

Evaluating the impact of energy management on deep-level mines during medium-term production stoppages

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Mini-dissertation accepted in partial fulfilment of the requirements for the degree *Master in Business Administration* at the North-West University

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Graduation: June 2021

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ABSTRACT

Deep-level mining is a significant contributor to the South African gross domestic product and employs about 450 000 people. South African mining companies face profitability challenges due to high operating costs. Electricity consumption contributes to about 20% of the operating costs at deep-level mining operations and increasing electricity costs is a major concern. Some South African mining companies warn that marginal mines may become unprofitable due to the high electricity cost. This is a major concern since it affects shareholder returns, employment opportunities as well as the South African gross domestic product.

High underground rock temperatures, as high as 64°C, require large cooling and ventilation systems to cool underground work areas. Integrated cooling and ventilation systems contribute to about 41% of the total electricity consumption of deep-level mines. This is one of the reasons why deep-level mines are about seven times more energy-intensive than surface operations.

Research has shown that energy efficiency improvements have the potential of improving the financial performance of companies and even their share prices. Previous studies that investigated the impact of energy management interventions at South African deep-level mining companies proved energy savings worth R75 million per annum. This has significant implications for South African deep-level mining companies since dedicated energy management has the potential of reducing operating costs.

These interventions are often implemented by energy services companies (Escos) that are paid based on proven savings. Savings are typically quantified by comparing the actual electricity usage with the baseline energy usage. Baseline models frequently use adjustment techniques to estimate what the electricity usage would have been in the absence of any saving interventions. A baseline is normally only valid within predefined operating conditions.

The Covid-19 lockdown severely affected the profitability of many companies. A significant challenge for deep-level mines is the high baseload electricity usage that represents as much as 70% of their total electricity usage during full production. This leaves a very small margin for electricity cost reductions without a dedicated electricity cost-saving drive and is a major concern for a mine that is not able to generate any revenue. This has significant financial implications for deep-level mining companies that are already under pressure due to increasing operating costs. Escos often enter into performance contracts and are only paid if they realise electricity cost savings. The services of Escos can be used to assist mining operations to reduce baseload electricity usage during shutdown periods.

A challenge with electricity baseline models is that they are developed for normal operating conditions. Additional electricity demand reductions occur during such medium-term production stoppages. Examples include the complete shutdown of processing plants and offices. The predefined baseline models are not always valid for events such as the Covid-19 lockdown period due to the long production shutdown. This creates a challenge if the impact of an Esco must be quantified during periods when there is no reference point to be used as a baseline. This increases the business risk for the Esco as well as the client.

A need was identified to identify and evaluate a business case for energy management at deep-level mines during medium-term production stoppages. This study evaluated the financial feasibility of a mine entering into a performance-based contract with an Esco to assist with energy management services during a medium-term production stoppage. Focused energy management at a South African deep-level mine during the April 2020 Covid-19 lockdown was identified as a suitable case study.

Seven evaluation strategies were investigated to determine the impact of an integrated energy management approach at deep-level mines during the Covid-19 lockdown period. A cost-saving of R7 million was proven in one month compared with an estimated Esco contracting fee of R2 million. The benefit of the energy management service outweighs the service at a ratio of 3.5:1. It can be concluded that it was beneficial for the mining company to use the services of an Esco during a medium-term production stoppage.

This study proves that there is a business case for dedicated energy management at deep-level mines during medium-term production stoppages. It is suggested that baselines be agreed upon for both normal operating conditions as well as longer stoppages. More effort can then be applied towards a continuous improvement approach if such events occur in future. It is recommended that a high-level record must be kept of all interventions to ensure that all parties agree to the real benefit of the Esco.

KEYWORDS: Energy management, deep-level mining, measurement and verification, Esco, energy efficiency, energy efficiency.

ACKNOWLEDGMENTS

I dedicate this page to everyone who assisted me in the completion of my MBA degree.

Firstly, I wish to thank the Lord Almighty for the ability and patience that was awarded to me to complete this dissertation as well as the other MBA subjects.

I want to also thank the following people that assisted me with the completion of this study:

- My wife, Barbara, for all the support and assistance throughout the completion of this dissertation as well as the other MBA subjects. You are a wonderful wife and mother.
- My children, Eric, Joop and Johan, for accepting the divided attention and helping out where possible. You are the best gift that anyone can hope for.
- My parents, for their examples of being hard-working people, for raising me as a Christian, for always supporting me with my studies, and for understanding that I was not always able to join family gatherings.
- My parents-in-law for their support and assistance and for understanding that I was not always able to join family gatherings.
- My MBA syndicate group members, who had the same passion for high-quality work, and who were always willing to help out where possible.
- The lecturers and support staff at the North-West University Business School, especially Dr Johan Jordaan for your guidance and supervision to complete this dissertation.
- All my family, friends and co-workers for all your support and assistance.
- The Esco for providing access to the information.
- The deep-level mining operation for their support with energy management.
- A special thanks to my brother, Christiaan, for your assistance with the statistical analysis.
- Marike van Rensburg for your assistance to proofread this document.

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ABBREVIATIONS

3CPFS	Three-Chamber-Pipe-Feeder-System
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BAC	Bulk Air Cooler
CV(RMSE)	Coefficient of Variation of the Root Mean Squared Error
DIKW	Data Information Knowledge Wisdom
DPSA	Department of Public Service and Administration
Esco	Energy Services Company
EVO	Efficiency Valuation Organization
GDP	Gross Domestic Product
IEA	International Energy Agency
IPMVP	International Performance Measurement and Verification Protocol
KPI	Key Performance Indicator
M&V	Measurement and Verification
MWhSO	Megawatt-hour Sent Out
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
SANAS	South African National Accreditation System
VSD	Variable Speed Drive

CHAPTER 1: NATURE AND SCOPE OF THE STUDY

1.1 Introduction

Mining contributed to just over 7% of South Africa's gross domestic product (GDP) in 2019 (Department of Statistics, 2020b:8). This makes the mining industry an important role player in the South African economy. Unfortunately, the contribution from the mining industry to the GDP of South Africa decreased by 1.7% from 2017 to 2018 and 1.9% from 2018 to 2019 (Department of Statistics, 2020b:9). Statistics of South Africa (Stats SA, 2020e:1) reported in their Quarterly Labour Force Survey for the second quarter of 2020 that South Africa had an unemployment rate of 23%. The observed decline in mining production is not only bad for the GDP, but will most likely also add more pressure to the high unemployment rate in South Africa.

Stats SA (2020d:5) stated in their quarterly employment statistics that 450 000 people were employed in the mining industry in June 2020. This is a contribution of 4.76% to non-agricultural employment in South Africa when considering total employment of 9 548 000 in non-agricultural businesses as reported in the same publication. The mining sector is, therefore, an important contributor to employment. It is clear that the downscaling in the mining sector will be detrimental to the South African economy and employment.

Mining companies have been experiencing a downward trend in terms of return on invested capital along with declining productivity (McKinsey Global Institute, 2017:4). This downward trend shows a decline rate of about 4% per annum and was reported to be at a 30-year low in 2015. Stats SA reported in February 2020 that the South African gold mining industry has shown a consistent decline in production from 1994 except for 2002 and 2013 where increases were noted (Department of Statistics, 2020c). The trajectory of the production decline suggests an uncertain future for the South African mining industry.

A major concern for South African mines is the high operating costs that can lead to a reduced life of mine (van Staden *et al.*, 2020:3). Electricity costs account for as much as 20% of a deep-level mine's total operating costs (Sibanye Stillwater, 2019:22). The impact of the high electricity costs is of great concern to mining groups, especially mines with narrow profit margins (Harmony Gold, 2019:29). High electricity costs are, therefore, one of the reasons that the South African mining industry is declining and losing its competitiveness.

Holmberg *et al.* (2017:118) estimated that the global mineral mining industry consumes 12 exajoule (EJ) of energy per year. This is equivalent to about 6% of the total global energy consumption (Holmberg *et al.*, 2017:134). They regarded the energy intensity of underground

mines as seven times higher than surface mining. According to Homberg *et al.* (2017:122), underground mining contributes to about 30% of total worldwide mining energy consumption.

South Africa is home to some of the deepest mines in the world (AngloGold Ashanti, 2019:73). Gold mines in South Africa reach depths of 4 km below surface (Cilliers, 2016:136). These depths present many operational challenges such as underground virgin rock temperatures as high as 64°C (Pretorius *et al.*, 2019:232). Large cooling systems are needed to cool deep-level mines, which contribute 16% to the mine's total electricity consumption (Bredenkamp, 2016:137).

Deep-level gold mines in South Africa furthermore need to pump significant volumes of water from underground to surface to prevent flooding (Winde *et al.*, 2017:679). Winde *et al.* (2017:679) mentioned that South African deep-level gold mines have the largest underground hydraulic heads worldwide. They asserted that this places additional strain on mining companies due to the electricity costs associated with pumping systems.

It is observed from the previous discussion that the competitiveness of South African deep-level mining is hampered by high electricity costs associated with the nature of the depth of these operations. The World Energy Council (2020:41) stated that energy affordability is one of the critical uncertainties in terms of South Africa's energy situation. High debt levels at Eskom is a major contributing factor to these uncertainties (World Energy Council, 2020:41).

Eskom supplies approximately 90% of the electricity consumed in South Africa (Department of Energy, 2019:15). Eskom is ranked as the 17th largest power company in the world based on installed generation capacity according to the International Monetary Fund (IMF, 2020:313). The World Energy Council (2020:41) highlighted exchange rates, capital markets, decentralised systems and corruption as critical uncertainties for South African energy situation. The risk of high electricity prices is of significant concern considering that electricity costs contribute as much as 20% to total operating costs. This means that deep-level mining companies must take action to reduce electricity costs to ensure that they can remain competitive.

The International Energy Agency (IEA, 2018:332) predicted that worldwide annual electricity demand in the industrial sectors will grow by 4 100 TWh by 2040. The IEA (2018:332) forecasted that energy efficiency measures have the potential to reduce annual industrial electricity usage by 3 900 TWh per annum during the same period. This suggests that energy efficiency improvements can contribute significantly to counter electricity growth in the industry due to business expansion. Mining companies must consider the financial implications of electricity-saving initiatives to ensure that they can maximise the benefit to the shareholders of the companies.

Martí-Ballester (2017:S35) found that implementing energy management systems shows significant effects on the short-term financial performance of companies. An interesting finding from their research was that energy management does not present such a significant impact on the performance over the long run (Martí-Ballester, 2017:S45). Martí-Ballester (2017:S45) argued that long-term impacts are not as significant because initial improvements focus on “low-hanging-fruits”. She determined that companies often remove the focus from energy improvements once initial improvements have been made. The study by Martí-Ballester was based on data from 574 multinational companies in 36 countries for a period spanning from 2008 to 2013. It is important to observe that companies often lose focus after the initial improvements. It can be argued that a dedicated effort is required to ensure that energy management is aimed at continuous improvement.

Bassetti *et al.* (2020:9-11) analysed data from 998 companies in the United States of America for the period from 2003 to 2017. They found that environmental performance positively affects returns on assets and equity. Their research concluded that firms with good environmental performance were better at generating future wealth than firms that did not display the same environmental performance. Bassetti *et al.* (2020:11) proved that environmental performance is linked to sustaining a competitive advantage. This suggests that mining companies can improve the benefit to their shareholders by ensuring that they have energy management plans in place to strive towards continuous improvement.

Manrique and Martí-Ballester (2017:21) evaluated data for the period between 2008 and 2015 for 2982 large companies. They concluded that environmental practices had a significant positive impact on corporate financial performance. They found that the financial impact of firms operating in developing countries was more significant than in developed countries. The environmental improvements included enhancements to the efficiency of the systems to reduce energy usage. Such improvements resulted in resource cost savings while providing products with reduced environmental impacts. The study by Manrique and Martí-Ballester (2017:21) further showed that mining companies in developing countries can improve the benefit to their shareholders by reducing electricity usage.

South Africa is classified as a sub-Saharan, emerging market and developing economy (IMF, 2020:7). It is therefore beneficial for South African companies to adopt environmental practices since there is a good possibility that this will lead to improved financial performance. The Eskom generation fleet is dominated by coal-powered generators, which result in particulate emissions of 0.47 kg/megawatt-hour sent out (MWhSO) compared with a target of 0.33 kg/MWhSO (Eskom, 2020a:86). Thus, there is a good possibility that reduced electricity consumption in the South

African mining industry can improve their financial performance based on the findings from Manrique and Martí-Ballester (2017:21).

Endrikat (2016:544) found that share prices were influenced by the environmental performance of companies. An interesting finding from his research was that markets react stronger to negative performance than to positive performance. Endrikat (2016:545) further established that the influence of positive environmental performance was stronger after the year 2000 than the period before 2000. Research showed that environmental and energy efficiency objectives complement one another (Costa-Campi *et al.*, 2015:237). The research by Costa-Campi *et al.* (2015:235) highlighted that innovative firms are more likely to strive towards energy efficiency improvements. This implies that energy efficiency improvements in the mining industry can potentially influence the share prices of these companies positively due to their large dependence on electricity generated by coal-fired power plants.

The preceding section proved that South African mining companies can increase their financial performance by implementing electricity-saving measures at their operations. There are other positive implications such as potential share price improvements. Existing research further showed that deep-level mining companies must take a continuous improvement approach to ensure long-term financial benefit.

It has been observed that mining companies are relatively slow at adopting new technology (McKinsey Global Institute, 2017:9), which is partially due to the severe impact if new technologies were to fail and affect production at capital-intensive operations. Major South African mining companies do, however, realise that they are under pressure to implement energy-saving measures to keep these costs under control (Anglo American Platinum, 2019:91; AngloGold Ashanti, 2019:51; Goldfields, 2019:69; Implats, 2019:72; Harmony Gold, 2019:135; Sibanye Stillwater, 2019:212).

Bredenkamp *et al.* (2016:138) proved that a focused energy management strategy implemented on a South African deep-level gold mine can deliver significant electricity savings. They realised an 18.5% reduction in electricity costs, worth approximately R75 million per annum, through focused energy management at a deep-level gold mine. Their impact was based on the 2015/2016 Eskom electricity tariffs and is worth even more now due to the increase in electricity tariffs. Bredenkamp *et al.* (2016:139) estimated that this energy management approach had a potential benefit of R238 million per annum if rolled out to the other mineshafts in the same mining company. This proves that there is a significant cost-saving potential to reduce electricity costs in the South African deep-level mining industry, which can assist mining companies to keep their energy-intensive operations competitive.

Existing research has shown that it is difficult to recommend best practices for mining operations due to the diversity between operations (Awuah-Offei, 2016:95). This suggests that energy efficiency interventions must be customised as there is not a one-size-fits-all solution. Other research has proven that industrial companies are hesitant to invest in the research and development of energy efficiency improvements (Bukarica & Tomšić, 2017:970).

Finnerty *et al.* (2018:916) found that evaluation processes, fiscal rules, and investment parameters influence the uptake of energy efficiency measures. They established that company culture can play a role in whether energy efficiency projects are implemented. Finnerty *et al.* (2018:916) mentioned that energy efficiency projects are often not implemented – either because they are not seen as a high priority or due to a lack of capital (Finnerty *et al.*, 2018:924, 925).

Granderson and Fernandes (2017:15) suggested that energy project developers, more often referred to as energy services companies (Escos), must be reimbursed based on proven savings. Such a business plan moves the risk of the project to the Esco. This solution may overcome the financial barriers that prevent the industrial sector from implementing energy-saving projects. Newsham (2019:2) agreed with this approach and stated that Escos sometimes enter into energy performance contracts to overcome capital constraints.

Some South African deep-level mining companies appoint Escos to assist with energy optimisation strategies (Harmony Gold, 2019:136; Implats, 2019:45; Sibanye Stillwater, 2019:209). Energy management solutions are typically implemented as a cost-saving measure during normal production levels (Bredenkamp, 2016:162). South African deep-level mines do unfortunately suffer from prolonged production stoppages during which events such as strikes (Sibanye Stillwater, 2019:50) and government-enforced lockdowns such as the Covid-19 lockdown occur (AngloGold Ashanti, 2019:19; Harmony Gold, 2020; Sibanye Stillwater, 2019:21). This creates a peculiar situation for mining companies since operations may be required to be put on temporary care and maintenance at short notice (AngloGold Ashanti, 2019:19; Goldfields, 2019:11; Harmony Gold, 2020; Implats, 2019:88; Sibanye Stillwater, 2019:21).

The Covid-19 lockdown resulted in reduced production for prolonged periods with negative consequences for the mining companies (Harmony Gold, 2020; Implats, 2019:90; Sibanye Stillwater, 2019:21). A significant challenge for mining companies is managing operating costs during such challenging times (Implats, 2019:96). Cost-cutting measures must be implemented to minimise financial losses, including cancelling subcontracted services temporarily.

