to carry out the overall process evaluation. Additionally, the fuzzy set theory was infused into the hierarchical structure analysis to evaluate the quantitative economic criterion and also curb uncertainty and imprecision.

The result of the overall evaluation showed that AI ($\boldsymbol{A_3}$) is the most preferred technology alternative, provided a single choice of technology is needed for adoption. In addition, the calculation of the hierarchal weights using AHP technique showed that the economic criteria, followed by operational safety had the highest weights relative to the other criteria, indicating the decision maker paid more attention to them.

The ability of the decision algorithm proposed in this study to solve decision problems under a fuzzy environment and not only precision-based (non-fuzzy) problems makes these ideally suitable for real-life decision-making scenarios. This is because, most times, while selecting technologies or evaluating them for a proposed project, the information available to make those decisions are usually imprecise and uncertain.

In addition to the above stated, this study has:

a) Provide the basis for which a technology business case, strategy or roadmap can be built for any technology adopting mining company;

b) Provided an insightful and clearer understanding of how various new and emerging technologies can be adopted along the existing mining value chain; and
c) Provided the fundamentals for more specific and targeted studies in the space of technology and its adoption within the metals, mining and mineral processing industry.

6.2 Recommendations

Based on this hypothetical study, the mining company planned to adopt just one technology and based on this research; the highest-ranked technology option can be selected for adoption. However, the cost of adopting and implementing the highest-ranked technology is a fraction of the budget. It is therefore recommended that two technology options be chosen for adoption. The highest and the second-highest ranked technologies (AI and UAVs) can both be adopted to tackle the health hazard faced by the company.

Alternatively, AI, being the best option can be adopted. Thereafter, another choke point can be identified within the operation where the same stepwise assessment algorithm used in this study can be applied again to identify the most suitable technology to tackle the challenge.

It can be recommended that the mining industry use the multi criteria analytical tools in decision making mainly because of its flexibility of the methodological framework. This is because the structure and themes of the evaluation criteria hierarchy can be reformed and refined without having to alter the “backbone” of the methodology.

6.3 Limitation of Study and Future Research Work

This study was particularly limited due to its hypothetical nature. It was also limited because it involved just one decision maker. However, a typical mine would have multiple decision makers. Therefore, a technology decision problem modelling more decision-makers can be investigated in future research.

Further research that uses this study's methodology and Jacobs (2016) technology map can be employed to determine, what equipment/systems that use modern technologies, can best supplement an existing mine's infrastructure.

Another research approach can be, to identify a technology option that is applicable across several operational phases of the value chain from Jacobs (2016) technology map and determine how and where best to apply that selected technology within the organisation.

The PROMETHEE preference function (Appendix B) used in this study is the "usual" function, however, some other studies identify the existence of at least five other preference function types (Appendix B). Drawing from this, a study using other PROMETHEE preference functions can be conducted.

Lastly, this study focused on the use of two MCDA methods. Further studies can be conducted using other MCDA methods which can be applied to solving similar decision problems.

REFERENCES

Abdullah, L., Chan, W., & Afshari, A., 2019. Application of PROMETHEE method for green supplier selection: a comparative result based on preference functions. *Journal of Industrial Engineering International, 15*(2). pp. 271-285.

Accenture, 2011. *Global Operating Models for Mining Companies: Adding value beyond the individual assets*. Retrieved from: https://www.accenture.com/t20150527T211403__w__/jp-ja/_acnmedia/Accenture/Conversion-Assets/DotCom/Documents/Local/ja-jp/PDF_2/Accenture-Mining-Global-Operating-Models-POV-FINAL.pdf [Accessed: 1 June 2019].

Bartos, P. J., 2007. Is mining a high-tech industry?: Investigations into innovation and productivity advance. *Resources Policy, 32*(4). pp. 149-158.

Bazzazi, A. A., Osanloo, M., & Karimi, B., 2009. Optimal Open Pit Mining Equipment Selection Using Fuzzy Multiple Attribute Decision Making Approach. *Archives of Mining Sciences, 54*. pp. 301-320.

Bryant, P., 2015. *The Case for Innovation in the Mining Industry.* Tech. report, Coalition for Energy Efficient Communition. Retrieved from http://www.ceecthefuture.org/wp-content/uploads/2016/01/Clareo_Case-for-Innovation-in-Mining_20150910_lo.pdf. [Accessed: 13 May 2019].

Bye, A., 2006. The strategic and tactical value of a 3D geotechnical model for mining optimization, Anglo Platinum, Sandsloot open pit. *The Journal of The South African Institute of Mining and Metallurgy, 106.* pp. 97 - 104.

Callahan, A., & Long, G., 2017. *Digital in Mining: Progress and Opportunity.* Tech. report, Accenture. Retrieved from https://www.accenture.com/za-en/_acnmedia/PDF-51/Accenture-Digital-in-Mining-Progress-and-Opportunity.pdf. [Accessed: 6 June 2019].

Chan, F., Chan, M., & Tang, N., 2000. Evaluation methodologies for technology selection. *Journal of Materials Processing Technology, 107*. pp. 330-337.

Collins, B., 2018. Anglo Using 'Digital Twins', Robotics to Boost Mining: Q&A. *BloombergNEF*. Retrieved from: https://about.bnef.com/blog/anglo-using-digital-twins-robotics-boost-mining-qa/ [Accessed: 4 July 2019].

Crawford, A., 2018. *Innovation in Mining: Report to the 2018 International Mines Ministers Summit.* Tech. rep., The International Institute for Sustainable Development, Winnipeg: IISD.

CSIRO., 2017. *Mining Equipment,Technology and Services: A Roadmap for unlocking future growth opportunities for Australia.* Tech. rep., The Commonwealth Scientific and Industrial Research Organisation(CSIRO). Retrieved from https://www.csiro.au/en/Do-business/Futures/Reports/METS-Roadmap. [Accessed: 25 June 2019].

Deloitte., 2015. *Tracking the trends 2015: The top 10 issues mining companies will face this year.* Tech. rep., Deloitte. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/fpc/Documents/secteurs/energie-et-ressources/deloitte_etude-tracking-the-trends-2015-en.pdf. [Accessed: 1 June 2019].

Deloitte., 2019. *Tracking the trends 2019: The top 10 issues transforming the future of mining.* Tech. rep., Deloitte. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Energy-and-Resources/gx-er-tracking-the-trends-2019.pdf. [Accessed: 31 May 2019].

Deloitte & Touche, 2014. *The Future of Mining in South Africa - Innovation imperative*. Retrieved from: https://www2.deloitte.com/content/dam/Deloitte/za/Documents/energy-resources/ZA_Mine_of_the_Future_06022015.pdf [Accessed: 14 June 2019].

Dessureault, S., 1999. *Capital investment appraisal for advanced mining technology : case studies in GPS and information based surface mining technology*. Vancouver, Canada: University of British Columbia.

Dessureault, S., & Scoble, M. J., 2000. Capital investment appraisal for the integration of new technology into mining systems. *Mining Technology, 109*, 30-40.

Dey, P. K., & Ramcharan, E. K., 2008. Analytic hierarchy process helps select site for limestone quarry expansion in Barbados. *Journal of Environmental Management, 88*. pp. 1384-1395.

Drake, J. I., Hart, J. C., Monleón, C., Toro, W., & Valentim, J., 2017. Utilization of multiple-criteria decision analysis (MCDA) to support healthcare decision-making FIFARMA, 2016. *Journal of Market Access & Health Policy, 5*(1). p. 10.

Durrant-Whyte, H., Geraghty, R., Pujol, F., & Sellschop, R., 2015. *How digital innovation can improve mining productivity | McKinsey.* Tech. rep., McKinsey Inc. Retrieved from https://www.mckinsey.com/industries/metals-and-mining/our-insights/how-digital-innovation-can-improve-mining-productivity. [Accessed: 24 Jan 2019].

Dyson, N., 2018. *Newcrest calls on crowd*. Mining Journal. Retrieved from: https://www.mining-journal.com/innovation/news/1345672/newcrest-calls-on-crowd [Accessed: 3 July 2019].

Ernst & Young., 2017a. *Productivity in mining now comes the hard part*. Retrieved from: https://www.ey.com/Publication/vwLUAssets/EY-productivity-in-mining-now-comes-the-hard-part/$FILE/EY-productivity-in-mining-now-comes-the-hard-part.pdf [Accessed: 11 March 2019].

Ernst & Young., 2017b. *Tomorrow's mine: How digital can shape the future?* Tech. rep., Ernst & Young LLP, India. Retrieved from

https://www.extractiveshub.org/servefile/getFile/id/7400 [Accessed: 22 June 2019].

