



Faculty of Engineering and Technology
Department of Mining and Geological Engineering

**DEVELOPMENT OF A HYBRID FUZZY-TOPSIS MCDA FRAMEWORK FOR
DEBSWANA JWANENG MINE CONTRACT MINING DECISION MODELLING**

by

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Fulfilment of the Requirements for the Award of the Degree of Master of Engineering in
Mining Engineering

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ABSTRACT

Contract mining has been rapidly growing worldwide, in scale, scope and magnitude. The nature and scope of mining outsourcing decision problems have also changed with time leading to the development of different decision analysis methods. Hence, the development of a Multiple Criteria Decision Making (MCDM) framework which uses empirical evidence for decision making was crucial. This study sought to determine the factors that affect the decision to outsource some mining projects and operations, the possible variations of contract mining alternatives and the methods that could be used in decision analysis. A hybrid MCDM method utilising the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) technique, and the fuzzy logic was developed and incorporated into a framework for solving decision problems with multiple and conflicting criteria.

The decision framework was demonstrated and validated using data from Modular Dispatch system, Oracle system and questionnaire responses from Debswana Jwaneng Mine. The comparative analysis of the Hybrid Fuzzy Technique for Order Preference by Similarity to Ideal Solution (HFTOPSIS) method with TOPSIS, Fuzzy Technique for Order Preference by Similarity to Ideal Solution and Balance Score Card, has proven the HFTOPSIS method to be highly effective in ranking alternatives based on multiple criteria. It is recommended that Debswana Jwaneng Mine adopts the HFTOPSIS method in their decision analysis process, that further studies using data sets from other mines be used to test the efficacy of the method and that the model be tested on the decision problems of other industries.

DEDICATION

This thesis is dedicated to my son Rafael Mbako Letlotlo Medupi and my father Ketlhabanetswe Samuel Munyadzwe.



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GLOSSARY OF ABBREVIATIONS AND KEY TERMS

The list of abbreviations comprises of:

AHP - Analytical Hierarchy Process

BSC - Balance Score Card

BTM - Blasting Time Deviation

CAPEX - Capital Expenditure

CBR - Case-based Reasoning

CC - Closeness Coefficient

CER - Capital Efficiency Ratio

CR - Capital Resource

CSR - Corporate Social Responsibility

D&B - Drilling and Blasting

DCF - Discounted Cashflow

DEA - Data Envelopment Analysis

DM - Decision Maker

DRD - Drilling Rate Deviation

EBIT - Equity Before Interest and Taxes

EBITD - Equity Before Interest, Taxes, and Depreciation

ESG - Environmental, Social, and Governance

FTOPSIS - Fuzzy Technique for Order Preference by Similarity to Ideal Solution

HFTOPSIS - Hybrid Fuzzy Technique for Order Preference by Similarity to Ideal Solution

HR - Human Resource

IRR - Internal Rate of Return

MCDA - Multiple Criteria Decision Analysis

MCDM - Multiple Criteria Decision Making

MH - Materials Handling

MHRD - Materials Handling Rate Deviation

MO - Mining Operations

MRD - Mining Rate Deviation

MS Excel - Microsoft Excel

NIS - Negative Ideal Solution

NPV - Net Present Value

NWC - Net Working Capital

OEE - Overall Equipment Efficiency

PBP - Payback Period

PIS - Positive Ideal Solution

ROCE - Return on Capital Employed

TFN - Triangular Fuzzy Number

TOPSIS - Technique for Order Preference by Similarity to Ideal Solution



CHAPTER 1

INTRODUCTION

1.1 Background Information

Contract mining, a process of outsourcing mining operations, has been rapidly growing worldwide (Suglo, 2009). Contract mining is used in both surface and underground mines for different operations. The demand for minerals, which is driven by industrialisation and the need for materials, has been growing rapidly over the years. Consequently, it is necessary to produce more minerals to meet the ever-increasing demand and this requires exploring for new ore deposits or mine the existing pits at deeper depths. Open pit mining at very deep depths complicates the materials handling processes and leads to increased costs. Therefore, it requires improved technology, larger equipment, and improved mining techniques. Deposits located in remote areas require high levels of investment in infrastructure which leads to an intricate mining value chain. Therefore, as an open pit becomes deeper, the mining operations become more complex and most of the operations require great expertise and have to be contracted out. This results in an increased diversity of contract mining.

Outsourcing mining operations differ by mine, location and company based on the needs of the project or part of, that is being outsourced. In surface mining, contractors may be used for rock breakage (drilling and blasting), materials handling (loading and hauling of ore and waste), mine planning and design, supply and maintenance of equipment, scheduling and budgeting (Dunlop, 2004; Suglo, 2009). Mine owners may decide to use contract mining in some or all their operations or only for some other operations in the mine like catering. The other alternative is to use them to provide certain capital resources like equipment or explosives, technical services or provide human resources or both. In all cases the choices are mutually exclusive (Suglo, 2009). Hence, the decision to outsource any operation becomes more complex with the growing number of options that are available for contract mining and a proper decision framework is required in that regard.

A decision framework highlights the factors that influence the choice of one option over the others. The choice of contract mining is controlled by several factors such as economic and

operational factors (Steenkamp and Van Der Lingen, 2014). Engaging contractors is usually done to manage costs, expedite project life, ensure quality, and share risks. It is better to use contractors when either the life of the project is short and equipment life will not be fully utilised or when specialised skills sets are required for a project (Luxford, 1998; Rupprecht, 2015). Keel (2018) lists the advantages of contract mining as economies of scale, scope through access to capital equipment and human resources, optimised mining, plant, equipment utilisation rates and labour productivity and minimisation of the owner's capital exposure, which allow the company to better utilise its capital and equip (or re-equip) for mines with restricted capital budget. However, contract mining poses several risks to the owner. Contractors are tasked with the paramount task of balancing quality and quantity. Hence, the main operating risk of contract mining is quality. For example, hard rock miners usually engage contractors to mine waste while they handle all the ore mining operations (Allonby, 1998). In that case the quality and safety of work will be highly defined by the final wall conditions and floor grade which requires effective contract management between the client and the contractor. On the other hand, operating risks also affect the contractor because contracts are about risk sharing (Peters, 2019). Therefore, mining outsourcing decisions are influenced by multiple criteria, making them multicriteria decision making (MCDM) problems.

Since contracts are commonly driven by costs it is important to view their performance from financial and operating points of view. Mining is a high risk investment sector and miners engage mining contractors to spread their risks (Dunlop, 2004). This reduces their risks in terms of capital investment, increases their net present value (NPV), internal rate of return (IRR) and enhances their operational efficiency (Peters, 2019). This perspective affects issues of productivity in mining, commodity prices, cost performance and income improvement. In general, performance in mining industry is weighed by production, cash flow, return on investment and meeting the safety and environmental standards of the mine (O'Callaghan, 2019a). Thus, operational, and financial performance analysis are critical in mining outsourcing decision problems. Consequently, understanding their impact as outsourcing factors at a strategic level enables sound decision making in view of the volatile mining market, fluctuating commodity prices, declining ore grades and productivities, and increasing risks. Such uncertainties and risks in mining operations could be translated into meaningful multicriterial decision making models and reports for interpretation by decision makers who are usually not directly involved in such operating processes. The challenge is

operating and financial analysis, even at a strategic level, does not give a full perspective of the decision problem due to increasing multiple dimensional factors affecting outsourcing of mining operations.

To make outsourcing decisions, it is critical to understand the contract agreement and the impact of environmental, social and governance (ESG) issues, manage risks, and synchronise client and contractor operating models. The decision to outsource the core business of a mine is more than any other operational decision as it involves strategic factors that also require careful consideration. Hence, the need for a decision framework that views contract mining holistically and considers multiple and conflicting strategic factors as inevitable when making decisions. A lot of research has been conducted since the 20th century to establish contract agreements, provide guidelines on how to choose a contractor and ways of managing a contractor-client relationship from the legal perspective. While some researchers provided basic frameworks on the broad decision to contract or not to contract, there is still a gap in evaluating the various options available when outsourcing mining operations.

1.2 Problem Statement

Currently, there is limited research work on the balanced appraisal of contract mining as an alternative to handling strategic problems in mining. As a result, managers in the mining industry use subjective trial-and-error methods based solely on experience than balance of expertise, experience, and empirical evidence, which are biased and subsequently fail to come up with feasible solutions to outsourcing decision problems. This research seeks to establish an empirical model for integrated analysis of contract mining decision problem attributes and alternatives, viewing outsourcing as an alternative solution to strategic problems in mining operations, through multi-criteria decision analysis.

1.3 Objectives of the Research

The main objectives of this research are to:

- a). Study how contract mining value chain, operations, market and risk trends influence decisions to outsource mining operations.
- b). Develop a multicriteria decision-making model for building a decision-making framework for mining operations outsourcing decision problems.

- c). Develop decision criteria and sub-criteria satisfying the decision goal for the mining outsourcing decision framework.
- d). Classify mining contracts and establish decision alternatives for the mining outsourcing decision-making framework.
- e). Validate the mining outsourcing decision framework using a case study and other multi-criteria decision-making methods.

1.4 Research Methodology

A mixed method of literature review and quantitative techniques were used to establish parameters for the model and to validate the model. The research methodology is summarised in Figure 1, with each objective highlighted and relevant methods shown for each objective.

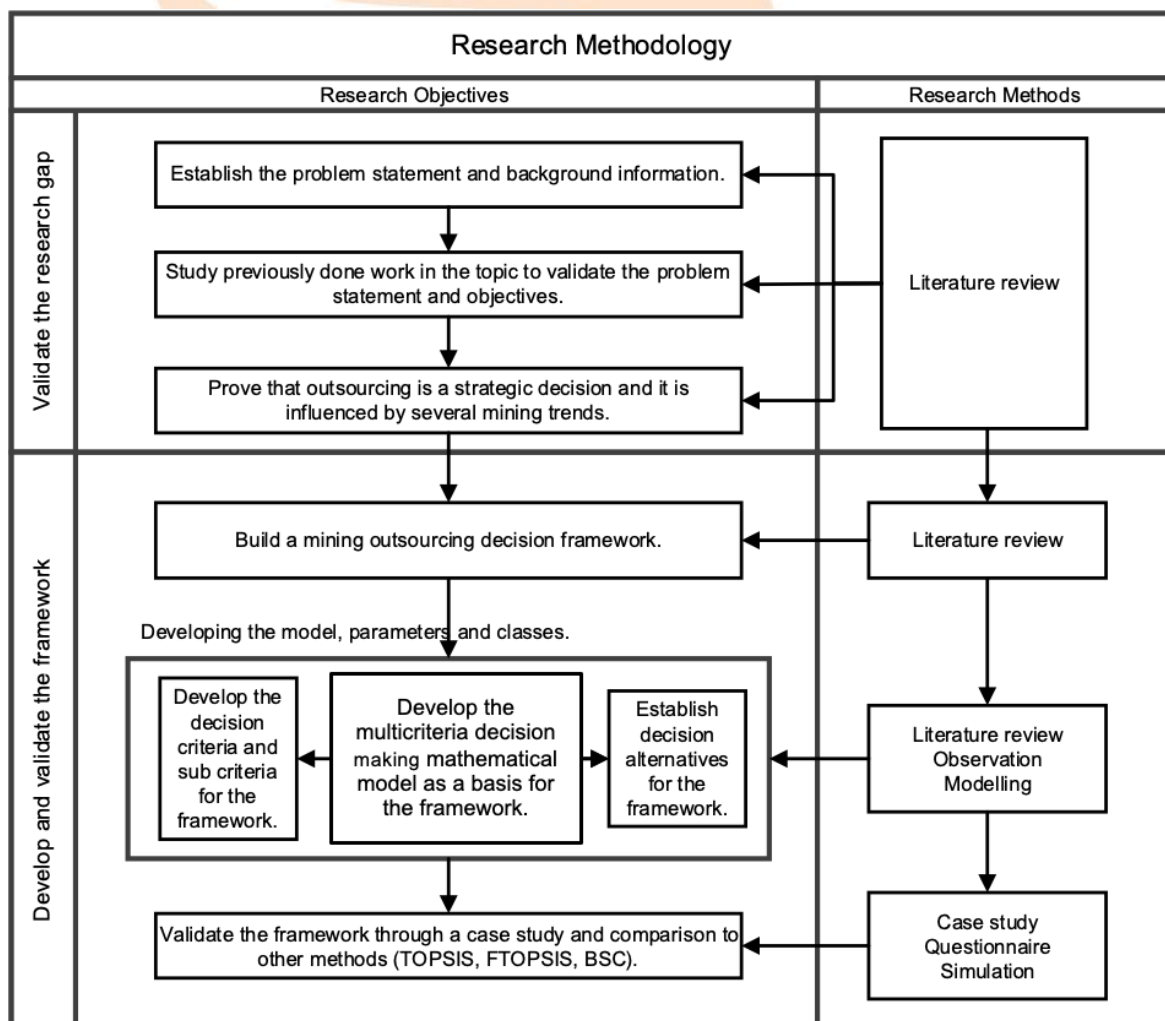


Figure 1 Research Methodology Framework

1.4.1 Literature Review

Journal articles, reports and other published information on contract mining were explored. These sources were used to study previous work done in the area, identify the problems involved in contract mining, pinpoint key contract agreements and regulations that are used to classify different mining contractors. Secondly, literature was done to develop a mathematical model as a basis for the mining outsourcing decision making framework. Lastly, the documents on contract miners were reviewed to study their operating models, historical financial performances and associated risks which were used in the model.

1.4.2 Observations

Observations at the selected mine for the case study were used to study the operations of the mine. The outcomes were used to understand the classes of contract mining that contribute to outsourcing decision parameter identification.

1.4.3 Modelling

Statistical and mathematical techniques were used to identify the possible combinations of contract mining options to establish contract mining categories using data from the mine and literature sources. The classes established were validated for practicality through a case study.

1.4.4 Case Study and Simulation

A case study of Debswana Jwaneng Mine was used for validating the model developed in this study. Data used for validation was collected from various databases of the owners and contractors at Jwaneng Mine. The data was obtained from January 2018 to December 2020 records and downloaded as Microsoft Excel (MS Excel) files. The data was processed in two software platforms, MS Excel and R-software. A working space using MS Excel is shown in Figure 2. R-software was used to clean and analyse the data, while MS Excel was used to build models, correlate the models and validate them. The data was used to develop parameters which affect the decision to outsource mining operations using the techniques adapted from literature.

1.4.5 Questionnaires

Information obtained from questionnaires was used for testing and validating the model. A prototype of the framework in MS Excel application together with the questionnaire was

sent to the participants for a trial-and-response session to get the feedback on the model and validate it for practicality and usability.

HFTOPSIS DECISION MATRIX 1

Criteria	Social license to operate	Transactional cost	Operating cost	Project life	Profit margin risk	Capital efficiency ratio	OEE	Mining rates	Attraction and retention of talent	Project core competence	Quality	Technological competitiveness	Strategic relationship	Environmental sustainability
CRITERIA CLASSIFICATION	COST	COST	COST	COST	BENEFIT	BENEFIT	BENEFIT	BENEFIT	BENEFIT	BENEFIT	BENEFIT	BENEFIT	BENEFIT	BENEFIT
MD Labour	1.00	1.00	0.50	0.33	0.25	0.20	0.60	0.60	0.40	0.40	0.40	0.89	0.89	0.89
MD Capital	0.25	0.20	0.17	0.17	0.14	0.13	0.30	0.30	1.00	1.00	1.00	0.99	0.99	0.99
MD Labour and Capital	1.00	0.50	0.33	0.25	0.20	0.17	0.25	0.25	1.00	1.00	1.00	1.00	1.00	1.00
Owner Mining	0.14	0.13	0.11	1.00	1.00	0.50	1.00	1.00	0.19	0.19	0.19	0.70	0.70	0.70

HFTOPSIS NORMALISED WEIGHTED MATRIX 1

Criteria	Social license to operate	Transactional cost	Operating cost	Project life	Profit margin risk	Capital efficiency ratio	OEE	Mining rates	Attraction and retention of talent	Project core competence	Quality	Technological competitiveness	Strategic relationship	Environmental sustainability
WEIGHTS	38.2844	3.9494	12.7305	3.9494	19.7345	1.3644	9.5908	0.3100	0.1223	2.0021	0.8763	4.7921	0.4157	2.1586
DMB Labour	38.28	19.14	12.76	0.99	0.79	0.66	11.87	11.87	0.88	0.88	0.88	14.78	14.78	14.78
DMB Capital	9.57	7.68	6.38	0.56	0.48	0.44	8.82	8.82	1.13	1.13	1.13	16.22	16.22	16.22

Figure 2 Working Space for MS Excel

This research focused on surface hard rock mining projects with emphasis on the extraction stages of the mining cycle (prospecting, exploration, development, mining, and reclamation). This involved core unit mining operations such as rock breakage, materials handling, equipment maintenance, mine planning and mineral resource management.

1.5 Organisation of the Thesis

Chapter 1 has the background information, statement of the problem, objectives of the research, and research methodology. Chapter 2 has the general information about Jwaneng Mine and an overview of its mining operations outsourcing. Chapter 3 has the literature review justifying the research gap and covering the outsourcing decision process. Chapter 4 has the data collection and analysis while Chapter 5 contains the Conclusions and Recommendations arising from the work.

1.6 Significance of Study

This research provides new insights into the mining outsourcing decision process. Through the framework developed in this research, decision makers in the mining industry can consider polychotomous alternatives of mining outsourcing methods contrary to the common dichotomous alternatives of generic contract mining and owner mining. This can be especially relevant for the ranking and selection of outsourcing methods in a multiple and conflicting criteria scenario. Moreover, the analysis in this study can convey valuable information for future researchers who wants to explore the various applications and testing of the multicriteria decision analysis framework for mining operations outsourcing in other mines.



CHAPTER 2

GENERAL INFORMATION ABOUT MINE

2.1 Background Information on Jwaneng Mine

The Jwaneng Mine is located in South Central Botswana, 160 km west of Gaborone. It was discovered in 1972 and came into full production in July 1982. The Jwaneng Mine is owned by Debswana, a partnership between the De Beers Company and the Government of Botswana.

The mine operates a split shell pushback approach, using both conventional and dip-slope open pit mining techniques to recover diamonds from three kimberlite pipes. It is currently mining Cut 7 to the west of the pit and Cut 8 to the east as shown in Figure 3. The pit has an area of 520,000 m² at ground level and is currently at a depth of 560 m which is about 810 m above mean sea level (Gabanakgosi and Mosebi, 2017). The major axis of the pit has a general NNE-SSW orientation, with the waste dumps located to the west of the pit and the processing plant to the east.

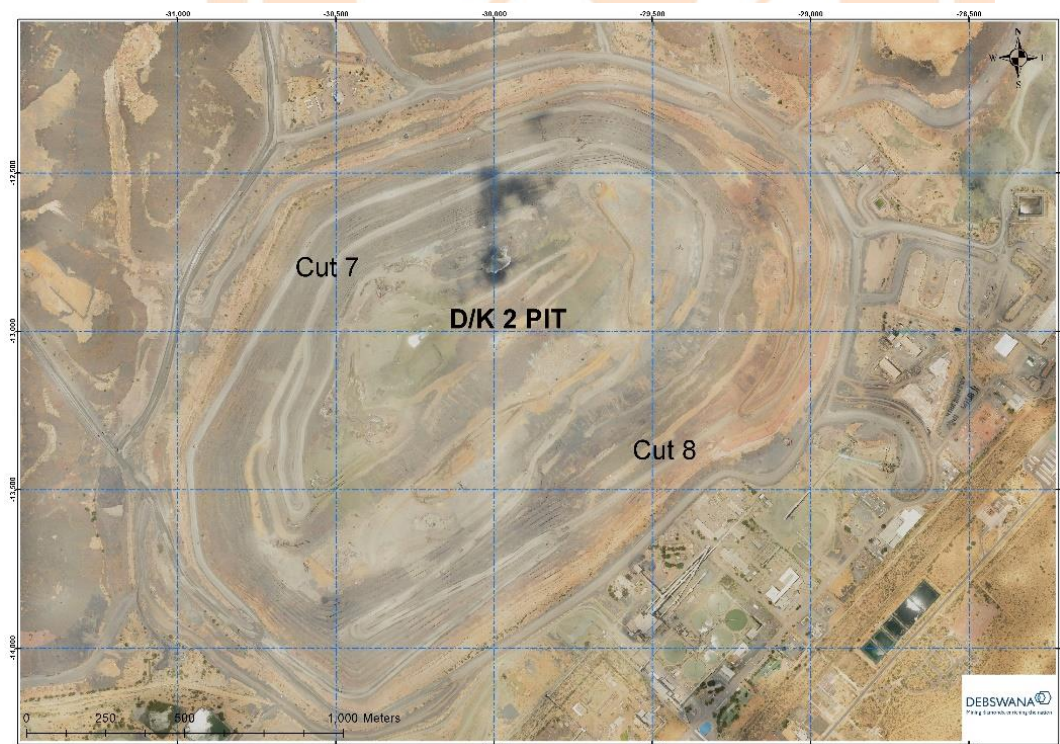


Figure 3 Aerial View of Jwaneng Pit showing Cuts 7 and 8 (Gabanakgosi and Mosebi, 2017)

2.2 Geology of Jwaneng Mine

The resource consists of three separate volcanic pipes, namely the north, south and centre pipes. Two small kimberlite bodies were also intersected within the pit. The pipes erupted through the Transvaal strata and the overlying Karoo sediments about 245 million years ago (Gabanakgosi and Mosebi, 2017). The country rocks hosting the ore at the Jwaneng Mine are the late Archean to early Proterozoic, mixed siliclastic-carbonate sediments of the Transvaal Supergroup. This supergroup is located within three structurally constrained basins on the Kaapvaal craton of southern Africa: the Transvaal and Griqualand West Basins in South Africa and the Kanye Basin in Botswana. The upper-most stratigraphic units are the aeolian Kalahari sands as well as paedogenic calcretes. These are underlain by the Timeball Hill Formation, which comprises a complex assemblage of laminated shales, quartzitic shales and siltstones combined into one laminated shale unit. A consistent carbonaceous shale layer marks the base of the Timeball Hill Formation (Anon., 2018a). The country rock consists of sedimentary rocks that occur as a collection of tilted and displaced blocks with dolomites at the base of these blocks. The tilted nature of these blocks resulted in high pit wall instability which led to the need to implement dip slope mining.

2.3 Production and Operations of Jwaneng Mine

The Jwaneng Mine is the largest diamond mine by production in the world and produces approximately 11 million carats per year from a recoverable ore grade of about 1.25 carats per tonne. The mine produces 9.3 million tonnes of ore per year and strips 37 million tonnes per year of waste rock. In 2017, the mine life was estimated to be 25 years.

2.4 Contract Mining Profile of Jwaneng Mine

The mine has utilised different types of contractors in its operations for a very long time. The most significant contract mining projects are the Cut 8 waste stripping project which was valued at over US\$ 30 billion to remove 713 million tonnes of waste to expose 75 million tonnes of ore and recover about 95 million carats of diamonds. Also, the Cut 9 waste stripping project which is estimated at US\$ 18 billion for 9 years, is expected to extend the life of mine to 2035 and yield an estimated 53 million carats of rough diamonds from 44 million tonnes of ore. Other contractors provide mining equipment, explosives for blasting, fleet management systems and technical services within the value chain.

There are other logistical services which are also outsourced such as cleaning, catering, accommodation, domestic and clinical waste management, overhaul maintenance and the supply of personal protective clothing. These services form a critical part of the mining operations, but they are not covered in this research. The focus of this study is on the core mining activities of drilling, blasting, and materials handling. Hence, the focus of this work is on the two main and latest projects at the Jwaneng Mine, considered for outsourcing.

The management of the Jwaneng Mine considered outsourcing mining operations on a large scale with over one billion dollars' worth of contracts in the Cut 8 project. After completion of the Cut 8 waste stripping project, the Cut 9 project was also considered for outsourcing. The decision makers had different criteria and alternatives for each project. The common criteria were cost and the social impact of the projects. Other criteria varied from technical details to the life of mine. While alternatives were limited and not generalised for precise and clear decision analysis, the intent of this study is to precisely identify them.

2.4.1 Cut 8 Project

The outsourcing decisions of the Cut 8 waste stripping project were not generalised but the main considerations were on whether to use owner mining, labour outsourcing, equipment outsourcing or contract mining (which was defined to be full outsourcing of the project to a contractor) alternatives for the outsourcing decision problem. The main criteria for the Cut 8 project were transaction costs, operating costs, life of mine, mining rates, capital efficiency, quality, and social licence to operate. Six decision parameters were considered in the decision process and the balanced score card (BSC) method was used for the decision analysis (Anon., 2018a). Contract mining, which included both labour and partly capital resources for the main mining unit operations, was the alternative chosen. When reviewing the performance of the project against the criteria, the chosen alternative proved to be the best. The target goal was achieved as the project was completed on schedule, within budget, with good highwall and floor grade quality though there were the occasional minor ore contamination challenges.

2.4.2 Cut 9 Project

The outsourcing decision for the Cut 9 waste stripping project was not the best alternative compared to that of the Cut 8 project because the alternative could not overcome the risks and challenges of the project. This may have been caused by several aspects which included

the drastic change in budget relative to the scope, the onset of the Covid-19 pandemic which seriously affected the sales of diamonds, the impact of environmental, social and governance (ESG) requirements in mining decision making processes and the rapid change of risks from manageable operational risks to interoperable strategic risks that span from mining operations to financial management (Anon., 2020).

Outsourcing decision alternatives for the Cut 9 waste stripping project were very similar to the alternatives for the Cut 8 project decision problem, the only difference was that Cut 9 did not have equipment outsourcing as a decision alternative. The decision alternatives for Cut 9 were generalised as owner mining, labour outsourcing and contract mining. However, the main criteria changed drastically. The criteria used in the Cut 8 project which were transaction cost, operating costs, life of mine, mining rates, capital efficiency, quality and social licence to operate, were maintained and the most critical criteria which had affected the decision outcome were the strategic relationship and environmental sustainability. Six decision parameters were involved in the decision process and like the Cut 8 project decision process, the balanced score card (BSC) method was used in the decision analysis (Anon., 2018a).

The BSC method has proved to be inadequate for multi-criteria decision problems with highly diverse and conflicting attributes because the same alternative of contract mining, which included both labour and partly capital resources for main mining unit operations, was the chosen alternative. The decision had to be reconsidered less than 2 years into the start of the project out of 9 years. When reviewing the performance of the project against the criteria, the chosen alternative showed some inadequacies. The project was already spending beyond the budget, with continuous quality complaints and inadequacies in environmental, social and governance aspects though the project was still on schedule. The chosen alternatives were changed and different alternatives and adopted on a pilot basis.

CHAPTER 3

LITERATURE REVIEW

3.1 Introduction

The importance of contract mining can be traced back to the 1980s during the gold mining booms (Luxford, 1998; Dunlop, 2004) with significant growth through each decade from the 1990s to the 2010s. Contract mining is expected to be widely and intensively adopted by many mining companies in the future (Suglo, 2009; Steenkamp and Van Der Lingen, 2014). Today contract mining makes large contribution towards the amount of material moved per year compared to owner mining. The Construction, Infrastructure, Mining and Concessions (CIMIC) Group, through Thiess have moved over 2 billion tonnes of waste in the past 5 years (Anon., 2018a). This includes other specialised mining services and product deliveries such as explosives manufacturing and delivery, fleet management systems, materials handling equipment and other technology driven solutions. In 2020, the mining service industry made up 40% of the total mining industry worth (Hart, 2020). Some major mining companies in mining-intensive countries such as Australia, Canada, USA, Ghana and South Africa have dedicated their core businesses to offering mining services instead of exploring and developing their own deposits, while doing work similar to that of owner miners. Some companies have further specialised in specific complex operations or products that are required by the mines, the need to outsource, the decision and the growth of contract mining is dependent on several factors which are mainly economic.

3.1.1 Principal Factors Determining the Outsourcing Decisions

Information in literature indicates that contract mining is driven by costs. The status quo and practicality of contract mining have proven to be more than just costs as it covers a large spectrum of economic, sustainability and governance issues. The decision to outsource is a strategic one involving a number of factors that could be considered in the decision making process (Steenkamp and Van Der Lingen, 2014). Therefore, the context within which outsourcing decisions are made is extremely important and making the decision on cost alone is dangerous and short-sighted (Fill and Visser, 2000). Furthermore, those that have widened their spectrum to cover economic issues further highlights the need for the mining companies to focus on their core businesses as the main reason behind the decision to

outsource (Allonby, 1998; Suglo, 2009; Rupprecht, 2015). This perspective brings to the fore the definition of ‘core business’ and what it entails when all the mining operations are outsourced. Allonby (1998) states that strategic economic and sustainability factors such as commodity prices, selling volumes, effect of exchange rates, share price, capital constraints, land claims, as well as community and environmental issues relating to mining are some of the main components of the ‘core business’ in addition to mining operations. This view extends to the economic, sustainability and governance spectrum because the core operations of mining companies are those operations that are outsourced.

In an apparent contradiction with conventional outsourcing theory which dictates that companies should focus outsourcing efforts on non-core competencies, many mining companies have considered outsourcing their main mining operations such as drilling, blasting, loading and hauling (Quelin and Duhamel, 2003). This research will consider the core business of mining companies beyond operating activities. As the mining industry grows, diversifies and companies are pressured by different stakeholders, their focus will likely shift from profits, safety, and operational efficiency to a wider spectrum of a detailed business model which caters for both operational, organisational and environmental risk factors. In multinational companies with more offshore than onshore operations, the decision to outsource is made by a subsidiary of such companies, usually a daughter company or a fully-fledged section with the authority to make independent decisions. Hence, the decision to outsource is heavily influenced by geo-political and socio-economic factors which differ by location and state. This is usually driven by the obligations that are imposed by the licences to operate and pressure from the local authorities and governments based on corporate social responsibility issues. Regardless of the nature of contract mining, outsourcing operations require a wide consideration of both economic and non-economic factors.

3.1.2 Variations of Contract Mining

The available literature shows that outsourcing of mining operations is from a more tactical than strategic decision view with only two options available - the decision to outsource (contract mining) or not to outsource (owner mining) and the analyses focusing mainly on the comparison between the two options though it is acknowledged that different types of contract mining exists. Suglo (2009) states that outsourcing mining operations is mutually exclusive, where the choice of contract mining eliminates that of owner mining and vice

versa with the distinction between the two being control over mining operations. This view is supported by Allonby (1998) who highlights operational productivity, efficiency and cost reduction as the key factors of contract mining. Luxford (1998) postulates that the success of contract mining is dependent upon people (e.g. the relationship between the owner and the contractor), but both with a twist on the options available for outsourcing. Options for outsourcing mining operations range from parts of mines, through stand-alone mining operations within a lease to total mine operations and the engagement methods also vary from the fixed price type to the cost over margin type (Allonby, 1998). Steenkamp and van Der Lingen (2014) have alluded that the decision factors can be categorised into classes ranging from cost analysis, associated risks, supplier influences, to strategic intent by focusing more on strategic than operating factors. They subsequently developed a framework which enables practical implementation of such decision factors on the decision to outsource but the options evaluated remain as owner vs. contract mining.

Over the years, outsourcing of mining operations has evolved to such a stage that its complexity is not limited to a single option like “contract mining”. It must be broken down into units and sub-units to analyse all the practical and theoretical options available when outsourcing. Many sources in the literature support such distinctions in contract mining. Luxford (1998) states the importance of managing people in contract mining and placing a lot of attention on labour contracting as one of the distinctions. The dynamics of resources as a distinguishing factor in contract mining is mainly tied to the two important classes of resources i.e., human and capital resources. While outsourcing capital resources is widely chosen to reduce costs, outsourcing human resources is driven by expertise and skills requirements (Suglo, 2009; Steenkamp and Van Der Lingen, 2014). The other distinction is on payment agreements, with available options ranging from the lump sum contract, the unit rate contract, the fixed price type to the cost reimbursable plus fee (cost plus) contract (Bowen, 1997; Allonby, 1998; Suglo, 2009).

3.1.3 Outsourcing in Mining

The complexity of contract mining has increased with the intensity of mining activities, advancement in technologies and the complex nature of the orebodies. Thus, outsourcing cannot be viewed as an independent operational decision but as an intricate decision that affects the outlook and vision of a mining company. In most cases the companies are outsourcing to share different types of risks ranging from operating to capital risks (Dunlop,

2004; Suglo, 2009; Steenkamp and Van Der Lingen, 2014). The decision to outsource any mining activity involves a trade-off between mining risks and profits, and the choice of contractor is based on their risk profile because all contractors are motivated by profit (Golosinki, 1998; Dunlop, 2004). All the aspects must be managed beyond the mining project's operational objectives by incorporating the corporate perspective. The trade-off cannot be avoided because choosing owner mining means the company assumes all the risks involved in the project while they benefit from all the profits they make. This means they have avoided the cost incurred from the profit margin gained by the contractor while they have exposed themselves to the cost of project risks. On the contrary, engaging a contractor means they have split both the risks and profits with the contractor, incurring the cost of shared profits while avoiding some costs related to project risks. With mining companies adopting different outsourcing strategies and incorporating contract mining into their business models, it is imperative to consider all the aspects of the project or work that leads to the consideration of outsourcing as an option.

In addition, it has become a norm that these outsourcing strategies require contractors not only to provide such services or products but become part of the mine environment and be accountable for the non-operational requirements that include legal, environmental and sustainability issues within the mine's premises as contractors. Hence, this exposes them to litigation risks beyond just operating and economic risks which are normally considered in the scope of the project. Furthermore, contractors are now required to be connected to the owner's culture (Rupprecht, 2015), share mining risks and profits (Dunlop, 2004), have a relationship and share responsibilities with the owner (Golosinki, 1998; Luxford, 1998) and fit into the business model of the owner (Steenkamp and Van Der Lingen, 2014).