Escos that are contracted under performance agreements, such as suggested by Granderson and Fernandes (2017:15) and Newsham (2019:2), must invest capital to implement electricity cost-saving initiatives. Prolonged production stoppages increase the financial risk for Escos as

their contracts may be placed on hold for extended periods. The findings from Finnerty *et al.* (2018:924, 925) suggest that mining companies do not focus on electricity cost-saving measures when production stops. Awuah-Offei (2016:95) also found that there is not a one-size-fits-all solution for energy management.

It is, therefore, argued that Escos can play an important role in reducing operational costs through electricity cost-saving interventions at deep-level mines during prolonged production stoppages. Energy management interventions are typically aimed at cost savings while maintaining normal production volumes (Bredenkamp, 2016:162). The quantification of energy savings during non-routine events, such as strikes and government-enforced lockdowns, is a major challenge (Granderson & Fernandes, 2017:15). This is a concern because existing performance contracts are typically aimed at production-as-normal situations. Therefore, research regarding the financial feasibility for focused energy management during medium-term production stoppages is required.

1.2 Problem statement

Deep-level mining companies recently faced challenges with forced closures due to a Covid-19 lockdown that had a detrimental impact on their income. The companies had to reduce operational expenditure through cost-cutting interventions to minimise financial losses. A possible focus area is to reduce electricity costs by stopping nonessential electric equipment. This is, however, a challenging task due to the complexity of mining operations.

Mine employees are experienced and focused on maximising production. They do not necessarily have a mindset of reducing electricity costs. Some energy-intensive companies such as deep-level mines enter into agreements with Escos to identify and implement measures to reduce electricity costs. These companies are generally tasked with implementing these measures for business-as-usual conditions. Escos are often contracted on shared savings or minimum impact cost models with clear guidelines for calculating the impact for business-as-usual conditions. There are unfortunately no clear guidelines for distinguishing between the reduction in electricity usage because of reduced production and the effort of Escos. This creates a significant financial risk for both the Escos and the mining companies.

Existing research focuses on evaluation methods that quantify the impact of Escos during normal production levels. There is, therefore, a need to investigate the benefit of performance-based contracts with Escos during times when production is either halted completely or reduced.

1.3 Objectives of the study

The primary objective of this study was to evaluate the financial impact of dedicated energy management on deep-level mines during medium-term production stoppages. This was achieved by evaluating the cost-saving impact of electricity cost reduction interventions during medium-term production stoppages.

Deep-level mining operations are complex and up to seven times more energy-intensive than surface mining operations (Holmberg *et al.*, 2017:118). An overview of the mining equipment that contributes the most to electricity usage at deep-level mines was needed to understand the complexity of the research objective. Literature regarding these systems was analysed and will be presented to provide background on electricity consumption at deep-level mines.

Available research regarding typical electricity cost-saving interventions at deep-level mining operations was evaluated to provide the context of typical interventions. The cost savings achieved as well as the quantification thereof were evaluated to identify possible solutions for quantifying the impact of energy-saving interventions during prolonged production stoppages.

Existing research relating to the quantification of energy-saving interventions was evaluated critically and will be presented in the literature review in Chapter 2. This assisted in identifying solutions for quantifying the impact of prolonged production stoppages. Available research regarding benchmarking studies was evaluated to identify possible solutions for saving quantification during prolonged stoppages.

The electricity usage during the Covid-19 lockdown period was analysed in detail and will be presented in Chapter 3. Usage patterns during the lockdown period were compared with other similar periods during which no energy-saving interventions were implemented. These comparable differences were used to evaluate electricity savings from dedicated energy management interventions. The financial benefit of the saving interventions was quantified by converting the electrical energy savings to electrical cost savings by considering the applicable electricity cost tariffs.

The monetary impact of the saving interventions was compared with the implementation costs of these interventions. The study objective would be reached if the impact of energy management could be quantified and compared with the implementation cost of the interventions. A secondary objective of this study was to provide high-level guidelines for evaluating the impact of energy-saving initiatives at other deep-level mines during medium-term production stoppages. These guidelines will be provided in Chapter 4 based on the lessons learned during this study.

1.4 Scope of the study

The study aimed to quantify the financial benefit of an Esco during a production stoppage of between one week and four weeks. The study only considered the application for deep-level South African mines. The savings were not quantified based on the typical standards used for government-funded schemes, such as tax and/or carbon offset incentives, since these schemes require strict measures for ensuring that savings are proved with little doubt. Government-funded schemes are further aimed at interventions that run over longer periods than medium-term production stoppages and are, therefore, not applicable to this study.

1.5 Research methodology

1.5.1 Literature study

Bryman *et al.* (2017:5) stated that the critical evaluation of existing research is a vital component when performing an evidence-based management approach. This approach is grounded on the belief that management decisions must be based on the best available evidence. Bryman *et al.* (2017:5) further noted that it is important to evaluate recommendations and findings from other researchers critically without bias.

The process of deductive research as summarised by Bryman *et al.* (2017:9) is shown in Figure 1-1. A functionalist paradigm is a problem-solving based orientation used frequently in business research (Bryman *et al.*, 2017:20). This paradigm leans towards objective research that views an organisation from an external viewpoint. This study aimed to analyse the impact of energy management from an external viewpoint.

Existing research relating to the theory of energy-saving quantification was evaluated, which ensured that best practice approaches were followed to quantify the impact of energy savings. The preceding section highlighted significant cost-saving potential at deep-level mining operations. It was hypothesised that dedicated energy management interventions could also realise cost savings during medium-term production stoppages.

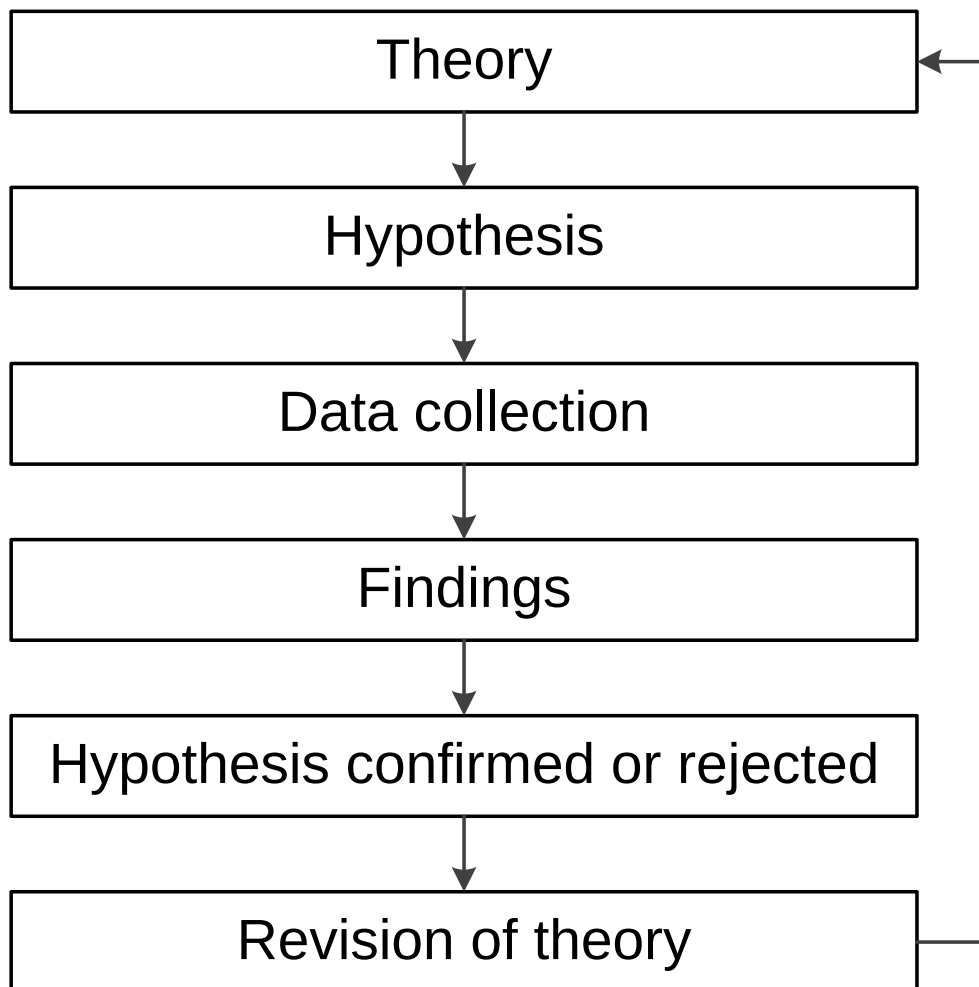


Figure 1-1: The process of deduction

[Adapted from Bryman et al. (2017:9)]

1.5.2 Empirical study

A case study was identified in which an Esco implemented dedicated energy-saving interventions at a deep-level South African mine during the Covid-19 lockdown. Electricity usage and production data was accessed from the internal database of the Esco. Confidentiality requirements prevent the divulging of the name of the mining operation.

The study used actual electricity and production data available from a case study mine. The impact of energy-saving measures at deep-level mines was evaluated by subtracting actual electricity usage from baseline electricity. The primary aim of this study was to identify whether the decreases observed on electricity power meters happened by chance or due to the involvement of an Esco. The hypothesis would be confirmed if savings were proved that exceeded potential costs of implementing the interventions. The study will end in Chapter 4 with a review of the research findings and will provide recommendations for further work.

1.6 Limitations of the study

The study aimed to quantify the savings as accurately as possible. The results of this study will, however, not be suitable for government-funded incentives due to the stringent requirements for government grants and subsidies for which savings must be quantified at a high level of confidence.

1.7 Definition of key concepts

The Efficiency Valuation Organization EVO (2017:3) developed the International Performance Measurement and Protocol (IPMVP), which defines **avoided energy consumption and demand** as *“Reduction in Energy Consumption, demand, or cost that occurred in the reporting period, relative to the baseline period, as adjusted for the Reporting Period Conditions. Avoided Energy Consumption is determined by adjusting the Baseline Period Energy to the Reporting Period conditions by using Routine Adjustments and Non-Routine Adjustments”*.

EVO (2017:3) further defines a **baseline** as *“Referring to systems, time-period, energy use, or conditions that provide a reference to which later performance of an Energy Conservation Measure (ECM) or measures can be compared”*. They define an independent variable as *“a parameter that is expected to change routinely and have a measurable impact on the energy use of a system or facility”*.

Greyling (2014:49) defines **baseload electricity usage in the mining industry** as *“the minimum load that is required by the mine to sustain workable environmental conditions without production”*.

Mines that are deeper than 1.5 km are generally regarded as **deep-level mines** (Maré, 2017:18).

EVO (2017:4) defines an **energy-conservation measure** as *“measures to improve efficiency or conserve energy or water, or manage demand”*.

Li and Tao (2017:204) define **energy efficiency** as the ratio between the useful output of a process and energy input. Awuah-Offei (2016:93) explains the **energy efficiency for mine loading operations** as *“the ratio of production per unit time to energy input (or volume of fuel, for non-electric excavators)”*.

Trianni et al. (2019:1619) define **energy management practice** as follows: *“an energy management practice is a technique, method, procedure, routine or rule adopted at a precise stage of the industrial energy management setting to achieve the company’s energy efficiency objectives. It acts on technological, non-technological, or of support aspects, by improving the energy performance directly or indirectly in a specific area of the company”*.

In this study, **energy management** refers to a structured approach to ensure adequate energy efficiency.

The term **measurement and verification (M&V)** is used to describe the process of evaluating and verifying the impact of energy-saving initiatives.

The case study mine typically halts production at the end of the calendar year from about 24 December to 2 January. This is referred to as the **Christmas break** or **end of the year break**.

In this study, a **medium-term production stoppage** is defined as a completed production stoppage of longer than the normal Christmas break period. It does not include the impact of a shaft that is put in long-term care and maintenance.

1.8 Layout of the study

Chapter 1 provided some background information about the study. The importance of the study objectives, research methodology as well as the limitations of the study were discussed.

Chapter 2 comprises a detailed literature review that provides information about deep-level mining, industrial energy management, benchmarking, and existing M&V techniques.

Chapter 3 provides information on the detailed data collection approach and information regarding the research design. The gathered data is analysed based on typical M&V approaches. This is followed by a critical discussion of results.

Chapter 4 summarises the results and general findings from the research. Recommendations for further work are discussed.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

It is important to understand the complexity of deep-level mining operations to evaluate interventions. Many South African gold mines extend beyond three kilometres below ground level and are among the deepest mines worldwide (Sibanye Stillwater, 2019:165). This makes it much more challenging to implement cost-saving interventions than at industrial operations that operate above ground.

Harmony Gold consumed 3.3 TWh of electricity at their deep-level gold mines in their 2019 financial year at a cost of R3.2 billion (Harmony Gold, 2019:7). It is observed that these operations are extremely energy-intensive. Electricity expenditure at these operation accounts for more than 37% of their total discretionary procurement costs and close to 16% of total operating costs (*ibid.*). Harmony Gold (2019:29) stated that marginal operations are at risk of closure due to electricity cost increases. This proves the impact of electricity usage at deep-level mining operations and the risk associated with this high-cost element.

Sibanye Stillwater (2019:48), another major South African based mining group, reported an annual electricity consumption of 5.98 TWh during their 2019 financial year. Their electricity expenditure contributes to more than 20% of the operating costs at their South African gold mines (*ibid.*). Sibanye Stillwater warned investors in their annual report that electricity cost increases pose a significant risk to marginal operations. They declared that electricity costs are ranked as one of their top ten risks. It is clear that electricity costs must be managed to ensure sustainable competitiveness.

Sibanye Stillwater (2019:48) asserted that this risk is controlled through the implementation of electricity efficiency improvement projects and usage optimisation. The company reported a reduction of 29 654 ton of carbon dioxide emissions by implementing energy efficiency initiatives (Sibanye Stillwater, 2019:209). It is clear that Sibanye Stillwater takes the impact of electricity costs seriously. It is, however, expected that most businesses focus on production rather than on cost-saving initiatives. This was evident in the research of Goosen *et al.* (2016:3) who acknowledged that employees at energy-intensive industries often increase production at the expense of poor system efficiency just to reach production targets and other production-related key performance indicators (KPIs).

2.2 Deep-level mining overview

2.2.1 Overview

It is important to distinguish between surface mining operations and deep-level mines. Limited literature was found that clearly differentiated between the reference to an underground mine and a deep-level mine. Maré (2017:18) defined a deep-level mine as a mine deeper than 1.5 km from the surface. The research in this mini-dissertation is related to South African gold and platinum mines with depths that exceed 1.5 km. For the purpose of this study, the term 'deep-level mining' refers to mines over 1.5 km in depth.

Some South African gold mines are situated in an area referred to as the East and West Rand Goldfields (Fuchs *et al.*, 2016:151). Other mining operations are located close to Carletonville, Klerksdorp and Welkom, as well as on the Transvaal basin. A simplified geological map of the Transvaal Supergroup and the Witwatersrand Goldfields in South Africa is provided in Figure 2-1. It is observed from the figure that some operations have grades of less than one gram of gold per tonne of rock. This information does not provide any academic value for this study and is merely provided as background information.

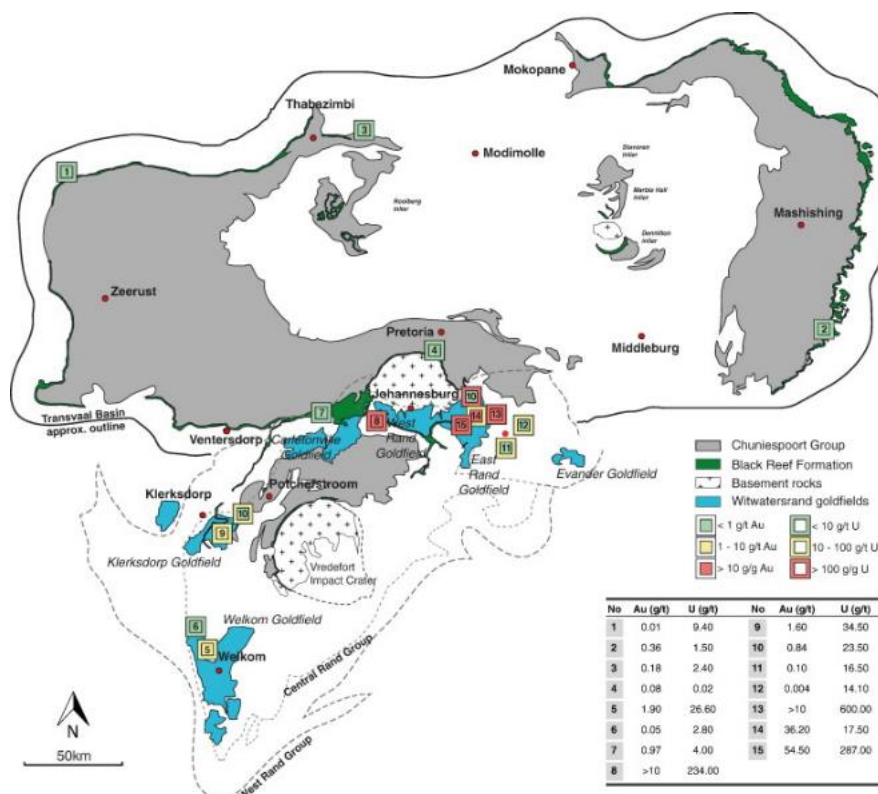


Figure 2-1: Simplified geological map of the Transvaal Supergroup and Witwatersrand goldfields

(Fuchs *et al.*, 2016:151)

It is necessary to comprehend the extent and complexity of South African deep-level mining to understand the unique challenges at these operations. A top view of the layout of a single underground level in a South African deep-level mine is shown in Figure 2-2. An underground mining level can span an area that is 10 km in width and length. These large underground areas can only be accessed through dedicated travelling ways.