Ernst & Young, 2018. *Worldwide Capital and Fixed Asset Guide.* United Kingdom: Ernst & Young Global Limited. Retrieved from https://www.ey.com/Publication/vwLUAssets/ey-2018-worldwide-capital-and-fixed-assets-guide/$FILE/ey-2018-worldwide-capital-and-fixed-assets-guide.pdf [Accessed: 21 January 2020].

Exarro, 2018. *Delivering a digital twin to South Africa*. Exxaro. Retrieved from: https://www.exxaro.com/media-centre/2018/delivering-a-digital-twin-to-south-africa [Accessed: 4 July 2019].

Fernandez, V., 2018. Copper mining in Chile and its regional employment linkages. *Resources Policy*. Retrieved from: doi:10.1016/j.resourpol.2018.03.017 [Accessed: 10 May 2019].

Gorse, C., Johnston, D., & Pritchard, M., 2013. Technology. In *A Dictionary of Construction, Surveying and Civil Engineering.* Oxford University Press. Retrieved from http://0.www.oxfordreference.com/view/10.1093/acref/9780199534463.001.0001/acref-9780199534463-e-7195[Accessed: 4 July 2019].

Goumas, M., & Lygerou, V., 2000. An extension of the PROMETHEE method for decision making in fuzzy environment: Ranking of alternative energy exploitation projects. *European Journal of Operational Research, 123*(3). pp. 606-613.

Haddad, M., & Sanders, D., 2018. Selection of discrete multiple criteria decision making methods in the presence of risk and uncertainty. *Operations Research Perspectives, 5*. pp. 357-370.

Hall, A., & Hall, B., October 2006. Doing the Right Things Right — Identifying and Implementing the Mine Plan That Delivers the Corporate Goals.

Melbourne, Victoria. Australia: International Mine Management Conference.

Hoikkala, H. & Rolander, N., 2019. Diamond Trading Goes Online as Lucara Takes on Industry Goliaths. *Bloomberg*. . Retrieved from: https://www.bloomberg.com/news/articles/2019-04-28/diamond-trading-goes-online-as-lucara-takes-on-industry-goliaths [Accessed: 3 July 2019].

Hwang, C. L., & Yoon, K., 1981. *Multiple Attribute Decision Making.* Berlin, Heidelberg: Springer Berlin Heidelberg.

International Business Machine (IBM)., 2018. *Goldcorp, IBM develop 'first-of-a-kind' AI exploration tech*.. Mining Magazine. Retrieved from: https://www.miningmagazine.com/exploration/news/1351824/goldcorp-ibm-develop-%E2%80%98first-of-kind%E2%80%99-ai-exploration-tech [Accessed: 3 July 2019].

Jacobs, J., 2016. *Creating a technology map to facilitate the process of modernisation throughout the mining cycle.* Dissertation, University of Pretoria, Pretoria.

Jacobs, J., & Webber-Youngman, R. C., 2017. A technology map to facilitate the process of mine modernization throughout the mining cycle. *Journal of the Southern African Institute of Mining and Metallurgy, 117.* pp. 637-648.

Jordaan, J. T., & Hendricks, C., 2009. The Challenge of Technology Adoption and Utilisation in the Mining Industry – A Focus on Open Pit Mining Technologies. In *Base Metal Conferenc*, South Africa, The South African Institute of Mining and Metallurgy. p.14.

Kahraman, C., 2008. *Fuzzy multi-criteria decision making: theory and applications with recent developments.* New York: Springer.

Koksalan, M., Wallenius, J., & Zionts, S., 2011. *Multiple Criteria Decision Making: From Early History to the 21st Century.* Singapore, Singapore; Hackensack, NJ: World Scientific Publishing Co Pte Ltd.

Komolavanij, S., 1995. *Capital budgeting in a fuzzy world.* Texas, United States: The University of Texas at Arlington.

Kostoff, R. N., Boylan, R., & Simons, G. R., 2004. Disruptive technology roadmaps. *Technological Forecasting and Social Change, 71*. pp. 141-159.

Kumar, D., & Kumar, D., 2016. Rational Implementation of Mining Technology. In D. Kumar, & D. Kumar (Eds.), *Management of Coking Coal Resources.* pp. 113-176. Elsevier.

Lucara Diamond Corp, 2018. *Clara - Lucara's Next Generation Growth Project*.. Retrieved from: https://www.youtube.com/watch?time_continue=5&v=wEVltDU0R_I [Accessed: 4 July 2019].

Mahase, M. J., Musingwini, C., & Nhleko, A. S., 2016. A survey of applications of multi-criteria decision analysis methods in mine planning and related case studies. *Journal of the Southern African Institute of Mining and Metallurgy, 116*, 1051-1056.

Montazeri, I., & Taji, M., 2016. Ranking and comparing of traditional and industrial coke making by TOPSIS technique in Shahrood Simin Coke Company. *Journal of Mining and Environment, 7*. pp. 165-173.

Moore, E., 2018. *How to simulate an entire operation before production: Creating a simulation, or "digital twin," of a plant or piece of equipment can help operators prepare for any eventuality*. CIM Magazine. Retrieved from: http://magazine.cim.org/en/technology/digital-double-en/ [Accessed: 4 July 2019].

Musingwini, C., & Minnitt, R. C., 2008. Ranking the efficiency of selected platinum mining methods using the analytic hierarchy process (AHP). In: *Third International Platinum Conference 'Platinum in Transformation'*

2008, South Africa, The Southern African Institute of Mining and Metallurgy. p. 8.

Neingo, P.N., 2014. *Drivers, Measures and Rewards for Productivity and Financial Impacts/ Benefits in the Mining Value Chain at Bathopele, Kroondal and Mototolo Mines: An Investigation of Impacts from Short Term Planning to Mill*. Master's thesis. Johannesburg, South Africa, The University of the Witwatersrand.

Ordoobadi, S. M., 2012. Application of ANP methodology in evaluation of advanced technologies. *Journal of Manufacturing Technology Management; Bradford, 23*(2). pp. 229-252.

Owusu-Mensah, F., & Musingwini, C., 2011. Evaluation of ore transport options from Kwesi Mensah Shaft to the mill at the Obuasi mine. *International Journal of Mining, Reclamation and Environment, 25*. pp. 109-125.

Paterson, D. J., LaTourrette, T., & Bartis, J. T., 2001. *New Force at Work in Mining: Industry Views of Critical Technologies.* Tech. rep., RAND's Science and Technology Policy Institute., Santa Monica, Califonia. USA.

Poulin, P., Austen, L., Scott, C. M., Waddell, C. D., Dixon, E., Poulin, M., & Lafrenière, R., 2013. Multi-criteria development and incorporation into decision tools for health technology adoption. *Journal of Health Organization and Management; Bradford*, *27*(2). pp. 246-65.

Poulton, M.M., Jagers, S.C., Linde, S., Van Zyl, D., Danielson, L.J., Matti, S., 2013. State of the World's Nonfuel Mineral Resources: Supply, Demand, and Socio-Institutional Fundamentals. *Annual Review of Environment and Resources*. 38 (1). pp. 345–371.

PricewaterhouseCoopers(PWC)., 2015. *Mining Excellence in Africa.* Tech. rep., PricewaterhouseCoopers, South Africa. Retrieved from https://www.pwc.co.za/en/assets/pdf/mining-capability-statement-2015.pdf. [Accessed: 6 June 2019].

Quash, K., 2018. *IBM Canada and Goldcorp launch artificial intelligence tool for exploration: IBM Exploration with Watson developed using data from Goldcorp's Red Lake mine*. CIM Magazine. Retrieved from: http://magazine.cim.org/en/news/2018/ibm-canada-and-goldcorp-launch-artificial-intelligence-tool-for-exploration/ [Accessed: 3 July 2019].

Ramani, R. V., 2012. Surface Mining Technology: Progress and Prospects. *Procedia Engineering*, 46. pp. 9-12.

Runge, I. C., 1995. Economics, Technological Change and the Knowledge Problem.In: *Application of Computer and Operations Research in the Mineral Industries.* July 1995 Brisbane, Australia, The Australasian Institute of Mining and Metallurgy p. 6.

Saaty, T. L., 1995. Transport planning with multiple criteria: The analytic hierarchy process applications and progress review. *Journal of Advanced Transportation, 29*(1). pp. 81-126.

Sabaei, D., Erkoyuncu, J., & Roy, R., 2015. A Review of Multi-criteria Decision Making Methods for Enhanced Maintenance Delivery. *Procedia CIRP, 37*. pp. 30-35.