3.1.4 Mining Outsourcing Decision Evaluation

The literature is rife with economic reasons for outsourcing mining operations and support different economic motives as main drivers for contract mining, but little economic analyses have been undertaken to assess the economic impact of outsourcing mining operations. Detailed economic analysis could ultimately provide a framework to facilitate outsourcing decision making. Regardless of whether the owners outsource their operations or not, they will always be prone to mining risks (Suglo, 2009). Though it is commonly believed the risks are reduced with increased contract mining (Dunlop, 2004), risks can increase in some cases if the contract is not managed well from either side (Golosinki, 1998). On the other

hand, operating risks of the owner also affect the contractor because contracts are about risk sharing (Peters, 2019). In addition, performance in the mining industry is centred on production, free cashflow, return on investment and safety standards (O’Callaghan, 2019b). Hence, it is necessary to find out how each of these factors affect the decision to outsource mining operations at any time from a practical point of view. Steenkamp and van Der Lingen (2014) have developed a framework that is used to evaluate the choice between contract mining and owner mining based on strategic outsourcing decision factors. These factors are derived from outsourcing decision evaluation factors, which are cost based, competence based and relationship based (Freytag *et al.*, 2012), operating cost, capital usage and flexibility factors (Quelin and Duhamel, 2003). The framework is used to facilitate the choice between owner mining and contract mining, and the framework has a higher probability of making the correct decision, especially for greenfield mining projects (Steenkamp and Van Der Lingen, 2014). However, this does not take into consideration the types of contract mining options that are available, the dynamics of outsourcing mining operations and the details of economic factors that have been highlighted so far. Hence, a complete evaluation metric is needed to consider all the details of the decision-making process for it to be useful in practical evaluations situations.

3.2 Mining Industry Management Trends

The factors affecting the decision to outsource mining operations vary with time. These factors have generally changed from economically dominated factors to integrated factors classified as economic, sustainability and governance (Steenkamp and Van Der Lingen, 2014; O’Callaghan, 2019a). The factors are weighed against each available option for every project and the option with the highest score is implemented (Steenkamp and Van Der Lingen, 2014). These projects are economically driven with underlying motivation to curb growth challenges and mitigate organisational risks which drive miners to adapt to new ways of doing things to reduce costs and improve safety in their operations while meeting environment, sustainability and governance (ESG) requirements and decarbonisation efforts at a strategic level. The mining industry is a capital-intensive and complex industry beset by orebody constraints, challenging environmental, sustainability and governance issues, and rapidly changing technologies (O’Callaghan, 2019a; Valenta *et al.*, 2019; O’Callaghan, 2021; Hodges, 2021). The greatest challenge facing the mining sector is the fluctuating demand for raw materials (Hodges, 2021). Therefore, the fluctuating mineral commodity prices require certain measures to be taken from a business perspective both at strategic and

operational levels, whether the price is decreasing or increasing. When the demand for any commodity increases, its price rises and both greenfield and brownfield projects increasing together with an increased production rate for existing projects (Rötzer and Schmidt, 2020). On the contrary, a decrease in demand for any commodity, leads to reduction of that commodity's prices resulting in a race to reduce operating costs, improve productivity and sustain business operations (Calvo *et al.*, 2016; Hodges, 2021). In all cases, the future supply of minerals is dependent on a combination of expansion of existing mines, new mine discoveries, recycling and opening up of undeveloped deposits which have not yet commenced production (Corder, 2018; Valenta *et al.*, 2019). All these alternatives have common problems of mining pits to greater depths, increasing complexity of operations, remoteness of mine sites and decreasing ore grades.

3.2.1 Orebody Complexities

Mining companies are striving to meet the increasing demand for minerals and materials by human beings (Valenta *et al.*, 2019). As human technological development advances and the need for raw materials grows, the demand for minerals will also continue to grow and mining activities will become more complex (Corder, 2018; O'Callaghan, 2019b). As orebodies that were closer to the surface gets depleted, more identified orebodies will have to be developed and mined or available current orebodies will have to be mined to deeper depths. This means new mines will have to be developed in remote areas. In most operating surface mines, the net profits are decreasing due to the changes in shape with depth (generally narrow widths of deposits) and sparsity of the deposits (Calvo *et al.*, 2016). This means more waste must be stripped to extract the same quantity of ore at deeper depths. The ore grades are often lower for undeveloped mines and the quest to overcome this by economies of scale reaches the limit of effectiveness (Hodges, 2021). Ore grade challenges also extend beyond the geology of the mine to market conditions and trends. Several factors influence the price of a commodity, which consequently influences the cut-off grade of mines trading a certain metal or mineral.

3.2.2 Influence of Mineral Markets on Mining Management

The term ore is an inherently economic concept (Northey, 2014) and the expansion of existing mines or development of new mines is dependent upon ore grade and commodity prices (Calvo *et al.*, 2016). These factors also influence closure of mines and supply of mineral commodities. Hence, an economic analysis of all factors which drive the many

challenges and risks to the mining industry is very crucial. Commodity prices are influenced by the mining costs, the supply and demand of that mineral commodity, geopolitical situations, economic growth, etc. (Trench and Sykes, 2014). Both economic and geopolitical issues in the mining industry are very intricate and require detailed analysis and good management for the mining company to make a profit. These influences, together with the complexity of the orebody, increases the challenges that are faced by mining companies.

The main goal of mining companies is to make profit in an environmentally friendly and sustainable manner. Among the market factors, the price of the mineral is the main factor that determines profitability of the mine. Hence, volatility of mineral commodity prices over both the short and long terms, affect the profit margins of mining companies over time (Trench and Sykes, 2014). This is a result of underlying microeconomic and macroeconomic drivers pertaining to the supply and demand of minerals, in addition to the activities of financial participants within commodity markets (Tapia Cortez *et al.*, 2018). Fluctuations in both ore grade and mineral prices present a complex volatile market situation and presents several economic risks to mines. The operational decisions in a mine depend on the interplay of company-specific and mineral market factors (Trench and Sykes, 2014). These factors are highly unpredictable and volatile. Market price volatility and uncertainties in ore grade increase the risk profile of any mining operation, which makes it important to adopt integrated risk strategies along every major operational decision which will have high impact on the profit margins of the mine.

3.2.3 Productivity Improvement

The operating margin is a derivative of both costs and revenues. Thus, it is a common trend across different industries that in spite of stagnated growth and declining markets, focus should be placed on improving productivity of both human and physical assets to improve profitability (Dieppe, 2020). As open pit mines reach greater depths with decreasing widths of orebodies, the costs increase significantly and safety becomes even a bigger threat, while the ore grades may decline significantly. This reduces possible revenues and increases both the market and operating risks (Munyadzwe *et al.*, 2020). Consequently, this drives the need to improve operational performance to boost the operating margin. Depressing mineral prices are followed by pursuits to reduce operating costs and in doing so, most miners invest in equipment that might reduce labour costs and improve productivity. Mines that focus on the human asset as a way of improving productivity, must adopt novel strategies in

workforce engagement, motivation and direct performance which is measurable by each employee's output. In all cases, it is necessary to do business in a novel way outside the traditional culture (Topp *et al.*, 2008). In addition, the increasing demand for mineral commodities together with the complex orebodies drive the technologies that are developed in the mining industry to solve both strategic and tactical mining problems. Different solutions to mining risks and challenges have led to the development of numerous inventions in the fourth industrial revolution like other industries (O'Callaghan, 2019a). The main question is: Are they really solving the base problem - the need for sustainable profits?

3.2.4 The Fourth Industrial Revolution

The race has shifted from production-based parameters of volume increments and cost reduction as a way of maximising returns (Harvey, 2019). Both junior and corporate miners need to adopt strategy-based investment rather than operational-based mining. Volatility and cyclic recovery of the mineral commodities market have driven major miners to shift from traditional methods and resources to accelerate adoption of technology at a rapid rate that was not so common before the 2008 recession (Liu and Zhang, 2014; O'Callaghan, 2018). These changes have led miners to quickly consider information technology, automation and the recent development of artificial intelligence and cyber-security in their strategies. Therefore, different technologies have been developed to improve safety, efficiency and productivity. This widens the value chain and creates solutions that remain critical to solving traditional mining problems like volatility and safety concerns while achieving the main goal of sustainable profits. However, the technological trends are such that every company produces a stand-alone technological product (Goodman *et al.*, 2019; O'Callaghan, 2020a), which poses interoperability issues as more resources will be required to benefit from such products (Valenta *et al.*, 2019). This includes more workers to manage the growing number of products, more capital to bring in the products and more infrastructure to keep and service the products.

The greater the prevailing risks and challenges are, the larger the value chain grows and products geared towards interoperability are developed and this led to the birth of "the future mine" (Harvey, 2019). A fully automated and interoperable mine has been envisaged by main players in companies like Anglo-American, Glencore and Sandvik since the beginning of the fourth industrial revolution. Despite the stall in the development of fully automating mines, several technologies that have already been actively adopted have changed the way

mining is carried out in recent years. Thus, risks have been widened from the traditional predominant operating and financial risks to more diverse interlinked risks (Xu *et al.*, 2018). This has created a value conundrum which mandates miners to re-envision their strategies, strengthen their risk management and find better ways to protect their investments while actively engaging their stakeholders (O’Callaghan, 2020a). In addition, making sustainable investments requires careful management of risks which unlike typical financial and other industry investments, mining involves numerous stakeholders with rising demands which require a dynamic strategy to be applied to all the constraints and challenges faced by each miner.

3.2.5 Environmental, Social, Governance and Decarbonisation in Mining

Stakeholder engagement requirements in the mining industry have surged (O’Callaghan, 2020b) since the onset of the 20th century. Accountability is key and the traditional role of focusing on production is totally not working because of the demands of stakeholders. With the rise in environmental sustainability and governance requirements, the pressure is building, and the risks are rapidly changing creating both diverse and growing challenges for mineral market investments. Consumers are not the only stakeholders irrevocably altering the industry dynamics (Anon., 2018b). Government, communities, and investors have gained leverage and demand accountability. It is no longer a matter of compliance anymore, but it is drastically influencing strategies. Corporate social responsibility (CSR) is becoming part of the broad company strategy not only to ensure compliance but to reduce risks. CSR initiatives which were once approached as mere compliance exercises are now morphing into stakeholder engagement programmes (O’Callaghan, 2018; Valenta *et al.*, 2019) and the social licences to operate is becoming a top mining risk (Mitchell, 2019).

Investors are even looking beyond humans and CSR into current and future environmental issues. As a result, mining companies must bend to the pressure from such risks. Though climate change is eminent, the pressure that is mounting in the mining industry drives it side-ways. The real risk does not even lie in the requirements themselves but the resulting economic changes that can happen within the industry. With some mineral commodities experiencing a rise, while others are reaching bottom low in several decades, the dependency on metals as raw materials, which is cyclic within the industry, is very contradictory and adamant. For example, copper prices are rising amidst the rising demand for decarbonisation. With approximately a 500% rise in prices of most minerals over the

last two decades (Trench and Sykes, 2014), these surging prices are changing the value chain and putting more risks and challenges to core players: the mining companies (Valenta *et al.*, 2019). As more investors become interested in a commodity, it increases the investment conundrum. On the other hand, an increase in, say, copper price, drives secondary suppliers (those that support copper miners) to take the opportunity and increase output, which influences the market stability of the product considering the profit margins and efficiency of such mining companies. Lastly, the complexity is surged by the dependency of the mining industry on the same resources they supply, e.g., copper mines use the same electric-powered vehicles dependent on the product they mine. This creates an economic loop, because the rise in copper prices affects the prices of the vehicles which will in turn increase operating costs for the mines, thereby requiring a strategic approach to governance.

All these challenges, risks and numerous siloed solutions drive miners to rethink their strategy (Anon., 2018b). Therefore, the decision to outsource, just like all other alternative solutions, is a strategic rather than an operational solution, though it involves operating activities (Boyne and Walker, 2004). In addition, the decision requires environmental, social and governance consideration in varying magnitudes and scope and the balanced score solution is frequently chosen (Dierk-Oliver, 2019). Therefore, the main problem has multiple qualitative and quantitative objectives, and it needs multi-criteria analysis from a business strategic point of view.

3.3 Outsourcing Decision Problem

Outsourcing has become an intensive process and a critical part of business strategy and management for many organisations over time (Ghodeswar and Vaidyanathan, 2008). Over the past years, most mining organisations have preferred to outsource some of the functions they used to perform themselves (Karami and Guo, 2012; Alkhatib *et al.*, 2015). Numerous reasons have been identified by researchers for the outsourcing of functions. Organisations sometimes choose to outsource over insourcing for many different benefits, although there are significant risks that must be considered during the decision-making process. Outsourcing is a major decision problem in business and mining industry (Steenkamp and Van Der Lingen, 2014; Azarnivand and Azarnivand, 2016).

3.3.1 Outsourcing Decision Problem in Mining Industry

Most problems can be solved using numerous approaches from simple intuition to mathematical based methods. Decision making can be solely independent or be influenced by several factors and the level of influence dictates the method to be used to solve the problem (Nazam *et al.*, 2020; Wang *et al.*, 2021). The choice of method is also reliant upon the complexity of the decision required (Li *et al.*, 2018). In management, most decisions are not just multi-objective problems, they also involve many people and consequences (da Silva *et al.*, 2019). This is because multiple conflicting objectives or criteria must be considered before for every single decision. For example, a decision to outsource blasting explosives supply will have to consider the economic benefits, environmental implications, governance and sustainability factors. These factors have conflicting objectives. Hence, management's decisions on problems are complex in nature. Outsourcing is one of the growing trends in management (Kremic *et al.*, 2006; Mwaniki, 2015; Modak *et al.*, 2017) and the decision to outsource is proving to be even more complex than most of the traditional management decision problems like marketing and production processes optimisation (da Silva *et al.*, 2018; Nazam *et al.*, 2020). Mining outsourcing decisions are even more complex because the core competence is outsourced, contrary to the common notion that the organisations should outsource their non-core competencies (Suglo, 2009; Steenkamp and Van Der Lingen, 2014; Modak *et al.*, 2019). Therefore, the choice of methods used throughout the outsourcing process is critical. However, there is limited research work on methods that could be used to make outsourcing decisions in the mining industry, with just a few in supplier selection and the dichotomous contract mining (outsource) versus owner mining (insource) decision problem.

The outsourcing decision process involves several steps and areas that require careful attention throughout the decision process, from the selection of methods to the final selection of the subcontractor. In mining, the most important decision problem is the first step of deciding whether to outsource or insource certain or all mining operations (Steenkamp and Van Der Lingen, 2014) guided by knowledge from available literature that outlines the variations in contract mining (Dunlop, 2004; Suglo, 2009; Rupprecht, 2015).

3.3.2 Outsourcing Decisions Nature and Process

The quality and integrity of the output of the decision process depends on the quality of the decision process (Rezaeisaray *et al.*, 2016). Therefore, all the stages, from a clear

articulation of the decision objective to managing the work of the contractor, including the critical stage of scoping, are critical to the output of the decision process and achieving the objective of the decision. The process begins with the problem definition or motivation to outsource and ends with evaluation of the work that needs to be done (Kremic *et al.*, 2006; Damanpour *et al.*, 2020). In mining, the most critical stages of the process are to assess the core competencies required and examine the unit operations to outsource for a given project because the mining industry has normalised outsourcing of its core competencies (Allonby, 1998; Steenkamp and Van Der Lingen, 2014; Modak *et al.*, 2017). This process is summarised in Figure 4 which is adopted after (Kremic *et al.*, 2006; McIvor *et al.*, 2009; Westphal and Sohal, 2013; Anon., 2014; Damanpour *et al.*, 2020).

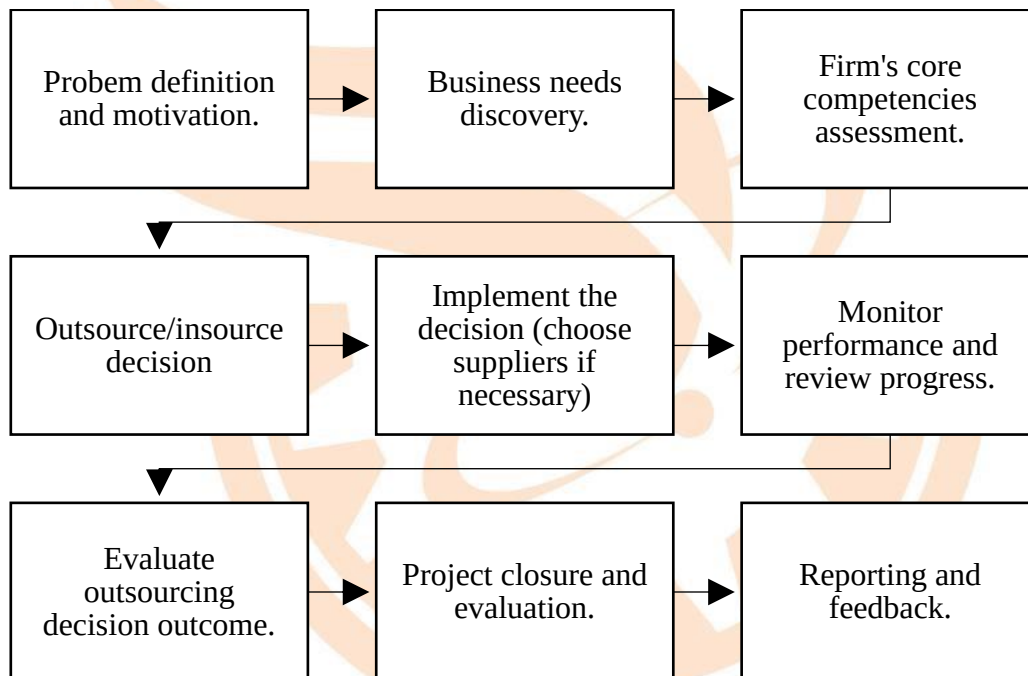


Figure 4 Outsourcing Decision Process

The problem is defined based on the situation faced by the mining company (owner/client). A problem statement that includes the background of the issue, the status quo and a review of the strategic goals that form a foundation for the decision problem. The subsequent stage is to determine business needs (Westphal and Sohal, 2013; Anon., 2014).

Based on the problem statement, the decision makers must explore the business functions and identify areas that can be examined for either alleviating an adverse economic, social,

or environmental situation faced by the company or improving the business strategic position within the industry. Once all the business needs have been identified out of the functions that have been explored, the core competencies must be assessed (Kremic *et al.*, 2006; Anon., 2014; Damanpour *et al.*, 2020). It was previously believed that a company cannot outsource its core competencies (Franceschini *et al.*, 2003; Steenkamp and Van Der Lingen, 2014). However, in mining it is a very common practice to outsource key competencies (Modak *et al.*, 2019). Hence in practical situations the core competence assessment stage in mining outsourcing may not be necessary unless mining support or auxiliary functions are being explored.

The scope of this study is on outsourcing of mining operations. Hence, more emphasis is given to the core activities of mining. The decision to either insource or outsource is made at the stage commonly referred to as the buy-or-make, insource-or-outsource decision, owner mining vs contract mining decision, or the decision to outsource (Suglo, 2009; Modak *et al.*, 2017). Due to the nature and complexity of this stage, this research recognises several alternatives that have not been explored in any previous research. Subsequent stages include making the decision from different expert opinions and objective analysis, defining the scope of work for the selected alternative, implementing the decision and choosing a supplier if the decision is to outsource, monitoring the work and evaluating the work (Kremic *et al.*, 2006; McIvor *et al.*, 2009; Damanpour *et al.*, 2020).

While the literature is rife with analysis of outsourcing problems up to the stage of choosing a supplier, there is limited literature on the insource or outsource decision stage. The decision-making problem being considered in this study is not simply choosing a company to outsource to. Rather, it considers all the possible alternatives for outsourcing in mining, including the decision to insource.

3.3.3 Outsource or Insource Decision Problem

The insource or outsource decision or owner mining vs contract mining is a critical and delicate stage in the outsourcing decision process (Suglo, 2009; Steenkamp and Van Der Lingen, 2014; Modak *et al.*, 2017; Modak *et al.*, 2019). Thus, more emphasis has been placed on that decision stage. Though supplier selection is important, more emphasis should be placed on the outsource-or-insource decision because whether a good supplier is chosen

or not, if a wrong decision is made from the outsource-or-insource decision stage, then the initial problem will not be solved.

It is imperative to put more emphasis on the decision to outsource for each mining project. The outsource-insource decision for mining operations includes several steps to be considered for each decision problem (Modak *et al.*, 2017). These steps include the selection of unit operations, resource choice, type of contract decision and the outlining of established lines of responsibility. Miners can outsource all or part of their unit operations or insource all for a given project. The key unit operations are drilling, blasting, materials handling, planning and scheduling, maintenance and pit services. Usually, drilling and blasting can be outsourced together while materials handling is outsourced separately. There are many alternative combinations for the unit operations that can be outsourced.

In addition, for each unit operation outsourced, there is a decision for the type of resources that have to be outsourced. The combination of resources and unit operations can consequently determine the type of contract and established responsibilities (Suglo, 2009; Rupprecht, 2015; Keel, 2018). When the scope of the contract is well defined, it is possible to eliminate the need for considering the options under each stage of the type of contract decision and established responsibility definition. There are two main classes of resources that can be outsourced for each alternative unit operation, the human resource (i.e. labour outsourcing) and the capital resources. Capital resources include raw materials like explosives, equipment and information technology while labour contracting involves the engagement of service from people due to their expertise and trades (Rupprecht, 2015). The most common combination for large miners is outsourcing drilling equipment, labour and explosives for blasting and maintenance of equipment (Luxford, 1998; Rupprecht, 2015) while junior miners outsource all resources for all unit operations except planning and scheduling.

3.3.4 MCDM Nature of the Outsourcing Decision Problem

There are several methods used to solve problems (Rezaeisaray *et al.*, 2016). Formal problems can be classified into single objective and multi-criteria problems with a number of problem types under each classification (Memari *et al.*, 2019; Dahooie *et al.*, 2021). The single objective problems are solved using different operational research methodologies like linear programming, dynamic programming, game theory and queuing theory - either

heuristic or stochastic methods. These methods use mathematical models to predict and optimise solutions for different practical problems with criteria that can be expressed with a single objective (Memari *et al.*, 2019). Many management problems are complex and have multiple conflicting objectives. For example, the need to maximise profit at the same time as maximising sustainability leads to two inversely proportional mathematical problems with conflicting parameters. Hence, a multi-criteria decision problem approach is required to solve such problems.

Mathematical models have been commonly used for different decision problems from prediction to optimisation. The work spans across planning and scheduling, productivity, cost management and rock stability. However, limited research work has been done on mathematical modelling of outsourcing problems, despite its increasing use (Hwang and Shen, 2015). The common mathematical models like single objective prediction and optimisation models are not very useful in outsourcing problems because they are complex and require a multi-criteria decision problem approach. Most multi-criteria decision making (MCDM) models are complex, hence the limited research available on the topic. Thus it is very critical to consider MCDM in depth, especially for the mining industry which has to approach mining operations considering a balance of environmental, social and governance as well as economic benefits (Steenkamp and Van Der Lingen, 2014; Modak *et al.*, 2019).

3.4 Multi-criteria Decision Making

Multiple-criteria decision-making (MCMD) is a decision analysis approach that deals with the ranking and selection of one or more alternatives (Deepa *et al.*, 2019). Multi-criteria analysis focuses mainly on three types of decision problems: choice to select the most appropriate (best) alternative; ranking (draw a complete order of the alternatives from the best to the worst) and sorting which is to select the best alternatives from a list (Roszkowska, 2011). Where the decision makers are interested in understanding the relative order of alternatives, the best alternative is usually not important and MCDM is only used for ranking purposes. The selection of one or more alternatives is based on the criteria and the assigned weights developed by expert decision makers. MCMD provides a framework for comparison of two or more alternatives based on evaluation of conflicting criteria (Roszkowska, 2011; Alshraideh *et al.*, 2021). There are several methods that have been developed to support decision making of MCDM problems.

3.4.1 Multiple-criteria Decision-making Methods

Several researchers have developed different methods that can be used for evaluating multi-criterial decision problems. Some of these methods are the balanced score card (BSC), case-based reasoning (CBR), analytical hierarchy process (AHP), analytical network process (ANP), data envelopment analysis (DEA), multi-attribute utility theory, simple additive weighting (SAW), ELECTRE, PROMETHEE, fuzzy set theory and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

MCMD methods have inadequacies and limitations for ranking alternatives accurately. The AHP/ANP methods have inter-dependency between the criteria and alternatives and this can lead to inconsistencies between expert judgement and ranking criteria (Senturk *et al.*, 2007; Rezaeisaray *et al.*, 2016; Kaur *et al.*, 2019; Nazam *et al.*, 2020) while case-based reasoning is highly sensitive to inconsistent data (Deepa *et al.*, 2019). Most of decision-making data is difficult to consolidate and clean. However, decisions must be made with the limited data in most cases. The DEA also relies heavily on accurate data because the results assume that the inputs and outputs are known (Rezaeisaray *et al.*, 2016). The ELECTRE method is difficult to interpret in practical terms and it has limited capacity for ranking alternatives based on the comparison of their weaknesses and strengths (Deepa *et al.*, 2019). The MAUT method requires a lot of inputs to give precise results (Deepa *et al.*, 2019). The PROMETHEE method has limited capabilities to accurately assign weights to criteria (Deepa *et al.*, 2019) while the results from the SAW method may be misinterpreted or be illogical (Kiani *et al.*, 2019; Dahooie *et al.*, 2021). To improve the accuracy of these methods most of their shortcomings are compensated for by combining them with other methods and in most cases fuzzy set theory.

Most of the MCDM methods have been complemented with fuzzy set theory to improve their accuracy in the decision-making process and give a clear reflection of the best alternative (criteria relationship needed to achieve the decision objective). Fuzzy set theory has been incorporated into several methods to remove human error, subjectiveness and ambiguity of decision outputs. Table 1 summarises the key areas for the application of the various methods.

Table 1 Summary of MCDM Methods Applications

Method	Application	Citation
MIC-MAC, Fuzzy-AHP and Fuzzy TOPSIS	Identifying the maintenance factors critical to enhance manufacturing sustainability.	(Kaur <i>et al.</i> , 2019)
BSC and Fuzzy AHP	Performance evaluation of outsourcing in coal mining.	(Modak <i>et al.</i> , 2017)
BSC-ANP	Selection of the best outsourcing strategy.	(Modak <i>et al.</i> , 2019)
Fuzzy SWARA and FUZZY AD	Evaluation of outsourcing provider selection.	(Perçin, 2019)
IV-Fuzzy QSPM	Determine most effective strategies for alliance evaluation.	(Barak and Javanmard, 2020)
Fuzzy TOPSIS	Evaluating the quality of tenders submitted for maintenance outsourcing.	(Alshraideh <i>et al.</i> , 2021)
Fuzzy TOPSIS and Fuzzy DEA-AHP	Determine the best combined outsourcing and offshoring strategy.	(Kaur <i>et al.</i> , 2019)
Fuzzy DEA-AHP	Decision framework for selecting IT service provider.	(Karami and Guo, 2012)
Fuzzy EDAS	Subcontractor evaluation.	(Keshavarz-Ghorabae <i>et al.</i> , 2018)
Fuzzy TOPSIS, Fuzzy ARAS, Fuzzy VIKOR, Fuzzy SAW, Fuzzy MABAC	Selecting the appropriate method of technology acquisition.	(Dahooie <i>et al.</i> , 2021)
DEMATEL, Fuzzy ANP, DEA	Pipe fitting and manufacturing outsourcing supplier selection.	(Rezaeisaray <i>et al.</i> , 2016)
Fuzzy AHP-TOPSIS	Analysing the barriers and prioritizing the possible pathways in adopting the SSCIs for the development of FPIs	(Nazam <i>et al.</i> , 2021)
Fuzzy TOPSIS	A novel model that includes the opinions of end users in decision making.	(Wang and Lee, 2009)
Fuzzy TOPSIS and Fuzzy DEMATEL	A novel technique for evaluating and selecting logistics service providers based on the logistics resource view.	(Alkhatib <i>et al.</i> , 2015)
IF-ANP and IF-DEMATEL	Customer relationship management partner evaluation.	(Büyüközkan <i>et al.</i> , 2017)
Fuzzy TOPSIS	Sustainable supplier selection considering the triple bottom line (TBL)	(Memari <i>et al.</i> , 2019)

3.4.2 Selection of MCDM Method for Study

The analytical hierarchy process (AHP), the analytical network process (ANP) and the technique for order preference by similarity to ideal solution (TOPSIS) are the most used

methods for outsourcing identified from the literature. While TOPSIS can be used as a single method with accurate results, AHP and ANP require the DEA, SAW or BSC to complement their accuracy and provide objective and clear results from decision making processes (Deepa *et al.*, 2019; Memari *et al.*, 2019; Modak *et al.*, 2019). Based on the preliminary assessment, TOPSIS is preferred for this study over other methods. Unlike AHP, the weights of the criteria and the ratings of alternatives with respect to criteria are evaluated independently and not relative to each other in TOPSIS (Roszkowska, 2011). Due to the nature of the alternatives developed for mining outsourcing decisions, the alternatives will probably score much the same, if not exactly the same, when standard Likert scales are used (Dahooie *et al.*, 2021).

From the literature, modified scales of weights and ratings that are sensitive to medium to minor differences for distinguishing between close alternatives has been proposed in this work, especially at the high ends of the scales. A decision-making model is developed based on the TOPSIS method. However, the TOPSIS method will likely give results that are ambiguous and may not allow for a clear comparison of alternatives because the criteria are often of incongruous dimensions in multi-criteria problems (Roszkowska, 2011). Accordingly, normalisation and clear representation of the rating of alternatives will be required (Neelima *et al.*, 2017). Therefore, the TOPSIS method will be complemented with fuzzy set theory and logic for accuracy and clear results. The final combination will give a combined MCDM method, the hybrid Fuzzy TOPSIS, which considers the rating of alternatives based on TOPSIS for quantitative criteria and uses Fuzzy TOPSIS for either qualitative or quantitative criteria without crisp values and cannot be estimated.

The TOPSIS is an MCDM method that provides compensatory aggregation, allowing for trade-offs between criteria, where a poor result in one criterion can be negated by a good result in another criterion (Roszkowska, 2011; Neelima *et al.*, 2017). This provides a more realistic form of modelling compared with non-compensatory methods, which include or exclude alternative solutions based on hard cut-offs. The method compares a set of alternatives by identifying weights for each criterion, normalising scores for each criterion and calculating the geometric distance between each alternative and the ideal alternative and gives the best score for each criterion (Roszkowska, 2011). TOPSIS assumes that the criteria are monotonically increasing or decreasing (Kaur *et al.*, 2019).

Fuzzy TOPSIS is one of the best methods of getting the best solution out of related alternatives. This method is very ideal for outsourcing problems because outsourcing problems seek to find the best alternative out of several outsourcing solutions (Kaur *et al.*, 2019). Also, it allows for process automation hence overcoming ambiguity and uncertainty in the selection process (Dahooie *et al.*, 2021). The challenge with Fuzzy TOPSIS is that it cannot capture crisp data in the decision model. Hence, even criteria with crisp data are estimated and represented through fuzzy numbers. This may reduce the credibility of the decision process because fuzzy numbers are meant to improve the accuracy of uncertain data and handling certain data as uncertain data reduces its accuracy. Thus, it is necessary to have a balance between methods to use for crisp and uncertain data. Therefore, this study uses a combination of TOPSIS for crisp data and Fuzzy TOPSIS for uncertain data.

The benefits of adopting the combined TOPSIS and Fuzzy TOPSIS hybrid methods are (Roszkowska, 2011; Neelima *et al.*, 2017; Galal *et al.*, 2018):

- Clear comparison of alternatives based on qualitative criteria which are expressed in linguistic terms.
- There is no need to convert quantitative criteria into fuzzy sets which preserves accuracy.
- Simple, rational and comprehensible concept.
- Intuitive and clear logic that represents the rationale of human choice.
- Ease of computation and good computational efficiency.
- A scalar value that accounts for both the best and worst alternatives' ability to measure the relative performance for each alternative in a simple mathematical form.
- Possibility for visualization.

The hybrid Fuzzy TOPSIS method simply uses the geometric distance between each alternative and the ideal alternative, expressed in a matrix and uses fuzzy numbers instead of real or interval numbers or qualitative labels in the MCDM matrix. Thus, it provides a simple and accurate method of decision analysis.

3.5 Hybrid Fuzzy TOPSIS Method

The Hybrid Fuzzy TOPSIS (HFTOPSIS) method takes advantage of the benefits of TOPSIS and Fuzzy TOPSIS by combining the two methods in a single matrix. The multi-criteria

decision-making technique accounts for the subjective judgement of humans by evaluating multiple alternatives against the selected criteria while adopting crisp values obtained from historical data to reflect objective judgement. In both the TOPSIS and the Fuzzy TOPSIS approaches an optimal alternative is one that has the shortest geometrical distance (closest) to the Positive Ideal Solution (PIS) and the longest geometrical distance (farthest) from the Negative Ideal Solution (NIS) (Roszkowska, 2011; Neelima *et al.*, 2017). The HFTOPSIS method uses real numbers for quantitative criteria with crisp values available for decision makers, then fuzzy numbers are used for qualitative criteria and quantitative criteria without crisp values separately and combines the results in the same matrix before normalizing it to arrive at the final ranking. Figure 5 shows the framework for using this method. The steps are explained in Section 3.6 of the literature review.