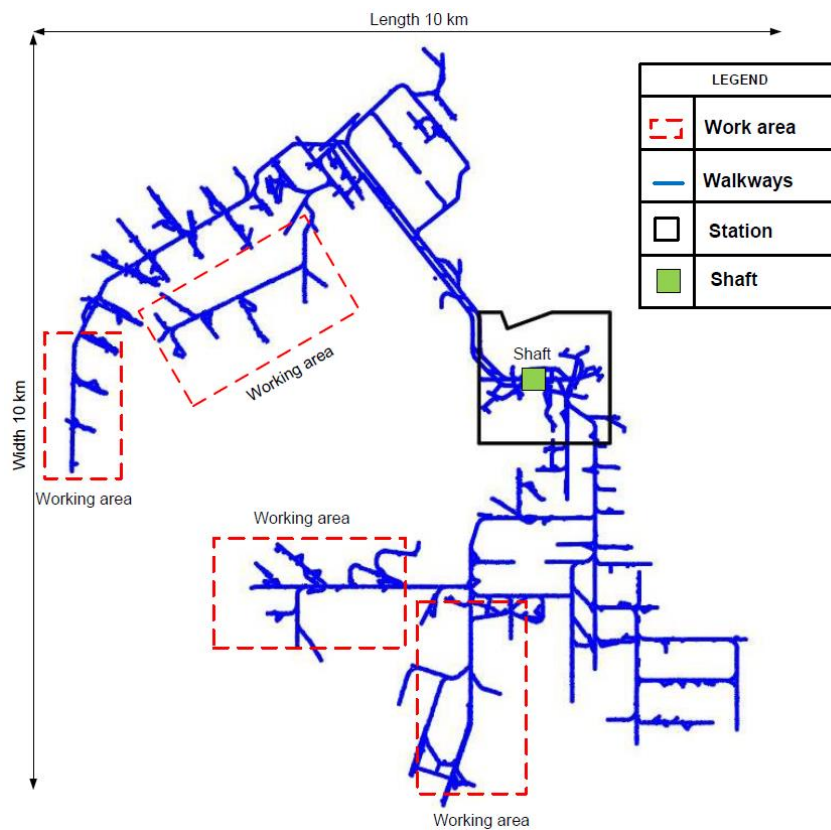


Figure 2-2: Top view of an underground level at a deep-level mine

(Du Plooy, 2019:5)

Mining companies employ up to 20 200 people at one deep-level mining complex (Sibanye Stillwater, 2019:147). A large number of these employees work underground in these complex operations. A photo of a mineworker in a stoping area in a deep-level mine is shown in Figure 2-3 (Malan & Napier, 2018:308). It is observed that workers need to work in confined spaces, which limit worker comfort. Nagel (2020:60) proved that the long travelling times from surface to underground working areas have a detrimental impact on production.

Deep-level mining operations have unique challenges to ensure worker safety and reasonable comfort that are not necessarily needed at opencast mines. This requires the operation of electrically intensive systems such as ventilation fans, cooling systems, dewatering pumps, compressors, and hoisting systems (Greyling, 2014:45). The electrical intensity of these systems are considered seven times higher than at surface mines (Holmberg *et al.*, 2017:122). The

operation of the electric systems that contribute significantly to total consumption will be discussed in the following sections.



Figure 2-3: Stoping area in a deep-level mine

[Adapted from Malan and Napier (2018:308)]

2.2.2 Compressed air systems

Typical mine compressed air systems contribute between 15% and 19% of the total electricity consumption at deep-level gold mines (Bredenkamp, 2016:104, 117). Compressed air is used as an energy carrier to power pneumatic equipment such as rock drills and loading machinery (Zietsman, 2019:43). Section 16.6(2) of the South African Mine Health and Safety Act 29 of 1996 states that respirable air must be supplied to underground refuge bays to ensure the safety of underground workers in the event of an emergency. Compressed air is typically used at deep-level mines to supply respirable air to refuge bays (Zietsman, 2019:68). The continuous operation of compressors is required while people are underground to ensure that refuge bays are life-sustaining.

Figure 2-4 provides the layout of a typical surface compressed air system at a deep-level platinum mine. It is observed that the specific mine compressed air system spans an area of 11.34 km² on surface. It has been reported that deep-level mine compressed air systems have total pipe lengths of as much as 105 km (Zietsman, 2019:113). It is expected that there may be a large number of leaks and other inefficiencies in such large systems. Figure 2-4 shows that a network comprising multiple compressors with installed capacities of up to 4.8 MW per compressor.

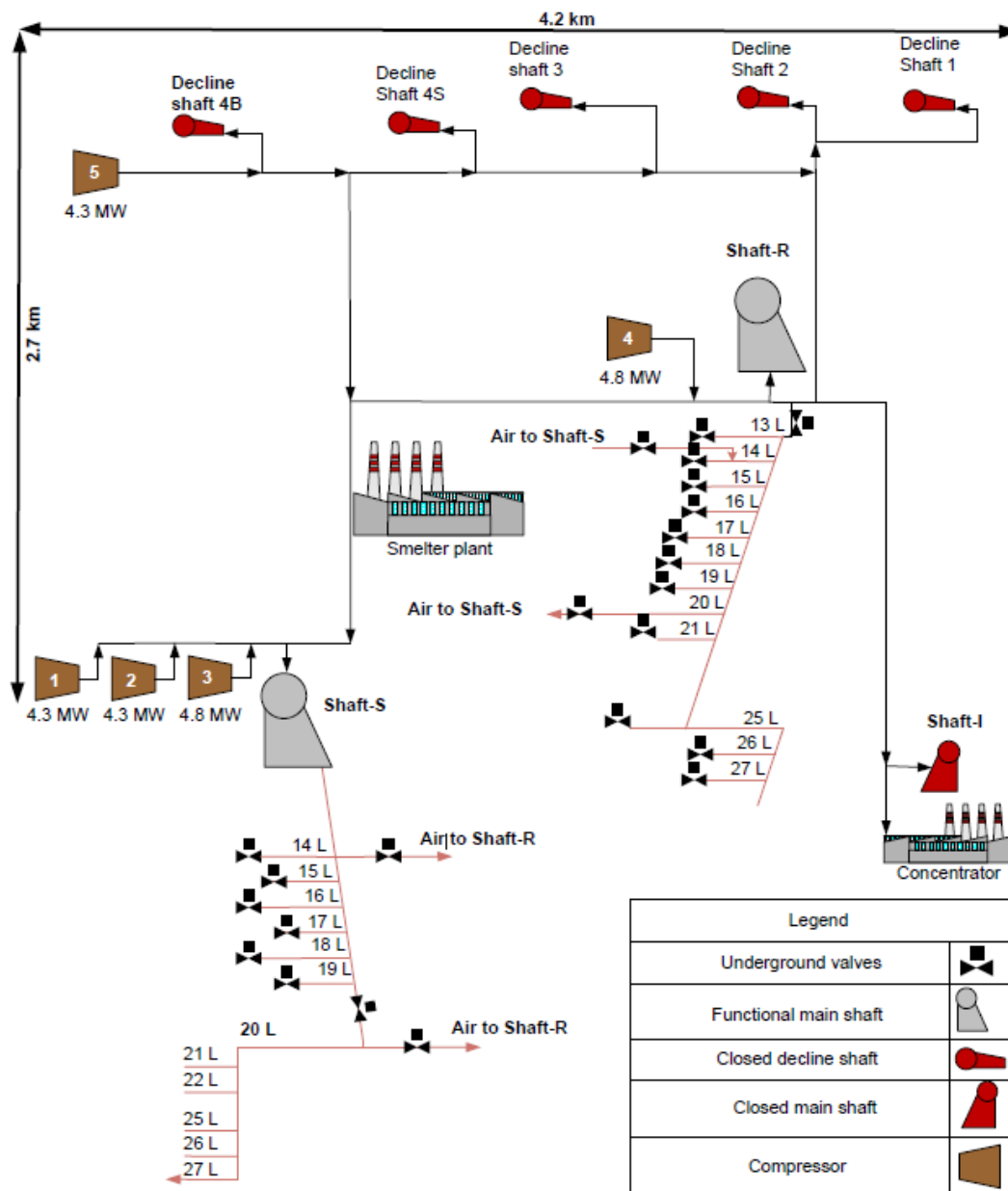


Figure 2-4: Simplified layout of a platinum mine compressed air system

(Vermeulen, 2018:104)

Compressed air is also sometimes used by mineworkers for ventilation in workplaces if other ventilation is not sufficient (Zietsman, 2019:103). Zietsman (2019:104) did an in-depth study regarding the use of unauthorised compressed air blowers at a deep-level platinum mine and found 41 unauthorised blowers in one shaft. These blowers are not nearly as efficient as purposefully designed cooling and ventilation equipment. It is, however, important to consider worker safety and comfort as underground mining conditions can quickly become unbearable if cooling and ventilation are not adequate. Unauthorised use of compressed air is expected when other ventilation and cooling systems are not available.

The legal requirement to have a continuous compressed air supply to refuge bays requires the continuous operation of at least one compressor, which could be why Greyling (2014:67) reported compressor baseload electricity consumption of more than 40% at deep-level mines. A 4.8 MW compressor will result in an estimated electricity bill of more than R40 million per year if operated continuously and the Eskom 2020/2021 Megaflex tariff structure for non-local authorities is applied (Eskom, 2020b). This calculation only includes the active energy charges and active energy-related subsidy charges for a 300 km transmission zone and a supply voltage of between 500 V and 66 kV. This tariff structure is used by many deep-level mining operations in South Africa and was used in this study to calculate the cost implications for electricity cost calculations.

This regulatory requirement is not applicable to surface mining operations. This contributes to the higher electricity intensity of deep-level mines than underground mines. The integrated network displayed in Figure 2-4 shows that four compressors are connected to a common compressed air line that supplies compressed air to eight shafts, a concentrator plant as well as a smelter plant. Vermeulen *et al.* (2018:124) estimated peak compressor power demand from 25 deep-level mines compressed air systems in South Africa at close to 467 MW.

Deep-level mine compressed air systems are prone to leaks and general inefficiencies (Zietsman, 2019:118). Zietsman (2019:12) developed a simulation for estimating expected compressed air consumption based on the requirements of authorised mining equipment. A comparison between the theoretical compressed air consumption and actual consumption is provided in Figure 2-5. It is evident from the graph that some deep-level mines' compressed air systems have baseload consumption of between 63% and 88%.

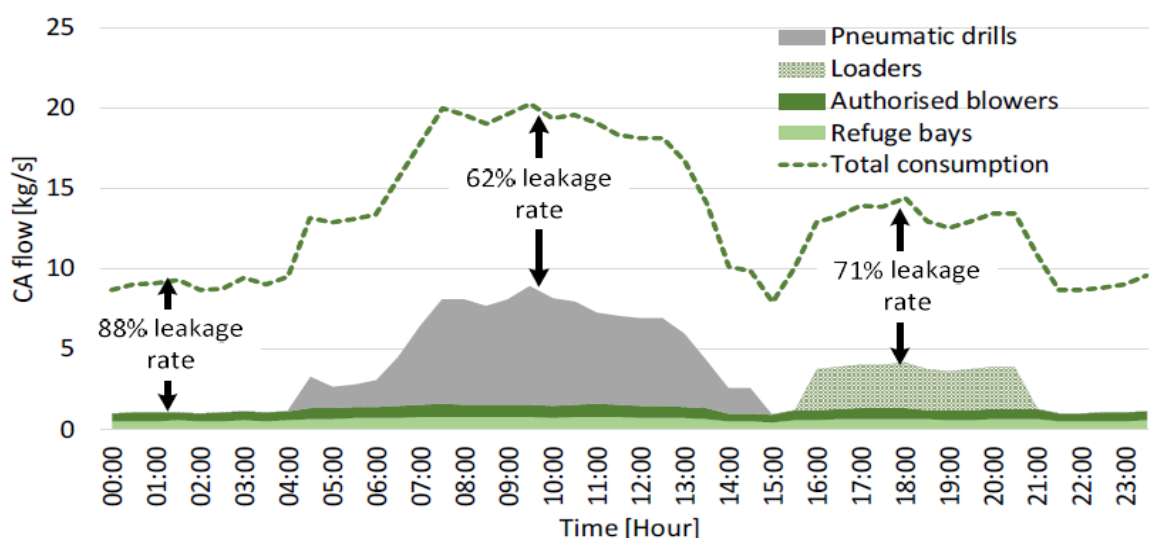


Figure 2-5: Deep-level mine compressed air consumption

(Zietsman, 2019:12)

2.2.3 Dewatering pumping systems

Pumping systems at deep-level mines typically account for 15% of the total electricity consumption at deep-level mines (Bredenkamp, 2016:13). The operation and need for these systems play an important role in the energy management of deep-level mining operations. These pumping systems are needed to pump the mining and fissure water to surface to prevent the flooding of underground operations (Greyling, 2014:44).

A study on a South African gold mine by Maré (2017:129) highlighted that an average continuous pumping rate of 16 l/s is needed to overcome fissure water influx. This represents a daily fissure water volume of 1.38 m³. Mengistu *et al.* (2019:11) argued that mine dewatering systems have the potential to reduce to underground water levels to the extent that nearby boreholes on farms could run dry. The influx of fissure water at deep-level mines does not stop when production is halted. The dewatering pumping system, therefore, still operates even when no production takes place. Greyling (2014:67) found that mine dewatering systems have baseload electricity usage of about 40%. This is most likely partially due to the influx of fissure water.

A high-level layout of the water reticulation at a deep-level gold mine in South Africa is displayed in Figure 2-6. It is clear from the figure that mine dewatering systems are very complex. Typical mine dewatering systems use up to four different pumping levels to pump water from underground areas to surface. Multiple underground dams, typically sized between 3 ML and 5 ML, store accumulated water. Water is pumped to the surface with centrifugal pumps that range between 1100 kW and 3800 kW. Some deep-level gold mines have five main pumping stations underground (Conradie, 2018:88). Up to five pumps per level are installed to ensure adequate dewatering capacity (Taljaard, 2018:111).

The impact of the operation of these systems is noteworthy as a single 3800 kW pump consumes about 33.3 GWh of electricity per annum if operated continuously. This is equivalent to annual electricity costs of more than R32 million if the Eskom 2020/2021 Megaflex tariff structure for non-local authorities is used (Eskom, 2020b). This calculation only includes the active energy charges and active energy-related subsidy charges for a 300 km transmission zone and a supply voltage of between 500 V and 66 kV.

The continuous influx of fissure water requires the operation of the dewatering system even when production is stopped. The electricity consumption may be less during stoppages if the mining water supply is isolated during production stoppages. A dedicated effort to isolate the water supply to working places may potentially reduce electricity usage during production stoppages.