Sganzerla, C., Seixas, C., & Conti, A., 2016. Disruptive Innovation in Digital Mining. *Procedia Engineering, 138*. pp. 64-71.

Simpson, M., Aravena, E. & Deverell, J., 2014. *The future of mining in Chile*. . Retrieved from: https://www.csiro.au/en/Research/Mining-manufacturing/CSIRO-Chile/Other-initiatives/Future-of-Mining [Accessed: 8 April 2019].

Sitorus, F., Cilliers, J. J., & Brito-Parada, P. R., 2019. Multi-criteria decision making for the choice problem in mining and mineral processing: Applications and trends. *Expert Systems with Applications, 121*, pp. 393-417.

Steen, J., Macaulay, S., & Hainsworth, D. W., 2018. Digital Mining: Past, Present, and Future. In *Extracting Innovations: Mining, Energy, and Technological Change in the Digital Age.* 1 ed., pp. 92-111. Florida, USA: CRC Press.

Stewart, P. & Pokracic, Z., 2018. *Worlds Digital Twin for Mine Value Chain Optimisation*. p. 2. Retrieved from: http://www.petradatascience.com/casestudy/worlds-first-digital-twin-for-mine-value-chain-optimisation/ [Accessed: 4 July 2019].

Stojanović, C. P., Bogdanović, D., & Urosević, S., 2015. Selection of the optimal technology for surface mining by multi-criteria analysis. *Kuwait Journal of Science, 42*(3), p. 170-190.

Taha, Z., Banakar, Z., & Tahriri, F., 2011. Analytical hierarchy process for the selection of advanced manufacturing technology in an aircraft industry. *International Journal of Applied Decision Sciences, 4*(2), p. 148.

Talukder, B., & Hipel, K. W., 2018. The PROMETHEE Framework for Comparing the Sustainability of Agricultural Systems. *Resources, 7*(4). p. 74.

Tilton, J.E., 2003. Creating wealth and competitiveness in mining. *Mining Engineering; Littleton*. 55 (9). pp. 15–22.

Triantaphyllou, E., 2000. *Multi-criteria Decision Making Methods: A Comparative Study.* Dordrecht, The Netherlands: Kluwer Academic Publishers.

Unearthed, 2018. *New Tools Accelerate Crowdsourcing: Newcrest reaches a global community with operational challenges.* Retrieved from: https://unearthed.solutions/industry [Accessed: 3 July 2019].

Upstill, G., & Hall, P., 2006. Innovation in the minerals industry: Australia in a global context. *Resources Policy, 31*. pp. 137-145.

Vujic, S., Hudej, M., & Miljanovic, I., 2013. Results of the promethee method application in selecting the technological system at the majdan III open pit mine. *Archives of Mining Sciences.* p. 58.

Wang, C., & Tu, S., 2015. Selection of an Appropriate Mechanized Mining Technical Process for Thin Coal Seam Mining. *Mathematical Problems in Engineering, 2015*(893232). p. 10.

Willis, P.H., 2000. Technologies required for safe and profitable deep level gold mining, South Africa. In: *CIM Bulletin* 90(1036). 2000 Canadian Institute of Mining, Metallurgy and Petroleum. pp. 151–155.

World Economic Forum (WEF), 2017. *Digital Transformation Initiative: Mining and Metals Industry*. Retrieved from: http://reports.weforum.org/digital-transformation/wp-content/blogs.dir/94/mp/files/pages/files/wef-dti-mining-and-metals-white-paper.pdf [Accessed: 31 May 2019].

Yuen, K.K.F & Ting, T.O., 2012. Textbook Selection Using Fuzzy PROMETHEE II Method. *International Journal of Future Computer and Communication*, 1(1), pp. 76-78.

Zavadskas, E., Turskis, Z., & Kildiene, S., 2014. State of art surveys of overviews on MCDM/MADM methods. *Technological and Economic Development of Economy, 20*. pp. 165-179.

APPENDIX

APPENDIX A

Table A1: Technology Map Showing the Mining Cycle and the Technologies that Facilitate Mine Modernization (Jacobs, 2016)

Technology map for the value drivers in the mining cycle to enable improvements in operational risk management strategies						
	Exploration and target generation phase	**Mine project evaluation/ planning phase**	**Mine design and construction phase**	**Operation phase (mine to mill)**	**Mine decommissioning and closure phase**	**Post closure**
Mineral Resources Management	**Initial target generation**	**Data collection**	**Data collation**	**Geology**	**Production planning**	**In situ reserves: monitoring/Mapping/sampling**
	[Aerial surveys & Mapping: UAVs]	[UAVs, AA, IoT]	[BD, IoT, Cloud, IoE, AA]	**Exploration**	[BD, IoT, AA, VR/AR, AI, Automation]	[Directional Drilling Technologies, 3D Seismics, Air Borne Gravimetry, IoT, BD, AA, UAVs, Predictive Modelling, 3P point-cloud technology]
	[Directional drilling, Airborne Gravimetry]	**Evaluation Studies**	**Geotechnical Planning**	[Direction Drilling Technologies, 3D Seismics, Air borne Gravimetry]		
	Target identification	[BD, AA, VR/AR, Visualisation]	[UAVs, AA, 3D Point-Cloud Geo Spatial Technology, AR, VR, BD, Predictive Modelling]	**Monitoring**		
	[Aerial Surveys & Mappin: UAVs]	**Desktop Study and Literature Review**	**Mining Method Confirmation**	[IoT, BD, AA]		
	[Directional Drilling, Airborne Gravimetry, AA]	**Conceptual Study**	[VR, AR, Predictive Modelling AA, BD, Cloud]	**Mapping & Modelling**		
	Target Definition and Discovery	**Pre-Feasibility Study**	**Mine Design**	[UAVs, AA, AR, VR, Predictive Modelling, 3D, point -cloud technology]		
	[Aerial Surveys & Mapping: UAVs]	**Bankable Feasibility Study (& Investment Decisions)**	**Iteration & Optimisation**	**Geotechnical Planning**		
	[Directional Drilling, Airborne Gravimetry, AA]	**Geological Models**	[VR, AR, AA, BD, Cloud]	[UAVs, AA, 3D Point-Cloud Geo-Spatial Technology, AR, VR, BD, Predictive Modelling]		
	Target evaluation	[UAVs, AA, AR, VR, Predictive modelling, 3D Seismics, Air borne Gravimetry, 3D point-cloud technology, AR, VR, BD, Predictive Modelling, Visualisation]	**Implementation**	**Hazard &Risk Management**		
	[Aerial Surveys & Mapping: UAVs]	**Mine Closure Planning**	**Monitoring of Construction & Development**	[BD, AA, IoT, Cloud, UAVs, Automation, AI, 5G]		
	[Directional Drilling, Airborne Gravimetry, AA]	[AR, VR, AA, BD]	[UAVs, AA, AI, AR, VR]	**Hydrology Monitoring & Mapping**		
	Geological model	**Mine planning**	**Mine Closure Preparation**	Aerial Surveys, Mapping & Monitoring: UAVs		
	[UAVs, AA, AR, VR, Predictive Modelling, 3D Seismics Airborne Gravimetry, 3D point-cloud technology, Visualisation]	[AR, VR, AA, BD]	[AA]	[Physical Monitoring: IoT, AA]		
	Hydro Geology	**Resource to Reserve Calculations**	**Operations Plan**	**Operations Plan**		
	[Directional drilling, AA, 3D Point – Cloud Geo Spatial Technology, AR, VR]	[AA]	**Planning & Scheduling**	**Development Planning & Scheduling**		
	Interpretations		[Aerial Surveys, Mapping & Monitoring: UAVs]	[Aerial Surveys, Mapping & Monitoring: UAVs]		
	[AA, Visualizations, Simulation and modelling, AR, VR]		[Physical Monitoring: IoT, AA]	[[Physical Monitoring: IoT, AA, BD, AI, Automation]]		
	Mineral Resource Evaluation		[Data Capture & Processing: IoT, AA, BD, Automation]	**Production Planning & Scheduling**		
	[AA]			[Aerial Surveys, Mapping & Monitoring: UAVs]		
				[Physical Monitoring: IoT, AA]		
				[Data capture & processing: IoT, AA, AI, BD, Automation, 5G]		