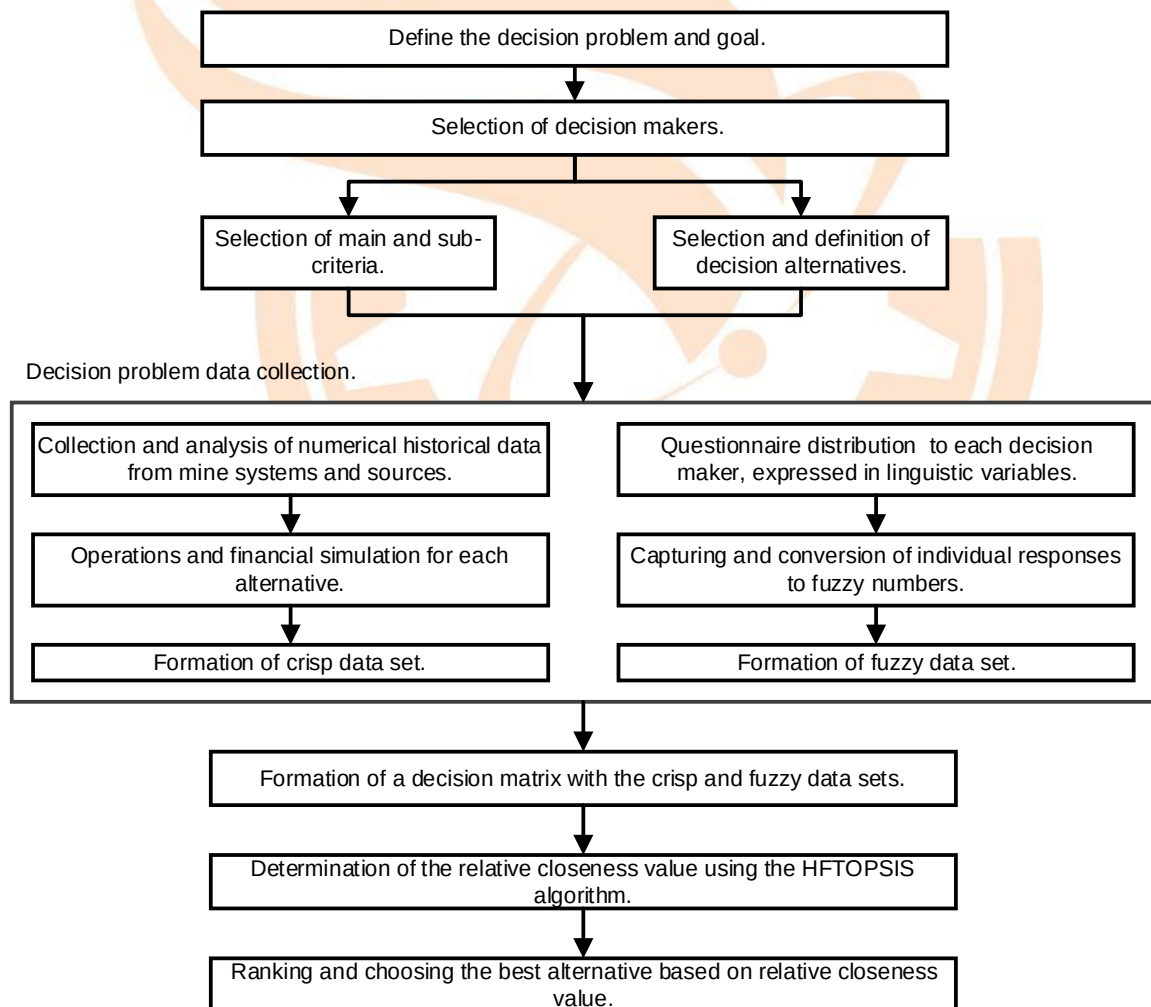


Figure 5 HFTOPSIS Framework for Mining Outsourcing Decision Problem

Utilising the fuzzy theory, decision makers (DMs) use linguistic assessments to overcome the need to provide crisp numerical values that they are not able to estimate in the first place (Dahooie *et al.*, 2021). Like other decision-making models, the solution of the decision problem is an alternative or set of alternatives that were derived based on a set of criteria.

3.5.1 Decision Criteria

The decision criteria are classified into two types: the “benefit criteria” and “cost criteria” as shown in Table 2 (Roszkowska, 2011; Neelima *et al.*, 2017). The benefit criteria are the decision factors that the decision makers are willing to maximise because when an alternative has a high value for the benefit criteria it becomes more attractive and when it has a lower value it becomes less attractive. This is contrary to the cost criteria. Cost criteria are decision factors that the decision makers will try to reduce because they create losses when an alternative has a high value for the cost criteria, while they will gain from a lower value in cost criteria. For example, operating cost and profit margin risks are cost criteria, while capital efficiency and quality are benefit criteria.

Table 2 Decision Criteria Classification and Hierarchical Structure

Level 1 Decision Goal	Level 2 Main Criteria	Level 3 Sub-criteria	Benefit/Cost Criteria
Selection of the best mining operations outsourcing method	Flexibility-based factors	Project life	Cost criteria
	Operating cost-based factors	Transaction cost	
		Operating cost	
	Relationship-based factors	Social licence to operate	Benefit criteria
	Relationship-based factors	Strategic relationship	
		Environmental sustainability	
	Capital efficiency-based factors	Capital efficiency ratio	
		OEE	
	Operating cost-based factors	Profit margin risk	
	Flexibility-based factors	Mining rates	
	Competence-based factors	Attraction and retention of talent	
		Protect core competence	
		Quality	
		Technological competitiveness	

The cost criteria are aimed to minimise the cost and the best value in the cost criteria is the minimum one (the lowest cost), while the benefit criteria should be maximised, and the best value is the highest value (most beneficial) (Jahan *et al.*, 2019). These criteria are applied to each alternative and there must be a minimum of two alternatives to apply the TOPSIS method. This requires determining the criteria first (Roszkowska, 2011; Neelima *et al.*, 2017). The fuzzy part of the TOPSIS is based on the type of numbers used in the decision matrix. The TOPSIS decision matrix is replaced with fuzzy numbers to make a Fuzzy TOPSIS decision matrix.

The decision on whether a criterion is used for ranking as a real or fuzzy number is based on the available information. Fuzzy numbers are used for subjective judgement. Where a criterion is quantitative and it can be measured but at the time of decision making there is limited information to compare alternatives based on crisp values, linguistic variables are used and Fuzzy TOPSIS is adopted for analysis. All qualitative criteria are measured based on linguistic variables and analysed as fuzzy numbers. Fuzzy TOPSIS analysis is based on the fuzzy set theory (Galal *et al.*, 2018).

3.5.2 Fuzzy Set Theory

Fuzzy set theory is an extension to the common set theory and it is commonly applied to problems relating to ambiguous, subjective and imprecise judgments (Nguyen *et al.*, 2021). It can quantify the linguistic facet of available data and preferences for individual or group decision-making (Azarnivand and Azarnivand, 2016). A crisp set has one object belonging to one and only one set (Roszkowska, 2011). This becomes a problem when dealing with ambiguous, vague and imprecise data like linguistic variables e.g. the Likert scale (Neelima *et al.*, 2017). Fuzzy sets handle such situations by attributing a degree to which a certain object belongs to a set. Fuzzy sets were first used by Zadeh (1965) to overcome the uncertainty stemming from inconsistencies and ambiguities. Fuzzy set theory is mostly useful for its capacity to represent uncertain data. The theory is quite suitable for mathematical operations and programming in the fuzzy area (Zadeh, 1965). The Fuzzy Set Theory is used to remove the uncertainty and subjectivity in the decision-making process by means of linguistic variables.

Fuzzy numbers are used in the evaluation of decision problems where linguistic variables are employed because crisp data is difficult to obtain when solving most multi-criteria

decision problems. A linguistic variable is a variable which applies words or sentences in a natural or artificial language to describe its degree of value. This kind of expression is used to compare each criterion by using comparative phrases in a fuzzy environment (Zadeh, 1965). For example, degree of weights could compare as “extremely low”, “very low”, “low”, “high”, “very high” and “extremely high” with respect to a fuzzy five level scale. The linguistic variables and corresponding fuzzy numbers developed for this study are summarised in Table 3.

Table 3 Linguistic Variables for Degree of Importance of Criteria and for Rating of Alternatives

Fuzzy Number	Weighting of Criteria	Rating of Alternatives
(1,1,2)	Extremely Low (EL)	Extremely Poor (EP)
(1,2,3)	Very Low (VL)	Very Poor (VP)
(2,3,4)	Low (L)	Poor (P)
(3,4,5)	Slightly Low (SL)	Slightly Poor (SP)
(4,5,6)	Medium (M)	Fair (F)
(5,6,7)	Slightly High (SH)	Slightly Good (SG)
(6,7,8)	High (H)	Good (G)
(7,8,9)	Very High (VH)	Very Good (VG)
(8,9,9)	Extremely High (EH)	Extremely Good (EG)

The absolute set theory may be inadequate in the presence of linguistic variables in solving a decision problem, because each linguistic variable is partially attributed to a set (Azarnivand and Azarnivand, 2016). The variables in fuzzy sets are attributed to a set with a certain degree. Many decision problems include unclear and imprecise data. Therefore, solution methods developed without considering the level of uncertainty and ambiguity do not always lead to accurate results. The fuzzy set is applied to represent ambiguity and subjective judgement.

The members of a fuzzy set $\mu_A(x)$ can take values between 0 and 1, which is called membership degree as shown in Figure 6. If x is definitely an element of set A , then it is defined as $\mu_A(x) = 1$. If not, then it is defined as $\mu_A(x) = 0$. The higher the value of the

membership degree is, the higher the degree of x as a member of set A (Nguyen *et al.*, 2021). There are different types of fuzzy numbers adopted for the fuzzy set theory and fuzzy logic. Triangular fuzzy numbers (TFN) are commonly used in most studies and in this study.

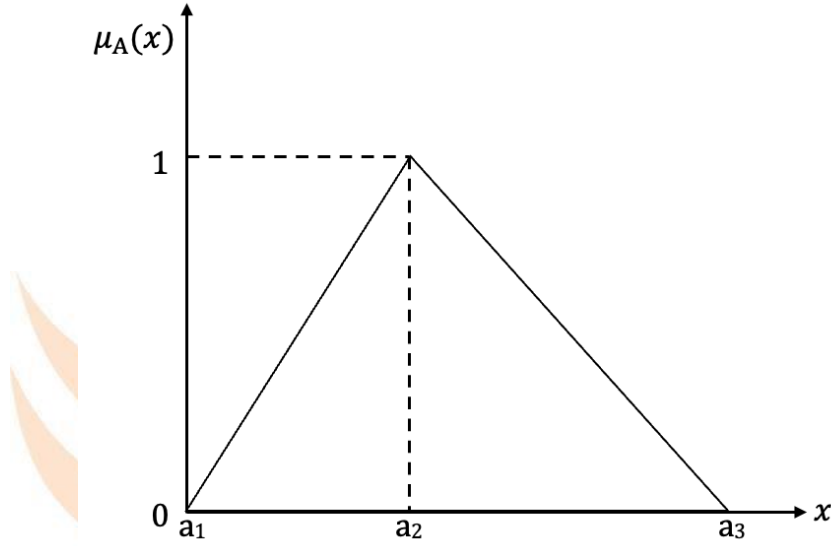


Figure 6 TFN Diagram

To describe the fuzzy set theory based on TFNs, some definitions are presented as follows (Neelima *et al.*, 2017; Keshavarz-Ghorabae *et al.*, 2018; Alshraideh *et al.*, 2021):

Definition 1: A fuzzy set A in a universe of discourse X is characterised by a membership function $\mu_A(x)$ that maps each element x in X to a real number in the interval $[0, 1]$ as expressed in equation 1. The function value $\mu_A(x)$ is termed the grade of membership of x in A . The nearer the value of $\mu_A(x)$ to unity, the higher the grade of membership of x in A .

$$A = \{(x, \mu_A(x)) \mid x \in X\} \quad (1)$$

Definition 2: A fuzzy number can be defined as a special case of a fuzzy set which is convex and normal.

Definition 3: A triangular fuzzy number (TFN) is represented as a triplet $A = (a_1, a_2, a_3)$. A TFN is defined by equation 2 and graphically by Figure 6 with three values defining the degree of membership.

$$\mu_A(x) = \begin{cases} (x - a_1)/(a_2 - a_1), & a_1 \leq x \leq a_2 \\ (a_3 - x)/(a_3 - a_2), & a_2 \leq x \leq a_3 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

When using TFNs or other types of fuzzy numbers, there is need for computations. Thus, it is necessary to clearly define how operations are carried out for the TFN. The arithmetic operations are expressed in definition 4 while defuzzification are expressed in definition 5.

Definition 4: Let $A = (a_1, a_2, a_3)$ and $B = (b_1, b_2, b_3)$ be two triangular fuzzy numbers which are also positive (i.e. $a_1 \geq 0$ and $b_1 \geq 0$) and suppose n is a crisp number. Then, equations 3 to 10 present the arithmetic operations of the two TFNs:

1. Addition:

$$A \oplus B = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \quad (3)$$

$$A + n = (a_1 + n, a_2 + n, a_3 + n) \quad (4)$$

2. Subtraction:

$$A \ominus B = (a_1 - b_1, a_2 - b_2, a_3 - b_3) \quad (5)$$

$$A - n = (a_1 - n, a_2 - n, a_3 - n) \quad (6)$$

3. Multiplication:

$$A \otimes B = (a_1 \times b_1, a_2 \times b_2, a_3 \times b_3) \quad (7)$$

$$A \times n = \begin{cases} (a_1 \times n, a_2 \times n, a_3 \times n), & \text{if } n > 0 \\ (a_3 \times n, a_2 \times n, a_1 \times n), & \text{if } n < 0 \end{cases} \quad (8)$$

4. Division:

$$A \oslash B = (a_1 \div b_1, a_2 \div b_2, a_3 \div b_3) \quad (9)$$

$$A \div n = \begin{cases} (a_1 \div n, a_2 \div n, a_3 \div n), & \text{if } n > 0 \\ (a_3 \div n, a_2 \div n, a_1 \div n), & \text{if } n < 0 \end{cases} \quad (10)$$

Definition 5: The crisp value of a triangular fuzzy number $A = (a_1, a_2, a_3)$ is defined by equation 11 to represent the defuzzification of the TFN.

$$D(A) = \frac{1}{3} \times (a_1, a_2, a_3) \quad (11)$$

3.5.3 The HFTOPSIS Solution

This is the matrix with the rows and columns and how a decision is made from them.

3.6 HFTOPSIS Model Algorithm

In HFTOPSIS, performance ratings and weights are represented by both real numbers (for available crisp data) and fuzzy numbers (for unavailable crisp data). The alternative rankings are determined by aggregating the product of criteria weights and alternative ratings, where alternatives with higher-ranking values are preferred. The TOPSIS method is used with real numbers while the Fuzzy TOPSIS method uses fuzzy numbers. Where crisp data are inadequate to model the real-life situation, linguistic variables are applied to specifically describe the degrees of a criterion in Fuzzy TOPSIS (Fadavi *et al.*, 2013).

The common TOPSIS method assumes that the ratings of alternatives and weights are represented by numerical data and the problem is solved by a single decision maker (Roszkowska, 2011). As a common practice, there are more than one decision makers, and this makes the decision process to be complex because the preferred solution must be agreed on by interest groups who usually have different goals. Nevertheless, algorithms are developed to assist and accommodate the number of decision makers. In HFTOPSIS, decision makers (DM) use fuzzy numbers based on two data sets for assessing criteria weights and alternative rating. One set is of linguistic terms and the other is of real numbers for crisp data. The linguistic variables are defined in Table 3. The multi-criteria group decision making HFTOPSIS algorithm is as illustrated in Figure 5.

3.6.1 Decide on the Criteria

The criteria and sub-criteria are determined based on factors that mostly influence the decision to be made and the problem to be solved (Deepa *et al.*, 2019). The details about the type of criteria and how they should be classified are explained in Section 3.5.1. Using HFTOPSIS, the criteria must be classified into qualitative and quantitative data i.e. those that have crisp data sets and those with linguistic data sets, and lastly into cost and benefit

criteria (Roszkowska, 2011). This is important because decision analysis is made based on such classifications.

3.6.2 Decide on the Alternatives

There are different possible alternatives that can be considered when making outsourcing decisions or the buy-or-make decision as it is commonly known. In mining the outsourcing decision is considered as the contract mining decision. The available literature has covered the alternatives of contract mining, owner mining and strategic alliance (Suglo, 2009; Steenkamp and Van Der Lingen, 2014; Modak *et al.*, 2019). The decision alternatives are sufficient to decide using the HFTOPSIS method, but they are limited, and they do not wholly reflect the outsourcing practices in mining operations. HFTOPSIS requires a minimum of two alternatives and a maximum of 20 alternatives for a decision matrix to be formed and solved (Deepa *et al.*, 2019). In this study, a set of alternatives are developed from the literature and observations for the outsourcing decision problems in the case study.

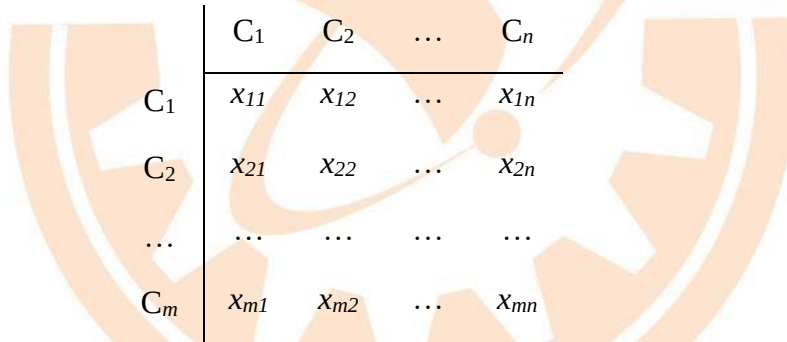
3.6.3 Determine Global Criteria Weights

Decision alternatives are chosen and ranked based on the criteria selected for the decision problem (Wang *et al.*, 2019). The criteria vary with the importance of the decision problem. Therefore, a decision hierarchy is usually adopted, and the criteria is weighted to determine the relative importance of each criterion. In this study, the AHP method was used to determine the weight of the criteria because it takes into consideration the interdependencies of the main and sub-criteria necessary for ranking alternatives. AHP develops a hierarchical structure of the decision problem with the goal at the level 1 and alternatives at the level 4 as shown in Table 2 (Nazam *et al.*, 2020). There are usually 3 or 4 levels, depending on whether the decision problem considers sub-criteria or not. At level 1 of the hierarchy, the goal of the decision problem is the objective of the decision process and it defines the purpose that the decision makers are pursuing throughout the decision process (Nazam *et al.*, 2020). For example, a decision goal could be to buy an equipment, outsource operations or select a contractor. From the decision goal, there are criteria or attributes at level 2 that should be considered to ensure that the decision goal is fulfilled by the alternative chosen (see Table 2). Level 3 is made up of sub-criteria and it is not always part of the hierarchy. The last level, which can be level 4 if the hierarchy includes sub-criteria or level 3 on a normal hierarchy consists of the alternatives. In this study, there are 4 levels (see Table 2) and global weights are considered.

Global criteria weights are the aggregated weights considering both the sub-criteria and the main criteria weights. The main criteria weights, which are the weights of classes of criteria grouped based on their relations for easy comparison with each other, are determined. The local weights within each main criteria are then determined and the product of local weights and corresponding main weights are calculated to find the global weights as described in the following steps (Azarnivand and Azarnivand, 2016; Nazam *et al.*, 2020).

Step 1: Develop a hierarchical structure as shown in Table 2. The goal is at the top level, the criteria at levels 2 and 3 and alternatives at level 4.

Step 2: Formulate a pairwise comparison of level 2 criteria (the main criteria) and determine the weights of the main criteria. The pairwise comparison is made of the main criteria in the columns and the same criteria in the rows as shown in Figure 7. Considering n criteria, $C_1, C_2, \dots, C_n$, to form columns and the same $C_1, C_2, \dots, C_m$, to form rows, a pairwise matrix $n \times m$ is formed where, $n = m$.



	C_1	C_2	$\dots$	C_n
C_1	x_{11}	x_{12}	$\dots$	x_{1n}
C_2	x_{21}	x_{22}	$\dots$	x_{2n}
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
C_m	x_{m1}	x_{m2}	$\dots$	x_{mn}

Figure 7 Matrix for Pairwise Comparison of Main and Sub-criteria

The matrix in Figure 7 is used for pairwise comparison. Each criterion in the row is compared to another criterion in a column to give a comparison value x_{ij} for each comparison using linguistic values in Table 4 ranging from equal importance to extreme importance. For each comparison, the question of how important criterion m is with respect to criterion n must be answered. The answer is given by linguistic variables. The values are then converted to real numbers through the pairwise scale in Table 4. The value for inverse comparison is assigned the inverse element. The normalised pairwise matrix is calculated by finding the sum of columns and dividing each element of the column by the sum of the

column. The criteria weights are then determined by calculating the average of all elements in the row giving the main criteria weights.

Table 4 Linguistic Variables for Pairwise Comparison for Defining Weights

Linguistic Variables	Pairwise Scale
Equal importance	1
Moderate importance	3
Strong importance	5
Very strong importance	7
Extreme importance	9
Intermediate values	2, 4, 6, 8
Values for inverse comparison	1/3, 1/5, 1/7, 1/9

Step 3: The same procedure in Step 2 is followed for the sub-criteria to obtain the local weights of decision criteria. The difference is that the sub-criteria are compared within a class of criteria (main criteria). Only the sub-criteria under the same main criteria are compared against each other. The results are the local criteria weights.

Step 4: The global criteria weights are determined by finding the product of local weights and corresponding main weights for each criterion. The global weights are normalised by dividing each weight w_n by the sum of all weights to form a weight vector W in equation 12:

$$W = [w_1, w_2, \dots, w_n]. \quad (12)$$

The global criteria weights are used in the HFTOPSIS decision matrix to form a weighted HFTOPSIS decision matrix.

3.6.4 Decision Matrix Formation

All TOPSIS methods start with the formation of a matrix (Roszkowska, 2011). In the HFTOPSIS method, two different matrices for the crisp data and for the fuzzy data are formed and the matrices are combined through addition. TOPSIS problems can be divided into classical and multiple criteria. The classical MCDM are among the set of problems

which the ratings and the weights of criteria are measured in crisp numbers (Roszkowska, 2011). The multiple criteria decision-making set of problems are those where the ratings and the weights of criteria are evaluated on incomplete information, imprecision, subjective judgment and vagueness and are usually expressed by interval numbers, linguistic terms, fuzzy numbers or intuitive fuzzy numbers (Neelima *et al.*, 2017). Therefore, the crisp and fuzzy data sets are formed independently.

MCDM problems can be solved by a single decision maker (DM) or by multiple DMs (Roszkowska, 2011). The nature of MCDM problems warrants the need of more than one decision maker (Uygun *et al.*, 2014). The HFTOPSIS developed from this study formulates the model based on multiple decision makers. Therefore, the decision matrix is formed by considering the number of decision makers as shown in Figure 8.

	C_1	C_2	$\dots$	C_n
A_1	x_{11}^k	x_{12}^k	$\dots$	x_{1n}^k
A_2	x_{21}^k	x_{22}^k	$\dots$	x_{2n}^k
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
A_m	x_{m1}^k	x_{m2}^k	$\dots$	x_{mn}^k

Figure 8 HFTOPSIS Decision Matrix

Let a set of decision makers or experts be denoted by $D = \{1, 2, \dots, K\}$, where K denotes the total number of DMs. Then the multi-criteria problem can be expressed in a k -matrix format (see Figure 8).

The $n \times m$ matrix denoted as $X^k = (x_{ij}^k)$ has n criteria and m alternatives (Roszkowska, 2011) where:

1. $A_1, A_2, \dots, A_m$ represent possible alternatives for DMs to choose from.
2. $C_1, C_2, \dots, C_n$ are decision criteria for the decision problem.
3. x_{ij}^k is the k -decision maker rating of alternative A_i with respect to the criterion C_j representing the value of i alternatives with respect to the j^{th} criterion for k -decision maker, for $i = 1, 2, \dots, n, j = 1, 2, \dots, m, k = 1, 2, \dots, K$.
4. x_{ij}^k is a real number for crisp matrix and a fuzzy number for fuzzy matrix.

5. The sizes of both the crisp matrix and the fuzzy matrix are the same.

The relative importance of each criterion is given by the normalised weights calculated through AHP. From equation 12, a weight vector that considers the number of decision makers is formed. If W^k be a weight vector for k -decision maker where $w_j^k \in \Re$ for $j = 1, 2, \dots, n$, is the k -decision maker weight of criterion of C_i and $w_1^k + w_2^k + \dots + w_n^k = 1$, then the weight vector for k -decision maker can be expressed by equation 13 as:

$$W^k = w_1^k + w_2^k + \dots + w_n^k \quad (13)$$

The crisp matrix is formed by real numbers representing ratings of each alternative with respect to the corresponding criterion (Roszkowska, 2011). This is done by inputting data collected from different sources representing each criterion for a given alternative. The values are real numbers, and they can be presented in any data format for use by the decision makers. The process of collecting data and presenting it in the format usable for decision making is explained for each quantitative criterion in Section 3.7. Elements representing ratings for alternatives with respect to linguistic variable criteria are assigned the value of zero. The size of the matrix should include all the criteria and alternatives.

Fuzzy matrix is formed by fuzzy numbers. Data is collected from the decision makers through a questionnaire. Each decision maker is given a questionnaire to rate alternatives against a set of criteria based on the linguistic variables. The linguistic variables are converted to fuzzy numbers using conversions in Table 3 to form a fuzzy decision matrix. The decision matrix for the linguistic variables takes the same form as of the crisp matrix as shown in Figure 8 and the elements that have non-zero values in the crisp matrix are to be assigned zero values on the fuzzy matrix.

The crisp and fuzzy matrices are combined through addition of matrices. The crisp and fuzzy criteria will not always be equal and this will create problems when combining the matrices, because addition of matrices is only possible for matrices of the same size (Roszkowska, 2011). Therefore, the matrices must be of the same size and for this decision process, the size of the matrices is accounted for by assigning zero for alternative ratings where the criteria are not considered in the specific matrix i.e. when cost criterion is considered in

matrix 1 and not in matrix 2, the value zero is assigned for cost to all alternatives in matrix 2. The combined matrix is the final decision matrix used for determining the relative closeness value (closeness coefficient) required for the HFTOPSIS algorithm.

3.6.5 Closeness Coefficient for Alternatives

The closeness coefficient (CC) is the basis of comparison for all TOPSIS methods (Deepa *et al.*, 2019). CC compares alternatives as a reflection of their distance to the positive ideal solution (PIS) and the negative ideal solution (NIS). The HFTOPSIS also uses the CC as basis for comparison. The objective of HFTOPSIS for solving any outsourcing decision problem is to determine the best solution. In HFTOPSIS, the best solution is the alternative with the shortest distance to the PIS and the longest distance to the NIS and that is reflected by the CC. To determine the CC, a series of steps are followed. From the decision matrix and the weight vector, the CC is determined as follows (Roszkowska, 2011):

Step 1: Calculate the normalised decision matrix: Normalising the decision matrix transforms various attribute dimensions like percentage, currency, time and tonnage into non-dimensional attributes which allows comparisons across criteria. In HFTOPSIS, the scores in the each decision maker's evaluation matrix, X^k , must be transformed to a normalised scale (Roszkowska, 2011). Each rating element is standardised using equation 14 and both the fuzzy and real numbers retain their form. Among several common normalisation methods, equation 14 is used for calculating the normalised value r_{ij} in HFTOPSIS for each decision maker (Roszkowska, 2011; Neelima *et al.*, 2017; Kaur *et al.*, 2019):

$$r_{ij}^k = x_{ij}^k / \sqrt{\sum_{i=1}^m (x_{ij}^k)^2} \quad (14)$$

for $i = 1, 2, \dots, m; j = 1, 2, \dots, n$.

Step 2: Determine the positive ideal and negative ideal solutions for each decision maker: The PIS is the extremely desired outcome on each criterion while the NIS is reverse extreme performance on each criterion (Deepa *et al.*, 2019). Both the PIS and the NIS are identified for each decision maker in this step. The ideal positive solution is the solution that maximises the benefit criteria and minimises the cost criteria whereas the negative ideal

solution maximises the cost criteria and minimises the benefit criteria (Neelima *et al.*, 2017). For HFTOPSIS, multiple decision makers are involved, and each k -matrix is considered separately at this stage. Hence the PIS and NIS are determined based on each k -matrix value.

The positive ideal solution A^{k+} for k -decision maker in matrix X^k is expressed by equation 15:

$$A^{k+} = \{r_1^{k+}, r_2^{k+}, \dots, r_n^{k+}\} = \{(\max_i(r_{ij}^k) \mid j \in B), (\min_i(r_{ij}^k) \mid j \in R)\} \quad (15)$$

The negative ideal solution A^{k-} for k -decision maker in matrix X^k is expressed in equation 16:

$$A^{k-} = \{r_1^{k-}, r_2^{k-}, \dots, r_n^{k-}\} = \{(\min_i(r_{ij}^k) \mid j \in B), (\max_i(r_{ij}^k) \mid j \in R)\} \quad (16)$$

where: B is associated with benefit criteria and R is associated with cost criteria, $i = 1, 2, \dots, m$; $j = 1, 2, \dots, n$.

Step 3: Calculate the separation measures from the positive ideal solution and the negative ideal solution: In this step, the DMs' matrices are aggregated, and the relative importance of each weight is factored in through weights. The weighted matrix is determined through the combined separation measure formulas in equations 17 and 18 for each k -matrix and the results are aggregated to obtain the group separation measures which are used to find the closeness coefficient (Roszkowska, 2011).

The separation of i^{th} alternative A_i from the PIS A^{k+} for each k -decision maker is given by equation 17:

$$d_i^{k+} = (\sum_{j=1}^m w_j^k (r_{ij}^k - r_j^{k+})^p)^{1/p}, i = 1, 2, \dots, m. \quad (17)$$

The separation of i^{th} alternative A_i from the NIS A^{k-} for each k -decision maker is given by equation 18:

$$d_i^{k-} = (\sum_{j=1}^m w_j^k (r_{ij}^k - r_j^{k-})^p)^{1/p}, i = 1, 2, \dots, m. \quad (18)$$

where: $p \geq 1$ For $p = 2$ the metric is a Euclidean metric.

The group separation measure is calculated by aggregating the separation measures calculated for each individual decision maker (Roszkowska, 2011). The aggregation of measure for the group measures of the positive ideal solution, d_i^{*+} , and negative ideal solution, d_i^{*-} , for the i^{th} alternative A_i is given by the arithmetic mean as given by equations 19 and 20 respectively:

Positive ideal solution measure of separation d_i^{*+} has the form as in equation 19.

$$d_i^{*+} = \sum_{k=1}^K d_i^{k+} / K \quad (19)$$

Negative ideal solution measure of separation d_i^{*-} has the form:

$$d_i^{*-} = \sum_{k=1}^K d_i^{k-} / K \quad (20)$$

Step 4: Calculate the relative closeness to the positive ideal solution: The separation measures are used to determine the relative closeness to the PIS or the CC (Neelima *et al.*, 2017). The relative closeness of the alternative A_i to the positive ideal solution R_i^* is calculated using equation 21, the CC values obtained are used for choosing the best alternative. The larger the index value, the better the evaluation of the alternative (Roszkowska, 2011).

$$R_i^* = d_i^{*-} / (d_i^{*-} + d_i^{*+}), i = 1, 2, \dots, m. \quad (21)$$

where $0 \leq R_i^* \leq 1$.

Step 5: Rank the preference order and choose the best alternative: A set of alternatives are then ranked in descending order by the value of R_i^* which is the closeness coefficient (CC) in the HFTOPSIS method. In this method the alternative with the value closest to 1 is the best solution (i.e., the alternative with the highest CC value is the best). The best alternative

is implemented according to stage 5 of the outsourcing decision process as outlined in Figure 4 and it is the solution to the outsourcing problem.

3.7 Decision Criteria Selection

The criteria used are selected from literature depending on the dichotomous choice between owner and contract mining. There is limited literature on the analysis which recognises the different polychotomous alternatives for mining operations outsourcing. The criteria were adopted from several literature sources and the analysis done with the summary of criteria results presented in Table 5 (Luxford, 1998; Suglo, 2009; Steenkamp and Van Der Lingen, 2014; Rupprecht, 2015; Keel, 2018).

Table 5 Decision Criteria Summary

Sub Criteria	Qualitative/ Quantitative	Desired Outcome
Operating cost-based factors		
Profit margin risk	Quantitative	Minimise risk
Transaction cost	Quantitative	Minimise costs
Operating cost	Quantitative	Minimise costs
Capital efficiency-based factors		
Capital efficiency ratio	Quantitative	Maximise return on capital resources
OEE	Quantitative	Maximise return on capital resources
Flexibility-based factors		
Project life	Quantitative	Minimise payback period
Mining rates	Quantitative	Minimise mining rates deviation
Competence-based factors		
Attraction and retention of talent	Qualitative	Maximise human resource competence
Protect core competence	Qualitative	Maximise on core competence
Quality	Qualitative	Minimise quality management challenges
Technological competitiveness	Qualitative	Maximise competitiveness
Relationship-based factors		
Social licence to operate	Qualitative	Minimise risk
Strategic relationship	Qualitative	Maximise client-contractor relationship
Environmental sustainability	Qualitative	Minimise adverse environmental impact

The criteria were developed to fulfil a decision goal for mining operations outsourcing decision process. Firstly, the main criteria are developed to satisfy the decision goal, then sub-criteria are developed to fulfil the main criteria. The decision goal for outsourcing mining operations is to optimise the strategic position of the mining company through balance of cost and strategic key performance indicators like quality and sustainability. The decision goals are summarised in Table 2 as the selection of the best mining operations' outsourcing method.

3.7.1 Operating Cost-Based Factors

Operating cost-based factors are those factors that are a result of the financial implications of the operational activities. These include profit margin risk, transaction cost and operating cost.

Profit margin risk: The profit margin is a profitability ratio that indicates the income per unit sale as expressed in equation 22. This measures the capacity of operations to make profit relative to the costs incurred by the company. The ratio decreases with high expenses, low selling prices and/or low sales volume and the opposite is true (Anon., 2018b).

$$\text{Net Profit Margin Ratio} = \frac{\text{Net Income}}{\text{Sales}} \times 100 \quad (22)$$

In the mining industry, the price of the mineral is determined mainly by external factors and companies have limited influence on it. For example, the price of diamonds is hugely controlled through an oligopolistic market through the supply and demand influence (Lilja *et al.*, 2015). This leaves companies with the two options of controlling sales volumes and expenses. In most cases the overhead costs are more than the operating costs (Nguyen *et al.*, 2021). Fixed labour costs constitute 40 to 60% of the total mining costs (Sloan, 2013). These costs are incurred whether the business is making profit or not because of employee contracts and other contractual obligations. Therefore, mining companies opt to change their fixed cost of operations to variable cost of operations to control the risk of running a negative profit margin under low sales volumes (Bryant, 2015) where they cannot make enough money to pay all their fixed costs. Outsourcing is one of the easy ways of changing fixed costs to variable costs especially when contracts are set on cost per unit delivered. Hence companies will opt for outsourcing to make sure they only pay for the volumes delivered,

in the case of mining for the tonnage of waste or ore that has been moved. In some cases, outsourcing can increase the cost incurred by a company despite increased production and sales volumes due to variations in claims and other financial factors. Hence, it is not obvious that outsourcing will always reduce the profit margin's risk and each case must be handled independently.