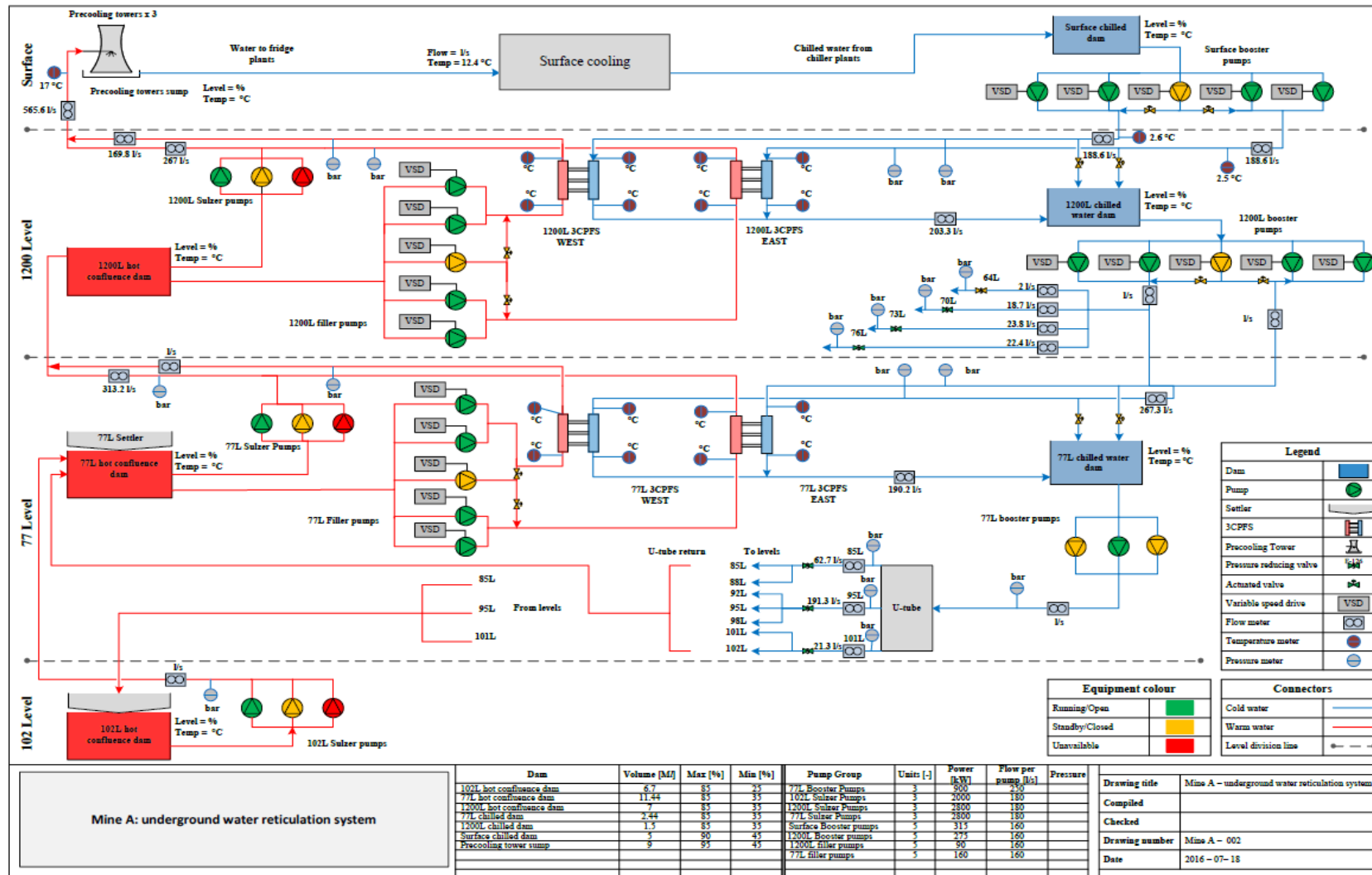


Figure 2-6: Overview of the water reticulation at a South African deep-level gold mine

(Maré, 2017:148)

2.2.4 Mine cooling systems

The environmental conditions in underground operations are significantly different from surface conditions. One of the major differences is high rock temperatures. Virgin rock temperatures of as high as 80°C have been reported in an underground mine in Japan (Sasmito *et al.*, 2015:1145). Sasmito *et al.* (2015:1148) stated mining machinery can increase the temperatures near the rock face by about 5°C and by as much as 10°C thirty metres from the rock face.

Pretorius *et al.* (2019:323) reported underground virgin rock temperatures of 64°C in a South African deep-level gold mine. Thus, large cooling systems are needed to provide suitable working conditions for underground mineworkers. The refrigeration systems used for cooling water are energy-intensive and contribute to approximately 16% to the mine's total electricity consumption (Bredenkamp, 2016:137). The integrated mine cooling system, if all pumps and refrigeration systems are considered, contributes about 41% to the mine's total electricity consumption (Maré, 2017:4).

Figure 2-7 provides a high-level layout of a typical cooling system at a deep-level mine. Chilled water at an average temperature of 3°C is supplied at a flow rate of approximately 440 l/s to underground working areas at some deep-level gold mines to allow sufficient underground cooling (Maré, 2017:147). Bulk air coolers (BACs) are used at deep mines to cool underground conditions (Bornman *et al.*, 2016:1004). These systems cool air by forcing air past the chilled water supplied by the refrigeration systems.

The requirement to use these large cooling systems is one of the reasons why deep-level mines are much more energy-intensive than surface operations. The electricity usage of these systems does not necessarily show a good correlation with production because it may be necessary to cool communal underground areas irrespective of the number of employees who work there. Greyling (2014:41) provided proof when he found that mine cooling systems have baseload electricity usage of more than 80%. This suggests that the variable load of the system is less than 20% for a typical deep-level mine, which has a knock-on effect on the pumping systems since used cooling water must be pumped to surface. The baseload usage on pumping systems, about 40% as reported by Greyling (2014:41), is then most likely due to a combination of fissure water influx as well as used cooling water that must be pumped to surface.

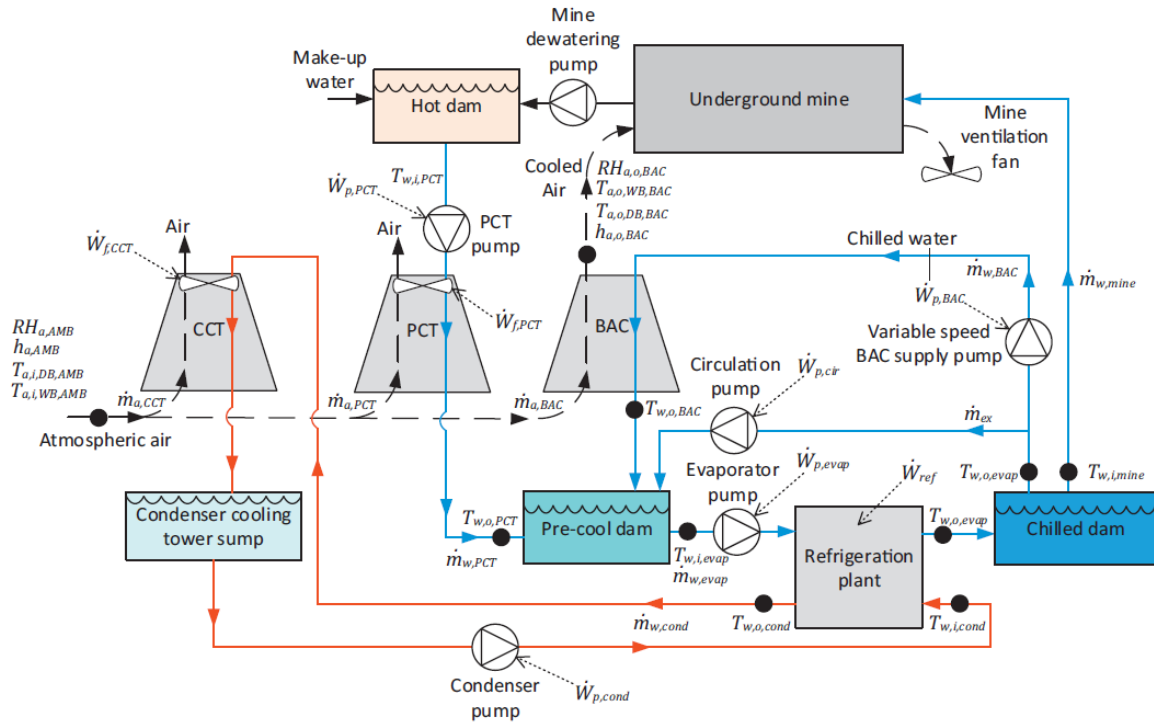


Figure 2-7: Deep-level mine cooling system overview

(Bornman *et al.*, 2017:999)

2.2.5 Ventilation systems

The previous section discussed the use of compressed air systems to supply respirable air to refuge bays and to augment cooling and ventilation. However, purposefully designed ventilation systems are preferred to ensure worker safety and comfort. It is important to understand the unique ventilation requirements for underground mining operations that are not needed for surface operations. High carbon monoxide concentrations and respirable dust in underground mines can lead to the death of miners (Mayala *et al.*, 2016:122). Mayala *et al.* (2016:124) further reported that miners are susceptible to other lung diseases such as tuberculosis and silicosis. Forced ventilation and dust suppression solutions are needed to prevent these unsafe conditions.

Mayala *et al.* (2016:121) reported air velocities of between 0.12 m/s and 0.2 m/s and carbon monoxide levels of between 23 ppm and 102 ppm in Tanzanian mines. Oxygen concentrations ranged between 20.3% and 20.7% while dust concentrations ranged between 6.6 mg/m³ and 10.2 mg/m³ (Mayala *et al.*, 2016:121). Temperatures ranged between 31°C and 34°C and humidity levels ranged between 89% and 93% (*ibid.*). The mines where Mayala *et al.* (2016:121) reported these readings are termed 'artisanal' mines with depths of between 340 m and 410 m. These informal underground mining operations experience ventilation and cooling challenges despite being much shallower than the deep-level mines found in South Africa. The Tanzanian

mining operations investigated by Mayala *et al.* (2016:123) lack proper health and safety practices because these mines are not owned and operated by registered companies. The inadequate health and safety practices at these informal mining operations resulted in several deaths due to suffocation (Mayala *et al.*, 2016:122).

The depth of deep-level mines results in additional temperature-related challenges. Rock temperatures, self-compression of air, and mining machinery contribute significantly to heat in underground mines (Wei *et al.*, 2020:3). Wei *et al.* (2020:4) measured humidity levels of up to 100% in the working areas of an underground gold mine. They stated that ventilation with flow rates of between 3 m/s and 4 m/s in workplaces make a significant contribution to improved working conditions.

A simplified overview of a typical deep-level mine ventilation network is provided in Figure 2-8. The primary ventilation fans have electrical capacities that range between 1 MW and 4.1 MW per fan for typical gold and platinum deep-level mines (Nel *et al.*, 2019:384). Some installations reportedly have more than one fan installed with a total installed capacity ranging between 3 MW and 12.3 MW for a deep-level mine. Nel *et al.* (2019:384) stated that primary ventilation fans account for about 12% of the mine's total energy consumption. These ventilation systems are used to draw fresh air into mines to improve worker safety and comfort.

A 12.3 MW ventilation system will result in an electricity bill of more than R104 million per annum if the Eskom Megaflex tariff structure is considered. This is an operational cost that is not needed by surface mining operations. These ventilation systems are typically in continuous operation, which contribute significantly to the total baseload electricity usage at the mine. The electricity usage of deep-level mine ventilation systems will not necessarily be reduced during production stoppages because these systems are typically designed to operate continuously. This was proven by Greyling (2014:41) who reported baseload electricity usage of more than 80% on the main ventilation fans at South African deep-level gold mines.

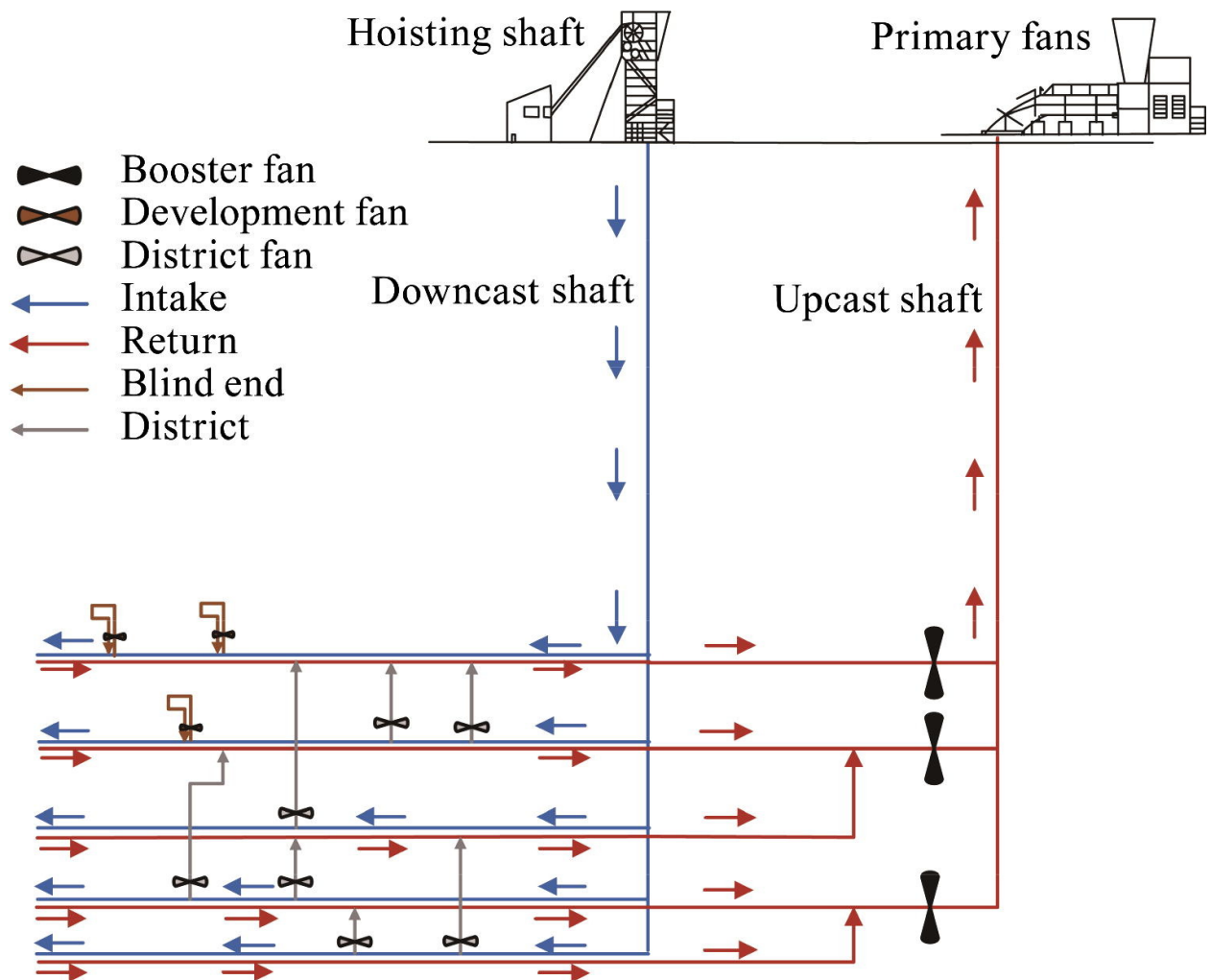


Figure 2-8: Simplified overview of a typical deep-level mine ventilation network

(De Villiers et al., 2019:934)

2.2.6 Summary

Mines are generally referred to as deep-level mines if they are deeper than 1.5 km from surface (Maré, 2017:18). Deep-level mines have unique challenges such as high underground temperatures and fissure water influx. This makes deep-level mines much more energy-intensive than surface mining operations. It has been reported that deep-level mines are about seven times more energy-intensive than surface mining operations (Holmberg et al., 2017:122).

The major electricity consumers on deep-level mines are compressed air systems, ventilation systems, pumping systems, and cooling systems (Greyling, 2014:45). Another challenge from underground operations is the long travelling distances from surface to underground working areas, which has a significant impact on personnel productivity (Nagel, 2020:60). Long travelling distances are due to the large underground areas where underground mining areas as large as 100 km² have been reported (Du Plooy, 2019:5).

Compressed air systems are primarily installed to power pneumatic equipment and to provide fresh air to refuge bays (Zietsman, 2019:43). Compressed air is, however, sometimes misused to provide cooling if other ventilation and cooling options are not adequate (Zietsman, 2019:68). This results in very poor system efficiencies. It has been reported that deep-level mine compressed air systems have total pipe lengths of as much as 105 km (Zietsman, 2019:113).

A single compressor sized at 4.8 MW will result in an estimated electricity bill of more than R40 million per year if operated continuously. The peak power demand for the compressed air systems in South African deep-level mines is estimated at close to 467 MW (Vermeulen et al., 2018:124). These systems have electrical baseload consumption values of as much as 88% (Zietsman, 2019:12). This suggests that compressed air systems at deep-level mines contribute significantly to total operational costs. This is a unique challenge that is not relevant to surface mining operations.

Another challenge experienced by deep-level mines is underground water. Large pumping systems are needed to ensure that mines do not flood due to the ingress of fissure water as well as water from mining operations (Greyling, 2014:44). It has been reported that some deep-level mines have an average fissure water influx of 1.38 m³ per day (Maré, 2017:129). Mine dewatering systems at typical deep-level mines have a baseload electricity usage of about 40% (Greyling, 2014). Some deep-level mines have up to five main underground pumping stations (Conradie, 2018:88) with up to five pumps installed per level (Taljaard, 2018:111). This has significant operational cost implications because deep-level mines need to pay for the electricity usage for the baseload operation of dewatering pumping systems even when production is stopped. The operation of a single 3.8 MW dewatering pump at a deep-level mine can lead to an annual electricity bill of R32 million. This shows that pumping systems contribute significantly to overall operating costs.