	Exploration and target generation phase	**Mine project evaluation/ planning phase**	**Mine design and construction phase**	**Operation phase (mine to mill)**	**Mine decommissioning and closure phase**	**Post closure**
Production	**Drilling Work & Blasting**	**Drilling Work & Blasting**	**Construction**	**Development**	**Closure of mine workings and associated Infrastructure**	**In-Situ Reserves: Renewed Production**
	[Directional Drilling, AR, 3D Seismics, UAV, Airborne gravimetry]	[Directional Drilling, AR, 3D Seismics, UAV, Airborne gravimetry]	[Green Cement]	[TBM, Automation, Remote Tech, IROC]	[Robotics, Automation, AA, UAVs]	[Mechanised Tech, Remote, Advanced Materials, Robotics, Hard-Rock, Mech Tech, Genomics]
	Site Establishment	**Mining Method Selection**	**Infrastructure & Physical Assets**	**Mineral/Ore and Waste extraction**	**Ramp-down Management**	
	Surveying & Sampling Efficiency	[BD, AA, AI, VR, AR, Simulation and Modelling]	**-Haul Roads & Mine Access**	**-Drill & Blast**	[BD, IoT, AA, VR/AR, Automation]	
	[AA, Genomics]	**Support method Selection**	**-Dumps, Stockpile, Dams**	***Blast design & Drill pattern**	**Rehabilitation Management**	
		[BD, AA, AI, VR, AR, Simulation and modelling]	**-Surface preparation or Shaft sinking**	[AR, UAVs]	[BD, IoT, AA, VR/AR, Automation, Genomics, Robotics]	
			Development: Opening up Reserves	***Drilling Work & Blasting**		
			[TBM, Automation, Remote tech, IROC]	[Advanced Materials, Non-Explosives, EDS, AR, IoT, AA, Directional Drilling, Precision Drilling, Automation]		
			Drill & Blast	***Pre- ^ Post – blast data**		
			-Blast design & Drill pattern	[AR, UAVs, BD, IoT, AA]		
			[AR, UAVs]	***Identification of misfires & wall damage**		
			-Drilling work & Blasting	[AI, AA, UAVs]		
			[Advancing Materials, Non-Explosives, EDS, AR, IoT, AA, Directional Drilling, Precision, Automation]	***Fragmentation**		
			-Pre & Post-blast data	***Management**		
			[AR, UAVs, BD, IoT, AA]	[AR, IoT, AA, BD, MI, 5G]		
			-Identification of Misfires & wall damage	**-Mechanised, Autonomous Mining**		
			[AI, AA, UAVs]	[Mechanised Tech, BD, AA, ML, AI, IoT, IoE, AR, MI, EAM, IROC, Tracking Tech, Robotics, Automation]		
			-Fragmentation	***Hard-Rock Narrow Reef Mining**		
			-Management	[Hard-Rock Mech Tech, Advanced materials, Nanomaterials, Robotics, Automation]		
			[AR, IoT, AA, BD, MI]	**Infrastructure**		
			Mechanised, Autonomous Mining	[Green Cement, Robotics, Automation, IROC]		
			[Mechanised Tech, BD, AA, ML, IoT, AR, MI, EAM, IROC, Tracking Tech, Automation, Robotics]	**Hazard & Risk Management**		
			-Hard-Rock Narrow Reef Mining	[BD, AA, IoT, Cloud, UAVs, Automation, AI]		
			[Hard – Rock Mech tech, Advanced materials, Nanomaterials, Robotics, Automation]	**Hydrology Management**		
			Hazard & Risk Management	[IoT, AA, BD, UAVs]		
			[BD, AA, IoT, Cloud, UAVs, Automation, AI]	**Reservoirs/Dams/Infrastructure**		
			Hydrology Management	**Dewatering**		
			[IoT, AA, BD, UAVs]	[Directional Drilling]		
			Reservoir/Dams/Infrastructure	**Labour**		
			Dewatering	**Communication, and collaboration**		
			[Directional Drilling]	[Wearables, AR, VR, MI and Smart Devices, IoT, Social Tech, AA, UAVs, Automation (of knowledge work), Robotics]		
			Labour	**Management & Leadership**		
			Communication and Collaboration	[BD, IoT, AA, Language Tech, Social tech, MI, AR, VR, AI]		
			[Wearables, AR, VR, MI and Smart Devices, IoT, Social Tech, AA, UAVs, Automation (of knowledge work) Robotics]	**Logistics**		
			Management & Leadership	**Mineral/Ore Transport**		
			[BD, IoT, AA, Language Tech, Social tech, MI, AR, VR, AI]	[Automation, Autonomous Eq & Tech, ML, AI, Conveyor Systems, AA, IoT, Tracking Tech]		
			Logistics	**Waste Transport**		
			Mineral/Ore Transport	[Automation, Autonomous Eq & Tech, ML, AI, Conveyor Systems, AA, IoT, Tracking Tech]		
			[Automation, Autonomous Eq & Tech, ML, AI, Conveyor Systems, AA, IoT, Tracking Tech]	**-Load & Haul / Tram / Hoist**		
			Waste Transport	[Automation, Autonomous Eq & Tech, ML, AI, AR, C-T-C Coms, Remote Tech, IoT, Tracking Tech, EAM]		
			[Automation, Autonomous Eq & Tech ML, AI, Conveyor Systems, AA, IoT, Tracking Tech]	**Operations Plan**		
			-Load & Haul / Tram / Hoist	[BD, AA, IoT, Cloud Computation, AR, VR, EAM, Visualisation]		
			[Automation, Autonomous Eq & Tech, ML, AI, AR, C-T-C Coms, Remote Tech, IoT, Tracking Tech, EAM]	**Plant Management**		
			Operations Plan	[IoT, BD, AA, Automation, Robotics, Flexible Closed-belt conveyor]		
			[BD, AA, IoT, Cloud Computation, AR, VR, EAM, Visualisation]	**Processing & Refining**		
			Plant Design & Construction	**Communication**		
			[VR, AR, AA, BD, Cloud]	[High Pressure Grinding Rolls, Transmission sorting or ore through X – Ray, DensityAssessment, 5G]		
			Production Management	**Mineral Extraction & Recovery**		
			Communication and Collaboration	[Genomic Applications, BD, AA, High Pressure leaching, Real-time, Accelerated rock sorting Technologies, Transmission sorting of ore through X – Ray, DensityAssessment]		
			[Wearables, AR, VR, MI and Smart Devices, IoT, Social tech, AA, UAVs, Automation (of knowledge work), Cloud, Robotics]	**Production Management**		
			Production rate calculation for LoM	**Communication and collaboration**		
			[AA, BD, Cloud]	[Wearables, AR, VR, MI and Smart Devices, IoT, Social tech, AA, UAVs, Automation (of knowledge work), Cloud, Robotics, 5G]		
			Tailing/Slime Dams/Waste Dumps: Plan vs. Construct	**Rehabilitation**		
			[Aerial Surveys, Mapping & Monitoring: UAVs]	[Automation]		
			[Physical Monitoring: IoT, AA]	**Stockpile management**		
				[Aerial Surveys, Mapping & Monitoring: UAVs]		
				[Physical Management and Monitoring: IoT, AA]		
				Tailing/Slime Dams, Waste Dumps: Management		
				[Aerial surveys, Mapping & monitoring: UAVs, Mapping & Monitoring: IoT, AA]		