Profit margin is a quantitative criterion which can be determined using equation 22. Both the net income and sales are obtained from the profit and loss or income statement of the 3-statement financial model of a project or company under study. The best alternative is one with the highest profit margin expressed as a percentage.

Transaction cost: This is the cost related to any form of trade or transfer of value. Transaction costs will occur when dealing with another external party from sourcing supplies and services to selling goods or services to customers (Golosinki, 1998). Examples of transaction costs include search and information costs to find the supplier; bargaining and decision costs to purchase the component and policing and enforcement costs to monitor quality (Beare, 2011). It is in the interest of management to internalise transactions as much as possible to remove these costs and the resulting risks and uncertainties about prices and quality (Steenkamp and Van Der Lingen, 2014). The longer the value chain for handling goods or services before they arrive at a company the higher the transaction costs for the goods or services. The advantage of a longer value chain is that it reduces the number of transactions that are to be handled over a company deciding to insource services or goods. On the other hand, handling many transactions is costlier than handling a few transactions that are afforded by a longer value chain. Hence it is imperative to analytically compare all polychotomous alternatives for insourcing and outsourcing decisions for all transaction costs involved before making any decisions.

Transaction cost is associated with the liquidity of a company and it is determined through different cash management models such as the Baumol, Miller-Orr or the Stone model (Kaur *et al.*, 2019). The Baumol model is adopted in this study. As a quantitative criterion, transaction cost is calculated using equation 23 which is adopted from the Baumol model (Baumol, 1952):

$$\text{Transaction Cost} = \sum(\text{Cost of transaction} \times \text{Number of transactions}) \quad (23)$$

According to the Baumol model, the parameters presented in equation 23 represent transaction costs in the financial market (Baumol, 1952) and they have been adopted for the commodity industries like mining. The cost per transaction represents the markup on each good or service by the supplier for adding value to the goods or service. Cost per transaction may be determined using equation 24:

$$\text{Markup} = \text{Selling Price} - \text{Cost of Production} \quad (24)$$

The number of transactions is the total transactions between a company and the specific supplier for the same transaction over a financial year period. The best alternative is one with the lowest transaction cost expressed in a chosen currency like the Botswana Pula (US\$) or the US dollar.

Operating cost: This is a quantitative criterion that determines the profitability of a company. Operating costs are the costs that are directly attributed to the core business of a company. It is the total cost of running the business determined by the sum of cost of goods sold and the operating expenses as expressed in equation 25:

$$\text{Operating Cost} = \text{Cost of Goods Sold} + \text{Operating Expenses} \quad (25)$$

Operating costs directly affect profit because net profit is a function of revenue and operating expenses. Hence management becomes cognizant of operating costs, especially when sales volume resulting in a decline in profit (Beare, 2011). Outsourcing is commonly considered as a way of reducing the operating expenses, specifically payroll and eventually the operating cost when revenue is declining. However, that notion is inaccurate and it requires case-by-case analysis because outsourcing brings redundancy of overheads as administrative functions will be duplicated both for the owner and the contractor (Steenkamp and Van Der Lingen, 2014; da Silva *et al.*, 2019).

From equation 25, both the cost of goods sold and operating expenses are obtained from the income statement of the 3-statement financial model of a project or company under study for a specific accounting period. The best alternative is one with the lowest operating cost expressed in a chosen currency.

3.7.2 Capital Efficiency-Based Factors

Capital efficiency-based Factors are the variables that depicts the performance of capital employed into the business.

Capital efficiency ratio: Every company is concerned about maximising the returns of their inputs. The capital efficiency measures the rate at which a company is gaining from their capital investment. The more efficiently capital is used to produce a product or service, the better chance a company has for approaching profitability (Beare, 2011). Therefore, it is critical to determine which capital resources to invest in, how the capital is used and where the most value will come from. In most cases, miners will not invest in capital with limited efficiency. A limited capital investment is made based on the scale of their operations and the project life. The goal is to maximise the return on investment for each capital cost.

The capital efficiency is quantitative and it is determined through a financial ratio, classified as a profitability ratio, the return on capital employed ratio (ROCE) (O’Callaghan, 2020a). The ROCE is calculated from equation 26 and it is expressed as a percentage.

$$\text{ROCE (\%)} = \frac{\text{Capital Employed}}{\text{EBIT}} \quad (26)$$

The EBIT is the earnings before interest and tax and it is obtained from the income statement of the 3-statement financial model of a project or company under study. The capital employed is calculated through equation 27.

$$\text{Capital Employed (\%)} = \text{Total Assets} - \text{Current Liabilities} \quad (27)$$

Total assets and current liabilities are also obtained from the statement of financial position or balance sheet of the 3-statement financial model. The best or high ranked alternative is the one with the highest ratio expressed in percentage.

Overall equipment efficiency (OEE): OEE is a performance index used by managers in measuring the rate of return for each equipment to its most productive capacity by combining availability, utilisation and quality. OEE originated from the manufacturing industry. It was then adopted by several industries including mining (Elevli and Elevli,

2010). There were several variations that had to be accounted for in developing a framework (Fourie, 2016), for adopting the model from manufacturing to mining. A noteworthy difference for OEE application between the mining industry and the manufacturing industry is the components of availability, utilisation and quality (Elevli and Elevli, 2010). Hence the equipment classification framework for losses associated with mining activities was developed. The OEE framework is shown in Table 6 (Elevli and Elevli, 2010; Fourie, 2016; Munyadzwe *et al.*, 2020). The framework breaks down each component according to the mining activities.

Table 6 OEE Framework

	Calendar Time				
	Equipment Calendar Time				Unscheduled Time
	Equipment Available Time			Planned Downtime	External/ Planned Loss of Efficiency
A	Net Available Time				External/ Planned Loss of Efficiency
	Operating Time			Availability Losses	
U	Net Operating Time			OEE Loss of Efficiency	
	Scheduled Operating Time		Utilisation Losses		
Q	Equipment Capacity		OEE Loss of Efficiency		
	Equipment Output	Quality Losses			

Subsequently OEE can be calculated using equation 28:

$$\text{OEE} = \text{Availability} \times \text{Utilisation} \times \text{Quality} \quad (28)$$

Availability is determined by dividing the hours the equipment is available and used (operating time) by the sum of the hours for which the machine is available and is used and the hour's the machine is available but not used i.e. projected available time (Topp *et al.*, 2008). The net available time excludes change of shift times, break times, briefing times and any other unplanned delays during the shift. Availability is calculated using equation 29:

$$\text{Availability (A)} = \frac{\text{Operating time}}{\text{Net available time}} \times 100\% \quad (29)$$

Utilisation represents the productive use of available equipment hours (Fourie, 2016). This is represented by the ratio of the hours the machine is used to the actual available hours as expressed in equation 30. Utilisation reflects the unused time of an equipment. This is a where an equipment is available for use but is not working during the available hours due to conditions like idling, operator convenience time, dozer work or limited muck pile.

$$\text{Utilisation (U)} = \frac{\text{Net operating time}}{\text{Scheduled Operating time}} \times 100\% \quad (30)$$

Quality measures work done by an equipment as a ratio of valuable production time to the net production time (Elevli and Elevli, 2010). The valuable time factors out human errors and any defects caused by the equipment like spillage and redrills. Quality can be calculated using equation 31:

$$\text{Quality (Q)} = \frac{\text{Payload}}{\text{Bucket capacity}} \times 100 \quad (31)$$

The operating time, net available time, net operating time, scheduled operating time, payload in equations 29 to 31 can be obtained from the fleet management system of the chosen mine or project, while the bucket capacity is obtained from the manufacturer's manual for the equipment in question. Usually, the fleet management system reports the availability, utilisation and productivity. Productivity is equivalent to quality, but it gives a fairer and more accurate value than quality. Productivity is specific to the equipment and it is calculated by the sensors placed on each equipment to account for any equipment defects or human errors like not loading to full capacity, bucket fill factors and drill rig penetration rate as controlled by the operator, while the quality parameters presented by Fourie (2016) in equation 31 are specific to shovels or loading equipment and exclude other mining equipment.

Capital investments are very sensitive relative to profitability. Hence, managing the return on investment is critical. OEE, as an operational parameter, helps in tracking how best the projected return on capital can be maximised. The performance index is a function of time and it measures the rate of converting the cost incurred in capital investment to returns (Topp *et al.*, 2008). Thus, it is a quantitative criterion that must be maximised. The alternative with

the highest OEE expressed in percentage is ranked high. That is the objective for this criterion is to reduce the OEE loss of efficiency as shown in Table 6.

3.7.3 Flexibility-Based Factors

Flexibility-based factors historically come second only to cost when outsourced mining is motivated, with various aspects to be analysed (Steenkamp and Van Der Lingen, 2014; Rupprecht, 2015).

Project life: The project life is determined by the period it will take to efficiently mine the ore deposit in a sustainable manner (Valenta *et al.*, 2019). Therefore, several factors determine the project life and consequently the life of mine. The life of mine is an aggregate of different project lives for a given mine. Consequently, the life of mine is affected by the project life (Calvo *et al.*, 2016). Hence, it is sufficient to consider the project life for a study reliant on life of mine. This study focuses on project life while adopting some of the information from the literature on the life of mine.

The project life affects outsourcing decisions because of capital investment and returns (Kienzler, 2015). A shorter project life would render the owner to outsource considering the payback period of the capital investment would have not been reached. Conversely, the owner might choose to insource because the return on capital investment is higher than outsourcing. Considering the polychotomous options of the outsourcing decision, the option which has a shorter payback period will maximise the return on capital investment. Hence, project life is a quantitative criterion measured by the payback period of the investment for a particular project for each option. Payback period is determined from a discounted cashflow statement (DCF) of the 3-statement financial model for a particular project using equation 32.

$$\text{Payback Period (PBP)} = \frac{\text{Initial Cost}}{\text{Uniform Annual Benefits}} \quad (32)$$

The equation for the payback period used in this study was adopted from initial project screening methods. There are two methods that can be used, the conventional payback period or the discounted cashback methods (Weingartner, 1969). The difference is that the former does not consider the time value of money while the latter does. Any of the methods

can be used, if there is consistency in the method used throughout the calculations. Equation 32 presents the conventional method. Using either the payback period or discounted payback period, the best alternative is the one with the shortest payback period in years because higher returns will be realised for the remaining years before the project life is reached (Weingartner, 1969). Thus, the objective of this criterion is to maximise the return on each capital employed by increasing the possible period of return - the difference between payback period and the end of project life period.

Mining rates: The mining sector is a capital intensive, commodity trading and time conscious industry. Time is highly valuable in mining. Therefore, mining is usually carried out in continuous operations with day and night shifts, to make use of all the available time. This is because there are large volumes of waste to move before the value can be realised. Mining rates are critical to make sure the target tonnage moved is achieved timely. Therefore, mine planners schedule operations based on the availability of resources. Consequently, the right level of investment in capital and human resources is required to meet the project life's timelines. Hence, outsourcing is usually considered as an option to expedite the mining rates. As much as it is important to expedite the rates, it is important to balance the resources, returns and time such that the profit can be maximised in a sustainable manner. Therefore, miners are often faced with the challenge of choosing an outsourcing option that has mining rates that closely corresponds to the plan.

Mining rate is a quantitative criterion and is determined for each alternative based on the mining rate deviation (MRD) using equation 33. The deviation of actual rates from planned rates is used for analysis. The sum of drilling, blasting and materials handling time deviations is determined as a percentage.

$$\text{MRD (\%)} = \text{DRD} + \text{BTD} + \text{MHRD} \quad (33)$$

The drilling rate deviation (DRD) is determined from equation 34 and expressed as a percentage. The planned and actual rates are measured in meters per hour (m/hr). The planned drilling rate is obtained from mining schedules over certain periods (daily, monthly, quarterly or annually). The actual rate is obtained from the drilling performance records (drilling time sheet, drilling machine performance record or from the fleet management system, if available) for the same period as for the planned rate.

$$\text{DRD} = (\text{Actual drilling rate} - \text{Planned actual rate}) \times 100\% \quad (34)$$

The blasting time deviation (BTD) is determined using equation 35 and expressed as a percentage. The planned and actual blasting times are measured in hours. The blasting time is determined as the period from the time when the last person clears from the blasting radius to the time when the blasting team announces re-entry into the blasting radius. The planned time is a standard time determined by the blasting team. While the actual time is determined from the blasting report.

$$\text{BTD} = (\text{Actual blasting time} - \text{Planned blasting time}) \times 100\% \quad (35)$$

Materials handling rate deviation (MHRD) can be determined from equation 36 and expressed as a percentage. The materials handling rate is the aggregate materials handled per cycle time for all loading and hauling equipment for a determined period (daily, monthly, annually, etc.) measured in tonnes per hour. The planned rate is predetermined as part of the mine schedules, while the actual rate is determined from the fleet management system or manually recorded in time sheets during production.

$$\text{MHRD} = (\text{Actual MH rate} - \text{Planned MH rate}) \quad (36)$$

The deviation is used as the metric for comparing mining rates for different outsourcing options. The best or high ranked alternative is the one with the lowest mining rate deviation expressed in percentage.

3.7.4 Competence-Based Factors

Companies protect their assets and keep innovating to ensure sustainability. Competence-based factors are the variables that measures the competitiveness of a company in relation to its core competence.

Attraction and retention of talent: Employees, as a resource to a company, are critical to the success of the business. It is not only about individual efforts, talents and expertise but also about their synergy and team efforts. When selecting employees, companies put much emphasis on the role a certain individual will play on adding value to the vision of the

business. It is a question of whether the expertise, goals, experience and traits of the potential employee will fit the required role or not.

Conversely, attracting and retaining competitive staff that complements all required roles as a team is costly. Labour costs make up to 60% of total mining costs (Sloan, 2013) and there is no mining company with all required roles filled with highly competitive staff. Therefore, the cost will certainly escalate when all roles are to be covered with highly competitive staff.

Owners must balance the cost of competitive labour with the attraction and retention of highly competitive labour when making decisions. Attraction and retention of talent is a qualitative criterion that decision makers must decide based on their expertise and experience. The best alternative must be the one which maximises on the talent that has been attracted and retain it for maximum human resource competence.

Protect core competence: Mining companies outsource their core competencies, contrary to the common notion that companies should outsource their non-core competencies (Steenkamp and Van Der Lingen, 2014). Nevertheless, they strive to protect core competencies within the outsourcing regimes they chose. The most important aspect of the business for miners is information. Hence, they protect it as their core competence (Modak *et al.*, 2017). The nature of the orebody, geological and geotechnical information, price, market conditions, planning and management processes are some of the information highly protected by businesses especially in the mining industry.

Decision makers must examine critical parts of their information, possible gaps and security breaches, potential loss of such information as intellectual property among other data protection factors when deciding on outsourcing alternatives. The most critical information might be in one unit operation over the other, while certain resources might cause severe data breach over others. Hence, core competence as a criterion is qualitative and it is decided by decision makers from their expertise and experience.

Quality: One of the hardest criteria to manage in an outsourcing decision is quality. Though there are several ways to measure quality, it is a subjective parameter which is determined through qualitative measures (Lala *et al.*, 2016). To quantify quality objectively, different factors are considered, examined, and analysed for comparison. Quality in hard rock surface

mining is determined through final wall, floor gradient, grade of ore loaded as the run of mine and ore dilution, etc. (Choudhary, 2015). These factors, final wall, floor gradient, grade of ore loaded as the run of mine and ore dilution, are the main determinant that mining experts can aggregately consider when making outsourcing decisions. The decision can be made based on the experience of available contractors for certain unit operations or the impact of outsourcing such unit operations on any of the factors evaluated for quality.

There is no direct way of measuring this criterion qualitatively and the decision is made on qualitative judgement. A group of experts decide on various factors to consider, and they make the judgement based on those factors. The best alternative is the one which leads to the highest level of quality considering all the other factors. Thus, the final wall is within limit and is smooth, the grade, ore dilution and run-of-mine ore grade are all within the accepted limits according to mine plans, with other factors that the decision makers may consider important also catered for.

Technological competitiveness: Every industry faces competition. Though, mining has been slow in adopting technology compared to other industries, technological competitiveness has been rapidly growing and it is one of the top 10 mining risks consecutively from the years 2018 to 2020 (O’Callaghan, 2020a). Technology builds competitiveness for companies through increased productivity, building of assets through protection of intellectual property, security, increased safety and other operating and strategic benefits (O’Callaghan, 2019a). Hence, companies strive to have technological resources and advancements over others to build a competitive edge.

There are many factors that hinder companies from owning technology or having more advanced technology than their competitors. These include limited capital, lack of expertise to run or use the technology, siloed operations that inhibit certain technologies to synchronise with existing mining infrastructure, etc. (Boudreau-Trudel *et al.*, 2015). Therefore, miners may opt to outsource any of their operations for such reasons. Contractors can bring technology to the owner’s operations at cheaper costs compared to owning such technology. They can also ensure infrastructural support for the technology and bring in expertise that can operate the technology without any cost of training and staff retention for the owner. The disadvantage is that the owner may lose the intellectual property, be more

prune to security risks and have limited control over core competence issues (Modak *et al.*, 2019).

It is critical to balance off all the factors that build technological competitiveness when making outsourcing decisions. Decision makers must consider capital resource constraints, interoperability, availability of infrastructure to support the technology and expertise requirements for operating the technology before deciding on the option.

Technological competitiveness is a qualitative criterion decided by a group of experts from aggregated individual alternative rankings. The decision is based on factors discussed earlier on and it is specific to each project and/or mine. The best alternative is one which will give the highest competitive edge based on technology.

3.7.5 Relationship-Based Factors

From social licence to operate to strategic relationships, the people aspect of every business is critical. It is important to consider the impact people have in decision making processes because without their acceptance, business processes will fail.

Social licence to operate: The acceptance of stakeholders for a mining project is critical. It is important to consider outsourcing decisions in line with what the government, community, customers, and other key stakeholders consider important. Social licence to operate is the acceptance by the local community for a certain project (O’Callaghan, 2018). This is based on several multi-dimensional factors that affect the community. This can be cultural, socio-economic, archaeological and environmental factors that affect communities in the sphere of influence of the mine (O’Callaghan, 2020b). This licence is informal, and it is offered by the community’s leadership in different setups like community meetings, environmental impact assessment engagement and others. The outcome is either they agree with the developments, or they are against them. In any case, this affects the business goals directly because other critical stakeholders like investors and customers make decisions based on the social licence to operate. Social licence to operate has been in the top 10 mining risks since the year 2018 (O’Callaghan, 2020b).

Outsourcing decisions are affected by social licence to operate. Critical areas to consider when outsourcing with respect to social licence to operate are with people and the

environment. For example, a decision to contract might lead to engagement of services from foreign companies based on competence and expertise while the local community believe they could have been engaged to do the same work. Another example is with resources used for a certain operating process, a certain product or equipment may be selected based on efficiency and productivity while it might have adverse environmental impact on the immediate community. It is very important to examine all these factors when making outsourcing decisions.

Social licence to operate is a qualitative criterion that requires the expertise and experience of decision makers to make case-specific decisions and be able to negotiate with all stakeholders for the greater benefit of all parties involved. The best alternative is one with minimum risk for withholding of social licence to operate.

Strategic relationship: This is another qualitative criterion that determines the strategic positioning of the firm, considering outsourcing, with respect to the industry (Modak *et al.*, 2017). The position can either be a strong connection with potential suppliers for specific unit operations, a good reputation and recognition within the industry, limited connections in the industry, a bad reputation in the industry or strategic absence in the industry. The main identifiers of these criteria are reputation, connection and recognition in the industry (Steenkamp and Van Der Lingen, 2014). The best position can be expressed as one where the company has a good reputation with suppliers within a specific alternative over the other. For example, a miner may be well connected to drilling contractors and have a bad reputation with explosives suppliers. In that case, the miner should consider outsourcing the drilling operations over blasting operations for strategic relationship reasons. The best alternative is the one which maximises the level of relationship between contractors and the client.

Environmental sustainability: It is important to consider the environmental impact of an outsourcing decision for sustainability. Several factors can be examined from carbon footprint to deforestation and water conservation (Valenta *et al.*, 2019; O'Callaghan, 2020b). These factors vary from operation to operation and experts in sustainability matters need to advice extensively on what factors should be considered for a project. This is a qualitative criterion, and the best alternative is the one with the lowest environmental impact. The decision is made by experts based on their experience and expertise.

3.8 Definition of Decision Alternatives

The decision alternatives for this study are identified through a combination of literature review on the outsourcing decision framework, the options available for each decision step and the factors that affect each decision step, together with combinatorics models. The decision alternatives from previous studies by Bowen (1997), Suglo (2009), Steenkamp and Van Der Lingen (2014) Rupprecht (2015) and Modak *et al.* (2017) were limited to the dichotomous outsourcing-insourcing decisions, while the other variations extended to strategic alliance as one of the alternatives (Modak *et al.*, 2019). Nevertheless, there is evidence in the literature that there is a finite number of alternatives that can be considered beyond the generic approach of insource-outsource or strategic alliance.

3.8.1 Outsourcing Decision Steps and Options

The outsource-or-insource decision stage depicted in Figure 4 is broad and it has several steps, with many options at each decision step. The main steps involved in the outsourcing decision of a mining operation include choosing the resource to be outsourced, the unit operations to be outsourced, contract type, the established responsibility and the selection technique (Dunlop, 2004; Suglo, 2009; Rupprecht, 2015). The order and sequence of the steps are not outlined in the literature but the sequence can be inferred from the evidence of the relationship they prove (Bowen, 1997; Dunlop, 2004; Suglo, 2009; Steenkamp and Van Der Lingen, 2014; Rupprecht, 2015). Also, it is common industry practice that there is preferred sequence for each set of decision-making problems. The sequence is usually based on the decision makers' preference, outsourcing standards and practice, company policies and the nature of the decision problem, etc.

The sequence of outsource-or-insource decision steps and their relationships are important where the decision-making processes consider the polychotomous alternatives as a finite set and the combination is critical because the alternative sets presented after the alternatives' decision process determines the outcome of the overall outsourcing decision problem (Franceschini *et al.*, 2003; Marshall *et al.*, 2005; Wang and Lee, 2009). For example, if only the dichotomous outsource-or-insource decision is considered, the choice of resources and unit operations to be outsourced are based on the discretion of decision makers and there is no clear comparison, based on defined criteria, among the possible alternatives that may arise due to the distinctions in resources and unit operations. While, for polychotomous

decisions, the finite set of alternatives may be too large to manage for a decision, if the sequence and relationship of the steps are overlooked.

3.8.2 Outsourcing Decision Framework

There are several theories that could accept one combination of decision steps over the other. The combinations are predominantly determined by the outsourcing theory and limited by the multi-criteria decision making (MCDM) methodologies (Modak *et al.*, 2017; Deepa *et al.* 2019). Usually, the MCDM models can only admit a limited number of options in the range of 2 to 20. The outsourcing theory considers some steps in choosing the combination of alternatives for outsourcing decision-making process redundant as the proper sequence eliminates some choices and eventually lead to a reasonable number of options that have covered all possible options (Marshall *et al.*, 2005; Kremic *et al.*, 2006). For example, if the unit operations and the resources that could possibly be outsourced are clearly defined, the need to choose a specific established responsibility is eliminated because the options are already limited by the resource and combination of alternative unit operations. Also, choosing a resource alternative eliminates the options of management contract or turnkey contract as established responsibility options. Some decision steps can run parallel while others are dependent on the outcome of the other steps (Kremic *et al.*, 2006; Damanpour *et al.*, 2020). Choosing one option at a certain step may limit the number of options available for the next stage. Hence, the sequence and relationship in which the outsourcing or insourcing decision steps are combined is critical to limit the outcome of alternatives.

Though sequence does not matter in coming up with all possible combinations, it is necessary for the MCDM methods (Roszkowska, 2011; Neelima *et al.*, 2017; Deepa *et al.* 2019). The possible alternatives can be up to hundreds of thousands with only 10 decision steps and 2 to 6 options per step involved in the combinations. For example, 10 steps with each having 4 options can give more than a million combinations of alternatives. Therefore, to limit them to 20, some steps can either be eliminated or some options combined or both approaches adopted. These approaches cannot just be adopted but intensive outsourcing and set theories with justification must be implemented together with scrutiny of the combined options for practicality in the mining industry (Kremic *et al.*, 2006; McIvor *et al.*, 2009; Modak *et al.*, 2017) to limit the options to less than 20.

3.8.3 Cartesian Product Theory and Application

In addition to outsourcing theory, one important mathematical theory, Cartesian Product, which involves sets is used to come up with a list of alternatives. The Cartesian product theory gives the results of multiplication of indexed family of sets (Anon., 2021a). The most common is the ordered pair, which is the result of multiplying two sets A and B as shown in equation 37. The most common example of an ordered pair is the deck of cards, where the 13 ranks (A, K, Q, J, ..., 2) and 4 suits (spades, clubs, diamonds, and hearts) are multiplied to give 52 cards of a deck. The more general form of Cartesian product is known as an ***n***-fold Cartesian product.

$$A \times B = \{(a, b) \mid a \in A \text{ and } b \in B\} \quad (37)$$

The ***n***-fold Cartesian product defines the Cartesian product of ***n*** sets, which can be represented by an ***n***-dimensional array, where each element is an ***n***-tuple (Anon., 2021b). An ordered pair is a 2-tuple or couple. The Cartesian product can be generalised to the ***n***-ary Cartesian product over *n* sets $X_1, \dots, X_n$ as the set *n*-tuple as shown in equation 38.

$$x_1 \times x_2 \times \dots \times x_n = \{(x_1, x_2, \dots, x_n) \mid x_i \in X_n \text{ for every } i \in (1, \dots, n)\} \quad (38)$$

Different mining outsourcing processes and classification of entities are considered as sets and their Cartesian products are determined to find the final classification of contract mining.

CHAPTER 4

DATA ANALYSIS

4.1 Choosing Decision Alternatives Using Cartesian Product

In this Chapter, all the possible decision outcomes were determined and reduced through Cartesian product formulations depending on the outsourcing decision process.

4.1.1 Mining Outsourcing Process and Entity Classifications

There were initially seven sets from critical outsourcing steps and entities as outlined in Table 7. Analysing the set through the Cartesian product generalised formula gives a total of 224,641 septuplets (equivalent to pairs for ordered pairs or two sets). This is a large number to manage as outsourcing decision alternatives in a practical setting. Therefore, the sets and/or their elements had to be reduced to a manageable number of n -tuples.

Table 7 Sets and Elements for Outsourcing Classification

Set Name	Set Elements
Ownership structures	Joint venture, Public limited company, Private limited company, Parastatal
Mineral Commodities	Single commodity trade, Multiple commodities trade
Resources	Labour, Capital, Labour, and Capital
Unit Operations	Drilling, Blasting, Loading, Hauling, Dewatering, Day works, Planning, Drilling, and blasting, Materials handling, Pit services, technical services, Mining operations
Contract Types	Fixed-price contract, Cost-reimbursement contract, Cost-plus contract, Time and materials contract, Unit price contract, Bilateral contract, Unilateral contract, Implied contract, Express contract, Simple contract, Unconscionable contract, Adhesion contract, Aleatory contract
Selection Technique	Open, Selective, Negotiated, Innovation partnership, public procurement, Restricted, Serial, Framework
Established Responsibilities	Target cost contract, Convertible contract, Management contract, Turnkey contract, Fast tracking contract, Package contract

4.1.2 Alternatives Reduction Outcome

Through literature review and review of the practical situation from the case study at Jwaneng Mine, the sets were reduced to two from seven to form 9 couples (outsourcing decision alternatives as a combination of elements from each set). Each set has 3 elements

as shown in Figure 9. The first set (the “Unit Operations” set) has “Drilling and Blasting”, “Materials Handling” and “Mining Operations” as elements. The second set (the “Resources” set) has “Labour”, “Capital”, “Labour and Capital” as elements. The decision alternatives were determined as couples from the Cartesian product of the unit operations and the resources sets.

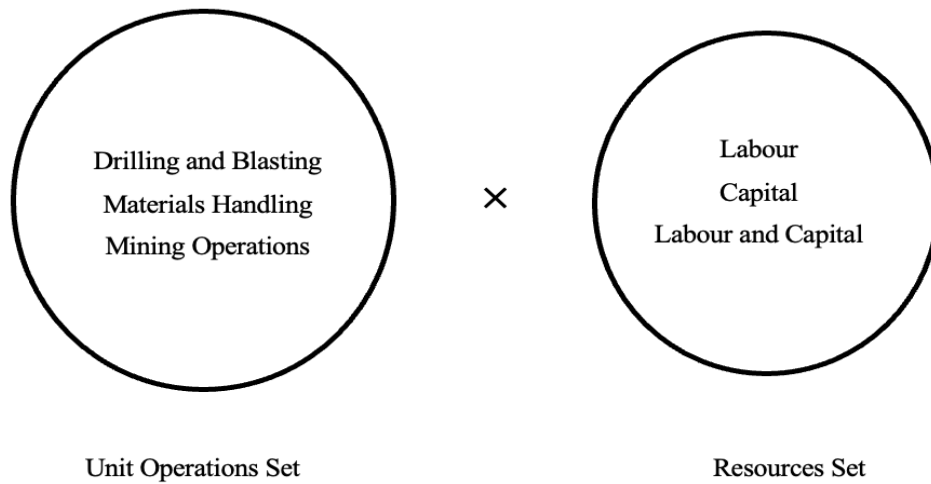


Figure 9 Decision Alternatives Sets and Elements

From Cartesian product of the two sets, there are 10 final decision alternatives obtained as summarised in Table 8. Nine of the alternatives are couples from the Cartesian product of the two sets while the last alternative represents elements not found in either of the two sets, practically, none of either the unit operations or the resources are outsourced.

4.1.3 HFTOPSIS Decision Alternatives Description

The outsourcing decision alternatives used in the HFTOPSIS model are a combination of outsourcing and insourcing of unit operations and/or resources. Each option is made up of owner mining and contractor mining to a certain degree. For each alternative, when certain unit operations or resources are chosen for outsourcing, those that are not chosen will be insourced. Thus, for each comparison, it is determined whether the combination of outsourcing and insourcing chosen will work. For example, for the “drill and blast (D&B) labour option” the D&B capital resource (CR) and the materials handling (MH) units are insourced, while only the human resource (HR) is outsourced. Thus, the financial and operational comparisons between the alternatives are made based on the combinations of the outsourced and insourced unit operations and resources for each alternative.

Table 8 Final Decision Alternatives

Unit Operations	Resources	Alternative Description	Shorthand	Notation
Drilling and Blasting	Labour	Drilling and blasting labour outsourcing	D&B labour	A1
Drilling and Blasting	Capital	Drilling and blasting capital outsourcing	D&B capital	A2
Drilling and Blasting	Labour and Capital	Drilling and blasting labour and capital outsourcing	D&B labour and capital	A3
Materials Handling	Labour	Materials handling labour outsourcing	MH labour	A4
Materials Handling	Capital	Materials handling capital outsourcing	MH capital	A5
Materials Handling	Labour and Capital	Materials handling labour and capital outsourcing	MH labour and capital	A6
Mining Operations	Labour	Mining operations labour outsourcing	MO labour	A7
Mining Operations	Capital	Mining operations capital outsourcing	MO capital	A8
Mining Operations	Labour and Capital	Mining operations labour and capital outsourcing	MO labour and capital	A9
Non applicable	Not applicable	Owner mining	Owner mining	A10

D&B labour decision alternative: The D&B Labour alternative means that human resources for the D&B unit is outsourced while D&B capital resources (drilling equipment, explosives, etc.) and all resources for the MH unit are insourced. The D&B unit labour cost and productivity data used for analysis are from the contractors while the rest of the data is from the owner. As shown in Figure 10, this alternative is made up of D&B HR outsourcing and MH HR plus D&B CR plus MH CR insourcing.

HR		CR	
D&B	MH	D&B	MH

KEY

Colour code

Contractor contribution



Owner contribution



Figure 10 Schematic of D&B Labour Option

D&B capital decision alternative: The D&B Capital alternative means that capital resources (drilling equipment, mobile manufacturing units for explosives (MMUs), explosives and consumables) for the D&B unit are outsourced while D&B human resource and all resources for the MH unit are insourced. The cost and productivity data relating to D&B unit equipment and consumables used for analysis are from the contractors while the rest of the data is from the owner. As shown in Figure 11, this alternative is made up of D&B CR outsourcing and MH CR plus D&B HR plus MH HR insourcing.

HR		CR	
D&B	MH	D&B	MH

KEY	Colour code
Contractor contribution	
Owner contribution	

Figure 11 Schematic of D&B Capital Option

D&B labour and capital decision alternative: The D&B Labour and Capital alternative means that all D&B unit resources are outsourced while all the resources for the MH unit are insourced. The D&B unit cost and productivity data used for analysis are from the contractors while MH unit data is from the owner. As shown in Figure 12, this alternative is made up of D&B HR plus D&B CR outsourcing and MH CR plus MH HR insourcing.

HR		CR	
D&B	MH	D&B	MH

KEY	Colour code
Contractor contribution	
Owner contribution	

Figure 12 Schematic of D&B Labour and Capital Option

MH labour decision alternative: The MH Labour alternative means that human resources for the MH unit is outsourced while MH unit capital resources (loaders, trucks, support equipment and consumables) and all resources for the D&B unit are insourced. The MH unit labour cost and productivity data used for analysis are from the contractors while the rest of the data is from the owner. From Figure 13, this alternative is made up of MH HR outsourcing and D&B HR plus D&B CR plus MH CR insourcing.