Complex energy-intensive cooling systems are needed due to underground rock temperatures of as much as 80°C and humidity levels of as high as 100% (Sasmito *et al.*, 2015:1145). Large surface ventilation fans with electrical capacities of up to 4.1 MW provide fresh air to underground operations and to assist with cooling. This ensures worker safety since it has been reported that suffocation in underground artisanal Tanzanian mines, where ventilation is not up to standard, led to the death of workers (Mayala *et al.*, 2016:122). Proper ventilation is, therefore, regarded as essential to ensure worker safety (Nel *et al.*, 2019:384). Some deep-level mine installations reportedly have more than one fan with a total installed capacity ranging between 3 MW and 12.3 MW (Nel *et al.* 2019:384). A 12.3 MW ventilation system will result in an electricity bill of more than R104 million per annum when considering the Eskom Megaflex tariff structure. This is an operational cost that is not needed by surface mining operations.

A major challenge for deep-level mining operations is the high contribution of baseload electricity usage. Cooling and ventilation systems have baseload electricity usage of more than 80% (Greyling, 2014:41). This suggests that the reduction in electricity costs due to production stoppages will be negligible compared with the large baseload usage. Research regarding energy management initiatives to curb the impact of these operational costs will be discussed in the following section.

2.3 Energy management

2.3.1 Overview

The previous section provided information on the deep-level mining systems that contribute the most to electricity consumption at these operations. It was stated in Chapter 1 that electricity costs account for as much as 20% of a mine's total operating costs (Sibanye Stillwater, 2019:22). It was further mentioned that the impact of the rising electricity costs is of great concern to mining groups, especially mines with narrow profit margins (Harmony Gold, 2019:29). It is important to remember that energy affordability is noted to be one of the critical uncertainties in South Africa (World Energy Council, 2020:41).

The previous section highlighted the significant challenges faced by deep-level mining companies regarding the baseload electricity usage at these operations. These baseloads contribute significantly to operating costs and remain high even during production stoppages. Initiatives aimed at electricity cost-saving measures on deep-level mines should be considered to improve the profitability of these operations. McKinsey Global Institute (2017:6) estimated that energy efficiency improvements have the potential for realising global cost savings of as much as \$540 billion by 2035. They also predicted that worldwide energy efficiency will increase by between 40% and 70% by 2035 (McKinsey Global Institute, 2017:35).

The McKinsey Global Institute (2017:29) estimated that advanced sensors, control systems, analytics and modelling have the potential for reducing the industrial sector's energy intensity by between 10% and 30%. They noted that industrial companies will adopt new technologies over a period of 20 years (McKinsey Global Institute, 2017:39). It is expected that energy efficiency improvements have the potential for reducing the impact of rising electricity costs at deep-level mines.

Energy conservation can be achieved in various ways that range from making simple behavioural changes to implementing sophisticated technologies (Kanneganti *et al.*, 2017:122). Finnerty *et al.* (2017:17) stated that energy management on a practical level is "*the control of energy-related*

activities”. They further stated that “an energy management system (EnMS) outlines the strategic steps required to implement a systematic process for continually improving energy performance”.

A differentiation between energy management, energy efficiency measures and energy management systems as proposed by Finnerty *et al.* (2018:914) is provided in Figure 2-9. Energy management is aimed at planning and executing initiatives that reduce energy consumption (Kanneganti *et al.*, 2017). Energy management systems comprise procedures and steps for realising energy management (Finnerty *et al.*, 2017:914). Escos use energy management systems to collect and process energy-related data (Goosen *et al.*, 2016:9). These systems are configured to generate reports related to energy management services. Energy efficiency measures are the implementation of specific actions aimed at improving energy usage (Finnerty *et al.*, 2017:914).

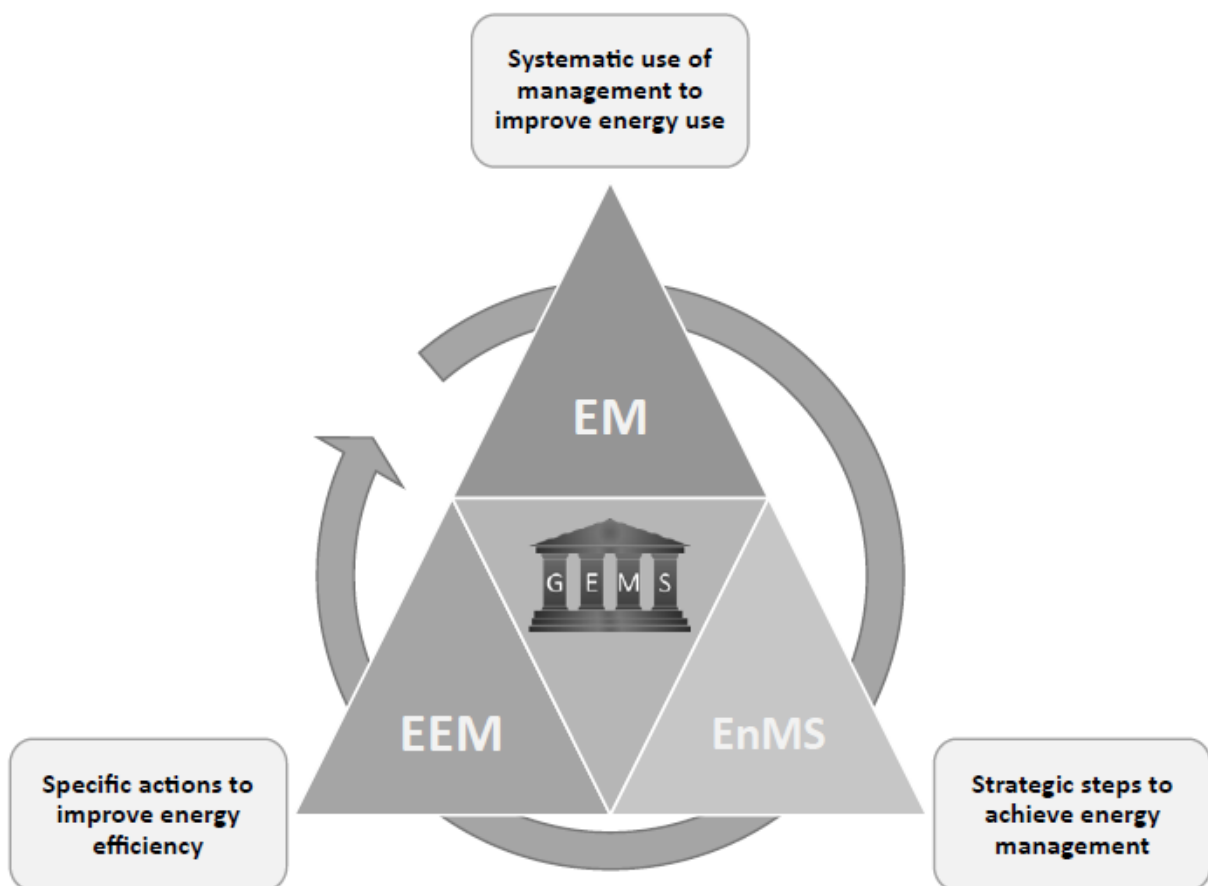


Figure 2-9: Comparison of energy management, energy efficiency measures and energy management systems (Finnerty *et al.*, 2018:914).

Energy management is seen as being essential for ensuring sustainable competitiveness (Trianni *et al.*, 2019:1614). Trianni *et al.* (2019:1619) stated that the level at which a company implements energy management can be related to a list of 51 energy management practices. Examples of

these practices include adopting benchmarking, implementing employee incentives, procuring green energy, and applying energy efficiency KPIs.

Trianni *et al.* (2019:1619) defined an energy management practice as follows: *“a technique, method, procedure, routine or rule adopted at a precise stage of the industrial energy management setting to achieve the company’s energy efficiency objectives. It acts on technological, non-technological, or of support aspects, by improving the energy performance directly or indirectly in a specific area of the company”*.

The previous section highlighted the significant cost implications for deep-level mines due to the costs of operating large electric equipment. It is important to understand the main factors and challenges that influence electricity usage. The main internal drivers for energy management at businesses are cost reductions, long-term energy strategies, ambitious people who drive behavioural change, and awareness regarding non-energy benefits (Finnerty *et al.*, 2018:929). External factors that drive the implementation of energy efficiency measures are energy prices, regulatory requirements, demand for eco-friendly products, and the availability of cheap cleaner technology (Finnerty *et al.*, 2018:916).

Internal factors such as evaluation processes, fiscal rules such as payback periods, and investment parameters influence the uptake of energy efficiency measures (Finnerty *et al.*, 2018:916). Finnerty *et al.* (2018:916) further found that company culture plays a role in whether energy efficiency projects are implemented. The predominant barriers to the implementation of energy efficiency projects are a lack of capital, low priority of energy efficiency, risk of production disruptions, and a lack of awareness (Finnerty *et al.*, 2018:924, 925). This shows that there are many factors at play that influence electricity usage at organisations in general.

Earlier research highlighted that industries are not always keen to invest in researching and developing energy efficiency improvements (Bukarica & Tomšić, 2017:970). They would rather wait until solutions are developed by others and then implement proven solutions at their own facilities. Bukarica and Tomšić (2017:970) identified barriers that prevent the adoption of energy efficiency. They stated that policy changes are needed before employees will put the required effort into implementing energy efficiency at their workplaces.

Rosenow *et al.* (2017:101) found that the industrial sector has a high appetite for more costly and complex energy efficiency solutions. Such expensive and complex solutions are often funded through loans, tax rebates and government grants. These solutions are not necessarily relevant to all deep-level mining operations in South Africa since some operations are expected to stop production within the next one to five years (Harmony Gold, 2019:104). Other shafts have

predicted ore reserves for up to 19 years (*ibid.*). More expensive solutions may be more feasible at these operations.

Barnard (2020:69) proved that solar installations at deep-level platinum mining operations have payback periods of close to six years. Such solutions will significantly reduce the operational costs of mining over the long run. A challenge with this solution remains that the electricity supply will only be augmented during daylight hours. Electricity will still be required from other sources such as Eskom during the night-time.

Energy-saving approaches include a combination of operational improvements, behavioural measures and multiple retrofit measures with the potential of realising savings on a high level (Granderson & Fernandes, 2017:8). Granderson and Fernandes (2017) found that operational improvement interventions are typically evaluated at the utility level (Granderson & Fernandes, 2017:15). They suggested that Escos must be reimbursed based on the realised savings.

Information that relates better to the mining industry was provided by Awuah-Offei (2016:95). He noted that there is a lack of public funding for mining energy efficiency research. He determined that it is difficult to recommend a particular set of best practices for mining due to the diversity of the sector. Awuah-Offei (2016:95) stated that a thorough return-on-investment study is needed for energy management programmes.

Newsham (2019:2) found that Escos enter into energy performance contracts with organisations due to capital constraints at the organisation implementing energy conservation. South African deep-level mining companies appoint energy management companies, often referred to as Escos, to assist with optimisation strategies (Harmony Gold, 2019:136; Implats, 2019:45; Sibanye Stillwater, 2019:209). These mining companies stated that energy management at their operations entails optimising pumping, refrigeration, ventilation and compressed air systems. Escos also use digital monitoring and control systems to improve system efficiency.

The preceding section highlighted the potential benefits of energy improvement measures at mining operations. Section 2 highlighted the unique challenges at deep-level mines that have a significant impact on electricity consumption at these operations. Insight relating to typical electricity cost-saving strategies at deep-level mines is needed to evaluate the business case for energy management at these operations during prolonged production stoppages. This will be achieved through a review of literature relating to electricity cost-saving measures typically implemented at deep-level mines. The review will be structured according to the predominant electricity users at deep-level mines.

2.3.2 Energy management at deep-level mines

2.3.2.1 Compressed air systems

Section 2.2 highlighted that compressed air is a major electricity consumer in the deep-level mining industry, which is why researchers often focus on these systems. Vermeulen *et al.* (2018:8) estimated a cost-saving potential of R60 million on South African deep-level mine compressed air systems by implementing energy-saving initiatives. More recent research from Zietsman (2019:99) estimated a much higher energy-saving potential of R620 million on the compressed air systems at deep-level mines.

Friedenstein *et al.* (2018:72) believed that the operational schedule of a mine has a direct impact on the feasibility of energy-saving projects on deep-level mine compressed air systems. Friedenstien *et al.* (2018:69) showed that simulation models can be used to evaluate potential energy-saving solutions based on potential operating scenarios. Friedenstien *et al.* (2018:81) found that the implementation of flow-regulating valves on refuge bays has a cost-saving potential of R6.3 million per annum for a single operation.

It was stated in Section 2.2 that it is a legal requirement to have compressed air available at underground refuge bays to ensure worker safety. This requirement is the same whether one only one employee or many workers employee are underground. The implementation of refuge bay flow-regulating valves delivers electricity cost savings even if production is halted for short- to medium-term periods. It was further discussed in Section 2.2 that other mining equipment such as pumping systems must be operated to prevent flooding even while no production is taking place. It can be argued that the implementation of refuge bay flow control valves will realise cost savings regardless of the production level.

Du Plooy (2019:9, 10) conducted a review of existing literature regarding operational improvement strategies on compressed air systems. His research highlighted the following initiatives as typical measures for reducing electricity usage on deep-level mine compressed air systems:

- Controlling the discharge flow rate of centrifugal compressors by implementing guide vane control;
- Scheduling compressor combinations based on their efficiency and the demand patterns of the system;
- Implementing automated control valves on strategic points on the compressed air network to regulate air supply throughout the network based on the mining schedules;
- Implementing leak repair programmes; and

- Replacing and reconfiguring compressed air network piping to reduce friction losses.

The initiatives identified by Du Plooy (2019:9, 10) also apply during no-production periods due to the need to operate the compressed air network to supply the refuge bay valves. The second and third bullets listed above mention that control improvements are done based on mining schedules and demand patterns. It may be necessary for energy managers to change the scheduling of compressors during production stoppages to reduce the baseload usage. The sustainability of typical energy-saving measures will be discussed later in this chapter to investigate the requirement of keeping a watchful eye on improvements.

Du Plooy *et al.* (2019:134) found that supplying compressed air to inactive mining sections contributed significantly to compressed air wastage. They identified cost-saving opportunities of \$380 000 per annum on the underground network at a South African gold mine. Energy cost savings realised by an Escos through a dedicated effort to close inactive areas will realise cost savings regardless of the production output provided that the mine is not put under long-term care and maintenance. The same reasoning applies to improved compressor scheduling, compressed air flow control, leak repair programmes, and the isolation of old inactive areas.

It can be argued that Escos compensated based on performance agreements as suggested by Granderson and Fernandes (2017:15) and Newsham (2019:2) should be compensated for saving interventions regardless of the production levels of the mine. Nonetheless, compressor power consumption does vary based on production levels. However, it is not fair that electricity cost reductions due to lower compressed air demand as a result of production stoppages provide an unfair advantage to Escos. This research aimed to isolate the reduction in electricity usage due to production changes from the impact of energy-saving measures. The impact quantification methodology in the event of medium-term production stoppages will be investigated later in this document.

2.3.2.2 Dewatering systems

Section 2.2 highlighted the need to operate large dewatering pumps to prevent flooding in deep-level mines (Greyling, 2014:44). It was also shown that the influx of fissure water requires the operation of pumping systems even during production stoppages (Maré, 2017:129). These systems contribute significantly to deep-level mine electricity costs. Existing energy management projects aimed at reducing evening peak loads have been funded by Eskom and implemented by Escos (Van der Merwe *et al.*, 2017:2). Many projects focused on implementing control systems and strategies to shift pumping load at deep-level mines to periods when the electricity network is less constrained (*ibid.*).

An example of the electricity consumption profile of a mine dewatering pumping system is shown in Figure 2-10. The grey vertical bars represent the Eskom peak tariff periods. Visual interpretation indicates how periods with high electricity costs are avoided between 06:00 and 09:00 in the mornings and between 17:00 and 19:00 in the afternoons. Van der Merwe *et al.* (2017:5) proved annual savings of up to R8.1 million per year at one mining operation by implementing such a load shifting initiative.