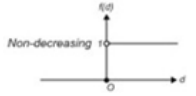
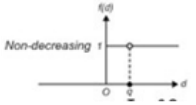
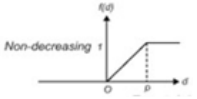
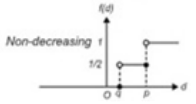
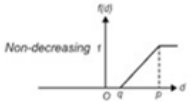
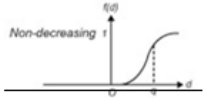
	Exploration and target generation phase	Mine project evaluation/ planning phase	Mine design and construction phase	Operation phase (mine to mill)	Mine decommissioning and closure phase	Post closure
Productivity & Asset Efficiency	**Drilling Equipment**	**Drilling Efficiency & Accuracy**	**Asset Management**	**Asset Management**	**Asset & Equipment Management**	
	[AR, EAM, EDS, Automation]	[Directional Drilling, AR, 5G]	**Communication and collaboration**	**Communication and collaboration**	[Tracking Tech, EAM, IoT, BD, AA, Automation, 5G]	
			[Tracking Tech, IoT, Automation, BD, AA, EAM, AI, MI, 5G]	[Tracking Tech, IoT, Automation, BD, AA, EAM, AI, MI, 5G]		
	Drilling Efficiency & Accuracy	**Equipment Selection**	**Asset connectedness**	**Asset connectedness**	**Human Resources**	
	[Directional Drilling, AR, 5G]	[AR/VR, BD, AA, Simulation and modelling]	[IoT, Tracking Tech, AI, ML, MI, wearables, AA, 5G]	[IoT, Tracking Tech, AI, ML, MI, Wearables, AA, MI, 5G]	**Communication and Collaboration**	
	Human Resources	**Human Resources**	**Cyber Risks**	**Cyber Risks**	[Wearables, AR, VR, MI, Cloud, IoT, Social Tech, Voice Interfaces, Language Translation Tech, 5G]	
	[Amplified Intelligence, AI, AR, VR, MI, BD, AA, Cloud, Automation, Automation of Knowledge work, IoT, Robotics]	**Communication and Collaboration**	[Cyber security, Blockchain, 5G]	[Cyber security, Blockchain]	**Difficult, repetitive and/or dangerous human tasks**	
	Metallurgical Processing	[Wearables, AR, VR, MI, Cloud, IoT, Social Tech, Voice Interfaces, Language Translation Tech, 5G]	**Data Capture, Processing, Analysis & Output**	**Data Capture, Processing, Analysis & Output**	[Robotics, Exoskeletons, AI, ML, MI, Automation, MI, IoT, AA, BD, Anthropomorphic Robots, Automation of Knowledge work, Nano – Technology, UAVs]	
	[AA, Genomics, 5G]	**Efficiency**	[EAM, IoT, IoE, AA, BD, Automation, Cloud, Ai, Super Calculators & Computers, 5G]	[EAM, IoT, IoE, AA, BD, Automation, Cloud, Ai, Super Calculators & Computers, 5G]	**Efficiency**	
		[Amplified Intelligence, AI, AR, VR, MI, BD, AA, Cloud, Automation, Automation of Knowledge work, IoT, Robotics]	**Communication and Collaboration**	**Availability**	[Amplified Intelligence, AI, AR, VR, MI, BD, AA, Cloud, Automation, Automation of Knowledge work, IoT, Robotics]	
		Human – Asset/Human-Machine interaction	[Wearables, AR, VR, MI, and Smart Devices, IoT, Robotics Social Tech, AA, UAVs, Automation (of Knowledge work), 5G]	[IoT, AA, AR, Automation]	**Human – Asset/Human-Machine interaction**	
		[AR, AI, ML, IoT, Brain-Machine Interfaces, Ambient User Experience, Visualization & Visual Technologies, 5G]	**Equipment Selection**	**Contractor Management**	[AR, AI, ML, IoT, Brain-Machine Interfaces, Ambient User Experience, Visualization & Visual Technologies, 5G]	
		Metallurgical Processing	[AA, BD, AI, Cloud, VR, AR, Predictive Modelling]	**Communication and collaboration**		
		[Genomics, AA, BD]	**Hazard & Risk management**	[Wearables, AR, VR, MI, and Smart Devices, IoT, Robotics Social Tech, AA, UAVs, Automation (of Knowledge work), 5G]		
			[BD, AA, IoT, Cloud, UAVs, Automation, AI]	**Equipment improvement/Upgrades**		
			Human Resources	**Acquisition of new assets**		
			Sourcing	**Upgrading existing equipment.**		
			[BD, AA, AI, Cloud]	**Hazard & Risk Management**		
			Communication & Collaboration	[BD, AA, IoT, Cloud, UAVs, Automation, AI]		
			[Wearables, AR, VR, MI, Cloud, IoT, Social Tech, Voice Interfaces, Language Translation Tech, 5G]	**Human Resources**		
			Difficult, repetitive and/or dangerous human tasks	**Sourcing**		
			[Robotics, Exoskeletons, AI, ML, MI, Automation, MI, IoT, AA, BD, Anthropomorphic Robots, Automation of Knowledge work, Nano – Technology, UAVs]	[BD, AA, AI, Cloud]		
			Efficiency	**Communication and Collaboration**		
			[Amplified Intelligence, AI, AR, VR, MI, BD, AA, Cloud, Automation, Automation of Knowledge work, IoT, Robotics]	[Wearables, AR, VR, MI, Cloud, IoT, Social Tech, Voice Interfaces, Language Translation Tech,]		
			Human – Asset/Human-Machine interaction	**Difficult, repetitive and/or dangerous human tasks**		
			[AR, AI, ML, IoT, Brain-Machine Interfaces, Ambient User Experience, Visualization & Visual Technologies, 5G]	[Robotics, Exoskeletons, AI, ML, MI, Automation, MI, IoT, AA, BD, Anthropomorphic Robots, Automation of Knowledge work, Nano – Technology, UAVs]		
			Training & Inductions	**Efficiency**		
			[Social Tech, VR, AR, Language Tech, 5G]	[Amplified Intelligence, AI, AR, VR, MI, BD, AA, Cloud, Automation, Automation of Knowledge work, IoT, Robotics]		
			Rock Breaking Efficiency	**Human – Asset/Human-Machine interaction**		
			Mechanical Breaking	[AR, AI, ML, IoT, Brain-Machine Interfaces, Ambient User Experience, Visualization & Visual Technologies, 5G]		
			-Efficiency & Fragmentation	**Training & Inductions**		
			[Advanced Materials, nanomaterials, Mechanised Tech, Rock Breaking Tech]	[Social Tech, VR, AR, Language Tech, 5G]		
			Drill & Blast	**Maintenance, Repair & Inspection**		
			-Rock Abrasiveness & Drilling Efficiency and accuracy	[IoT, BD, AA, AR, 3D & 4D Printing, ML, AI, MI, EAM, Advanced Materials, Nano Materials]		
			[Advanced materials, Non-Explosives, EDS, AR, IoT, AA, Directional Drilling, Precision Drilling, Automation]	**Equipment**		
				Machinery		
				Infrastructure		
				Other Assets		
				Operation/Usage of Equipment & other Assets		
				Efficient Operation		
				[AR, MI, IoT, AI, BD, AA, Automation, Autonomous Eq & Tech, Brain – Machine Interfaces, Ambient User Experience, Visualization & Visual Technologies, 5G]		
				Fleet Management		
				[AR, MI, IoT, AI, BD, AA, cloud, Automation, Tracking Tech, C-T-C Coms, EAM, ML, 5G]		
				Road Breaking Efficiency		
				Mechanical Breaking		
				-Efficiency & Fragmentation		
				[Advanced Materials, Nanomaterials, Mechanised Tech, Rock Breaking Tech]		
				Drill & Blast		
				-Rock Abrasiveness & Drilling Efficiency and Accuracy		
				[Advanced materials, Non-Explosives, EDS, AR, IoT, AA, Directional Drilling, Precision, Automation, 5G]		
				Utilisation		
				[Automation, EAM, AA, AI, IoT, BD]		

	Exploration and target generation phase	Mine project evaluation/ planning phase	Mine design and construction phase	Operation phase (mine to mill)	Mine decommissioning and closure phase	Post closure
Profitability & Cost Control	**CAPEX**	**CAPEX**	**Capex Planning**	**Capex Management**	**CAPEX Management**	
	Investment Strategy	**Investment Strategy**	[BD, AA, AI, Cloud, VR/AR, Predictive Modelling]	[BD, AA, AI, Cloud, VR/AR, Predictive Modelling, EAM]	[BD, AA, Cloud, AI, Blockchain]	
	[AA, BD]	[BD, AA]	**OPEX Planning**	**Hazard & Risk Management**	**OPEX Management**	
	OPEX	**Extraction Ratio**	[BD, AA, AI, Cloud, VR/AR, Predictive Modelling]	[BD, AA, IoT, Cloud, AI]	[BD, AA, Cloud, AI, Blockchain]	
	Drilling Work	[AA, Automation]	**Pricing Forecasts**	**Market Analysis**		
	[Directional Drilling, AR]	**Mining Method, Selection**	[BD, AA, AI, Cloud]	[BD, AA, AI]		
	Sampling/Coring	[BD, AA]	**Unit operating Cost**	**Commodity Price**		
	[AA, Genomics]	**OPEX**	[BD, AA, AI, Cloud, VR/AR, Predictive Modelling]	**Operations Plan**		
		[BD, AA]		**Marketing Plan**		
		Pricing Forecasts		**Financial Plan**		
		[BD, AA]		**Administration Plan**		
				OPEX Management		
				[BD, AA, AI, Cloud, VR/AR, Predictive Modelling, EAM]		
				Consumable Resources		
				-Energy		
				***Costs**		
				[Renewables, Energy-Management Systems, AA, Smart Grids, MTRECs, LNG alternatives]		
				***Efficiency**		
				[Energy Tech & Equipment, EST, AA, BD, IoT, MTRECs]		
				-Water		
				[IoT, AA]		
				-Compressed Air		
				-Diesel/Fuel		
				[LNG Engine Technologies, Energy Tech & Equipment, EST]		
				Remuneration		
				[Automation]		