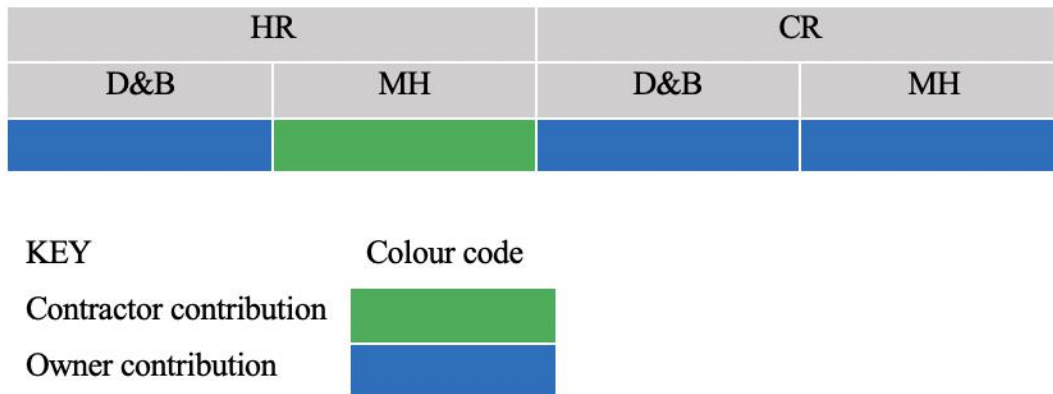


Figure 13 Schematic of MH Labour Option

MH capital decision alternative: The MH Capital alternative means that capital resources (loaders, trucks, support equipment and consumables) for the MH unit are outsourced while human resources related to MH and all resources for the D&B unit are insourced. The cost and productivity data relating to MH unit equipment and consumables used for analysis are from the contractors, while the rest of the data is from the owner. As shown in Figure 14, this alternative is made up of MH CR outsourcing and D&B CR plus D&B HR plus MH HR insourcing.

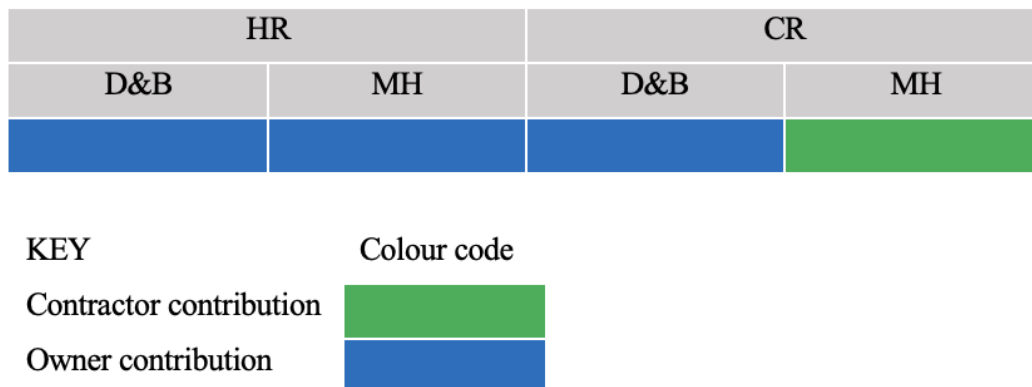


Figure 14 Schematic of MH Capital Option

MH labour and capital decision alternative: The MH Labour and Capital alternative means that all the unit resources related to MH are outsourced while all the resources for the D&B unit are insourced. The MH unit cost and productivity data used for analysis are from the contractors while the D&B unit data is from the owner. As shown in Figure 15, this alternative is made up of MH CR plus MH HR outsourcing and D&B HR plus D&B CR insourcing.

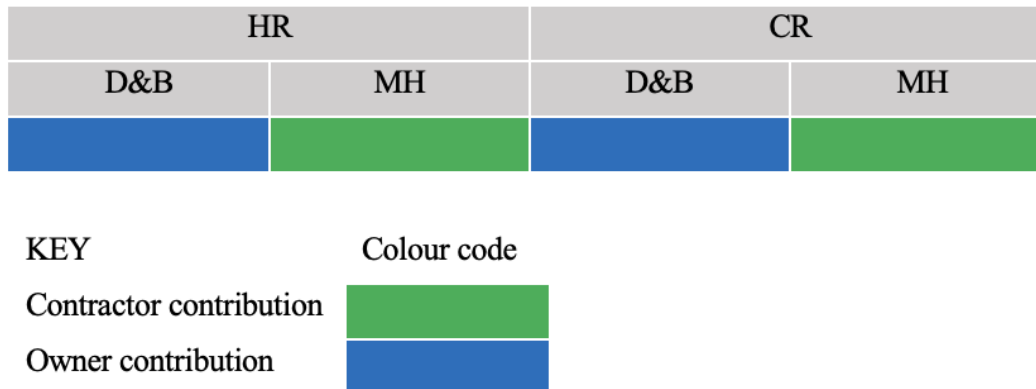


Figure 15 Schematic of MH Labour and Capital Option

MO labour decision alternative: The MO Labour alternative means that human resources for all mining operations section are outsourced while the capital resources (equipment and consumables) are insourced. The mining labour cost and productivity data used for analysis are from the contractors while the rest of the data is from the owner. From Figure 16, this alternative is made up of D&B HR plus MH HR outsourcing and D&B CR plus MH CR insourcing.

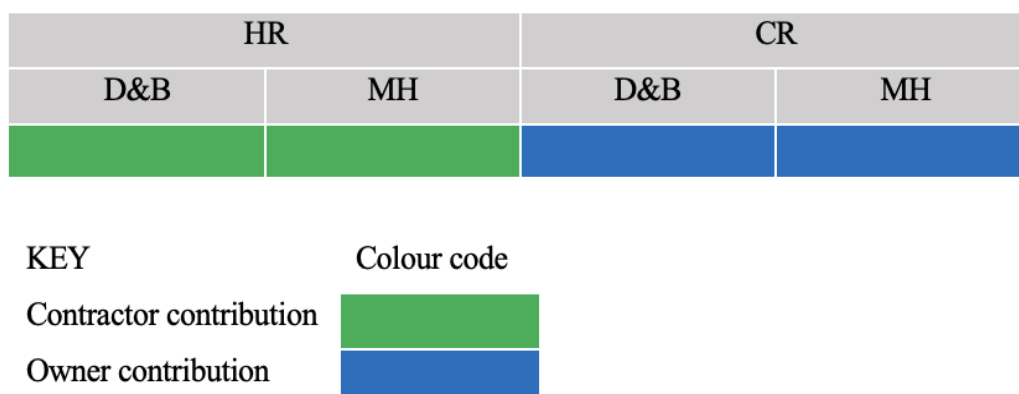


Figure 16 Schematic of MO Labour Option

MO capital decision alternative: The MO Capital alternative means that the capital resources (loaders, trucks, support equipment and consumables) for the mining operations section are outsourced while the human resources unit are insourced. The cost and productivity data relating to equipment and consumables used for analysis are from the contractors while the rest of the data is from the owner. As shown in Figure 17, this alternative is made up of MH CR outsourcing and D&B CR plus D&B HR plus MH HR insourcing.

HR		CR	
D&B	MH	D&B	MH

KEY	Colour code
Contractor contribution	
Owner contribution	

Figure 17 Schematic of MO Capital Option

MO labour and capital decision alternative: The MO Labour and Capital alternative means that all resources in the mining operations section are outsourced. All costs and productivity data used for analysis are from the contractors. As shown in Figure 18, this alternative is made up of MH CR plus MH HR plus D&B HR plus D&B CR outsourcing.

HR		CR	
D&B	MH	D&B	MH

KEY	Colour code
Contractor contribution	
Owner contribution	

Figure 18 Schematic of MO Labour and Capital Option

Owner mining decision alternative: The owner mining alternative means that all resources in the mining operations section are insourced. All costs and productivity data used for analysis are from the owners. As shown in Figure 19, this alternative is made up of MH CR plus MH HR plus D&B HR plus D&B CR insourcing.

HR		CR	
D&B	MH	D&B	MH

KEY	Colour code
Contractor contribution	
Owner contribution	

Figure 19 Schematic of Owner Mining Option

The 10 alternatives provide options for simulation and analysis of data for multicriteria decision analysis. The description of each alternative also shows what data to use for the HFTOPSIS model. The data used here is from the case study at Jwaneng Mine and questionnaires which were issued to 10 mining professionals.

4.2 Crisp Data Analysis

Data obtained from Jwaneng Mine's Modular Dispatch and Oracle systems was used as crisp data in the analysis. Crisp data for the HFTOPSIS model is data that has been precisely measured and has units. There is no readily available data for all the 10 alternatives, but simulations were used to come up with data for comparison of decision alternatives. Jwaneng Mine's operations are divided into 3 active cuts (i.e. Cuts 6/7, 8 and 9) with a combination of insourcing and outsourcing of both resources and unit operations for each of those cuts. Cut 9 is wholly mined by contract employees, Cut 8 is a combination of both insourcing and outsourcing while Cut 6/7 is wholly managed by the owner. The time and financial data from Cuts 6/7 and 8 were simulated to come up with data for each decision alternative.

4.2.1 Simulation Analysis

The simulations used actual financial statements and OEE reports from Jwaneng Mine's Cuts 6/7 and 8 operations. From the financial statements summarised in Appendix 1, 10 financial models were simulated based on varying run-of-mine (ROM) tonnage and operating costs, the results of the simulation are presented in Table 9. The data used is summarised in Appendix 2 according to the difference between owner data and contractor data. The sources of data for the simulations were from Jwaneng Cut 6/7 representing owner mining only and Cut 8 representing the contractors' contribution (see Figures 10 to 19). The combination of such data was modelled for each alternative according to the description of alternatives given in Section 4.1.3. The simulations were done separately for financial and time data. The financial data is reflected as costs in US\$ and time is represented by efficiency in percentage.

Table 9 Mining Operating Cost Simulations for each Decision's Alternatives

Data	Observation	D&B Labour (US\$ × 10 ⁶)	MH Labour (US\$ × 10 ⁶)	MH Capital (US\$ × 10 ⁶)	D&B Capital (US\$ × 10 ⁶)
Actual	Owner	1.61	12.89	45.40	6.54
	Contractor	3.35	26.93	94.84	13.65
Simulation	D&B Labour	3.35	12.89	45.40	6.54
	D&B Capital	1.61	12.89	45.40	13.65
	D&B Labour & Capital	3.35	12.89	45.40	13.65
	MH Labour	1.61	26.93	45.40	6.54
	MH Capital	1.61	12.89	94.84	6.54
	MH Labour & Capital	1.61	26.93	94.84	6.54
	MO Labour	3.35	26.93	45.40	6.54
	MO Capital	1.61	12.89	94.84	13.65
	MO Labour & Capital	3.35	26.93	94.84	13.65
	Owner Mining	1.61	12.89	45.40	6.54

Exchange rate: Botswana Exchange Rate against US\$ 1.00 averaged BWP 10.875

Financial simulations: In the financial simulations all the variables were fixed and only the operating cost and tonnage were varied for each observation. The actual data as summarised in Table 9 is for the mining operating costs. The owner observations were obtained from

Cut 6/7 operations while the contractor observations were obtained from Cut 8. Conversely, the actual tonnage data is presented as distributed tonnage per cost and summarised in Table 10. The simulations in Table 10 were for the actual tonnages as a combination of Cut 6/7 and Cut 8. The tonnage per cost (that is the amount of material that could be theoretically moved for every 1US\$ spent by the company on operational costs expressed in tonnes) were determined and the inverse calculations were done as a function of the cost for each attribute. The combinations were then derived from the tonnage per cost calculated using the same ratio analysis of owner mining and the contractors' contribution (see Figures 10 to 19).

Table 10 ROM Tonnage Simulation for each Decision Alternative

Data	Observation	D&B Labour (tonnes)	MH Labour (tonnes)	MH Capital (tonnes)	D&B Capital (tonnes)
Distributed Tonnage	Owner	20,145.18	161,691.75	569,487.08	81,974.13
	Contractor	106,865.62	857,738.28	3,021,000.57	434,854.29
Simulation	D&B Labour	106,865.62	161,691.75	569,487.08	81,974.13
	D&B Capital	20,145.18	161,691.75	569,487.08	434,854.29
	D&B Labour & Capital	106,865.62	161,691.75	569,487.08	434,854.29
	MH Labour	20,145.18	857,738.28	569,487.08	81,974.13
	MH Capital	20,145.18	161,691.75	3,021,000.57	81,974.13
	MH Labour & Capital	20,145.18	857,738.28	3,021,000.57	81,974.13
	MO Labour	106,865.62	857,738.28	569,487.08	81,974.13
	MO Capital	20,145.18	161,691.75	3,021,000.57	434,854.29
	MO Labour & Capital	106,865.62	857,738.28	3,021,000.57	434,854.29
	Owner Mining	20,145.18	161,691.75	569,487.08	81,974.13

Time simulations: The time data collected was used as the actual data together with the financial data. Table 11 summarises the OEE of the time efficiency simulated for each decision alternative according to the rules set in Section 4.1.3 as in the financial simulations. The only difference is that there are only two actual OEE values which means that the OEE value for Cut 6/7 for the owner contribution is similar for all decision alternatives for MH operations on labour, capital resources or when both are insourced. It is the same for the Cut 8 OEE (contractor's contribution) value for decision alternatives as the MH operations were outsourced.

Table 11 OEE Simulation for Each Decision Alternatives

Data	Observation	OEE
Actual	Owner	0.63
	Contractor	0.78
Simulation	D&B Labour	0.63
	D&B Capital	0.63
	D&B Labour & Capital	0.63
	MH Labour	0.78
	MH Capital	0.78
	MH Labour & Capital	0.78
	MO Labour	0.78
	MO Capital	0.78
	MO Labour & Capital	0.78
	Owner Mining	0.63

The time data, in the final form, is input as variables in the HFTOPSIS model while the financial data was input into the financial model first to obtain the financial parameters of interest.

4.2.2 Crisp Cost Criteria Analysis

Crisp cost criteria are the cost criteria summarised in Table 2 where the variables can be accurately measured, and the data is readily and sufficiently available for use. The operating cost and project life given by the payback period are the cost criteria considered to be crisp in the case study using the HFTOPSIS model. The operating cost and project life were variables used in this study and each alternative is an observation measured or determined relative to the two variables. Figures 20 to 22 show the operating cost, project life and aggregated crisp cost against the various criteria in this study.

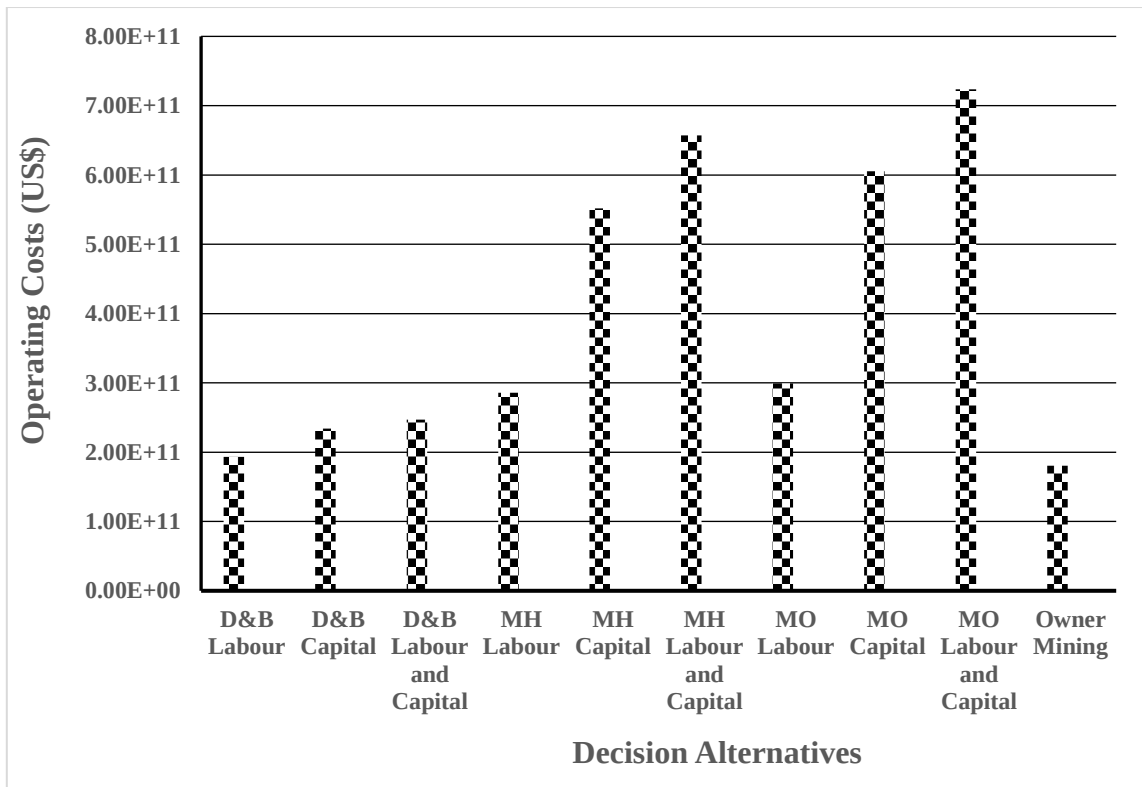


Figure 20 Operating Cost Criterion

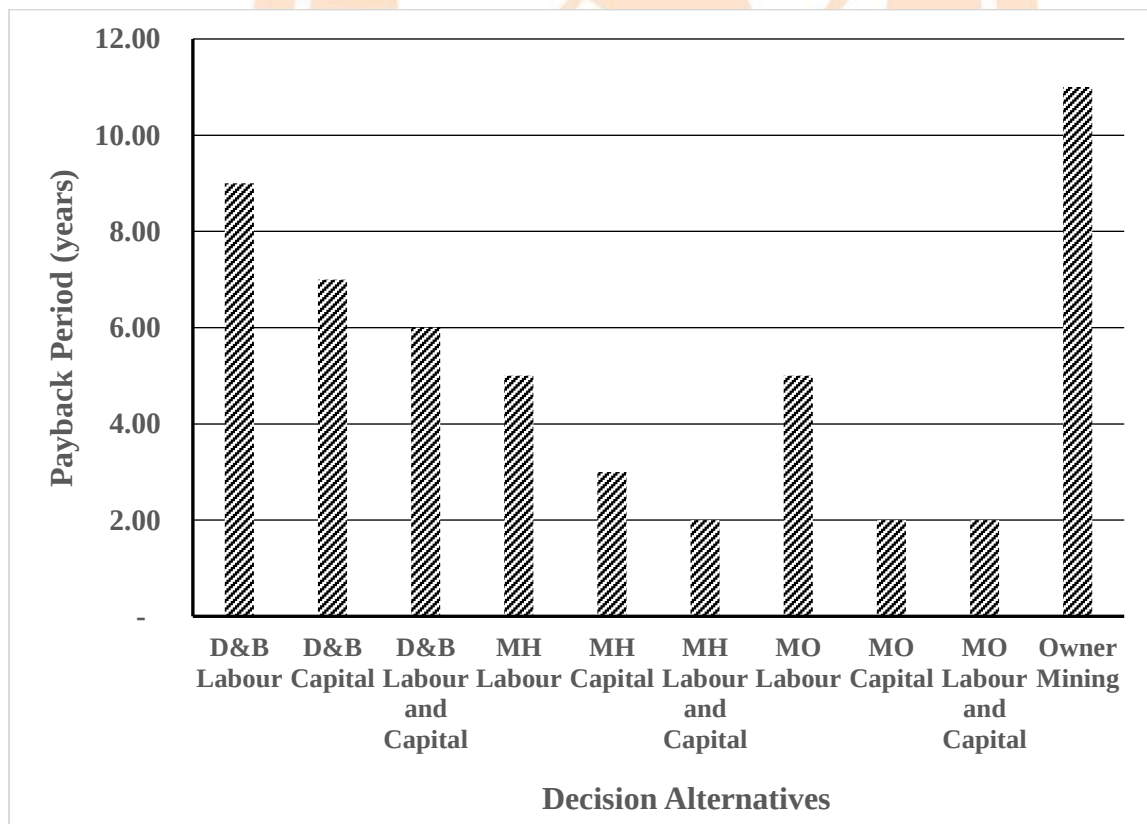


Figure 21 Project Life Criterion

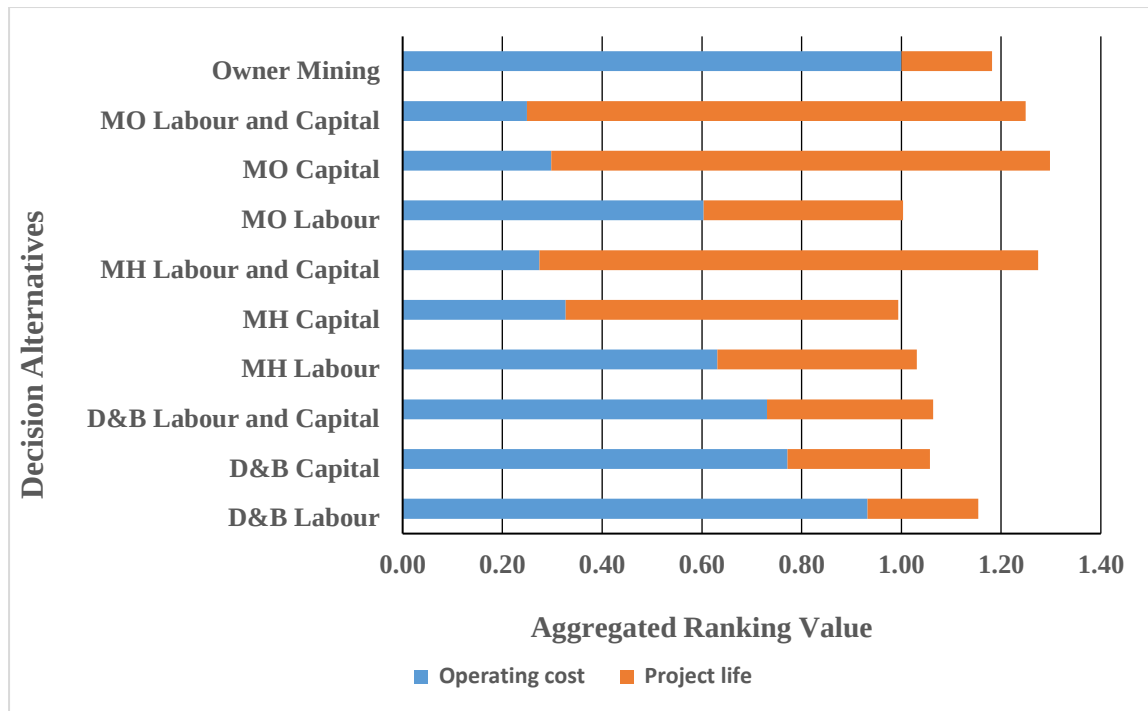


Figure 22 Aggregated Crisp Cost Criteria

Operating cost variable: Operating cost is a cost criterion. From Figure 20, the most desirable alternative is owner mining with a value of US\$ $16,587.37 \times 10^6$, ranking highest according to operating costs. The lowest ranking, at the value of US\$ $66,550.79 \times 10^6$, is MO labour and capital alternative.

Project life variable: The project life is also a cost criterion. From Figure 21, owner mining has a payback period of 11 years and ranks lowest while MO labour and capital and MO capital, each with a payback period of 2 years, rank highest. Thus, MO labour and capital and MO capital are the most desirable alternatives when ranking using project life.

Aggregated crisp cost criteria variables: The lowest cost is desirable for all cost criteria variables. While the analysis of each criterion is represented in a certain dimension, the aggregated crisp cost criteria present the normalised values which are dimensionless. From Figure 22, MH capital ranks highest with an aggregated crisp cost criteria value of 0.994 and MO capital ranks lowest with a value of 1.298. Owner mining and MO labour and capital (representing complete contract mining) rank 7th (1.182) and 8th (1.249) respectively.

4.2.3 Crisp Benefit Criteria Analysis

Crisp benefit criteria are the benefit criteria shown in Table 2, where the variables can be accurately measured, and the data is readily and sufficiently available for use. Profit margin risk, capital efficiency ratio and OEE are the benefit criteria that can be accurately measured with the available data in this study. The comparisons of the crisp benefit criteria are shown in Figures 23 to 26.

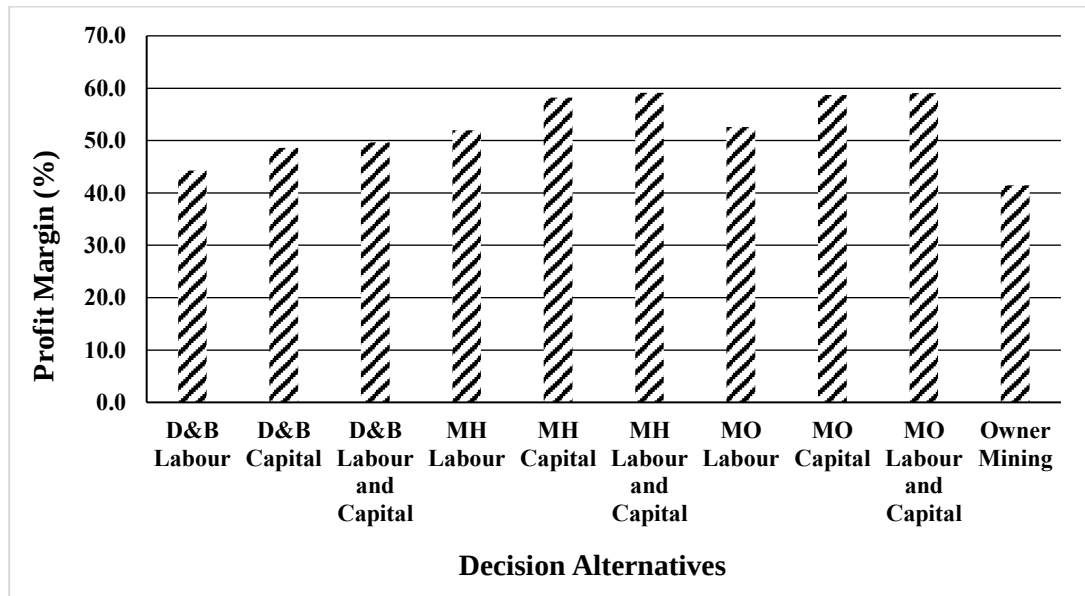


Figure 23 Chart of Profit Margin Risk Criterion

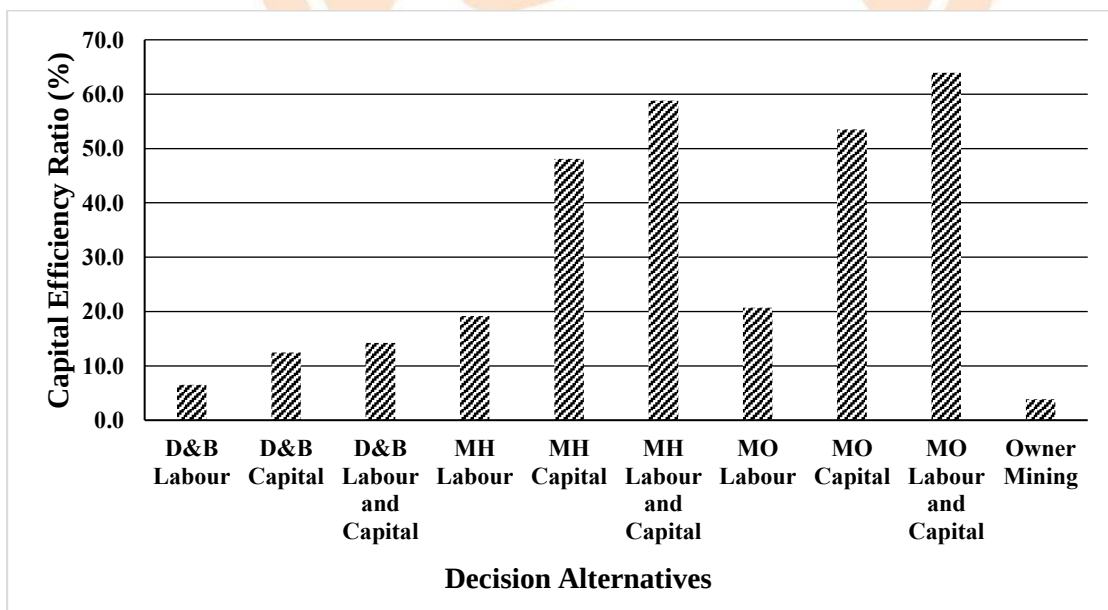


Figure 24 Chart of Capital Efficiency Ratio Criterion

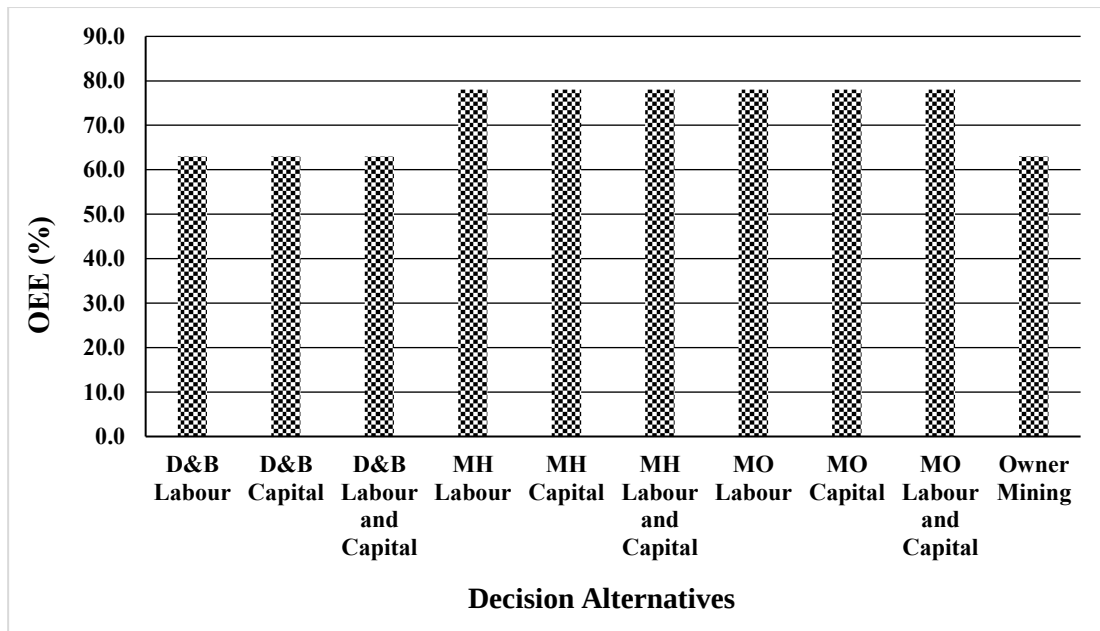


Figure 25 Chart of OEE Criterion

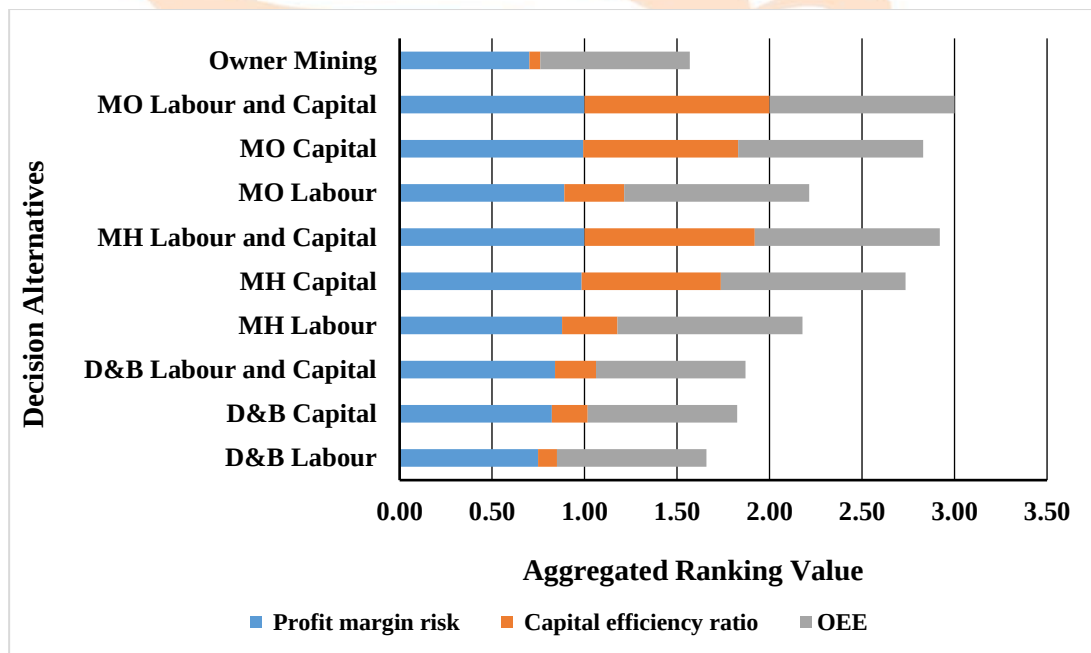


Figure 26 Aggregated Crisp Benefit Criteria

Profit margin risk variable: Profit margin risk is a benefit criterion, and the one with the highest value is the most desirable alternative. From Figure 23 the highest-ranking decision alternatives using profit margin are MH labour and capital and, MO labour and capital with 59.1%. So, they are the most desirable alternatives. The least desirable alternative is owner mining which has the lowest ranking at 41.5%.

Capital efficiency ratio (CER) variable: CER is also a benefit criterion. From Figure 24 owner mining has a ratio of 3.8% and ranks as the lowest among the parameters used. MO labour and capital, with a ratio of 63.9%, ranks highest. Thus, MO labour and capital is the most desirable alternative using project life as the ranking criterion.

OEE variable: OEE is a benefit criterion, and the most desirable alternative should have the highest value. From Figure 25, owner mining has an OEE of 63% and ranks the lowest while MO labour and capital has an OEE of 78% and ranks as the highest.