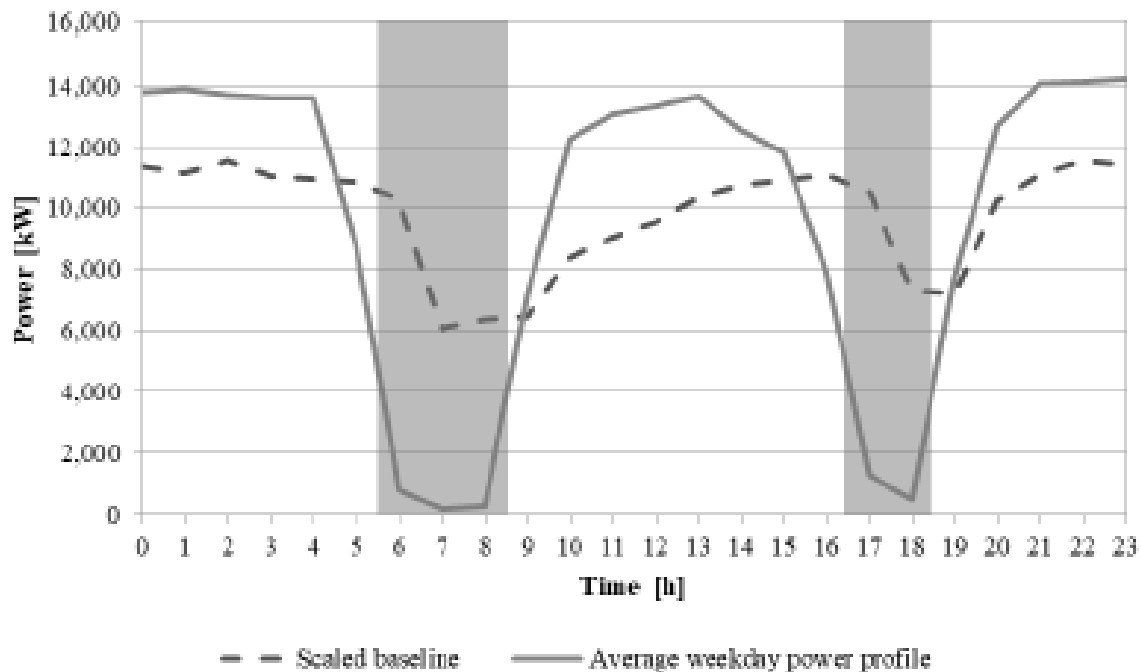


Figure 2-10: Example of electricity usage with load shifting

(Van der Merwe *et al.*, 2017:5)

Avoiding Eskom peak cost periods can realise cost savings even if no production takes place. The reduced water influx during production stoppages can potentially increase cost savings because this may present an opportunity for eliminating pumping during expensive periods. It is important to realise that load shifting projects are aimed at cost optimisation. Load shifting projects do not aim to realise energy savings because electricity usage is merely moved to different periods.

Conradie (2018:118) realised a reduction in electricity usage on the dewatering pumping system by replacing mobile chilled water cars, also referred to as cooling cars, with centralised BACs. He proved that less cold water is required when using centralised BACs than mobile cooling cars. The reduction in water usage decreased electricity usage on the dewatering system by 49 GWh per year at an equivalent annual cost-saving of R31.83 million when using 2017/2018 Eskom tariffs.

Conradie (2018:115) did not observe a notable effect on the electricity usage of the refrigeration system despite the claim that less water was used. He argued that the cooling water temperature decreased because less water was handled by the refrigeration plant. Conradie (2018:115) noted a decrease in underground temperatures of between 1°C and 3°C after implementing an electricity-saving intervention. He claimed a notable increase in production of 16% as a result of cooler working area temperatures after the improvement was made.

Research by Nagel (2020:60) suggested that underground ventilation conditions influence mining production output. This indicates that energy management interventions, such as the improved working conditions claimed by Conradie (2018:115), may have benefits in addition to electricity cost savings. However, it was not the aim of this study to investigate these added benefits, and they were not investigated in more detail.

Winde *et al.* (2017:679) stated that South African deep-level gold mines have the largest underground hydraulic heads worldwide. Some deep-level mines use energy recovery devices that convert the potential energy of cold water supplied to mining operations into useful energy. An example of such a device is a three-chamber-pipe-feeder-system (3CPFS) (Van der Wateren *et al.*, 2018:4). Figure 2-11 shows an example of a simplified deep-level mine water network using a 3CPFS.

Van der Wateren *et al.* (2018:7) proved that an optimisation strategy on a deep-level mine with a 3CPFS has the potential for realising electricity cost savings of R1.7 million per annum if the 3CPFS has a high availability factor. The 3CPFS at one of the mines in their case study had availability of less than 90% for two-thirds of the time. The poor availability was due to frequent breakdowns (*ibid.*). Their study highlighted the importance of dedicated maintenance on energy-saving interventions to ensure sustainable savings.

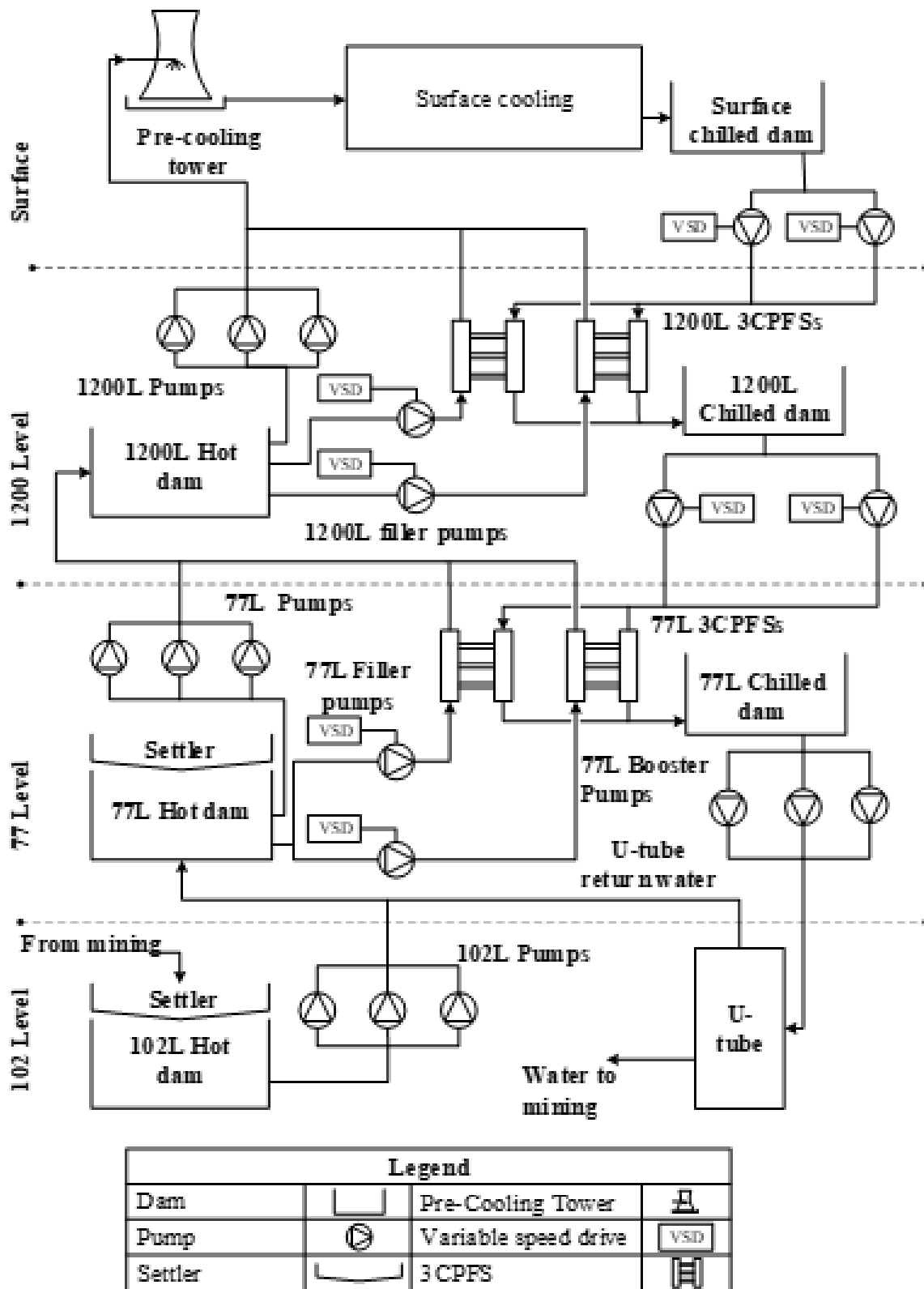


Figure 2-11: Simplified layout of a deep-level mine dewatering system with a 3CPFS energy recovery device

(Van der Wateren et al., 2018:4)

A schematic representation of a 3CPFS is provided in Figure 2-12. Cold-water supply to the mining levels is supplied at Point A and hot used water is dewatered at Point B (Van Niekerk, 2014:27). Booster pumps are used to overcome friction losses in the system. A series of automated control valves control water flow in and out of the pumping chambers, numbered as C, D and E.

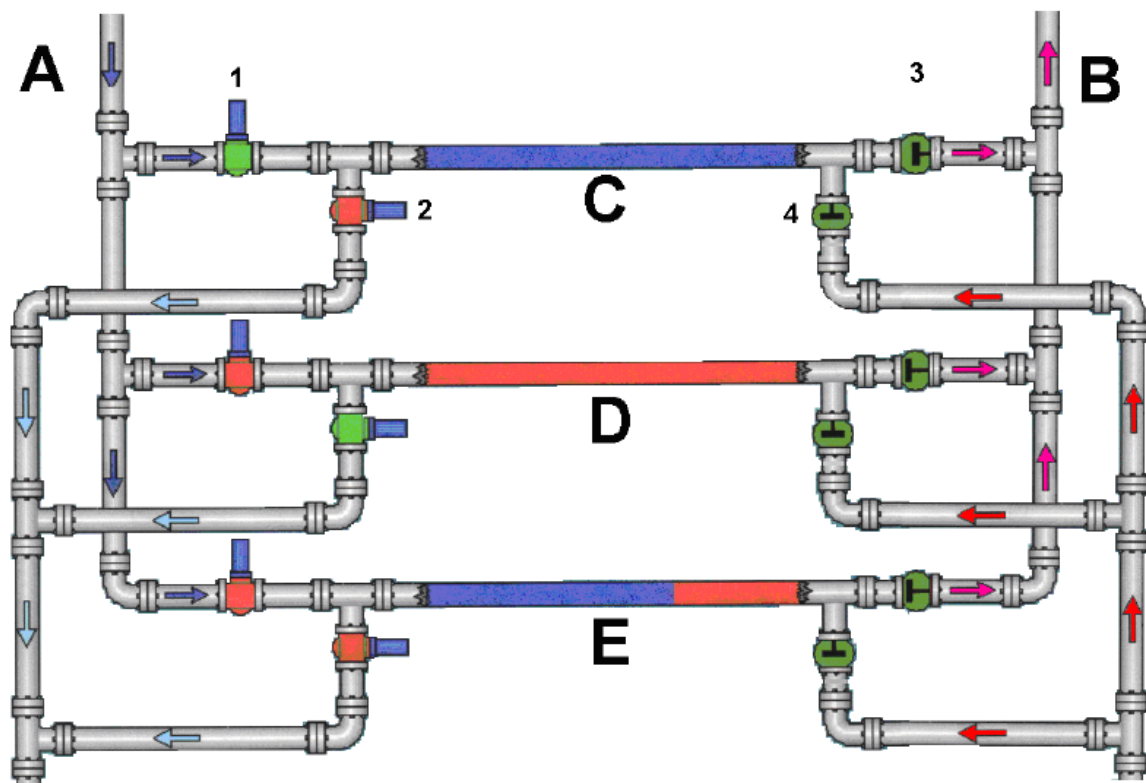


Figure 2-12: Simplified layout of a 3CPFS

(Van Niekerk, 2014:27)

An example based on an explanation by Momberg (2018:32) describes the following: cold water is supplied to Chamber C by opening Valve #1 and Valve #3. The influx of cold water from Column A forces the used warm mining water out through Valve #3 and Column B. Valve #1 and Valve #3 close after enough time has passed to allow the column to fill with cold water. Thereafter, Valve #2 and Valve #4 open to allow hot water to enter the chamber through Valve #4. Cold water then leaves the chamber via Valve #2. Valve #2 and Valve #4 close after the chamber has filled with warm water. The process is repeated from the point at which Valve #1 and Valve #3 opened. Chamber D and Chamber E follow a similar sequence, with each chamber taking turns to dewater hot water by using the potential energy of the cold water.

Momberg (2018:111) developed an optimisation strategy to improve the electricity cost savings on a mine water reticulation system that had a 3CPFS. His strategy realised an improvement with

an annual cost-saving potential of R4.4 million. The electricity cost savings from an optimisation strategy on an energy recovery device is linked to both the volume of water that must be pumped from underground and the volume of cold water that must be supplied to underground workplaces.

Section 2.2 revealed that mine cooling systems must be operated to counter underground heat sources such as exposed rock and the compression of air. Cooling must be provided at workplaces to ensure the health and safety of mineworkers. It may be possible to stop some cooling at areas where no care and maintenance tasks must be carried out during medium-term production stoppages. This reduces the volume of cold water supplied to underground and leaves less potential energy to pump water to surface with an energy recovery device. However, quantifying the impact of energy management initiatives as a result of reduced cooling may be more challenging. Quantifying the impact of reducing cold-water supply will be investigated in the empirical study in Chapter 3.

2.3.2.3 Mine cooling systems

Section 2.2 revealed that mine cooling systems contribute significantly to the electricity consumption at deep-level mines. This suggests that energy-saving initiatives on these systems have a significant cost-saving potential. Energy-saving opportunities on deep-level mines include optimisation of cooling systems (Peach *et al.*, 2018:202). Peach *et al.* (2018:202) argued that mine cooling systems may be outdated since they were designed for different mine layouts. They proved that operational improvements to cooling systems can lead to energy savings of between 18% and 30% while providing better system performance (*ibid.*).

Bornman *et al.* (2016:1005) developed an optimisation platform for reducing the electricity consumption of deep-level mine cooling systems. They realised a 13% reduction in electricity usage at a South African deep-level gold mine. The average reduction was equivalent to a demand reduction of 337 kW. This was achieved by varying the water flow through a BAC to achieve the required cooling duty. The impact of the results was quantified over three months. It is clear from the study by Bornman *et al.* (2016:1005) that deep-level mines do not necessarily vary cooling output according to varying conditions. This is possibly a major contributor to the high baseloads of about 80% as reported by Greyling (2014:41).

Maré (2017:165) developed a simulation strategy for reducing the energy consumption of mine cooling systems. He used simulations to conduct what-if analyses for system changes. His study revealed that the implementation of variable speed drives (VSDs) on the BAC feed and return pumps have project payback periods of less than one year. His project was aimed at varying pump rotational speed based on operational requirements. The study by Maré (2017:165)

provided further proof that it is not common practice to vary cooling at deep-level mines based on production output.

Maré (2017:169) suggested installing flow-regulating valves for controlling water supply to working areas to minimise wastage during periods when production does not take place. Other suggestions from Maré entailed making operational changes to the operation of cooling systems. His investigation identified savings with annual cost savings of R31 million per annum using 2016/2017 Eskom tariffs (Maré, 2017:181). The findings from Maré (2017:169) suggest that some deep-level mines do not have measures in place to reduce water usage during production stoppages.

Crawford (2019:53) recently evaluated existing research on energy management on mine cooling and ventilation systems. His findings are summarised in Table 2-1. It is evident from his research that mine cooling and ventilation systems are frequent targets for energy efficiency improvements. Many researchers have evaluated the potential for realising energy savings on surface refrigeration equipment with a specific focus on pump control. Crawford (2019:53) identified a gap in available research that focused on the automation of systems. This suggests that many energy-saving initiatives on mine cooling systems require manual intervention.

Crawford (2019:167) developed a dynamic control strategy to improve the efficiency of cooling systems at deep-level mines. He used an integrated control approach that improved service delivery and reduced energy use. The strategy entailed using a dynamic temperature set-point control algorithm. The mine previously used a manual control strategy that did not consider the holistic operation of the system. The dynamic control strategy developed by Crawford (2019:168) realised a service delivery improvement of 15% and an electricity demand reduction of 4%. The results of the study were published in the *Journal of Applied Thermal Engineering* (Crawford et al., 2019). Crawford (2019:168) proved that the old cooling system control did not account for the variance in mine cooling load. This recent study highlighted that deep-level mines do not necessarily have strategies in place to provide cooling based on actual requirements.

The summary of the existing research as presented in Table 2-1 highlights that most deep-level mines have static control measures in place for controlling cooling plant output. It can, therefore, be argued that electricity consumption of deep-level mine cooling systems does not vary significantly according to production levels.