	Exploration and target generation phase	Mine project evaluation/ planning phase	Mine design and construction phase	Operation phase (mine to mill)	Mine decommissioning and closure phase	Post closure
Supply chain	**Access to site**	**Assets Acquisition Strategy**	**Acquisition of Assets**	**-Electricity & Energy**	**Infrastructure Demolishing**	
	[UAVS, Hybrid Airships]	[AA, BD, VR/AR, Visualisation]	[Hybrid Airships, Modularisation, UAVs]	***Supply**	[Robotics, Automation]	
	Logistical Planning	**Infrastructural Planning**	**Equipment**	[EST, Renewables, Fusion, Hybrid Systems]		
	[AA, Visualisation, AR/VR, UAVs]	**Logistical Planning**	**Machinery**	**Generation**		
	Consumables	**Supplier Establishment**	**Other Assets**	[EST, Renewables, Hybrid Systems]		
	Assets	**HR Sourcing**	**Materials**	**Storage**		
	Human Resources	**Electricity Supply & generation**	**Human Resources**	[EST]		
		[EST, Renewables, Fusion, Hybrid Systems]	**Electricity Supply & Generation**	**Finance/Procurement/Transactions**		
			[EST, Renewables, Fusion, Hybrid Systems]	[Blockchain, Cyber Security, AR, VR, AA]		
			Infrastructure Design	**Hazard & Risk Management**		
			[AA, AR, VR, Visualisation]	[BD, AA, IoT, Cloud, UAVs, AI, EAM]		
			Infrastructure Development	**Infrastructure Maintenance**		
			[Green Cement UAVs, AA, AR]	[UAVs, AA, Automation]		
				Primary Access/Ore Transport Route		
				-Haul Roads		
				-Conveyor System		
				Secondary Access/Delivery of Consumables		
				Ore & Waste Transportation		
				[Hybrid Airships, EAM, (Semi) Autonomous Equipment, Electric/Hybrid/Hydrogen Engines, Synthetic Biology Technologies, AA, IoT]		
				Procurement of Consumables, Parts & Assets		
				[UAVs, Hybrid Airships, AA, 3D & 4D Printing, Modularisation, AI]		
				Product/Market Delivery		
				[Hybrid Airships, EAM, AA, AI]		
				Waste Transportation		
				[Hybrid Airships, EAM, (Semi) Autonomous Equipment, Electric/Hybrid/Hydrogen Engines, Synthetic Biology Technologies, AA, IoT]		
	Exploration and target generation phase	**Mine project evaluation/ planning phase**	**Mine design and construction phase**	**Operation phase (mine to mill)**	**Mine decommissioning and closure phase**	**Post closure**
Socio-Economic Factors	**Corporate Governance**	**Corporate Governance**	**Communities**	**Communities**	**Communities**	**Communities**
	[Blockchain, Social media/technologies, AA]	[Blockchain, Social media/technologies, AA]	**Corporate Social Responsibility**	**Corporate Social Responsibility**	**Corporate Social Responsibility**	**Corporate Social Responsibility**
	Labour and Communities	**Labour and Communities**	[Green Cement, Precision Agriculture, Genomics]	[Green Cement, Precision Agriculture, Genomics]	[Green Cement, Precision Agriculture, Genomics]	[Green Cement, Precision Agriculture, Genomics]
	Corporate social responsibility	**Corporate social responsibility**	**Engagement & Communication**	**Engagement & Communication**	**Engagement & Communication**	**Engagement & Communication**
	[Visualisation and simulation technologies, AR, VR, Precision Agriculture, Blockchain, Genomics, AA, Social media technologies]	[Visualisation and simulation technologies, AR, VR, Precision Agriculture, Blockchain, Genomics, AA, Social media technologies]	[Social Tech, UAVs, VR, AR, Language Tech]	[Social Tech, UAVs, VR, AR, Language Tech, Secure Messaging]	[Social Tech, UAVs, VR, AR, Language Tech]	[Social Tech, UAVs, VR, AR, Language Tech]
	Shareholders and other stakeholders	**Shareholders and other stakeholders**	**Corporate Governance**	**Corporate Governance**	**Corporate Governance**	**Corporate Governance**
	[Visualisation and simulation technologies, AR VR, Blockchain, Social Media/technologies, AA]	[Visualisation and simulation technologies, AR VR, Blockchain, Social Media/technologies, AA]	[Blockchain, Social Tech, UAVs]	[Blockchain, Social Tech, UAVs]	[Blockchain, Social Tech, UAVs]	[Blockchain, Social Tech, UAVs]
			Hazard & Risk Management	**Hazard & Risk Management**	**Hazard & Risk Management**	**Hazard & Risk Management**
			[Social Tech, UAVs, VR, AR, Language Tech, BD, AA, IoT, Cloud, AI]	[Social Tech, UAVs, VR, AR, Language Tech, BD, AA, IoT, Cloud, AI]	[Social Tech, UAVs, VR, AR, Language Tech]	[Social Tech, UAVs, VR, AR, Language Tech]
			Labour	**Labour**	**Labour**	**Labour**
			Engagement & Communication	**Engagement & Communication**	**Engagement & Communication**	**Engagement & Communication**
			[Social Tech, UAVs, VR, AR, Language Tech]	[Social Tech, UAVs, VR, AR, Language Tech, Secure Messaging]	[Social Tech, UAVs, VR, AR, Language Tech]	[Social Tech, UAVs, VR, AR, Language Tech]
			Other Stakeholders	**Other Stakeholders**	**Other Stakeholders**	**Other Stakeholders**
			Engagement & Communication	**Engagement & Communication**	**Engagement & Communication**	**Engagement & Communication**
			[Social Tech, UAVs, VR, AR, Language Tech]	[Social Tech, UAVs, VR, AR, Language Tech, Secure Messaging]	[Social Tech, UAVs, VR, AR, Language Tech]	[Social Tech, UAVs, VR, AR, Language Tech]
			Shareholders	**Shareholders**	**Shareholders**	**Shareholders**
			Engagement & Communication	**Engagement & Communication**	**Engagement & Communication**	**Engagement & Communication**
			[Social Tech, UAVs, VR, AR, Language Tech]	[Social Tech, UAVs, VR, AR, Language Tech, Secure Messaging]	[Social Tech, UAVs, VR, AR, Language Tech]	[Social Tech, UAVs, VR, AR, Language Tech]
	Exploration and target generation phase	**Mine project evaluation/ planning phase**	**Mine design and construction phase**	**Operation phase (mine to mill)**	**Mine decommissioning and closure phase**	**Post closure**
Health, Environmental Safety & Legal	**Environmental Impact Assessment**	**Environmental Impact Assessment**	**Civil Geotechnical Work on Foundations & Roads**	**Environmental Engineering**	**Emergency Management**	**Emerging HES Issues**
	[IoT, IoE, BD, AA, UAVs]	[IoT, IoE, BD, AA, UAVs]	**Environmental Engineering**	**Ventilation Engineering**	[Tracking Tech, IoT, AA, AR, VR, Cloud, UAVs, Robotics]	[3D, Printing, Social Tech, Genomics: bio-remediation, AMD & containment treatment, enhanced agriculture applications, medical applications for monitoring diagnostics and treatment]
	Mineral Rights	**Water**	**Ventilation Engineering**	[Automation, Energy Tech, IoT, BD, AA]	**EMP Compliance**	**EMP Non – Compliance**
	[Genomics, Precision Agriculture, Social Media and Social Technologies, Genomics, Blockchain]	**Energy**	**Cooling**	**Cooling**	[VR or AR comparisons to original agreement]	[VR or AR comparisons]
	Prospecting Rights	**Fauna & Flora**	[Clean air environments: Immersion-cooling technology, Liquid-desiccant systems, Pressurized-Plenum-recirculation-air system]	[Clean air environments: Immersion-cooling technology, Liquid-desiccant systems, Pressurized-Plenum-recirculation-air system]	**HES monitoring**	**HES monitoring**
	Exploration rights	**Carbon Emission Management**	**Environmental Management Program**	**Environmental Management Program**	**Hazards & Risk management**	**Malpractice**
	Mining Rights	**Environmental Management plan**	**-Carbon Emission Management**	[AA, IoT, UAVs, BD, AI, Cloud, IoE, Automation]	**Long term Stability of workings**	**Mineral Rights**
		[BD, IoT, AA, VR/AR, Simulation and modelling]	[Electrical Technologies and Equipment, IoT, AA, Renewables]	**-Carbon Emission Management**	**Malpractice**	[Blockchain, Cyber security]
		Operational EMP	**-Water**	[Electrical Technologies and Equipment, IoT, AA, Renewables, Energy Tech, MTRECs]	**Rehabilitation & Remediation**	**Surface stability / Infrastructure stability**
		Post – Closure & rehab plan	[Desalination plant technology, Graphene biofilter purification]	**-Water**	[Genomics: bio-remediation, AMD & containment Treatment, enhanced agriculture applications]	
		Mine Workings Layout	**-Energy**	[Desalination plant technology, Graphene Biofilter purification, IoT, BD, AA, Genomics]	**Surface Stability / Infrastructure Stability**	
		[BD, AA, VR/AR, Simulation and Modelling]	[Automation, Energy Tech]	**-Energy**		
			-Fauna & Flora	[Automation, Energy Tech, MTRECs]		
			[Genomics, Precision Agriculture]	**-Fauna & Flora**		
			-Recycling	[Genomics, Precision Agriculture]		
			[Genomics]	**-Recycling**		
			Geotechnical Engineering	[Genomics]		
			-Implementation and Design (Planning CoPs)	**Geotechnical Engineering**		
			[BD, AA, IoT, Predictive Modelling]	**-Implementation and Design (Planning CoPs)**		
			-Monitoring (Seismic/Non-Seismic)	[BD, AA, IoT, Predictive Modelling]		
			[UAVs, IoT, AA]	**-Monitoring (Seismic/Non-Seismic)**		
			Emergency management	[UAVs, IoT, AA]		
			[Tracking Tech, IoT, AA, AR, VR, Cloud, UAVs, Robotics, Automation, Exoskeletons, UAVs, IoT, Wearables, ICTs, nano-Technology, nano-particles, biotechnology, AR, VR]	**Emergency management**		
			Hazard Identification	[Tracking Tech, IoT, AA, AR, VR, Cloud, UAVs, Robotics, Automation, Exoskeletons, UAVs, IoT, Wearables, ICTs, nano-Technology, nano-particles, biotechnology, AR, VR]		
			[AR, AA, AI, UAVs, IoT, IoE]	**Hazard Identification**		
			Hazard & Risk Management	[AR, AA, AI, UAVs, IoT, IoE]		
			Difficult and/or dangerous human tasks	**Hazard & Risk Management**		
			[Automation, Robotics, Exoskeletons, AA]	**Difficult and/or dangerous human tasks**		
			Monitoring	[Automation, Robotics, Exoskeletons, AA]		
			[IoT, BD, AA. Tracking Tech]	**Monitoring**		
			Legislation	[IoT, BD, AA. Tracking Tech]		
			Safety	**Legislation**		
			Surveillance and monitoring	**Safety**		
			[Tracking Tech, IoT, AA, AR, VR, Cloud, UAVs, Robotics, Wearables]	**Surveillance and monitoring**		
			Tracking of people and assets	[Tracking Tech, IoT, AA, AR, VR, Cloud, UAVs, Robotics, Wearables]		
			[Tracking Tech, AR, VR, IoT, AA, BD, Wearables]	**Tracking of people and assets**		
			Continuous Improvement	[Tracking Tech, AR, VR, IoT, AA, BD, Wearables]		
			[AA, BD, IoT, AI, ML]	**Continuous Improvement**		
				[AA, BD, IoT, AI, ML]		