Aggregated crisp benefit criteria variables: The benefit criteria variable with the highest value is more desirable. Therefore, the aggregated value for benefit criteria which rank as the highest value are more desirable. The aggregated crisp benefit criteria present the normalised values which are dimensionless. The lowest possible value is 0.000 while the highest possible value is 3.000. From Figure 26, MO labour and capital ranks highest with an aggregated crisp benefit criteria value of 2.999 while owner mining ranks as the lowest with a value of 1.569. The results are summarised in a crisp matrix as presented in Table 12.

Table 12 Raw Crisp Matrix

	Criteria	Operating Cost (US\$ × 10 ⁶)	Project Life (Years)	Profit Margin Risk (%)	Capital Efficiency Ratio (%)	OEE (%)
Alternatives	D&B Labour	17,795.25	9.00	44.3	6.5	63.0
	D&B Capital	21,502.43	7.00	48.6	12.5	63.0
	D&B Labour and Capital	22,710.30	6.00	49.6	14.2	63.0
	MH Labour	26,282.19	5.00	52.0	19.1	78.0
	MH Capital	50,733.04	3.00	58.2	48.1	78.0
	MH Labour and Capital	60,427.85	2.00	59.1	58.8	78.0
	MO Labour	27,490.06	5.00	52.6	20.7	78.0
	MO Capital	55,648.09	2.00	58.7	53.5	78.0
	MO Labour and Capital	66,550.79	2.00	59.1	63.9	78.0
	Owner Mining	16,587.37	11.00	41.5	3.8	63.0

Exchange rate: Botswana Exchange Rate against US\$ averaged 10.875 (BWP/US\$)

4.2.4 Crisp Matrix

The crisp data have real numbers that can be measured and obtained accurately. The crisp criteria are the operating costs, project life, profit margin risk, capital efficiency ratio and OEE. The raw crisp data have been summarised in Table 12. The values are presented in different units, and it is not possible to make any comparison between the values. Therefore, the raw crisp data were normalised using equation 14. The normalised crisp matrix values are summarised Table 13.

Table 13 Normalized Crisp Matrix

	Criteria	Operating Cost	Project Life	Profit Margin Risk	Capital Efficiency Ratio	OEE
Alternatives	D&B Labour	0.932	0.222	0.749	0.102	0.808
	D&B Capital	0.771	0.286	0.822	0.195	0.808
	D&B Labour and Capital	0.730	0.333	0.839	0.222	0.808
	MH Labour	0.631	0.400	0.879	0.299	1.000
	MH Capital	0.327	0.667	0.984	0.752	1.000
	MH Labour and Capital	0.274	1.000	1.000	0.920	1.000
	MO Labour	0.603	0.400	0.890	0.324	1.000
	MO Capital	0.298	1.000	0.993	0.837	1.000
	MO Labour and Capital	0.249	1.000	0.999	1.000	1.000
	Owner Mining	1.000	0.182	0.701	0.060	0.808

4.3 Fuzzy Data Analysis

The fuzzy data used in the analysis in this study was obtained from responses in 10 questionnaires administered and but answered by 6 respondents. The responses expressed in linguistic terms were collected, aggregated, and converted to fuzzy numbers using fuzzy ratings corresponding to rating of alternatives as summarised in Table 3. Each respondent's data was converted to fuzzy numbers and re-arranged as a fuzzy matrix. The questionnaires template is shown in Appendix 3.

4.3.1 Questionnaire Analysis

Ten questionnaires were sent to mining professionals, who either have worked at Jwaneng Mine or have intricate knowledge about its mining operations. Out of the 10, only 6 responded. The responses from the Google Forms were cleaned, arranged into matrices, and recorded in MS Excel to form part of the model according to the HFTOPSIS algorithm discussed in Section 3.6. The individual responses were tabulated as numerical data using a range of discrete values ranging from 1 to 9.

All 6 responses were analysed individually and fitted into the HFTOPSIS model. Each response was recorded in a separate MS Excel sheet and linked to the HFTOPSIS analysis sheet to pool all the responses together and aggregate them. The respondents were considered as decision makers in this study. Therefore, each response was recorded as k -decision maker fuzzy matrix according to the HFTOPSIS algorithm. The whole process was programmed in MS Excel using the HFTOPSIS algorithm using equations 13 to 21. From the formation of the matrix to the calculation of the separation measures, each individual matrix was analysed separately. The results of the responses to the questionnaires are analysed in the following sections.

4.3.2 Fuzzy Cost Criteria Analyses

Fuzzy cost criteria are qualitative variables and those quantitative variables that cannot be accurately measured and/or the data is not readily and sufficiently available for use are classified as cost criteria in Table 2. In the HFTOPSIS model in this case study, fuzzy cost criteria are the social licence to operate, which is a qualitative variable and transaction cost, which has limited data for analysis. The two fuzzy cost criteria were variables in this study and each alternative was an observation measured or determined relative to the two variables. The results from the questionnaires were analysed and the plotted into graphs as shown in Figures 27 to 30 to show the ranking of alternatives by decision makers (DMs). The multiple DMs represent a group decision making process as outlined in Section 3.6.4.

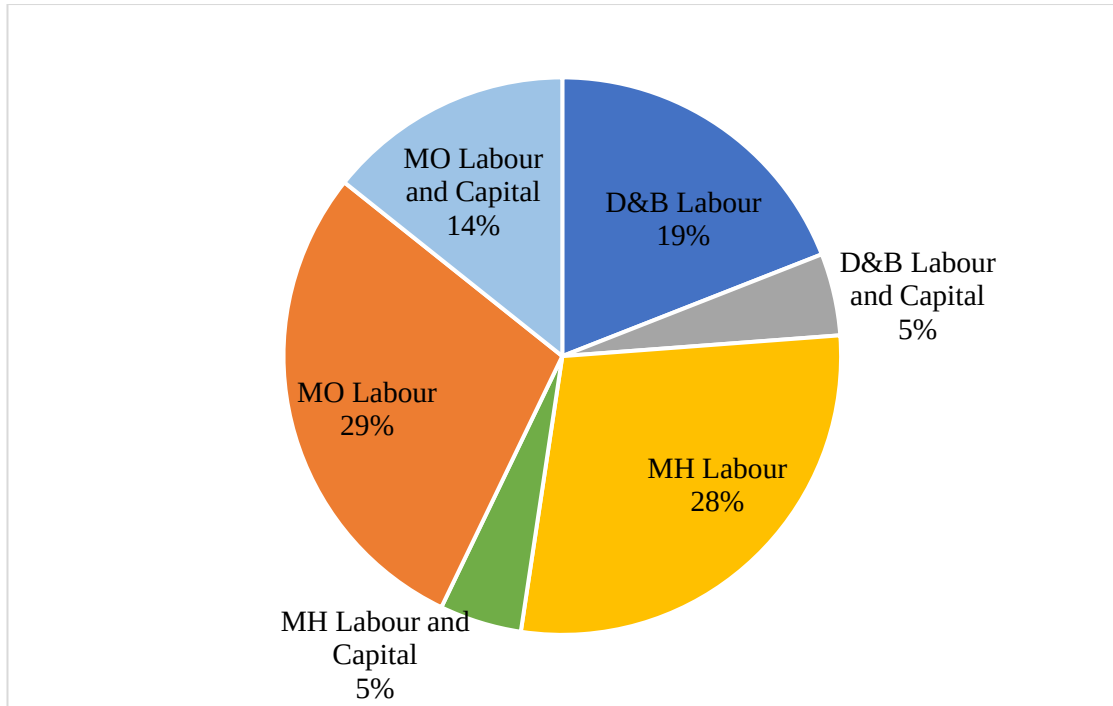


Figure 27 Percentage of DMs Ranking an Alternative as Highest on Social Licence to Operate Criterion

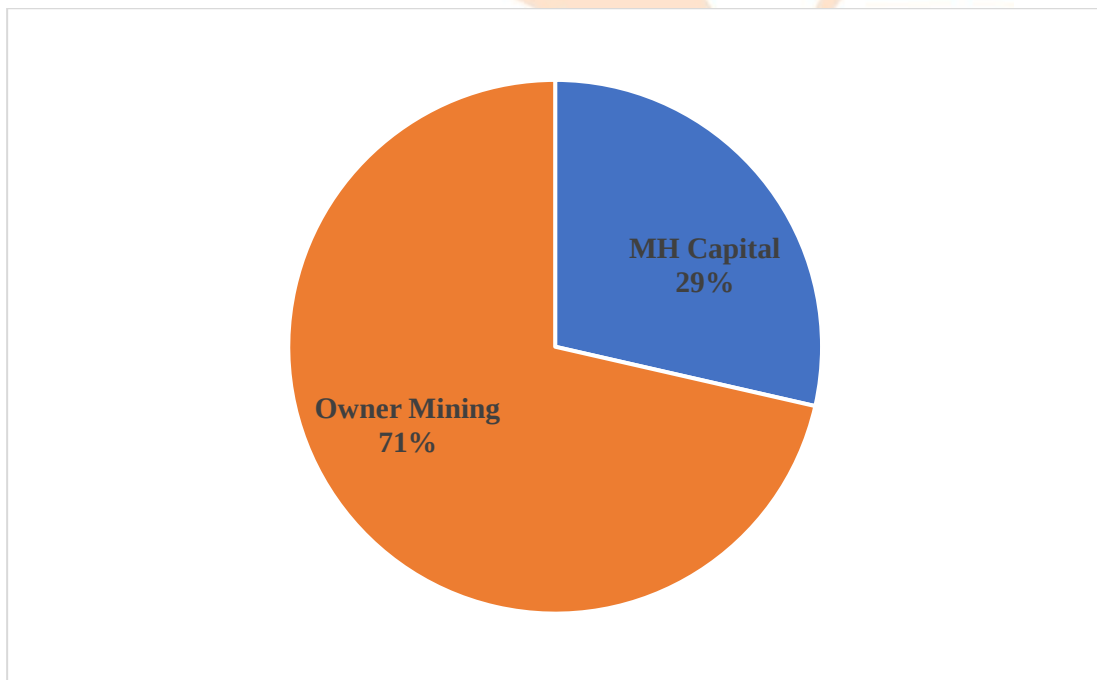


Figure 28 Percentage of DMs Ranking an Alternative as Lowest on Social Licence to Operate Criterion

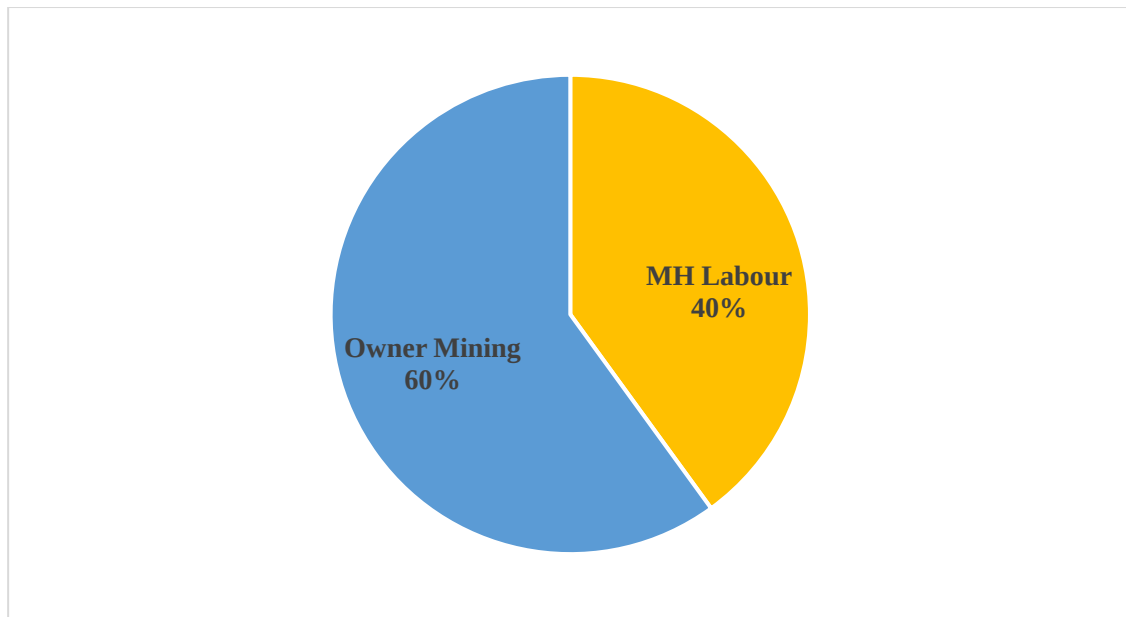


Figure 29 Percentage of DMs Ranking an Alternative as Highest on Transaction Cost Criterion

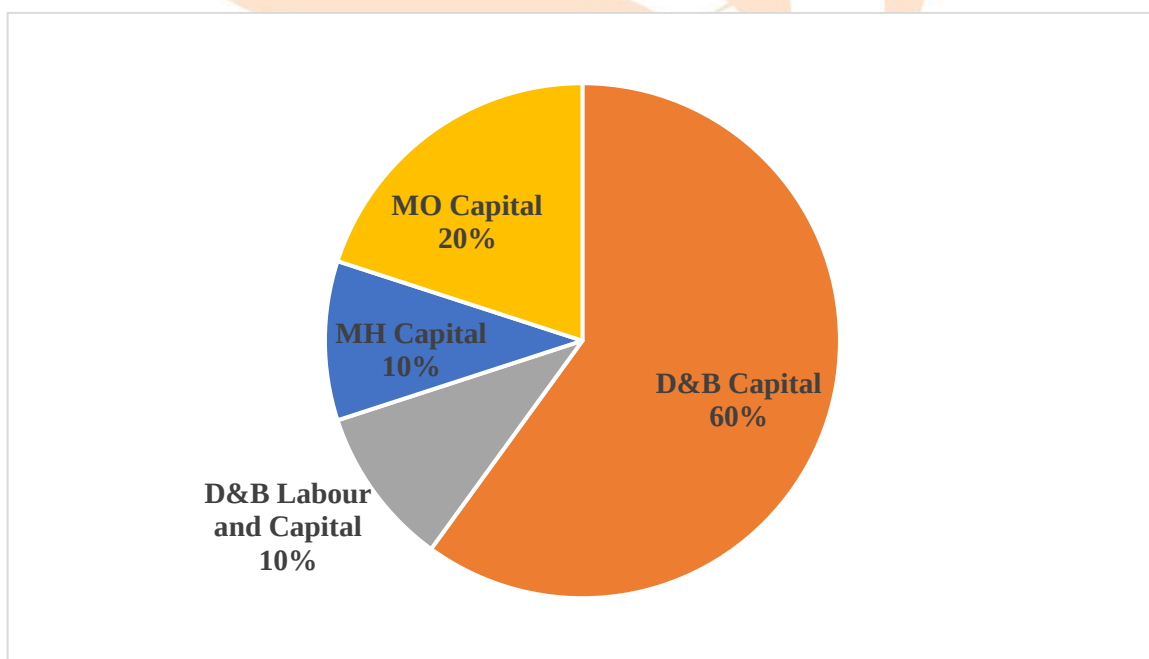


Figure 30 Percentage of DMs Ranking an Alternative as Lowest on Transaction Cost Criterion

Social licence to operate criterion: The social licence to operate variable is a cost criterion. As a cost criterion, the most desirable value for the variable is the lowest value. It is difficult to find the lowest value for each variable using fuzzy data from multiple DMs. Thus, each DM's matrix is solved separately until the closeness coefficient is determined for each

alternative. From Figure 27 MO labour has the highest frequency and is ranked the highest by DMs on social licence to operate criterion with 29% followed by MH labour with 28%. They are thus the most desirable alternatives. Also, from Figure 27, MO labour and capital has been ranked as the highest alternative by 14% of DMs. Owner mining is the least desirable alternative in terms of social licence to operate as shown in Figure 28 with 71% of DMs.

Transaction cost criterion: Transaction cost variable is also a cost criterion. From Figure 29, owner mining is ranked highest by 60% of the DMs as a transaction cost criterion which makes it the most desirable alternative. D&B capital is the least desirable alternative as a transaction cost variable as shown in Figure 30 with 60% of DMs ranking it as the lowest among other alternatives.

4.3.3 Fuzzy Benefit Criteria Analyses

Fuzzy benefit criteria are represented in Table 2 as qualitative variables and among the quantitative variables that cannot be accurately measured and/or the data is not readily and sufficiently available for use. Other fuzzy benefit criteria in this study are qualitative variables. They include the attraction and retention of talent, quality, protection of core competence, technological competitiveness, strategic relationships and environmental sustainability. Mining rate is a quantitative fuzzy-benefit criteria which has limited data for analysis. The results from the questionnaires for benefit criteria ranking were analysed and the results discussed in the following sections.

Mining rates criterion: Mining rate is a benefit criterion for which the most desirable value is the highest value. From Figure 31 MO labour and capital has the highest frequency and is ranked highest by DMs on mining rates criterion at 86%. Also from Figure 32 owner mining is the least desirable alternative in terms of the mining rates criterion with 75% of DMs ranking it has the lowest.

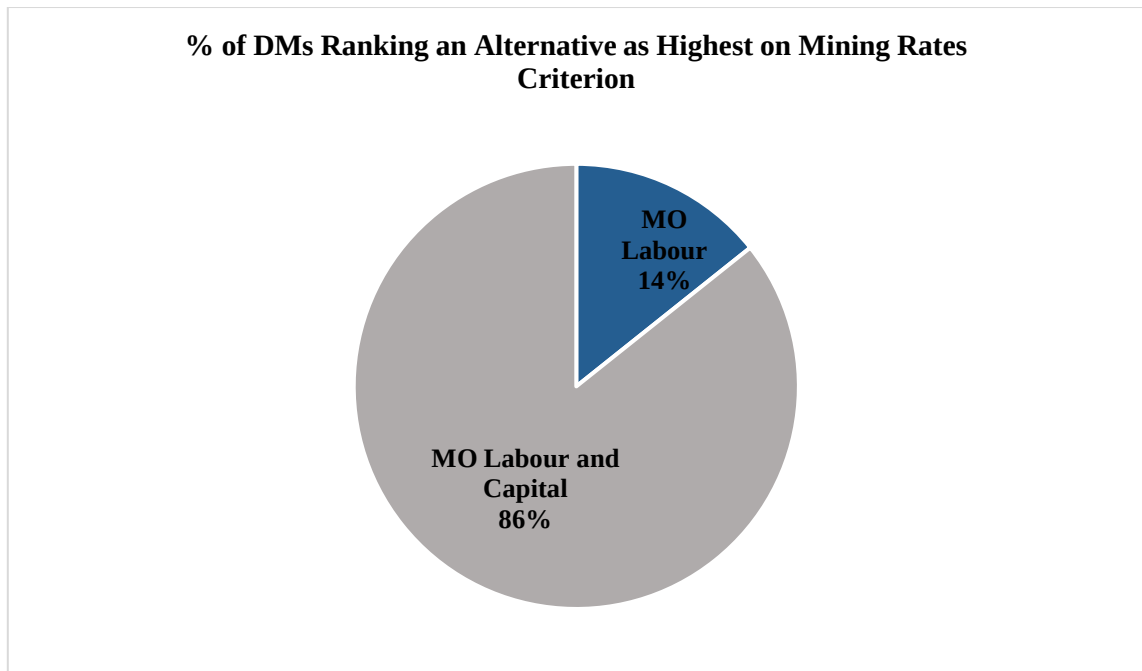


Figure 31 Percentage of DMs Ranking an Alternative as Highest on Mining Rates Criterion

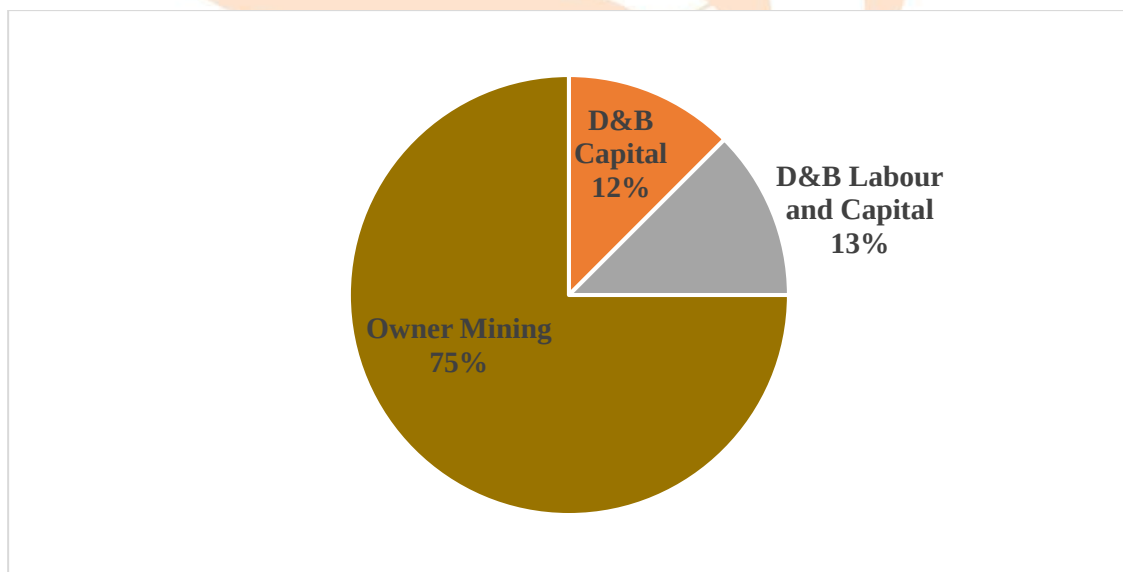


Figure 32 Percentage of DMs Ranking an Alternative as Lowest on Mining Rates Criterion

Attraction and retention of talent criterion: Attraction and retention of talent variable is also a benefit criterion. From Figure 33, MH capital is ranked highest by 37% of DMs using attraction and retention of talent criterion. This makes it the most desirable alternative. D&B labour is the least desirable alternative based on attraction and retention of talent variable as shown in Figure 34 as it was ranked by 43% of DMs.

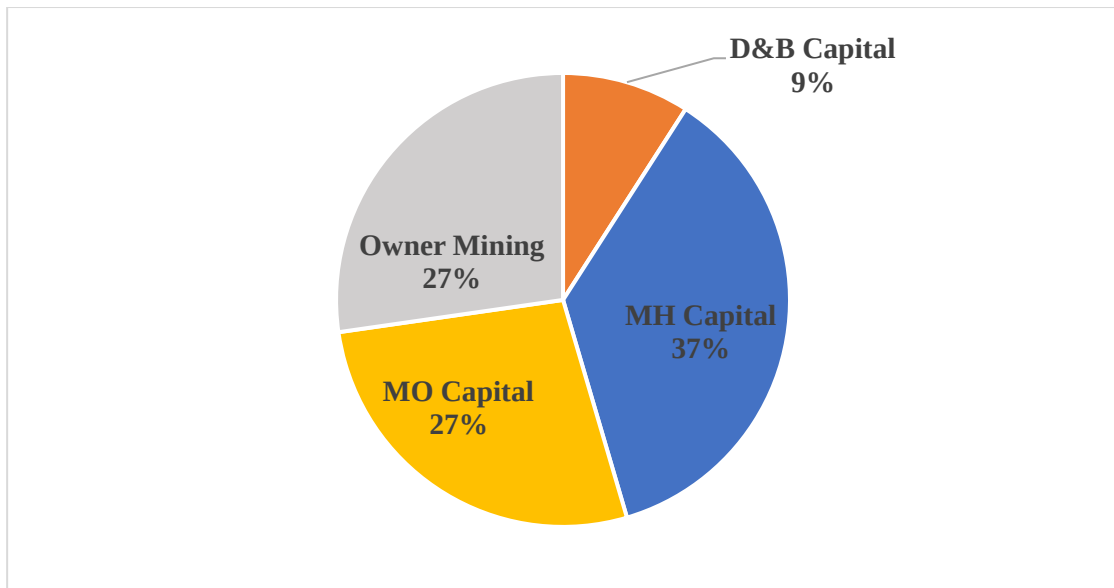


Figure 33 Percentage of DMs Ranking an Alternative as Highest on Attraction and Retention of Talent Criterion

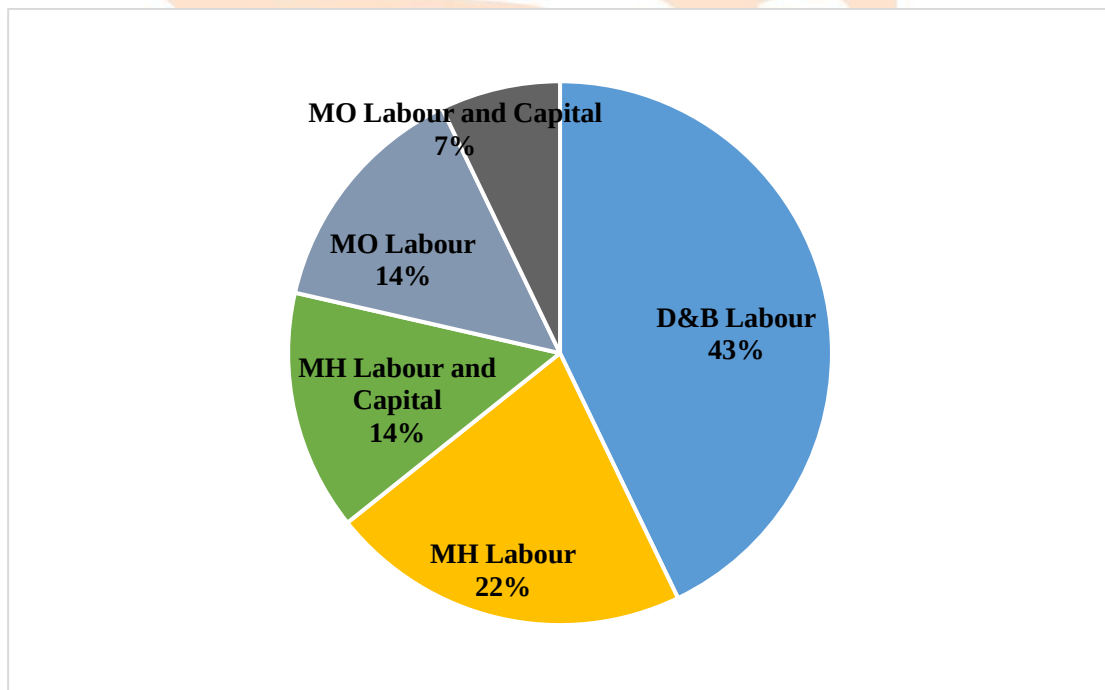


Figure 34 Percentage of DMs ranking an Alternative as Lowest on Attraction and Retention of Talent Criterion

Protect core competence criterion: Protect core competence variable is a benefit criterion. From Figure 35, owner mining is the most desirable alternative based on mining rates criterion as it was ranked by all the DMs using protect core competence criterion. Also, MO

labour and capital is the least desirable alternative based on protect core competence criterion as 50% of DMs ranked it as important (see Figure 36).

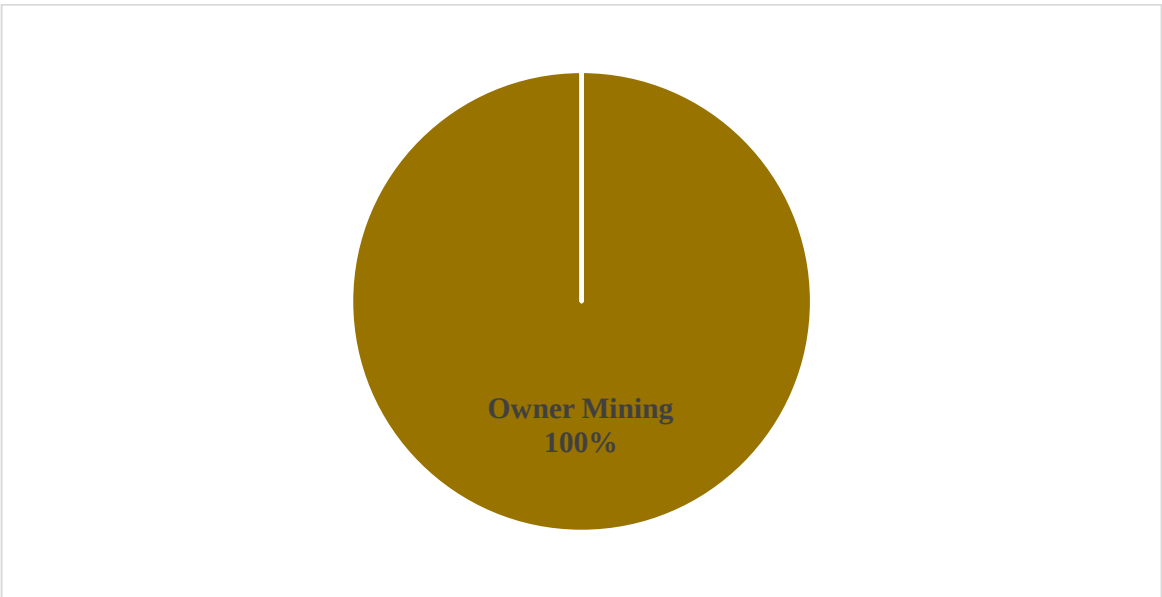


Figure 35 Percentage of DMs Ranking an Alternative as Highest on Protect Core Competence Criterion

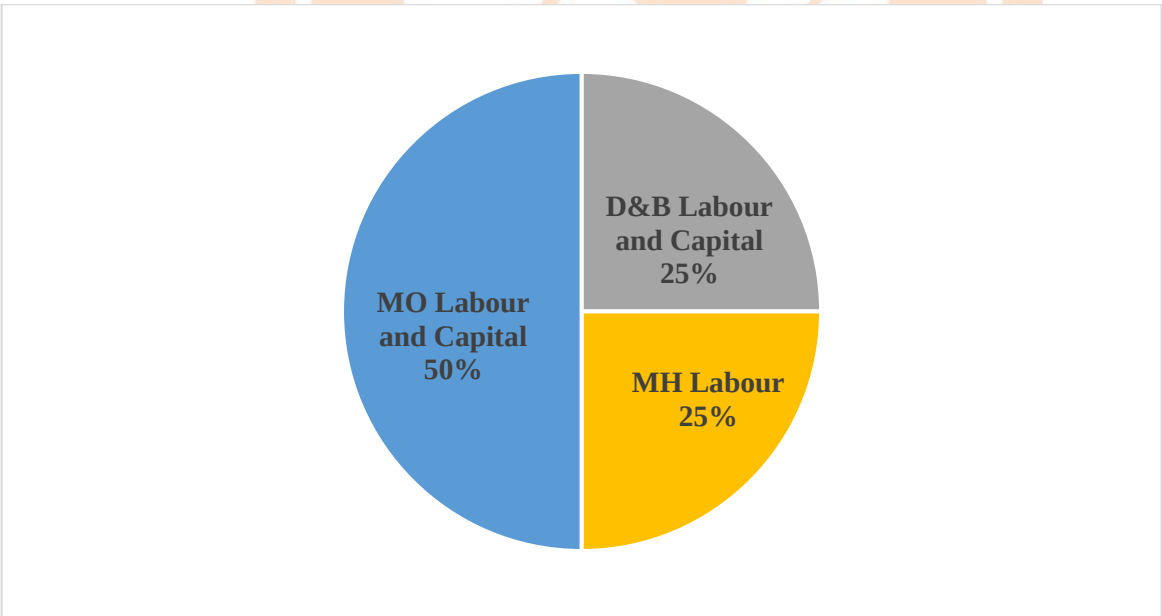


Figure 36 Percentage of DMs Ranking an Alternative as Lowest on Protect Core Competence Criterion

Quality criterion: Quality variable is a benefit criterion. From Figure 37, MO labour and capital is the only alternative ranked highest by the DMs as a quality criterion which makes

it the most desirable alternative. D&B labour and capital is the least desirable alternative based on quality criterion as shown in Figure 38, with 50% of DMs ranking it as the least among other alternatives.