Table 2-1: Summary of research relating to energy management on mine cooling and refrigeration systems

Author	Ventilation								Cooling							Implementation		Project		Operational performance	
	Surface			Underground					Surface				Underground					DSM			
	Fans	BACs	Reconfiguration	Fans	BACs	Mobile units	Development cooling	Reconfiguration	Refrigeration	Pump control	Pre-cooling towers	Reconfiguration	Refrigeration	Pump control	Reconfiguration	New equipment	Improved strategy	Automation	Energy efficiency		Load shift
Arndt, DC		x								x							x				x
Bluhm, SJ	x						x														x
Buys, JL		x								x						x			x		
Du Plessis, GE		x								x	x					x	x		x		
Du Plessis, JJJ	x		x																x		
Els, R	x								x	x			x	x			x			x	
Greyling, J						x	x						x								x
Holman, AM									x	x	x						x		x		
Kukard, WC	x			x															x	x	
Lambrechts, JV							x														x
Moropa, TS					x					x	x						x			x	
Maré, P									x	x	x					x	x		x		
Nel, AJH					x					x	x					x	x		x	x	
Oberholzer, KJ					x			x		x	x	x				x			x		x
Schutte, AJ		x							x	x						x			x	x	
Swart, C	x												x	x			x				x
Uys, DC									x	x		x							x	x	
Vosloo, JC									x	x				x					x	x	x

(Crawford, 2019:54)

2.3.2.4 Mine ventilation systems

Section 2.2 revealed that mine ventilation systems have baseloads of about 80%. A recent study by De Villiers *et al.* (2019:938) showed that the efficiency of some deep-level mine ventilation systems is as low as 2%. They found that such inefficient ventilation systems increase underground wet-bulb temperatures by as much as 2.2°C and dry-bulb temperatures by as much as 3°C. Their research highlights significant potential for energy savings on mine ventilation systems. De Villiers *et al.* (2019:938) found that fan and ducting inefficiencies were the largest contributors to total system inefficiency. High baseloads of 80% suggest a poor correlation with production output. Mine size and age will most likely present a much better correlation. It can, therefore, be stated with confidence that changes involving improvements to fan efficiencies and ducting on deep-level mines will realise electricity cost savings with little deviation due to production levels.

Other research relating to mine ventilation system optimisation studies has shown significant energy-saving potential with projects that showcase payback periods of as little as six days (Nel *et al.*, 2018:552). The installation of VSDs on the primary ventilation fans at deep-level mines has a return-on-investment potential that varies between 70% and 227% (Nel *et al.*, 2018:552). The payback period of some projects is reported to be as low as two days considering additional benefits such as improved production and reduced maintenance (*ibid.*). Deep-level mining companies should implement projects with such lucrative benefits without much consideration.

The implementation of a data information knowledge wisdom (DIKW) model at a deep-level gold mine in South Africa realised a 55% cooling system improvement (Pretorius *et al.*, 2019:326). Although the DIKW implementation did not realise energy cost savings, it did, however, increase the system efficiency by gaining more cooling using the same amount of energy. This reduced the requirement for additional cooling. Therefore, the success of the project was measured in terms of cooling improvement.

Nel *et al.* (2019:386) investigated the theoretical cost-saving potential at seven deep-level gold mines and three deep-level platinum mines in a very recent study. They found that such projects have payback periods that vary between eight and 22 months. They stated that these mines vary in terms of their production rates and complexity (Nel *et al.*, 2019:383). These mines had a total of 33 main ventilation fans installed with installed electric motor capacities ranging between 1 MW and 4.1 MW (Nel *et al.*, 2019:384). The static ventilation efficiencies ranged between 15% and 78% (Nel *et al.*, 2019:384). On average, these main ventilation fans contributed 12% to the mine's total electricity consumption (Nel *et al.*, 2019:384).

Nel *et al.* (2019:384) found that all the ventilation fans investigated as part of their study had inlet guide vanes installed. Inlet guide vanes are used to vary the mass flow rate delivered by the fan (Nel *et al.*, 2019:384). Nel *et al.* (2019:384) found that several vanes were fixed in set positions and some were broken. None of the fans investigated was equipped with VSDs (Nel *et al.*, 2019:384). Nel *et al.* (2019:387) believed that the main ventilation fans are typically designed based on the expected monthly production of the mine.

Figure 2-13 compares the existing airflow delivery at mines without any flow control versus the proposed dynamic control as proposed by Nel *et al.* (2019:387). An important finding from their study is that none of the fan installations showed any change in fan power consumption based on varying production requirements (Nel *et al.*, 2019:384). This recent study proves that deep-level mining operations hardly change ventilation systems. This provides some insight into the high baseload electricity usage at typical deep-level mining operations. Therefore, energy-saving measures that realise savings, where ventilation systems electricity usage is varied based on production requirements, will still be beneficial to mining companies. This further implies that Escos should be able to claim the benefit of these reductions during normal production and prolonged production stoppages.

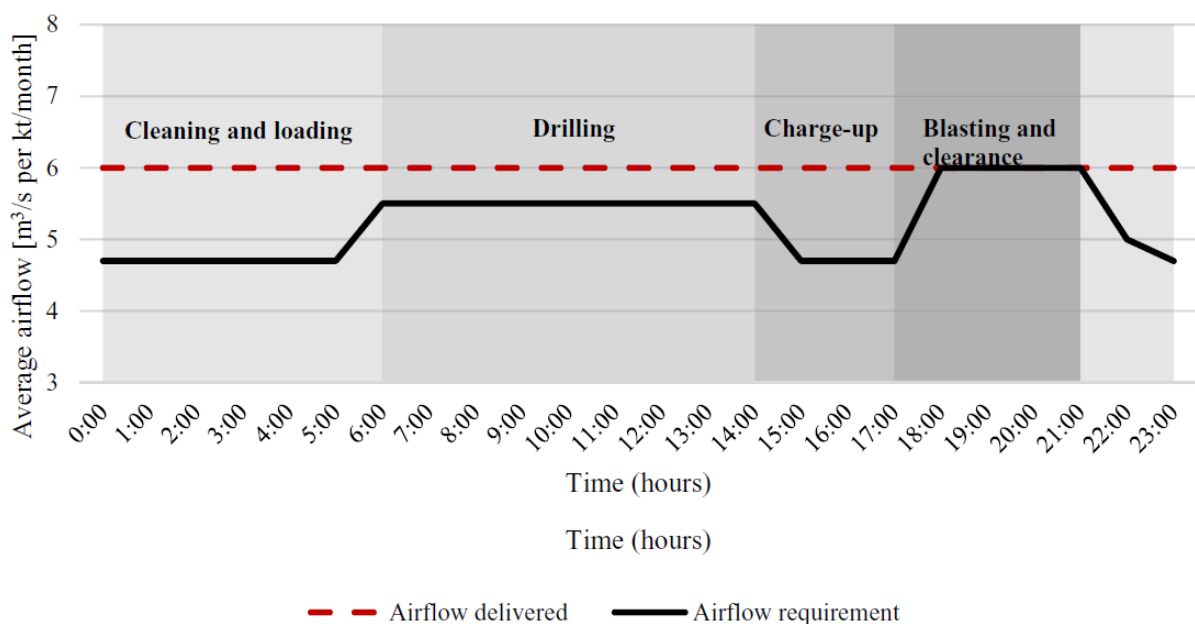


Figure 2-13: Typical main ventilation fan load on deep-level mines compared with proposed dynamic control
(Nel *et al.*, 2019:387)

2.3.2.5 Holistic energy management

The previous sections focused on specific interventions implemented at deep-level mines. The ISO 50 0001 energy management standard is based on the plan-do-check-act approach, which is centred on a process of continuous improvement to reduce energy intensity (Kanneganti *et al.*, 2017:121). The study by Kanneganti *et al.* (2017:135) evaluated the impact of an ISO 50 0001 approach based on performance indicators such as kWh per ton, kWh per customers served, or kWh per unit produced.

A significant challenge with these KPI indicators is their sensitivity to production. The baseload energy consumption in a system will indicate very poor energy performance for low production and favourable intensities if production volumes are high. The KPI indicators should, therefore, be considered only within certain operating boundaries if the baseload cannot be separated from the variable loads. Section 2.2 highlighted the large baseloads at deep-level mines. Energy performance indicators must consider the challenges associated with high baseload demands at mines.

Bredenkamp (2016:96) developed an integrated energy management system specifically for deep-level mines based on the ISO 50 001 energy management standard. Figure 2-14 displays the layout of the proposed strategy. The strategy developed by Bredenkamp (2016:162) was aimed at realising electricity cost savings on a shaft level based on a continuous improvement aim. The model prioritised new saving initiatives using a benchmarking model based on a kWh/ton of processed ore combined with annual electricity consumption (Bredenkamp, 2016:101). Bredenkamp (2016:101) purposefully developed the energy intensity model to prioritise energy-saving projects for normal production and it cannot be applied directly to medium-term production stoppages.

Bredenkamp (2016:162) proposed that baselines be constructed using average energy consumption values over 12 months. This ensures that all system changes such as seasonality effects are accounted for. This may be good practice for normal energy-saving projects implemented during business-as-usual operations; however, it is noted from his study that data over at least one year is preferable when developing baselines.

A key requirement of an ISO 50 001-based energy management standard is the availability and reliability of system data (TÜV NORD, 2014:13, 32). Bredenkamp (2016:113) suggested installing modern measurement equipment linked to a supervisory control and data acquisition system and a database for storing the historical data. This makes it possible to implement a continuous improvement strategy.

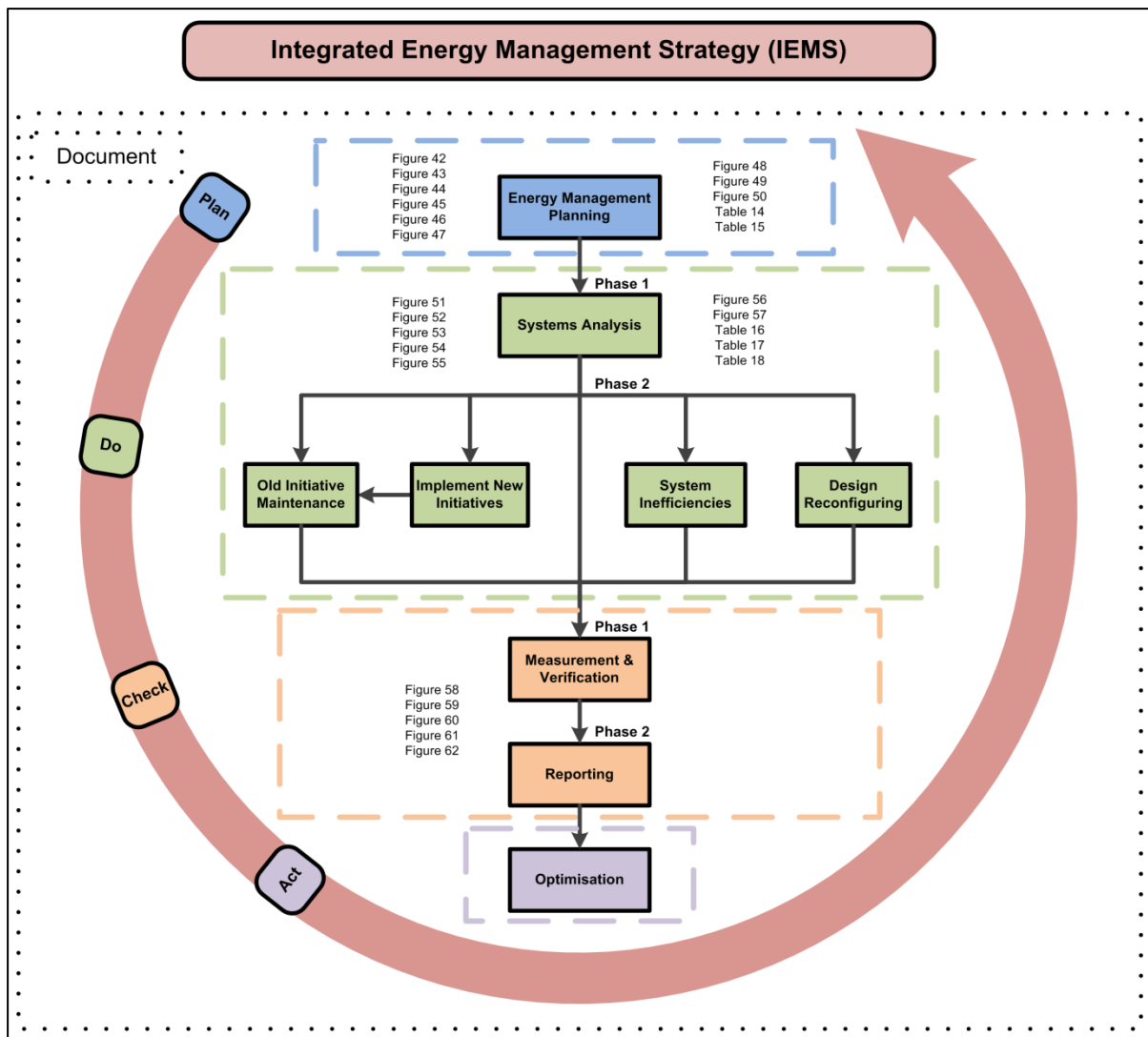


Figure 2-14: Layout of an ISO 5001-based integrated energy management strategy

(Bredenkamp, 2016:96)

A continuous improvement strategy has the advantage of the frequent identification of new energy-saving initiatives. Such a continuous improvement approach can also be followed during mine production stoppages. Figure 2-15 provides the layout for the implementation of energy-saving initiatives as proposed by Bredenkamp (2016:116). Bredenkamp (2016:119) argued that an energy management team must primarily be responsible for maintaining old energy-saving initiatives because they have the highest potential for missed opportunities if not maintained properly. He further stated that a continuous improvement approach to these old saving initiatives is essential for maximising electricity cost savings (Bredenkamp, 2016:12).

Bredenkamp (2016:150) claimed an 18.5% reduction in electricity usage by implementing the ISO 50 001-based approach, which resulted in an electricity cost saving of R75 million. Thus, it can be concluded that a continuous energy management drive can result in energy cost savings even during medium-term production stoppages.

2.3.2.6 Sustainability of energy management initiatives at deep-level mines

The preceding section showed that many energy management studies in the South African mining industry are aimed at trying to match the supply of services to varying demand. Bredenkamp (2016:119) found that maintenance of energy initiatives is important for maximising electricity cost savings. He further determined that a continuous improvement approach regarding the maintenance of old energy cost reduction initiatives can result in additional savings.

Groenewald (2015:145) analysed the performance of industrial energy management projects funded by Eskom. He found that industrial energy management projects that are not maintained through a performance-centred maintenance approach deliver only 35.6% of possible savings. The performance of projects that were not maintained is shown in Figure 2-16. The blue bar represents the contractual target and the red bar represents the performance of the projects after some time. It is important to note that the Esko had to prove that the contractual target could be reached before the project was handed over to the client. The contractual target was therefore realistic.

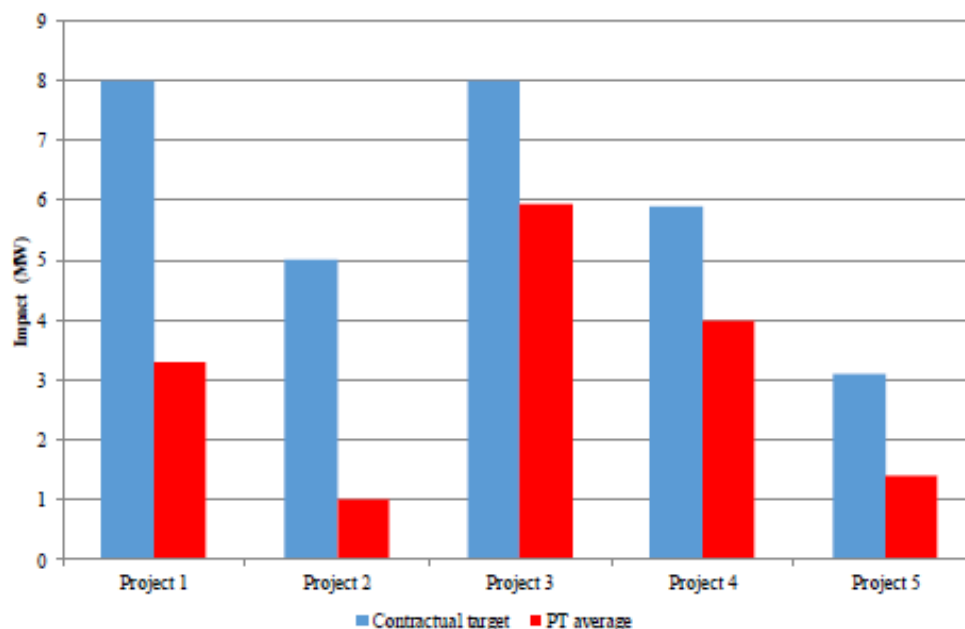


Figure 2-16: Performance of industrial energy management projects

(Groenewald, 2015:65)

Figure 2-17 shows the performance of Eskom-funded energy management projects. The client contracted an Esko to maintain the project performance after the initial three-month Eskom performance assessment period. It is clear that the performance of the projects that were maintained exceeded their contractual targets. This in contrast to Figure 2-16 that shows projects not reaching their contractual targets due to a lack of maintenance.