APPENDIX B

Table B1: The Preference Functions in PROMETHEE

Type of Preference	Description of the Preference	Graphical Presentation	Analytical Definition
I: True/Usual criterion	When the value of the criteria of alternative a exceeds alternative b, then there is a strict preference and the preference value is 1. In case of equal value of the criteria, there is no preference and the preference value is 0.		$f(d) = \begin{cases} 1 & \text{if } 0 < d \\ 0 & \text{if } d \leq 0 \end{cases}$
II: Threshold criterion	The decision maker defines the indifference threshold value of the criteria. If the value of the criteria of alternative a exceeds that of alternative b by an amount q, greater than or equal to the indifference value (q), then a is preferred over b.		$f(d) = \begin{cases} 1 & \text{if } q < d \\ 0 & \text{if } d \leq q \end{cases}$
III: Linear with threshold criterion	If the criteria value of alternative a is closer to the absolute preference than alternative b, then alternative a is better than alternative b. If the difference of the criteria of alternative a reaches the absolute preference, then alternative a is absolutely better than alternative b.		$f(d) = \begin{cases} 1 & \text{if } p < d \\ \frac{d}{p} & \text{if } 0 < d \leq p \\ 0 & \text{if } d \leq 0 \end{cases}$
IV: Linear over range criterion	First, an indifference value of the criteria is determined. When the difference of the criteria values of alternatives a and b moves from a value 0 to a value p, the preference function increases linearly from 0 to 1 over that range of differences. If the criteria value of alternative a passes the difference of the threshold value of 0, then a is preferred to b.		$f(d) = \begin{cases} 1 & \text{if } p < d \\ \frac{d-q}{p-q} & \text{if } q < d \leq p \\ 0 & \text{if } d \leq q \end{cases}$
V: Stair step/Level criterion	For this method, an absolute preference value and an indifference value are determined. If the criteria value of alternative a is less than the absolute preference value that gives a preference of 0, the difference between the absolute preference value and indifference value gives a preference of 1/2, and a difference greater than the absolute preference value gives a preference of 1.		$f(d) = \begin{cases} 1 & \text{if } d > p \\ \frac{1}{2} & \text{if } q < d \leq p \\ 0 & \text{if } d \leq q \end{cases}$
VI: Gaussian criterion	The s threshold value is somewhere between the q_j indifference threshold and the q_j preference threshold and it follows a normal distribution. This preference function is less often used due to the difficulty in the parameters.		$f(d) = \begin{cases} 1 - \exp\left(\frac{-d^2}{2\sigma^2}\right) & \text{if } 0 < d \\ 0 & \text{if } d \leq 0 \end{cases}$

Legend: d = the difference between two criteria a and b, p = the strict preference threshold, q = the indifference threshold, s = the standard deviation in Gaussian distribution. Source: (Talukder & Hipel, 2018).

APPENDIX C

Fuzzy Data Calculation

For technology A_1, at the end of year 0

$G_{10} = (0,0,0)$, $(1 - T_1)G_{10} = (0,0,0)$

$C_{10} = (0,0,0)$, $(1 - T_1)C_{10} = (0,0,0)$

$D_{10} = (0,0,0)$, $D_{10}T_1 = (0,0,0)$

$K_{10} = (9\ 300.0, 10\ 000.0, 10\ 700.0)$

By Equation (Eq.) 4.9

$X_{10} = (-10\ 700.0, -10\ 000.0, -9\ 300.0)$

For technology A_1, at the end of year 1

$G_{11} = (7905.0, 8500.0, 9095.0)$, $(1 - T_1)G_{11} = (4743.0, 5100.0, 5457.0)$

$C_{11} = (860.0, 2000.0, 2140.0)$, $(1 - T_1)C_{11} = (1116.0, 1200.0, 1284.0)$

$D_{11} = (3100.0, 3333.3, 3566.7)$, $D_{11}T_1 = (1240.0, 1333.3, 1426.7)$

$K_{11} = (0, 0, 0)$

By Equation (Eq.) 4.9

$$X_{11} = (7905.0, 8500.0, 9095.0)(1 - 0.4) - (1860.0, 2000.0, 2140.0)(1 - 0.4) + (3100.0, 3333.3, 3566.7)(0.4)$$

$$X_{11} = (4699.0, 5233.3, 5767.7)$$

The cash flow for the two subsequent years – Year 2 and Year 3 – will have the same values as Year 1