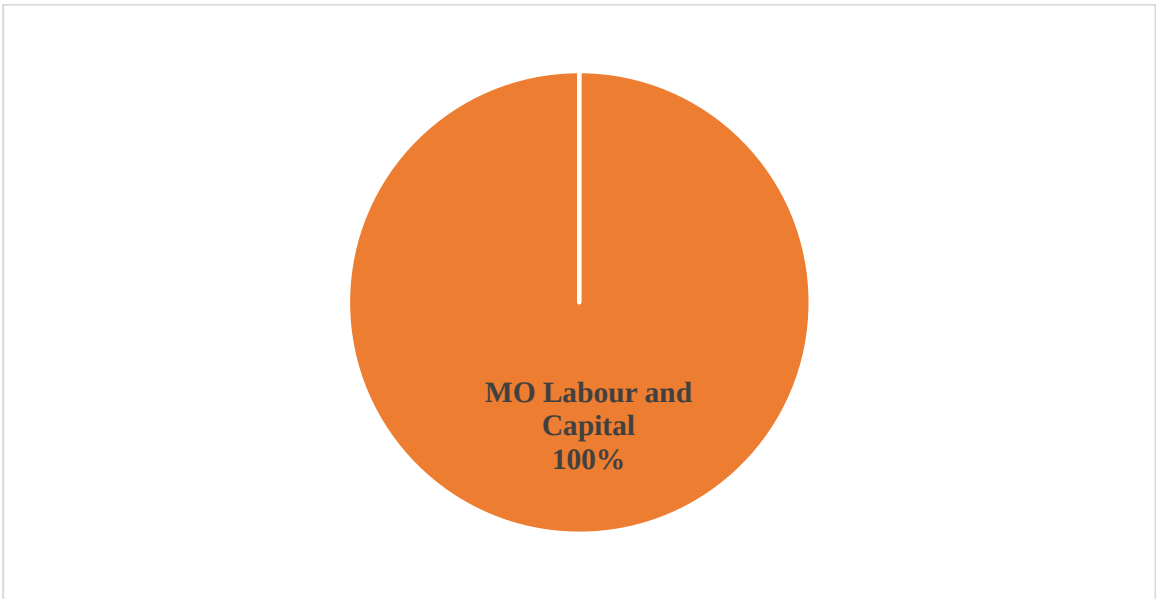


Figure 37 Percentage of DMs Ranking an Alternative as Highest on Quality Criterion

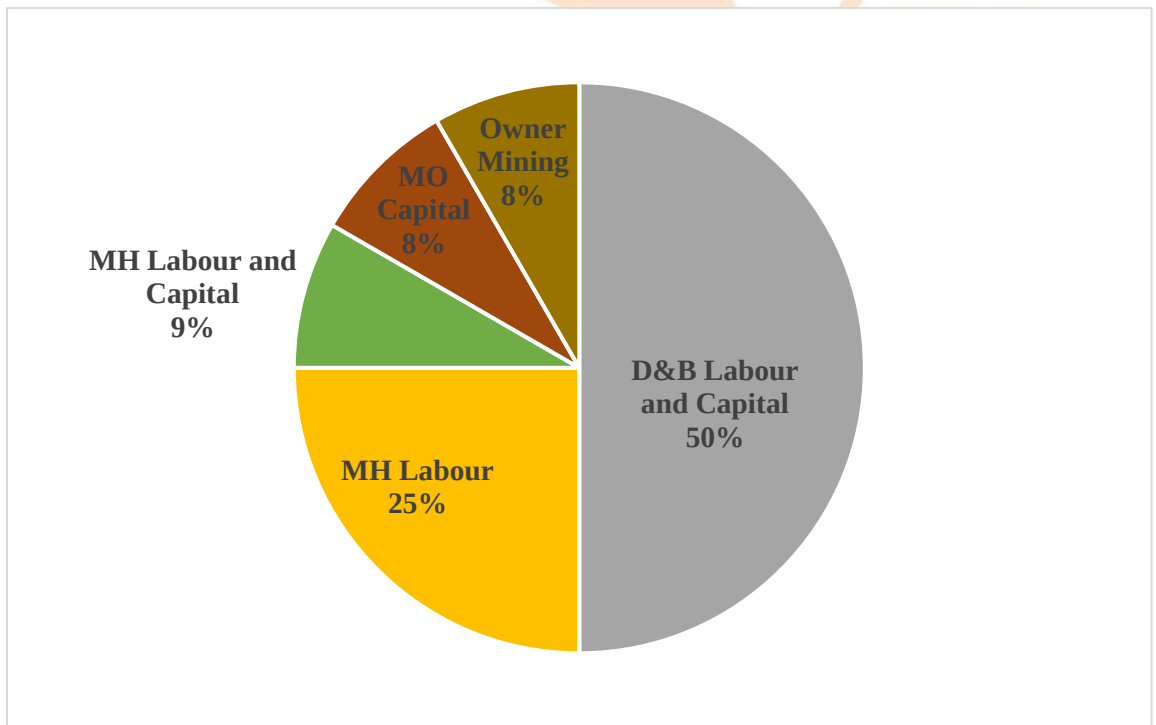


Figure 38 Percentage of DMs Ranking an Alternative as Lowest on Quality Criterion

Technological competitiveness criterion: Technological competitiveness variable is a benefit criterion. From Figure 39, MO capital is the most desirable alternative in terms of

technological competitiveness criterion, as 83% of the DMs ranked it as highest among all alternatives. Figure 40 shows that MO labour is the least desirable alternative based on technological competitiveness criterion with 75% of the DMs ranking it the lowest.

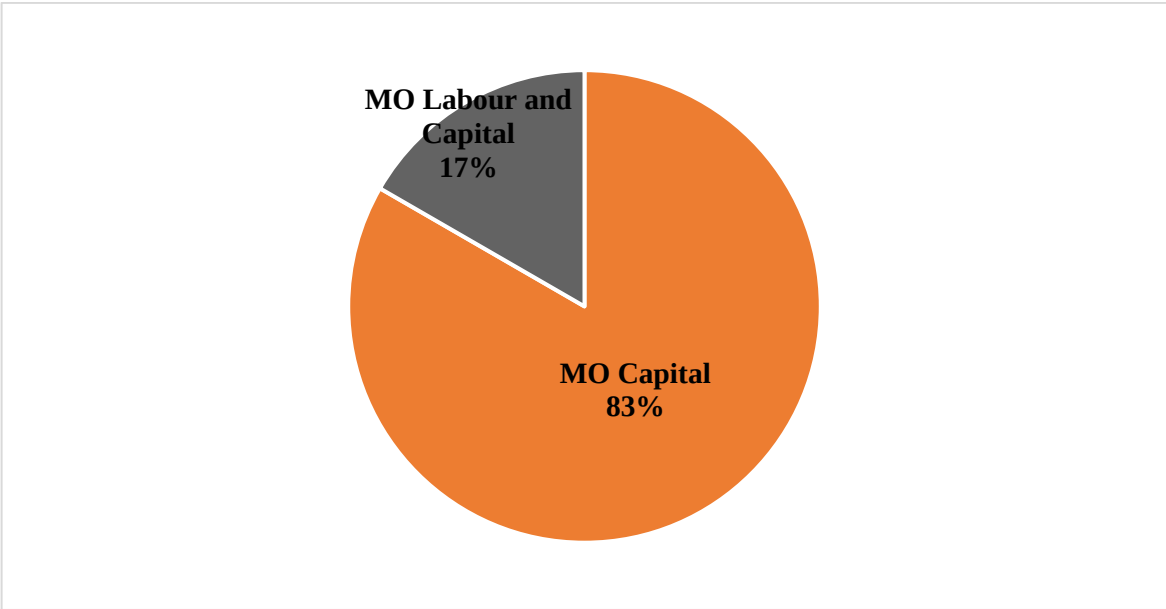


Figure 39 Percentage of DMs Ranking an Alternative as Highest on Technological Competitiveness Criterion

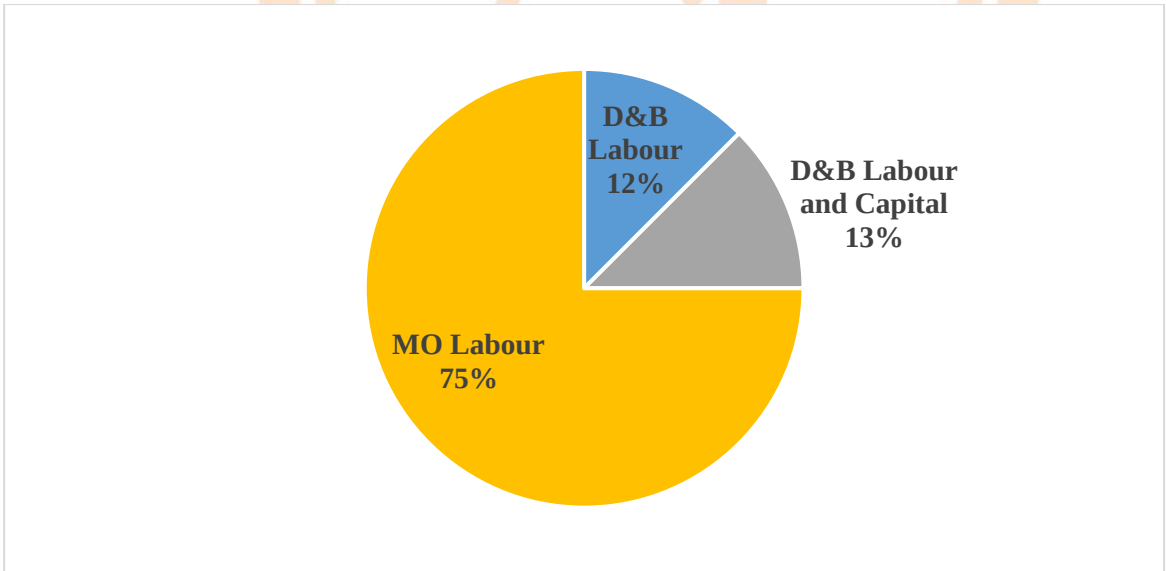


Figure 40 Percentage of DMs Ranking an Alternative as Lowest on Technological Competitiveness Criterion

Strategic relationship criterion: Strategic relationship variable is a benefit criterion. From Figure 41, MO labour and capital has the highest ranking as 86% of the DMs think it is

important based on strategic relationship criterion. This makes it the most desirable alternative. Owner mining is the least desirable alternative based on strategic relationship criterion as with 86% of the DMs ranked it as lowest among other alternatives (see Figure 42).

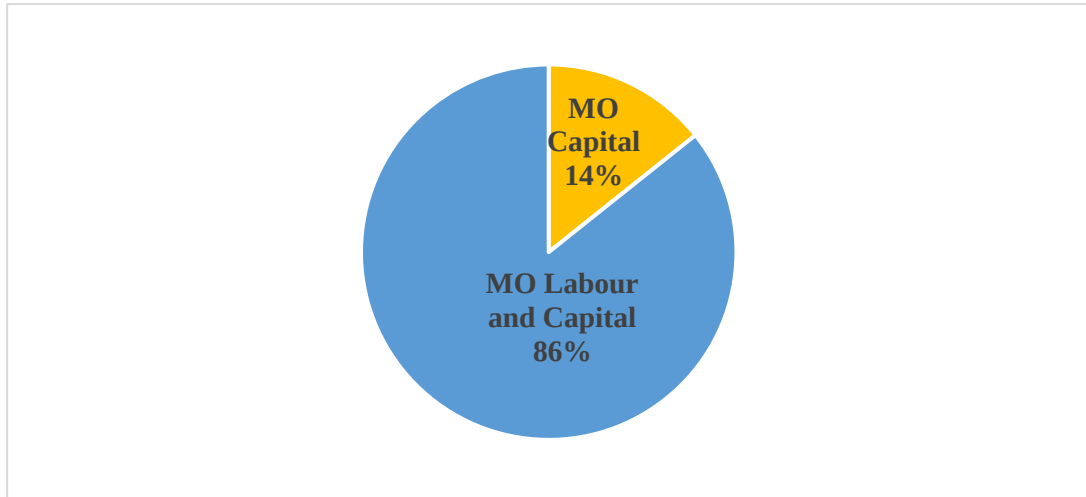


Figure 41 Percentage of DMs Ranking an Alternative as Highest on Strategic Relationship Criterion

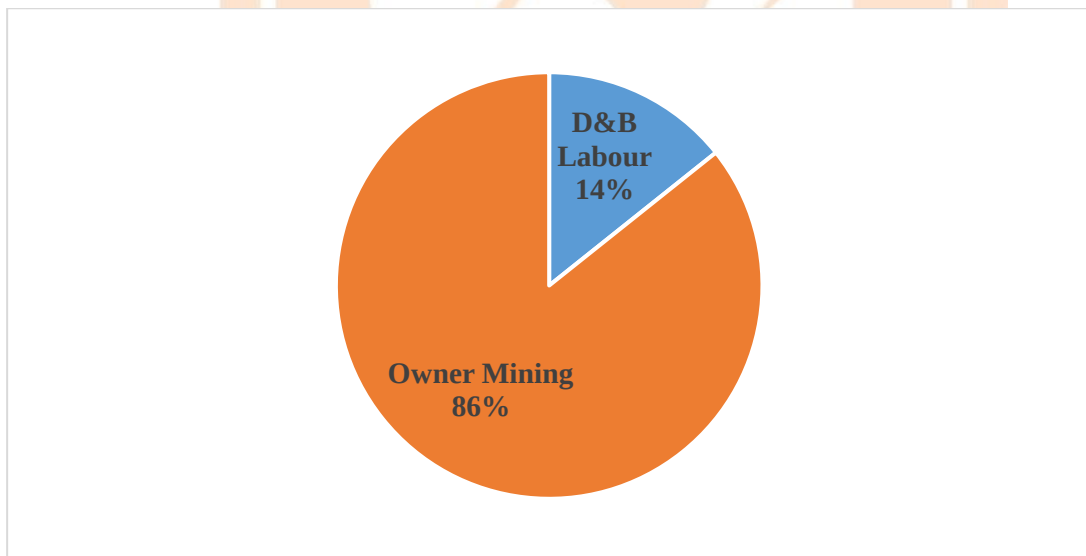


Figure 42 Percentage of DMs Ranking an Alternative as Lowest on Strategic Relationship Criterion

Environmental sustainability criterion: Environmental sustainability variable is a benefit criterion. From Figure 43, 71% of DMs ranked MO labour as the highest among all alternatives on environmental sustainability criterion. This implies that it is the most

desirable alternative in terms of environmental sustainability criterion. Also, from Figure 44 MO labour and capital is the least desirable alternative based on environmental sustainability criterion as 46% of the DMs ranked it as the lowest.

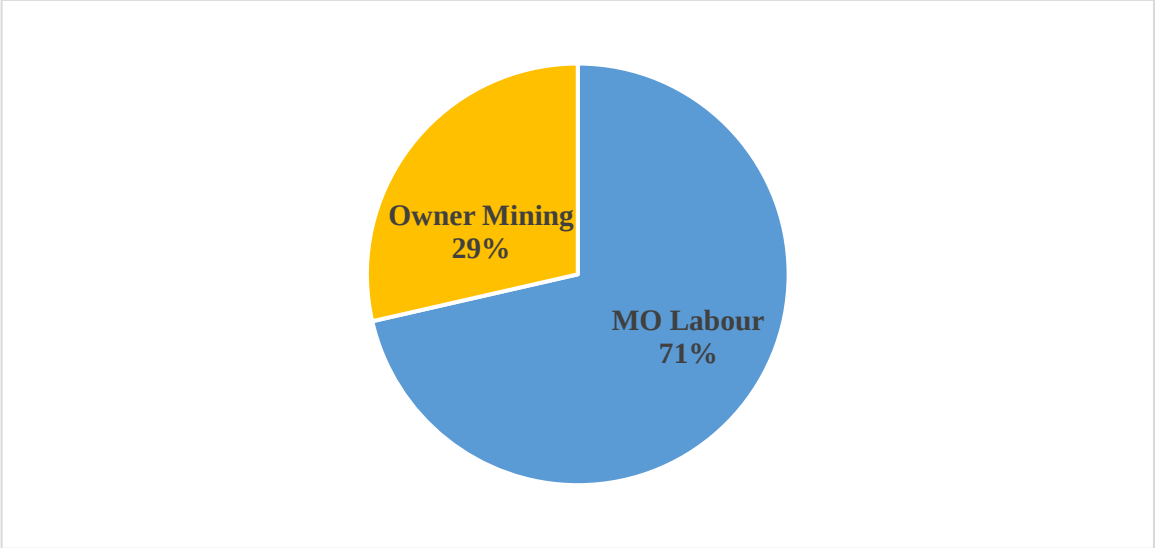


Figure 43 Percentage of DMs Ranking an Alternative as Highest on Environmental Sustainability Criterion

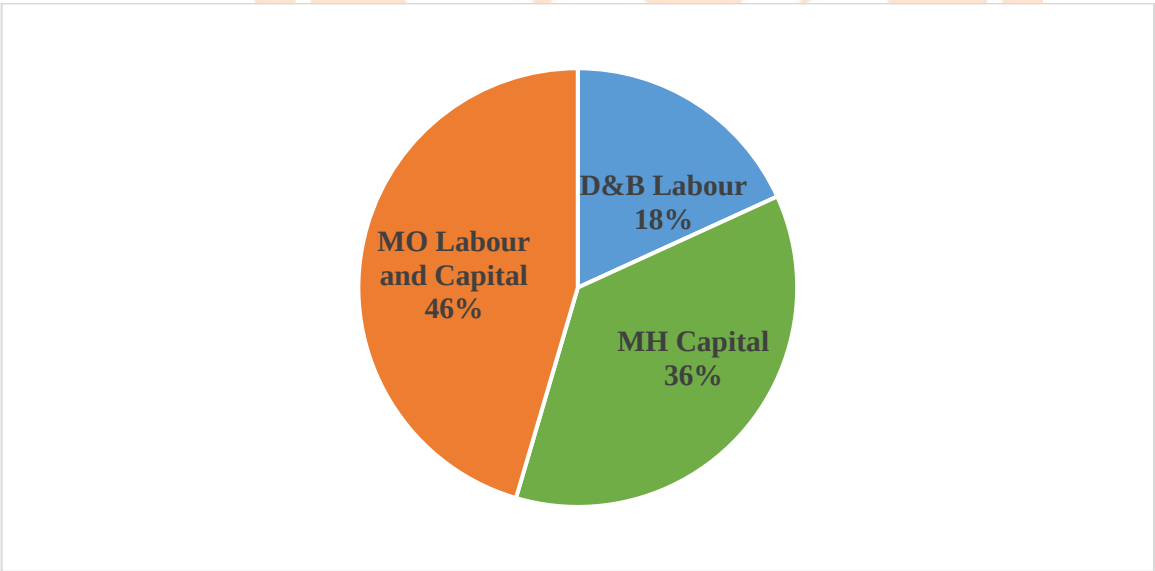


Figure 44 Percentage of DMs Ranking an Alternative as Lowest on Environmental Sustainability Criterion

4.3.4 Fuzzy Matrices

The fuzzy matrices are presented as fuzzy numbers in the HFTOPSIS model. Each *k*-decision maker matrix is converted from linguistic variables to fuzzy numbers using rating

of alternatives in Table 3 which were modelled in MS Excel. While there is only one crisp matrix, there are multiple fuzzy matrices formed from the data in the questionnaires, their number corresponds to the number of respondents (DMs). A sample of k -decision maker fuzzy matrix for one respondent is shown as linguistic variables and by their corresponding fuzzy notations and numbers in Tables 14 and 15 respectively. Comparison between crisp and fuzzy values is incongruous. Therefore, the fuzzy matrix in Table 15 was normalised using equation 14. Table 16 represents the k -decision maker normalised fuzzy matrix. Due to the large size of the matrices, alternatives are presented as notations from A1 to A10 in Tables 16 and 17. The corresponding descriptions for the A1 to A10 notations are shown in Table 8.

Table 14 Respondent's k -Decision Maker Fuzzy Matrix Showing Ranking of Alternatives Against Criteria in Linguistic Variables

	Criteria	Social licence to operate	Transaction cost	Mining rates	Attraction and retention of talent	Protect core competence	Quality	Technological competitiveness	Strategic relationship	Environmental sustainability
Alternatives	D&B Labour	VP	F	F	EP	SP	SG	SP	P	F
	D&B Capital	F	VG	SP	G	SP	G	SG	SP	F
	D&B Labour and Capital	SP	SG	SP	F	SP	SP	F	SP	SP
	MH Labour	EP	P	G	P	P	F	SP	F	F
	MH Capital	G	SG	SG	VG	SG	SG	G	SG	P
	MH Labour and Capital	SP	F	SG	SP	P	SG	SG	F	F
	MO Labour	EP	SP	G	P	SP	G	P	F	SG
	MO Capital	F	G	SG	VG	F	F	VG	SG	SP
	MO Labour and Capital	VP	F	EG	SP	VP	EG	G	VG	VP
	Owner Mining	VG	EP	VP	VG	EG	SG	F	EP	SG

Key: Extremely Poor (EP); Very Poor (VP); Very Good (VG); Extremely Good (EG); Good (G); Slightly Good (SG); Slightly Poor (SP); Poor (P); Fair (F)

Table 15 Respondent's *k*-Decision Maker Fuzzy Matrix showing Ranking of Alternatives Against Criteria as Fuzzy Numbers

	Criteria	Social licence to operate	Transaction cost	Mining rates	Attraction and retention of talent	Protect core competence	Quality	Technological competitiveness	Strategic relationship	Environmental sustainability
Alternatives	D&B Labour	(1,2,3)	(4,5,6)	(4,5,6)	(1,1,2)	(3,4,5)	(5,6,7)	(3,4,5)	(2,3,4)	(4,5,6)
	D&B Capital	(4,5,6)	(7,8,9)	(3,4,5)	(6,7,8)	(3,4,5)	(6,7,8)	(5,6,7)	(3,4,5)	(4,5,6)
	D&B Labour and Capital	(3,4,5)	(5,6,7)	(3,4,5)	(4,5,6)	(3,4,5)	(3,4,5)	(4,5,6)	(3,4,5)	(3,4,5)
	MH Labour	(1,1,2)	(2,3,4)	(6,7,8)	(2,3,4)	(2,3,4)	(4,5,6)	(3,4,5)	(4,5,6)	(4,5,6)
	MH Capital	(6,7,8)	(5,6,7)	(5,6,7)	(7,8,9)	(5,6,7)	(5,6,7)	(6,7,8)	(5,6,7)	(2,3,4)
	MH Labour and Capital	(3,4,5)	(4,5,6)	(5,6,7)	(3,4,5)	(2,3,4)	(5,6,7)	(5,6,7)	(4,5,6)	(4,5,6)
	MO Labour	(1,1,2)	(3,4,5)	(6,7,8)	(2,3,4)	(3,4,5)	(6,7,8)	(2,3,4)	(4,5,6)	(5,6,7)
	MO Capital	(4,5,6)	(6,7,8)	(5,6,7)	(7,8,9)	(4,5,6)	(4,5,6)	(7,8,9)	(5,6,7)	(3,4,5)
	MO Labour and Capital	(1,2,3)	(4,5,6)	(8,9,9)	(3,4,5)	(1,2,3)	(8,9,9)	(6,7,8)	(7,8,9)	(1,2,3)
	Owner Mining	(7,8,9)	(1,1,2)	(1,2,3)	(7,8,9)	(8,9,9)	(5,6,7)	(4,5,6)	(1,1,2)	(5,6,7)

Table 16 Respondent's *k*-Decision Maker Normalised Fuzzy Matrix Showing Ranking of Alternatives Against Criteria

Criteria		Social licence to operate	Transaction cost	Mining rates	Attraction and retention of talent	Protect core competence	Quality	Technological competitiveness	Strategic relationship	Environmental sustainability
Alternatives	A1	(1,0.5,0.33)	(0.25,0.2,0.17)	(0.44,0.56,0.67)	(0.11,0.11,0.22)	(0.33,0.44,0.56)	(0.56,0.67,0.78)	(0.33,0.44,0.56)	(0.22,0.33,0.44)	(0.57,0.71,0.86)
	A2	(0.25,0.2,0.17)	(0.14,0.13,0.11)	(0.33,0.44,0.56)	(0.67,0.78,0.89)	(0.33,0.44,0.56)	(0.67,0.78,0.89)	(0.56,0.67,0.78)	(0.33,0.44,0.56)	(0.57,0.71,0.86)
	A3	(0.33,0.25,0.2)	(0.2,0.17,0.14)	(0.33,0.44,0.56)	(0.44,0.56,0.67)	(0.33,0.44,0.56)	(0.33,0.44,0.56)	(0.44,0.56,0.67)	(0.33,0.44,0.56)	(0.43,0.57,0.71)
	A4	(1,1,0.5)	(0.5,0.33,0.25)	(0.67,0.78,0.89)	(0.22,0.33,0.44)	(0.22,0.33,0.44)	(0.44,0.56,0.67)	(0.33,0.44,0.56)	(0.44,0.56,0.67)	(0.57,0.71,0.86)
	A5	(0.17,0.14,0.13)	(0.2,0.17,0.14)	(0.56,0.67,0.78)	(0.78,0.89,1)	(0.56,0.67,0.78)	(0.56,0.67,0.78)	(0.67,0.78,0.89)	(0.56,0.67,0.78)	(0.29,0.43,0.57)
	A6	(0.33,0.25,0.2)	(0.25,0.2,0.17)	(0.56,0.67,0.78)	(0.33,0.44,0.56)	(0.22,0.33,0.44)	(0.56,0.67,0.78)	(0.56,0.67,0.78)	(0.44,0.56,0.67)	(0.57,0.71,0.86)
	A7	(1,1,0.5)	(0.33,0.25,0.2)	(0.67,0.78,0.89)	(0.22,0.33,0.44)	(0.33,0.44,0.56)	(0.67,0.78,0.89)	(0.22,0.33,0.44)	(0.44,0.56,0.67)	(0.71,0.86,1)
	A8	(0.25,0.2,0.17)	(0.17,0.14,0.13)	(0.56,0.67,0.78)	(0.78,0.89,1)	(0.44,0.56,0.67)	(0.44,0.56,0.67)	(0.78,0.89,1)	(0.56,0.67,0.78)	(0.43,0.57,0.71)
	A9	(1,0.5,0.33)	(0.25,0.2,0.17)	(0.89,1,1)	(0.33,0.44,0.56)	(0.11,0.22,0.33)	(0.89,1,1)	(0.67,0.78,0.89)	(0.78,0.89,1)	(0.14,0.29,0.43)
	A10	(0.14,0.13,0.11)	(1,1,0.5)	(0.11,0.22,0.33)	(0.78,0.89,1)	(0.89,1,1)	(0.56,0.67,0.78)	(0.44,0.56,0.67)	(0.11,0.11,0.22)	(0.71,0.86,1)

Table 17 HFTOPSIS *k*-Decision Maker Normalised Matrix with Positive Ideal Solution and Negative Ideal Solution

Criteria		Social licence to operate	Transaction cost	Operating cost	Project life	Profit margin risk	Capital efficiency ratio	OEE	Mining rates	Attraction and retention of talent	Protect core competence	Quality	Technological competitiveness	Strategic relationship	Environmental sustainability
Alternatives	A1	(1,0.5,0.3)	(0.3,0.2,0.2)	(0.9,0.9,0.9)	(0.2,0.2,0.2)	(0.7,0.7,0.7)	(0.1,0.1,0.1)	(0.2,0.2,0.2)	(0.4,0.6,0.7)	(0.1,0.1,0.2)	(0.3,0.4,0.6)	(0.6,0.7,0.8)	(0.3,0.4,0.6)	(0.2,0.3,0.4)	(0.6,0.7,0.9)
	A2	(0.3,0.2,0.2)	(0.1,0.1,0.1)	(0.8,0.8,0.8)	(0.3,0.3,0.3)	(0.8,0.8,0.8)	(0.2,0.2,0.2)	(0.8,0.8,0.8)	(0.3,0.4,0.6)	(0.7,0.8,0.9)	(0.3,0.4,0.6)	(0.7,0.8,0.9)	(0.6,0.7,0.8)	(0.3,0.4,0.6)	(0.6,0.7,0.9)
	A3	(0.3,0.3,0.2)	(0.2,0.2,0.1)	(0.7,0.7,0.7)	(0.3,0.3,0.3)	(0.8,0.8,0.8)	(0.2,0.2,0.2)	(0.3,0.3,0.3)	(0.3,0.4,0.6)	(0.4,0.6,0.7)	(0.3,0.4,0.6)	(0.3,0.4,0.6)	(0.4,0.6,0.7)	(0.3,0.4,0.6)	(0.4,0.6,0.7)
	A4	(1,1,0.5)	(0.5,0.3,0.3)	(0.6,0.6,0.6)	(0.4,0.4,0.4)	(0.9,0.9,0.9)	(0.3,0.3,0.3)	(0.6,0.6,0.6)	(0.7,0.8,0.9)	(0.2,0.3,0.4)	(0.2,0.3,0.4)	(0.4,0.6,0.7)	(0.3,0.4,0.6)	(0.4,0.6,0.7)	(0.6,0.7,0.9)
	A5	(0.2,0.1,0.1)	(0.2,0.2,0.1)	(0.3,0.3,0.3)	(0.7,0.7,0.7)	(1,1,1)	(0.8,0.8,0.8)	(0.2,0.2,0.2)	(0.6,0.7,0.8)	(0.8,0.9,1)	(0.6,0.7,0.8)	(0.6,0.7,0.8)	(0.7,0.8,0.9)	(0.6,0.7,0.8)	(0.3,0.4,0.6)
	A6	(0.3,0.3,0.2)	(0.3,0.2,0.2)	(0.3,0.3,0.3)	(1,1,1)	(1,1,1)	(0.9,0.9,0.9)	(0.4,0.4,0.4)	(0.6,0.7,0.8)	(0.3,0.4,0.6)	(0.2,0.3,0.4)	(0.6,0.7,0.8)	(0.6,0.7,0.8)	(0.4,0.6,0.7)	(0.6,0.7,0.9)
	A7	(1,1,0.5)	(0.3,0.3,0.2)	(0.6,0.6,0.6)	(0.4,0.4,0.4)	(0.9,0.9,0.9)	(0.3,0.3,0.3)	(0.2,0.2,0.2)	(0.7,0.8,0.9)	(0.2,0.3,0.4)	(0.3,0.4,0.6)	(0.7,0.8,0.9)	(0.2,0.3,0.4)	(0.4,0.6,0.7)	(0.7,0.9,1)
	A8	(0.3,0.2,0.2)	(0.2,0.1,0.1)	(0.3,0.3,0.3)	(1,1,1)	(1,1,1)	(0.8,0.8,0.8)	(0.9,0.9,0.9)	(0.6,0.7,0.8)	(0.8,0.9,1)	(0.4,0.6,0.7)	(0.4,0.6,0.7)	(0.8,0.9,1)	(0.6,0.7,0.8)	(0.4,0.6,0.7)
	A9	(1,0.5,0.3)	(0.3,0.2,0.2)	(0.2,0.2,0.2)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(0.9,1,1)	(0.3,0.4,0.6)	(0.1,0.2,0.3)	(0.9,1,1)	(0.7,0.8,0.9)	(0.8,0.9,1)	(0.1,0.3,0.4)
	A10	(0.1,0.1,0.1)	(1,1,0.5)	(1,1,1)	(0.2,0.2,0.2)	(0.7,0.7,0.7)	(0.1,0.1,0.1)	(0.8,0.8,0.8)	(0.1,0.2,0.3)	(0.8,0.9,1)	(0.9,1,1)	(0.6,0.7,0.8)	(0.4,0.6,0.7)	(0.1,0.1,0.2)	(0.7,0.9,1)
	A+	19.14	1.97	12.73	3.95	19.73	1.36	9.55	0.31	0.12	2.00	0.68	4.75	0.42	2.16
	A-	5.47	0.56	3.17	0.72	13.84	0.08	1.47	0.03	0.01	0.22	0.23	1.06	0.05	0.31

Table 18 Linguistic Variables Pairwise Matrix

Main Weights	Operating cost-based factors	Capital efficiency-based factors	Flexibility-based factors	Competence-based factors	Relationship-based factors
Operating cost-based factors	Equal importance	Strong importance	Very strong importance	Extreme importance	Extreme importance
Capital efficiency-based factors	Strong importance	Equal importance	Strong importance	Very strong importance	Strong importance
Flexibility-based factors	Very strong importance	Strong importance	Equal importance	Strong importance	Moderate importance
Competence-based factors	Extreme importance	Very strong importance	Strong importance	Equal importance	Strong importance
Relationship-based factors	Extreme importance	Strong importance	Moderate importance	Strong importance	Equal importance

4.3.5 Combination of Matrices

The crisp data and fuzzy matrices are combined by the addition of their matrices. There is only one crisp matrix and 6 fuzzy matrices. Therefore, the crisp matrix is added to each fuzzy matrix to form the HFTOPSIS k -decision maker matrices. Table 17 is a sample of the HFTOPSIS k -decision maker matrix. To form a uniform matrix, the crisp values are presented in fuzzy format as shown in equation 2 and Figure 6, with the lower (a_1), middle (a_2) and upper (a_3) values equal as summarised in Table 17. There are 6 HFTOPSIS matrices in this study and only one is presented as an illustration. The normalised crisp matrix in Table 13 is combined with the normalised fuzzy matrix in Table 16 to form a HFTOPSIS k -decision maker normalised matrix as shown in Table 17.

4.4 HFTOPSIS Decision Analysis

The final decision of the Hybrid Fuzzy TOPSIS model is either a rank of alternatives, selection of the best alternatives or both. The decision is made from the ranks determined using the closeness coefficient (CC). The closeness coefficient represents the geometric distance of an alternative from the positive ideal solution and the negative ideal solution. Therefore, the CC is determined from the HFTOPSIS k -decision maker matrix as detailed in the next sections.

4.4.1 Global Weights Determination

The global weights were calculated according to the procedure outlined in Section 3.6.3. The weights are summarised in Table 19. Firstly, the hierarchical structure shown in Table 2 was developed. The linguistic pairwise matrix for main weights were tabulated as summarised in Table 18. The linguistic pairwise matrix was then converted to numeric pairwise matrix as shown in Table 20 using the pairwise scale in Table 4.

Table 19 Global Criteria Weights

Criteria	Criteria Weights		
	Main	Local	Global
Profit margin risk	0.55	0.70	0.382844
Transaction cost	0.55	0.07	0.039494
Operating cost	0.55	0.23	0.127305
Capital efficiency ratio	0.24	0.17	0.039469
OEE	0.24	0.83	0.197345
Project life	0.11	0.13	0.013644
Mining rates	0.11	0.88	0.095508
Attraction and retention of talent	0.03	0.10	0.003100
Protect core competence	0.03	0.04	0.001223
Quality	0.03	0.64	0.020021
Technological competitiveness	0.03	0.22	0.006783
Social licence to operate	0.07	0.65	0.047521
Strategic relationship	0.07	0.06	0.004157
Environmental sustainability	0.07	0.29	0.021586

Table 21 summarises the values of the normalised numerical pairwise matrix which was obtained using procedures outlined in Step 2 of Section 3.6.3. The weights were then determined from the normalised numerical pairwise matrix by taking the row average of each criterion as shown in the last column of Table 21. The pairwise matrices for local weights are summarised in Appendix 4. The global weights were determined by finding the product of local weights and the corresponding main weights as summarised in Table 19. Global weights for criteria were presented in a row matrix as in equation 12. The global row

matrix was then multiplied by the HFTOPSIS k -decision maker normalised matrix to find the HFTOPSIS k -decision maker weighted normalised matrix as summarised in Table 22.