Using Eq. 4.10

$$NPV_1 = (-10\ 700.0, -10\ 000.0, -9\ 300.0) + \frac{(4699.0, 5233.3, 5767.7)}{(1.12,1.12,1.12)^1} + \frac{(4699.0, 5233.3, 5767.7)}{(1.12,1.12,1.12)^2} + \frac{(4699.0, 5233.3, 5767.7)}{(1.12,1.12,1.12)^3}$$

$$NPV_1 = (586.21, 2569.58, 4552.96)$$

For technology A_2, at the end of year 0

$G_{20} = (0,0,0)$, $(1 - T_2)G_{20} = (0,0,0)$

$C_{20} = (0,0,0)$, $(1 - T_2)C_{20} = (0,0,0)$

$D_{20} = (0,0,0)$, $D_{20}T_2 = (0,0,0)$

$K_{20} = (12090.0, 13000.0, 13910.0)$

By Equation (Eq.) 4.9

$X_{20} = (-12090.0, -13000.0, -13910.0)$

For technology A_2, at the end of year 1

$G_{21} = (10276.5, 11050.0, 11823.5)$, $(1 - T_2)G_{21} = (6165.9, 6630.0, 7094.1)$

$C_{21} = (2418.0, 2600.0, 2782.0)$, $(1 - T_2)C_{21} = (1450.8, 1560.0, 1669.2)$

$D_{21} = (4030.0, 4333.3, 4636.7)$, $D_{21}T_2 = (1612.0, 1733.3, 1854.7)$

$K_{21} = (0, 0, 0)$

By Equation (Eq.) 4.9

$X_{21} = (6108.7, 6803.3, 7498.0)$

The cash flow for the two subsequent years – Year 2 and Year 3 – will have the same values as Year 1

Using Eq. 4.10

$$NPV_2 = (-12090.0, -13000.0, -13910.0) + \frac{(6108.7, 6803.3, 7498.0)}{(1.115, 1.115, 1.115)^1} + \frac{(6108.7, 6803.3, 7498.0)}{(1.115, 1.115, 1.115)^2} + \frac{(6108.7, 6803.3, 7498.0)}{(1.115, 1.115, 1.115)^3}$$

$NPV_2 = (889.06, 3481.89, 6074.72)$

For technology A_3, at the end of year 0

$G_{30} = (0,0,0)$, $(1 - T_3)G_{30} = (0,0,0)$

$C_{30} = (0,0,0)$, $(1 - T_3)C_{30} = (0,0,0)$

$D_{30} = (0,0,0)$, $D_{30}T_3 = (0,0,0)$

$K_{30} = (19530.0, 21000.0, 22470.0)$

By Equation (Eq.) 4.9

$X_{30} = (-25680.0, -24000.0, -22320.0)$

For technology A_2, at the end of year 1

$G_{31} = (16600.5, 17850.0, 19099.5)$, $(1 - T_3)G_{31} = (9960.3, 10710.0, 11459.7)$

$C_{31} = (3906.0, 4200.0, 4494.0)$, $(1 - T_3)C_{31} = (2343.6, 2520.0, 2696.4)$

$D_{31} = (6510.0, 7000.0, 7490.0)$, $D_{31}T_3 = (2604.0, 2800.0, 2996.0)$

$K_{31} = (0, 0, 0)$

By Equation (Eq.) 4.9

$X_{31} = (9867.9, 10990.0, 12112.1)$

The cash flow for the two subsequent years – Year 2 and Year 3 – will have the same values as Year 1

Using Eq. 4.10

$$NPV_3 = (-25680.0, -24000.0, -22320.0) + \frac{(9867.9, 10990.0, 12112.1)}{(1.08, 1.1, 1.12)^1} + \frac{(69867.9, 10990.0, 12112.1)}{(1.08, 1.1, 1.12)^2} + \frac{(9867.9, 10990.0, 12112.1)}{(1.08, 1.1, 1.12)^3}$$

$NPV_3 = (1231.03, 6330.50, 11684.06)$

For technology A_4, at the end of year 0

$G_{40} = (0,0,0)$, $(1 - T_4)G_{40} = (0,0,0)$

$C_{40} = (0,0,0)$, $(1 - T_4)C_{40} = (0,0,0)$

$D_{40} = (0,0,0)$, $D_{40}T_4 = (0,0,0)$

$K_{40} = (22320.0, 24000.0, 25680.0)$

By Equation (Eq.) 4.9

$X_{40} = (-25680.0, -24000.0, -22320.0)$

For technology A_4, at the end of year 1

$G_{41} = (18972.0, 20400.0, 21828.0)$, $(1 - T_4)G_{41} = (11383.2, 12240.0, 13096.8)$

$C_{41} = (4464.0, 4800.0, 5136.0)$, $(1 - T_4)C_{41} = (2678.4, 2880.0, 3081.6)$

$D_{41} = (7440.0, 8000.0, 8560.0)$, $D_{41}T_4 = (2976.0, 3200.0, 3424.0)$

$K_{41} = (0, 0, 0)$

By Equation (Eq.) 4.9

$X_{41} = (11277.6, 12560.0, 13842.4)$

The cash flow for the two subsequent years – Year 2 and Year 3 – will have the same values as Year 1

Using Eq 4.10

$$NPV_4 = (-25680.0, -24000.0, -22320.0) + \frac{(11277.6, 12560.0, 13842.4)}{(1.06, 1.085, 1.11)^1} + \frac{(11277.6, 12560.0, 13842.4)}{(1.06, 1.085, 1.11)^2} + \frac{(11277.6, 12560.0, 13842.4)}{(1.06, 1.085, 1.11)^3}$$

$NPV_4 = (1879.24, 8078.52, 14680.90)$

For technology A_5, at the end of year 0

$G_{50} = (0,0,0)$, $(1 - T_5)G_{50} = (0,0,0)$

$C_{50} = (0,0,0)$, $(1 - T_5)C_{50} = (0,0,0)$

$D_{50} = (0,0,0)$, $D_{50}T_5 = (0,0,0)$

$K_{50} = (14880.0, 16000.0, 17120.0)$

By Equation (Eq.) 4.9

$X_{50} = (-17120.0, -16000.0, -14880.0)$

For technology A_5, at the end of year 1

$G_{51} = (12648.0, 13600.0, 14552.0)$, $(1 - T_5)G_{51} = (7588.8, 8160.0, 8731.2)$

$C_{51} = (2976.0, 3200.0, 3424.0)$, $(1 - T_5)C_{51} = (1785.6, 1920.0, 2054.4)$

$D_{51} = (4960.0, 5333.3, 5706.7)$, $D_{51}T_5 = (1984.0, 2133.3, 2282.7)$

$K_{51} = (0, 0, 0)$

By Equation (Eq.) 4.9

$X_{51} = (7518.4, 8373.3, 9228.3)$

The cash flow for the two subsequent years – Year 2 and Year 3 – will have the same values as Year 1

Using Eq. 4.10

$$NPV_5 = (-17120.0, -16000.0, -14880.0) + \frac{(7518.4, 8373.3, 9228.3)}{(1.08, 1.1, 1.12)^1} + \frac{(7518.4, 8373.3, 9228.3)}{(1.08, 1.1, 1.12)^2} + \frac{(7518.4, 8373.3, 9228.3)}{(1.08, 1.1, 1.12)^3}$$

$NPV_5 = (937.93, 4823.24, 8902.14)$

For technology A_6, at the end of year 0

$G_{60} = (0,0,0),$ $(1 - T_6)G_{60} = (0,0,0)$

$C_{60} = (0,0,0),$ $(1 - T_6)C_{60} = (0,0,0)$

$D_{60} = (0,0,0),$ $D_{60}T_6 = (0,0,0)$

$K_{60} = (14880.0, 16000.0, 17120.0)$

By Equation (Eq.) 4.9

$X_{60} = (-17120.0, -16000.0, -14880.0)$

For technology A_6, at the end of year 1

$G_{61} = (12648.0, 13600.0, 14552.0),$ $(1 - T_6)G_{61} = (7588.8, 8160.0, 8731.2)$

$C_{61} = (2976.0, 3200.0, 3424.0),$ $(1 - T_6)C_{61} = (1785.6, 1920.0, 2054.4)$

$D_{61} = (4960.0, 5333.3, 5706.7),$ $D_{61}T_6 = (1984.0, 2133.3, 2282.7)$

$K_{61} = (0, 0, 0)$

By Equation (Eq) 4.9

$X_{61} = (7518.4, 8373.3, 9228.3)$

The cash flow for the two subsequent years – Year 2 and Year 3 – will have the same values as Year 1

Using Eq. 4.10

$$NPV_6 = (-17120.0, -16000.0, -14880.0) + \frac{(7518.4, 8373.3, 9228.3)}{(1.08, 1.1, 1.12)^1} + \frac{(7518.4, 8373.3, 9228.3)}{(1.08, 1.1, 1.12)^2} + \frac{(7518.4, 8373.3, 9228.3)}{(1.08, 1.1, 1.12)^3}$$

$NPV_6 = (937.93, 4823.24, 8902.14)$