Table 20 Numeric Variables Pairwise Matrix

Main Numerical Weights	Operating Cost-based factors	Capital Efficiency-based factors	Flexibility-based factors	Competence-based factors	Relationship-based factors
Operating cost-based factors	1.00	5.00	7.00	9.00	9.00
Capital efficiency-based factors	0.20	1.00	5.00	7.00	5.00
Flexibility-based factors	0.14	0.20	1.00	5.00	3.00
Competence-based factors	0.11	0.14	0.20	1.00	0.20
Relationship-based factors	0.11	0.20	0.33	5.00	1.00
SUM	1.57	6.54	13.53	27.00	18.20

Table 21 Normalised Numeric Variables Pairwise Matrix

Main Normalised Weights	Operating Cost-based factors	Capital Efficiency-based factors	Flexibility-based factors	Competence-based factors	Relationship-based factors	Main Criteria Weights
Operating cost-based factors	0.64	0.76	0.52	0.33	0.49	0.55
Capital efficiency-based factors	0.13	0.15	0.37	0.26	0.27	0.24
Flexibility-based factors	0.09	0.03	0.07	0.19	0.16	0.11
Competence-based factors	0.07	0.02	0.01	0.04	0.01	0.03
Relationship-based factors	0.07	0.03	0.02	0.19	0.05	0.07

4.4.2 Closeness Coefficient Determination

The closeness coefficient was determined from the weighted normalised matrix HFTOPSIS k -decision maker. Firstly, the positive ideal solution and the negative ideal solutions were determined using equations 15 and 16 respectively. Table 17 summarises the positive ideal solutions (A+) and negative ideal solutions (A-) for each criterion from the sample k -

decision maker matrices. Both A^+ and A^- were determined from each DM's matrix and presented on each of their matrices.

Then the separation measure from both A^+ and A^- are determined, using equations 17 and 18 respectively, for each alternative. The separation measures for DMs are summarised in Table 23, where d^+ represents the separation measure from A^+ and d^- represents the separation value from A^- . The positive ideal solution measure of separation (d^{*+}) and negative ideal solution measure of separation (d^{*-}) values were determined by finding the arithmetic mean of the six DMs' d^+ using equation 19 and d^- using equation 20 respectively. The values are summarised in Figure 45. The measures of separation were used to determine the relative closeness to d^+ which is the closeness coefficient value (R^*) shown in Figure 45.

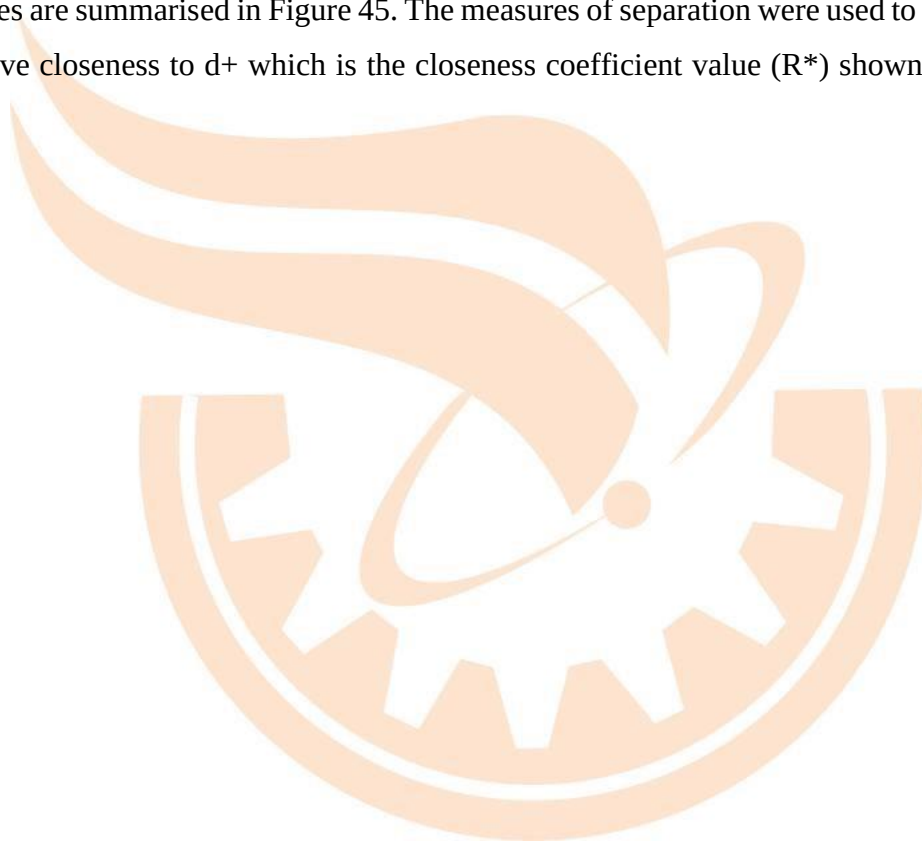


Table 22 HFTOPSIS k-Decision Maker Weighted Normalised Matrix

Criteria		Social licence to operate	Transaction cost	Operating cost	Project life	Profit margin risk	Capital efficiency ratio	OEE	Mining rates	Attraction and retention of talent	Protect core competence	Quality	Technological competitiveness	Strategic relationship	Environmental sustainability
Weights (%)		4.7521	3.9494	12.7305	1.3644	38.2844	3.9469	19.7345	9.5508	0.3100	0.1223	2.0021	0.6783	0.4157	2.1586
Alternatives	A1	(5,2,2)	(1,1,1)	(12,12,12)	(0,0,0)	(29,29,29)	(0,0,0)	(16,16,16)	(4,5,6)	(0,0,0)	(0,0,0)	(1,1,2)	(0,0,0)	(0,0,0)	(1,2,2)
	A2	(1,1,1)	(1,0,0)	(10,10,10)	(0,0,0)	(31,31,31)	(1,1,1)	(16,16,16)	(3,4,5)	(0,0,0)	(0,0,0)	(1,2,2)	(0,0,1)	(0,0,0)	(1,2,2)
	A3	(2,1,1)	(1,1,1)	(9,9,9)	(0,0,0)	(32,32,32)	(1,1,1)	(16,16,16)	(3,4,5)	(0,0,0)	(0,0,0)	(1,1,1)	(0,0,0)	(0,0,0)	(1,1,2)
	A4	(5,5,2)	(2,1,1)	(8,8,8)	(1,1,1)	(34,34,34)	(1,1,1)	(20,20,20)	(6,7,8)	(0,0,0)	(0,0,0)	(1,1,1)	(0,0,0)	(0,0,0)	(1,2,2)
	A5	(1,1,1)	(1,1,1)	(4,4,4)	(1,1,1)	(38,38,38)	(3,3,3)	(20,20,20)	(5,6,7)	(0,0,0)	(0,0,0)	(1,1,2)	(0,1,1)	(0,0,0)	(1,1,1)
	A6	(2,1,1)	(1,1,1)	(3,3,3)	(1,1,1)	(38,38,38)	(4,4,4)	(20,20,20)	(5,6,7)	(0,0,0)	(0,0,0)	(1,1,2)	(0,0,1)	(0,0,0)	(1,2,2)
	A7	(5,5,2)	(1,1,1)	(8,8,8)	(1,1,1)	(34,34,34)	(1,1,1)	(20,20,20)	(6,7,8)	(0,0,0)	(0,0,0)	(1,2,2)	(0,0,0)	(0,0,0)	(2,2,2)
	A8	(1,1,1)	(1,1,0)	(4,4,4)	(1,1,1)	(38,38,38)	(3,3,3)	(20,20,20)	(5,6,7)	(0,0,0)	(0,0,0)	(1,1,1)	(1,1,1)	(0,0,0)	(1,1,2)
	A9	(5,2,2)	(1,1,1)	(3,3,3)	(1,1,1)	(38,38,38)	(4,4,4)	(20,20,20)	(8,10,10)	(0,0,0)	(0,0,0)	(2,2,2)	(0,1,1)	(0,0,0)	(0,1,1)
	A10	(1,1,1)	(4,4,2)	(13,13,13)	(0,0,0)	(27,27,27)	(0,0,0)	(16,16,16)	(1,2,3)	(0,0,0)	(0,0,0)	(1,1,2)	(0,0,0)	(0,0,0)	(2,2,2)

Table 23 Positive Ideal Solution Measures of Separation and Negative Ideal Solution Measures of Separation for DMs

	Positive Ideal Solution Measures of Separation						Negative Ideal Solution Measures of Separation					
	d1+	d2+	d3+	d4+	d5+	d6+	d1-	d2-	d3-	d4-	d5-	d6-
D&B Labour	36.0	41.4	36.9	42.1	41.3	41.2	34.9	40.1	32.6	36.6	40.2	40.6
D&B Capital	29.0	25.1	25.5	25.4	26.0	25.6	23.4	28.8	27.3	25.9	28.0	28.4
D&B Labour and Capital	32.8	31.2	30.6	33.7	39.4	34.6	19.8	22.5	22.2	16.6	42.1	17.9
MH Labour	35.9	37.9	38.0	37.5	38.6	37.4	46.2	46.5	45.2	42.9	45.9	47.2
MH Capital	37.0	35.4	36.6	36.2	36.5	35.8	15.6	16.5	16.2	16.0	15.8	16.4
MH Labour and Capital	29.8	27.9	33.1	33.6	37.5	34.0	22.9	27.6	36.5	34.4	44.0	36.7
MO Labour	40.4	41.7	41.4	42.0	41.1	40.8	41.6	41.6	38.9	38.4	40.6	40.9
MO Capital	26.5	24.4	24.9	24.7	22.1	27.6	25.9	27.9	26.5	25.6	32.0	24.6
MO Labour and Capital	26.9	31.6	28.0	31.2	27.3	30.2	44.1	51.7	41.5	47.5	43.3	51.6
Owner Mining	31.7	32.8	29.7	30.1	32.5	32.0	24.8	23.5	24.7	25.2	24.0	24.5

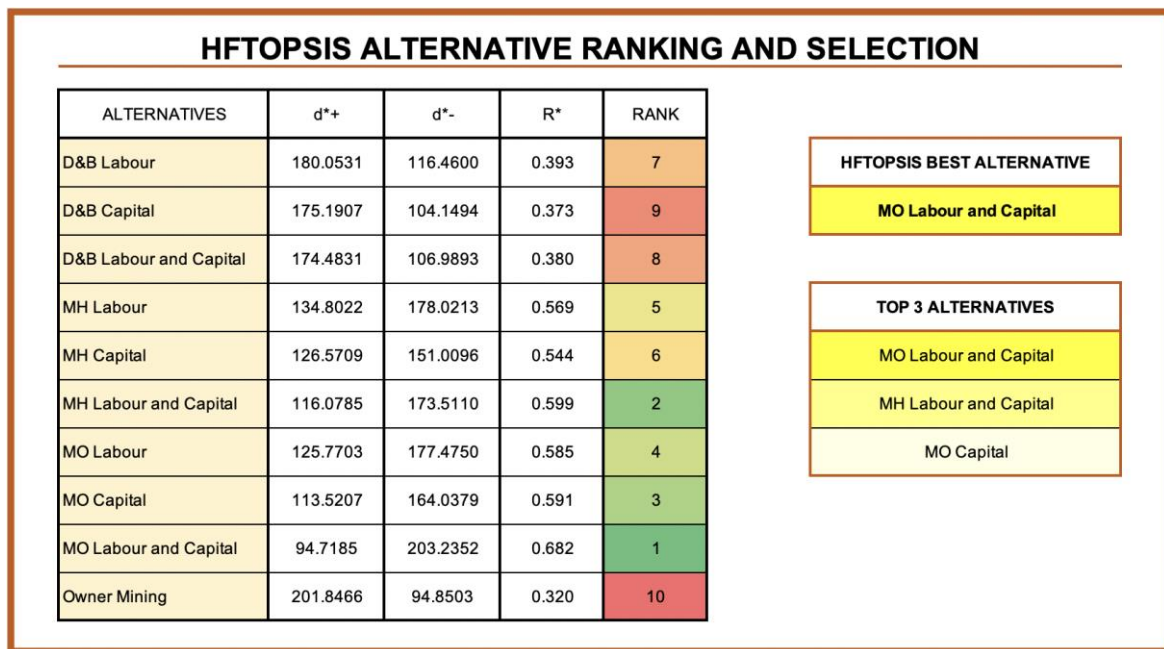


Figure 45 HFTOPSIS Decision

4.4.3 HFTOPSIS Decision

A set of alternatives were ranked in descending order of the R^{*} value as shown in Figure 45. In the HFTOPSIS method the alternative where the R^{*} value is closest to 1 is the best solution (i.e., the alternative with the highest R^{*}, (CC) value) is the best. The 10 alternatives were ranked from 1 to 10 based on the value of R^{*}. MO labour and capital had the highest R^{*} value of 0.682 and is considered as the best alternative followed by MH labour and capital, and MO capital with 0.599 and 0.591 respectively. The lowest ranked alternative is owner mining with R^{*} value of 0.320 (see Figure 45).

4.4.4 Validation Results

The HFTOPSIS method was compared to other MCDM methods against the actual performance of alternatives as measured from different Jwaneng Mine projects from 2009 to 2019. The projects considered include the Jwaneng Modular Plant (JMP) and Cuts 6 to 9. Out of the 10 alternatives, the actual performance ranks could only be measured for 9 alternatives: D&B capital (provision of drill rigs, supply of explosives; mobile manufacturing units and accessories); D&B labour and capital; MH labour; MH capital (loading, hauling and support equipment and accessories); MH labour and capital; MO labour; MO capital and, MO labour and capital and owner mining.

The actual performance ranking based on cost, efficiency and flexibility criteria was used as the base case. The results from HFOTOPSIS were then compared to those obtained using TOPSIS, FTOPSIS and BSC. Table 24 summarises the ranks for the base case and the MCDM methods as obtained from the case study.

Table 24 Comparison of MCDM Methods Rankings

Alternatives	Ranking of MCDM Methods				
	Base Case	HFTOPSIS	FTOPSIS	TOPSIS	BSC
MO Labour and Capital	1	1	1	3	1
MH Labour and Capital	2	2	3	1	3
MO Capital	3	3	2	2	2
MO Labour	4	4	4	4	4
MH Labour	5	5	5	5	6
MH Capital	6	6	6	6	5
Owner Mining	7	10	10	10	7
D&B Labour and Capital	8	8	8	8	10
D&B Capital	9	9	9	9	8
D&B Labour	NA	7	7	7	9
Ranks Predicted Correctly		8	6	5	2

From Table 24, the results indicate that there are minor variations between the ranks obtained from HFTOPSIS and the base case ranks. HFTOPSIS has ranks from 1 to 6 which are similar to the ranks in the base case. Out of 10 alternatives, HFTOPSIS correctly ranked 8 alternatives with respect to the ranks in the base case. The results of FTOPSIS correctly ranked only 6 alternatives out of the 10 alternatives compared to base case ranking. The results from TOPSIS and BSC show that only 5 and 3 alternatives were ranked correctly out of the 10 alternatives when compared to the base case respectively. The general prediction patterns for FTOPSIS and TOPSIS are not very related to the base case ranking because only the middle alternative ranks are similar to the base case ranking. Finally, there is no clear pattern for BSC ranking relative to base case ranking.

CHAPTER 5

OBSERVATIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Observations

The observations from this study are as follows:

1. The mining outsourcing decision problem is multi-objective.
2. The most important decision objective is cost, followed by efficiency while relationship and competence are the second least and least important objectives respectively.
3. Attraction and retention of talent, strategic relationships and protection of core competence sub-criteria are inconsequential.
4. Crisp criteria are generally more significant than fuzzy criteria.
5. The dichotomous owner mining and contract mining alternatives are insufficient in formal mining outsourcing decision analysis.
6. The formal classification of mining outsourcing decision alternatives according to unit operations and resources is imperative.
7. The validation results have proven that the results of HFTOPSIS are better than the other methods in ranking alternatives based on multiple criteria.
8. The comparison between TOPSIS methods and BSC clearly indicates that TOPSIS methods are more helpful in precisely ranking alternatives than BSC for MCDM methods.
9. HFTOPSIS improves the results of MCDM problems significantly because it is not only precise, but it is also accurate.

5.2 Conclusions

From the analyses in this study, it is concluded that:

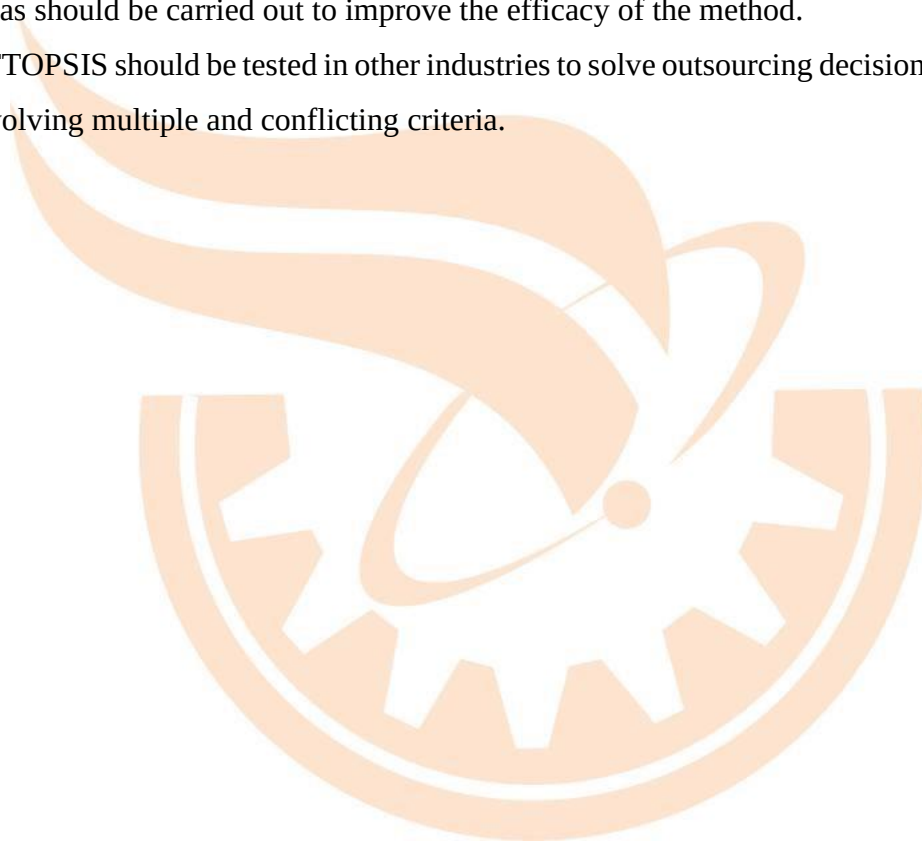
1. HFTOPSIS can improve the mining outsourcing decision process results significantly.
2. The HFTOPSIS method is a much better MCDM method compared to FTOPSIS, TOPSIS and BSC for mining outsourcing decision problem analysis when compared with the base case.

3. The generalised framework algorithm is not only applicable to mining industry and the developed conceptual framework can be instrumental in decision-making problems involving multiple criteria in any industry.

5.3 Recommendations

From the results of this work, it is recommended that:

1. Debswana Jwaneng Mine can adopt the HFTOPSIS method in their outsourcing decision analysis processes.
2. More case studies using HFTOPSIS on different minerals in different geographical areas should be carried out to improve the efficacy of the method.
3. HFTOPSIS should be tested in other industries to solve outsourcing decision problems involving multiple and conflicting criteria.



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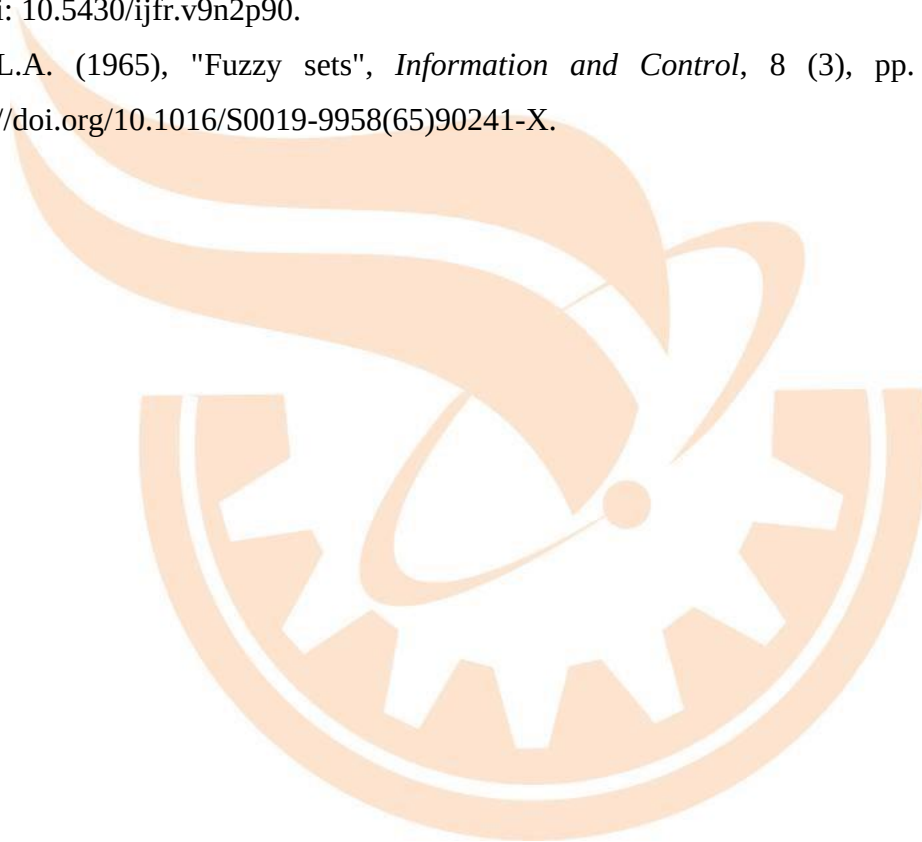
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APPENDICES



APPENDIX 1

FINANCIAL STATEMENTS FOR DEBSWANA JWANENG MINE OPERATIONS BETWEEN 2016 AND 2028

	2016	2017	2018	2027	2028
Assumptions					
Year	2016	2017	2018	2027	2028
Diamond Price (US\$)	4,344	4,344	4,344	4,344	4,344
Ore Milled (t)	8,490,230	7,027,996	8,390,909	5,664,084	10,188,581
Grade (carat/t)	1.3	1.5	1.4	1.0	1.7
Recovery (%)	89.1	88.6	89.7	89.5	88.4
Percent of Mine Life (%)	7.4	6.6	8.4	6.2	11.9
Mine Operating Costs					
Mining (\$/t)	644.78				
Processing (\$/t)	805.00				
Transport and Refining (\$/t)	10.00				
General and Administration (\$/t)	217.00				
	1,676.78				
Exploration (\$/carat)	27.00				
Mining					
Opening Balance	115,413,637	106,923,407	99,895,410	91,504,501	85,840,416
Less: Ore Mined/Milled (t)	(8,490,230)	(7,027,997)	(8,390,909)	(5,664,085)	(10,188,581)
Closing Ore Balance (US\$)	106,923,407	99,895,410	91,504,501	85,840,416	75,651,835

Strip Ratio (US\$)		4.0	4.0	4.0	4.0	4.0
Waste Mined (t)		33,960,920	28,111,987	33,563,637	22,656,339	40,754,325
Total Material Moved (t)		42,451,150	35,139,984	41,954,547	28,320,423	50,942,907
Ore mined (t)		8,490,230	7,027,997	8,390,909	5,664,085	10,188,581
Diamond Grade (carats/t)		1.35	1.54	1.44	1.03	1.71
Contained Diamonds (carats/t)		11,422,760	10,789,088	12,098,313	5,811,674	17,420,968
Milling Schedule						
Mill Feed (tonnes)		8,490,230	7,027,997	8,390,909	5,664,085	10,188,581
Recovery (%)	Diamonds	89.1%	88.6%	89.7%	89.5%	88.4%
Production (t)	Diamonds	10,177,679	9,559,132	10,852,187	5,201,448	15,400,136
Payability (%)	Diamonds	99.9%	99.9%	99.9%	99.9%	99.9%
Payable Metal (t)	Diamonds	10,171,064	9,552,918	10,845,133	5,198,067	15,390,126
Financials						
Metal Prices (US\$)	Diamonds	4,344	4,344	4,344	4,344	4,344
Payable Metal (US\$)	Diamonds	10,171,064	9,552,918	10,845,133	5,198,067	15,390,126
Tonnage (t)	Mill Feed	8,490,230	7,027,997	8,390,909	5,664,085	10,188,581
Financial Statements						
Gross Revenue (US\$)	Diamonds	44,183,100,654	41,497,877,842	47,111,256,269	22,580,404,503	66,854,705,447
Royalties (US\$)	Average	6,185,634,092	5,809,702,898	6,595,575,878	3,161,256,630	9,359,658,763
Less Total Operating Costs (US\$)						
Mining		5,474,332,263	4,531,513,167	5,410,292,220	3,652,089,663	6,569,395,577
Processing		6,834,635,183	5,657,537,364	6,754,681,992	4,559,588,147	8,201,807,998
Transport & Refining		84,902,300	70,279,967	83,909,093	56,640,847	101,885,814
General & Admin		1,842,379,919	1,525,075,289	1,820,827,320	1,229,106,370	2,210,922,156

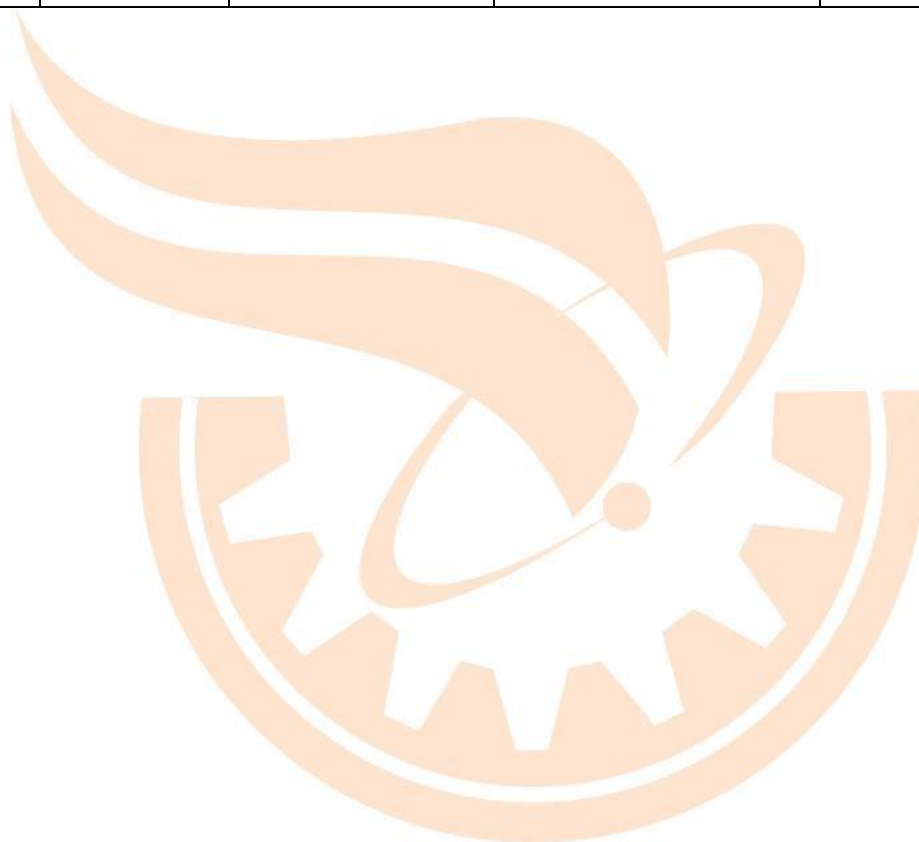
Total	(14,236,249,664)	(11,784,405,788)	(14,069,710,624)	(9,497,425,027)	(17,084,011,544)
Less Total Capital Costs (US\$)	(1,769,201,956)	(1,464,500,431)	(1,748,505,410)	(1,180,287,178)	(2,123,105,970)
EBITDA (US\$)	21,992,014,942	22,439,268,725	24,697,464,356	8,741,435,668	38,287,929,170
Less Depreciation (US\$)					
Percent of Production	7.4%	6.6%	8.4%	6.2%	11.9%
Opening Balance	17,850,000,000	18,175,944,972	18,349,493,404	18,409,828,309	18,377,496,749
Add: Capital Expenditures	1,769,201,956	1,464,500,431	1,748,505,410	1,180,287,178	2,123,105,970
Subtotal	19,619,201,956	19,640,445,403	20,097,998,815	19,590,115,487	20,500,602,718
Less: Depreciation	(1,443,256,985)	(1,290,951,999)	(1,688,170,506)	(1,212,618,738)	(2,433,260,086)
EBIT (US\$)	20,548,757,957	21,148,316,726	23,009,293,851	7,528,816,929	35,854,669,084
Less Taxes (US\$)	(6,164,627,387)	(6,344,495,018)	(6,902,788,155)	(2,258,645,079)	(10,756,400,725)
Net Income (US\$)	14,384,130,570	14,803,821,708	16,106,505,696	5,270,171,851	25,098,268,359
Asset Level Balance Sheet Items					
Accounts Receivable	242,099,181.67	227,385,632.01	258,143,869.97	123,728,243.85	366,327,153.13
Inventory (US\$)	780,068,474.76	645,720,865.08	770,943,047.91	520,406,850.81	936,110,221.60
Accounts Payable (US\$)	1,170,102,712.15	968,581,297.61	1,156,414,571.87	780,610,276.21	1,404,165,332.41
Non-cash working capital	(147,935,056)	(95,474,801)	(127,327,654)	(136,475,182)	(101,727,958)
Free Cash Flow					
EBIT (US\$)	20,548,757,957	21,148,316,726	23,009,293,851	7,528,816,929	35,854,669,084
Adjustments: (US\$)					
Plus: Depreciation	1,443,256,985	1,290,951,999	1,688,170,506	1,212,618,738	2,433,260,086
Less: CAPEX (US\$)	(1,769,201,956)	(1,464,500,431)	(1,748,505,410)	(1,180,287,178)	(2,123,105,970)
Less: Taxes (US\$)	(6,164,627,387)	(6,344,495,018)	(6,902,788,155)	(2,258,645,079)	(10,756,400,725)
Less: Increase in NWC	(1,176,064,944)	(52,460,255)	31,852,853	9,147,528	(34,747,224)

Less: Reclamation	-	-	-	-	-
Total Adjustments	(7,666,637,303)	(6,570,503,706)	(6,931,270,207)	(2,217,165,991)	(10,480,993,833)
Free Cash Flow (US\$)	12,882,120,654	14,577,813,020	16,078,023,644	5,311,650,939	25,373,675,252
Asset NPV (US\$)	12,882,120,654	14,577,813,020	16,078,023,644	5,311,650,939	25,373,675,252
Free Cash Flow (undiscounted)			12,882,120,654	14,577,813,020	16,078,023,644
Total	12,882,120,654	14,577,813,020	16,078,023,644	5,311,650,939	25,373,675,252
Cumulative	(122,117,879,346)	(107,540,066,326)	(91,462,042,681)	54,863,653,340	73,178,983,888
Years	2	3	4	9	9

APPENDIX 2

AGGREGATED JWANENG MINE PRODUCTIVITY DATA FOR THE PERIOD BETWEEN 2011 AND 2019

Location	Availability	Utilisation	Productivity/Quality	OEE
Cut 6/7	74.7%	61.9%	76.0%	63.0%
Cut 8	91.2%	86.8%	82.0%	78.0%



APPENDIX 3

QUESTIONNAIRE TEMPLATE FOR FUZZY DATA COLLECTION FROM JWANENG MINE PERSONNEL

Introduction

My name is Desmond Munyadzwe, and I am currently pursuing a degree of Master of Engineering in Mining Engineering at the Botswana International University of Science and Technology (BIUST). The purpose of this questionnaire is to explore the impact of outsourcing mining operations on the performance of the owner or mining company. The research is being undertaken as part of my degree of Master of Engineering in Mining Engineering qualifications.

Participation is voluntary and your completion of the questionnaire would be highly appreciated. Your responses will be treated with utmost confidentiality and will only be used for research survey purposes. Please note there is no right or wrong answer and the accuracy of results of this research is entirely dependent on how honest you can be. Your responses will be helpful in establishing empirical methods for mining operations outsourcing decision making.

Please answer all questions by ticking the correct box or writing as required. Please feel free to comment at the end of the questionnaire if you feel so.

Thank you.

Part 1: Personal Attributes

1.1. What is your occupation?

1.2. What is your job title?

1.3. How many years of experience do you have in the mining industry? Put a cross **x** on the right answer.

< 1 year	1-3 years	4-10 years	> 10 years

Part 2: Questions

2.1. Please indicate the projected performance of each outsourcing option against the given criteria as illustrated on the table below using the answers "poor" or "good" that ranges between extremely poor (1), very poor (2), slightly poor (3), poor (4), fair (5), slightly good (6), good (7), very good (8) and extremely good (9). There are 10 theoretical scenarios (alternatives) presented below.

	Criteria	Social licence to operate	Transaction cost	Mining rates	Attraction and retention of talent	Protect core competence	Quality	Technological competitiveness	Strategic relationship	Environmental sustainability
Alternatives	A1									
	A2									
	A3									
	A4									
	A5									
	A6									
	A7									
	A8									
	A9									
	A10									

APPENDIX 4

LOCAL WEIGHTS NORMALIZED NUMERICAL PAIRWISE MATRICES AND CORRESPONDING WEIGHTS

Capital efficiency-based Factors			
	CER	OEE	Sub Criteria Weights
CER	0.17	0.17	0.17
OEE	0.83	0.83	0.83

Flexibility-based Factors			
	Project life	Mining rates	Sub Criteria Weights
Project life	0.13	0.13	0.13
Mining rates	0.88	0.88	0.88

Operating cost-based factors				
	Profit margin risk	Transaction cost	Operating cost	Sub Criteria Weights
Profit margin risk	0.74	0.54	0.81	0.70
Transaction cost	0.11	0.08	0.03	0.07
Operating cost	0.15	0.38	0.16	0.23

Relationship-based factors				
	Social licence to operate	Strategic relationship	Environmental sustainability	Sub Criteria Weights
Social licence to operate	0.69	0.53	0.72	0.65
Strategic relationship	0.08	0.06	0.03	0.06

Environmental sustainability	0.23	0.41	0.24	0.29
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Competence-based Factors					
	Attraction and retention of talent	Protect core competence	Quality	Technological competitiveness	Sub Criteria Weights
Attraction and retention of talent	0.07	0.23	0.08	0.02	0.10
Protect core competence	0.01	0.05	0.08	0.02	0.04
Quality	0.59	0.41	0.73	0.84	0.64
Technological competitiveness	0.33	0.32	0.10	0.12	0.22