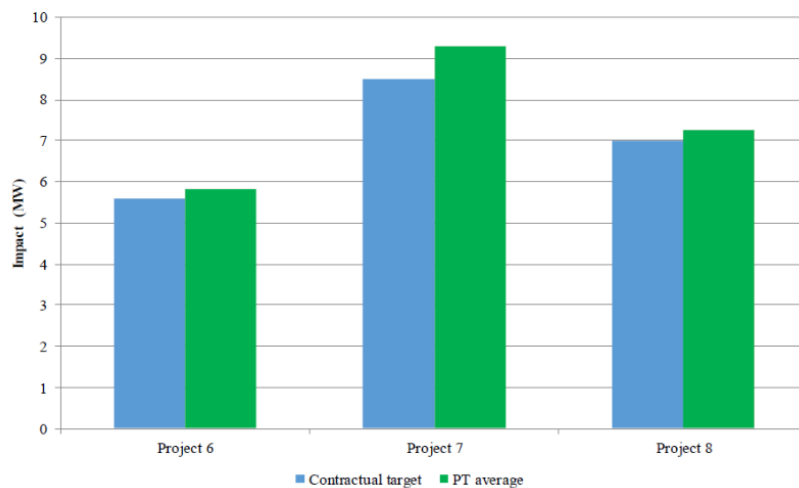


Figure 2-17: Performance of industrial energy management projects with a maintenance agreement in place

(Groenewald, 2015:66)

Figure 2-18 shows the performance of an industrial electricity cost-saving project investigated by Groenewald (2015:142). An increase in project performance is evident in month 4 and month 5 when a performance-centred approach was followed. A significant decrease in performance is noted from month 6 onwards when the Esko was not involved.

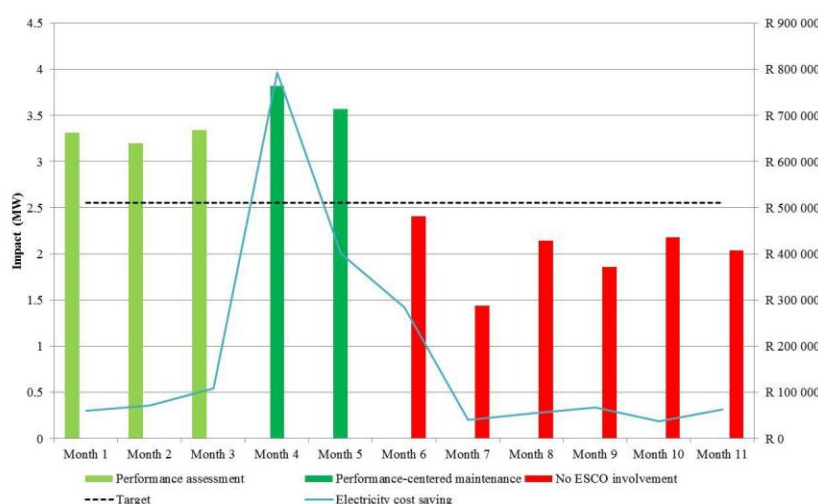


Figure 2-18: Savings deterioration for an industrial energy-saving project without performance-centred maintenance

(Groenewald, 2015:142)

Groenewald (2015:123) also investigated the performance increase after a performance-centred maintenance approach was applied to a project that has underperformed previously. The project performance is displayed in Figure 2-19. The performance-centred approach resulted in a 58% improvement in project performance (Groenewald, 2015:123). Groenewald (2015:143) estimated the financial impact of the increase in savings at R3 million per annum based on Eskom 2015/2016 tariffs.

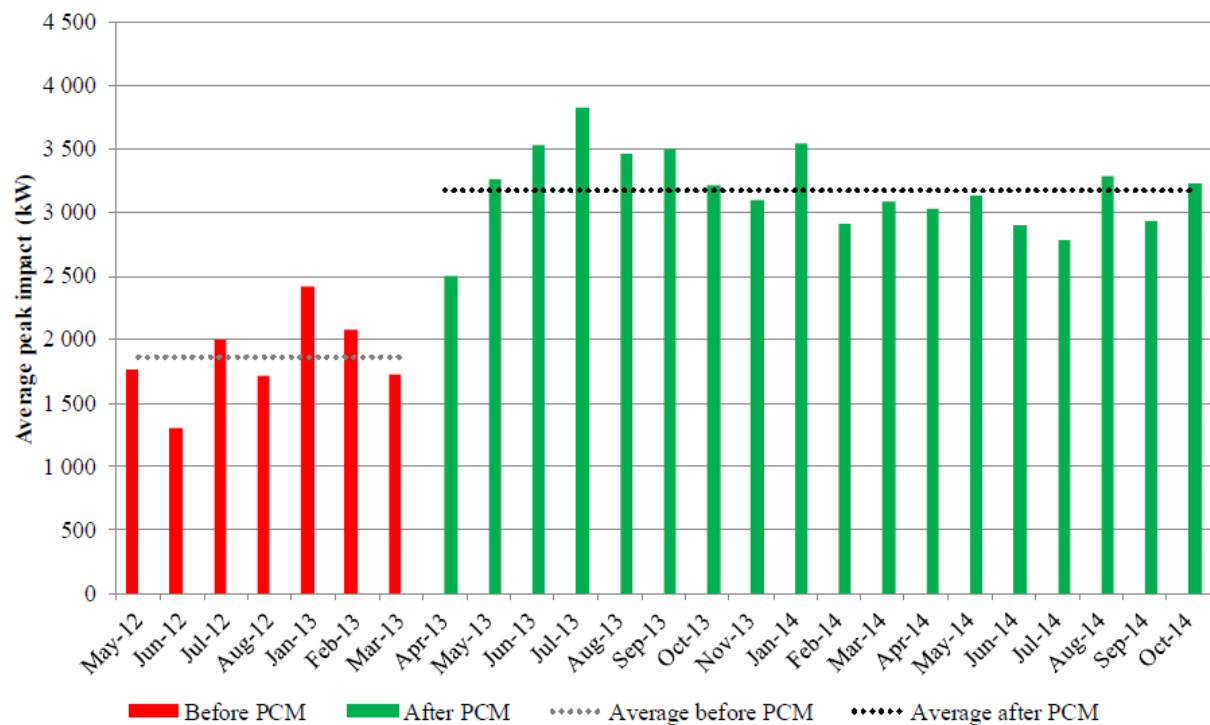


Figure 2-19: Performance comparison for an industrial energy management project before and after implementing a performance-centred management (PCM) approach

(Groenewald, 2015:123)

Groenewald (2015:143, 144) developed a performance-centred maintenance strategy for industrial energy management projects, which was tested on ten industrial energy management projects. The implementation of his strategy realised increased project savings of R37 million per annum using Eskom 2015/2016 tariffs at a yearly maintenance cost of R3.9 million.

Groenewald (2015:171) identified the following main causes for energy efficiency projects on mine compressed air systems deteriorating:

- Control room operator negligence;
- Increases in underground compressed air use;
- Disabling and sabotage of control equipment;

- Energy-saving measures are disabled since they get the blame for system pressure drops while the real cause is undersized piping and valves; and
- Failure to update control schedules in line with changes to the mining schedules.

Groenewald (2015:170) recognised the following as the dominant reasons for energy efficiency projects on mine pumping systems deteriorating:

- Control room operator negligence;
- Increased service water usage;
- Failure to update control schedules in line with changes to the mining schedules;
- Equipment breakdown;
- Incorrect valve specification resulting in cavitation;
- Water hammer due to incorrect valve operation; and
- Sabotage of control equipment.

Groenewald (2015:172) identified the following as the main causes for energy efficiency projects on mine cooling systems deteriorating:

- Control room operator negligence;
- Disabling and sabotage of control equipment; and
- Equipment breakdown.

It is clear from the research by Groenewald (2015) that Escos have proven their value by being contracted to realise energy savings through dedicated maintenance strategies of energy-saving measures at deep-level mines. The research by Groenewald (2015) did unfortunately not provide case studies of the impact of Esco involvement during medium-term production stoppages.

Groenewald (2015:146) developed a performance-centred approach to maintain Eskom-funded energy management projects. The facility owner where the energy-saving initiative was implemented was required to maintain these projects after the Esco proved that the projects delivered the promised savings. Many projects showed substantial saving deterioration if not maintained by an Esco. Eskom also realised this shortcoming after some time and changed their funding model to a new model that required the Esco to maintain the project for three years after implementation (De Canha & Pretorius, 2015 as cited by Van der Merwe et al., 2017:1).

Chapter 1 revealed that South African mining companies are active in engaging with energy-saving initiatives. More recent research by Van Staden *et al.* (2017:5) did, however, show that there is still room for improving old energy-saving measures. They investigated the performance of an Eskom-funded energy management initiative on a mine compressed air system. The project

in question was not maintained properly by the mine after the Esko handed it over. The investigation by Van Staden *et al.* (2017:5) revealed that it was possible to reinstate the project by performing maintenance on the control valves. They were also able to increase the electricity savings by optimising pressure control schedules. They realised an improvement with an annual cost-saving benefit of R8 million when using 2015/2017 Eskom tariffs.

Van Staden *et al.* (2017:4) found that project performance deteriorated due to a lack of project ownership after the project was handed over to the mine. Mine personnel did not monitor the project performance and were not aware of the cost implications due to poor maintenance. An important finding from their study was that the control set points were not updated following changes in mining schedules.

Van Staden *et al.* (2017) suggested that an energy management team be established to take ownership of the project. They recommended that the performance and benefits of the projects be communicated to all stakeholders. Van Staden *et al.* (2017:5) noted that it is important to adapt control set points based on changes to mining schedules. The name of the mining operation was not revealed by Van Staden *et al.* (2017:5). It is possible that this initiative now forms part of the energy-saving strategies that are reported in the most recent annual reports from Harmony Gold (2019), Implats (2019) or Sibanye Stillwater (2019).

The preceding discussion proves that energy management projects implemented at mining operations are prone to deteriorate after implementation if not maintained. It is evident from the studies that mining personnel do not have the time and/or skills to maintain energy-saving projects. Groenewald (2015:144) evaluated the business case for a mine to pay an Esko to maintain energy-saving initiatives. The results from his research showed that additional cost savings of R37 million per annum were achievable at a maintenance cost of only R3.9 million per annum. This proves that active Esko involvement has the potential of ensuring the sustainability of existing projects at a cost financially feasible to mining companies. The available research further showed instances of savings increasing over time, thereby making it even more feasible.

2.3.3 Summary

Electricity cost is of great concern to deep-level mining companies because it contributes significantly to overall expenses (Sibanye Stillwater, 2019:22). Deep-level mining companies caution that high electricity costs can contribute to mine closures (Harmony Gold, 2019:29). This suggests that energy management can notably reduce operating costs at deep-level mines. Some researchers believe that energy management is essential to ensure sustainable competitiveness (Trianni *et al.*, 2019:1614). Solar installations may be a feasible option at some deep-level mining

operations since these projects have estimated payback periods of close to six years (Barnard, 2020).

Lack of funding is unfortunately seen as a barrier to the implementation of energy initiatives (Finnerty *et al.*, 2018:924, 925). Escos sometimes enter into energy performance contracts to overcome this barrier (Granderson & Fernandes, 2017:15; Newsham (2019:2). The Escos are required to accept more risk by providing guaranteed savings to minimise the risk to the client.

Employees at industrial operations are not always keen to implement energy-saving interventions (Bukarica & Tomšić, 2017:970; Finnerty *et al.*, 2018:924, 925). This may be why some deep-level mining companies in South Africa outsource their energy management to Escos (Harmony Gold, 2019:136; Implats, 2019:45; Sibanye Stillwater, 2019:209). Escos typically focus their attention on systems that contribute the most to total electricity usage. This provides the best benefit-to-cost ratios for customers. The main focus areas for Escos at deep-level mines are compressed air, dewatering, cooling, and ventilation systems.

Pumping systems are also targeted for projects that move electricity usage from peak tariff periods to off-peak tariff periods. Annual electricity cost savings of R8.1 million were achieved on deep-level mine pumping systems by implementing load shifting strategies (Van der Merwe *et al.*, 2017:5). Other researchers aimed to reduce the volume of water that is supplied underground to operations. This decreases the electricity usage of the pumps that must pump the water to surface.

Annual cost savings of as much as R31.8 million were reported for mine dewatering systems by reducing water usage by changing from localised cooling systems to centralised systems (Conradie, 2018:118). Another study optimised the operation of energy recovery devices in combination with electric pumps and improved existing savings by R4.4 million per annum (Momberg, 2018:111). Annual cost savings of R31 million were identified when flow-regulating control valves were installed in the cold-water supply systems (Maré, 2017:181).

Studies on mine ventilation systems revealed that some systems have efficiencies of as low as 2% (De Villiers *et al.*, 2019:938). It is thus not a surprise that the baseload electricity usage of deep-level mine ventilation systems is approximately 80% of the peak consumption (Greyling, 2014:41). Existing initiatives realised system improvements of as much as 55% from baseline usage (Pretorius *et al.*, 2019:326). Researchers estimated additional savings potential of as much as R620 million per annum on mine compressed air systems (Zietsman, 2019:99). This suggests that there is still significant room for improvement to reduce electricity usage at deep-level mines.

Some researchers focus on holistic energy management and follow an ISO 50 001 plan-do-check-act approach. Electricity cost savings of R75 million were realised by implementing an ISO 50 001-based approach at South African deep-level mines (Bredenkamp, 2016:150). Many studies highlighted the importance of maintenance and benefits of a continuous improvement approach. Savings improvements worth R37 million per annum were realised for an energy management fee of only R9.3 million (Groenewald, 2015:143, 144).

Existing energy management research often highlights challenges to quantifying the impact of energy savings due to the dynamic nature of deep-level mines. Benefits were quantified by comparing the actual energy usage after implementation with the energy usage before implementation. Normal production periods were chosen as reference points. None of the studies evaluated project performance during prolonged shutdowns such as experienced during the Covid-19 lockdown. A critical analysis of available M&V techniques is required to identify a suitable approach for evaluating the impact of energy management during prolonged shutdown periods.

2.4 Measurement and verification of energy-saving initiatives

2.4.1 Overview

Management personnel must ensure that they maximise the benefit for their shareholders. They are accountable for expenses incurred, such as sub-contracting costs to appoint Escos. Diligent performance measurement of completed electricity cost-saving interventions can be used as proof of money well spent (or wasted). The aim of M&V of energy-saving projects is to evaluate the difference between the energy usage after project implementation and what the energy usage would have been in the absence of the project (Hamer *et al.*, 2017:131). Hamer *et al.* (2017:131) acknowledged that the quality of a baseline has a significant effect on the reported project impact. They mentioned that a concern with M&V practices is the lack of benchmarks regarding what can be considered as acceptable.

Finnerty *et al.* (2017:17) stated that performance evaluation is a key component of a global energy management system. They further noted that a baseline is one of the most important elements of an energy management system. Bredenkamp (2016:105) suggested that baselines be developed and agreed upon before any energy-saving measures are implemented. This will minimise conflict after projects are implemented. Jank (2017:529) analysed the existing guidelines for energy-efficient communities and concluded that it is important to consider the impact of interventions holistically.

Gallagher *et al.* (2019:26) stated that baseline development is typically done by developing energy models. The baseline is normalised to reflect the current operating conditions through regression analysis. The normalised baseline is sometimes referred to as an adjusted baseline that is only valid under a certain set of common operating conditions (Gallagher *et al.*, 2018:647). This may be the largest challenge faced when implementing energy-saving interventions during abnormal conditions, such as a national lockdown. It is challenging to differentiate between electricity demand reduction as a result of a completed production stoppage and savings that were realised due to active energy management. A detailed review of available research, standards protocols and guidelines is needed to identify a solution for quantifying the business case for energy management during medium-term production stoppages.

The IPMVP is published by EVO (2017:3). The protocol aims to increase the uptake of water and energy efficiency, demand management and renewable energy projects around the globe. This protocol is often used a reference point in scholarly research that relates to M&V. The IPMVP defines energy-conservation measures as *“actions or set of actions designed to improve efficiency or conserve energy or water, or manage demand”* (EVO, 2017:4). It is clear from this definition that the typical electricity improvement initiatives discussed in Section 2.3 fall under the IPMVP definition of energy-conservation measures.

The IPMVP states that the M&V costs should be small relative to the monetary savings of the impact being evaluated (EVO, 2017:7). Reported savings must focus on quantifying significant effects while less significant effects can be estimated. This is especially relevant when the cost-saving impact of medium-term production events is evaluated since these events do occur for extended periods.

The IPMVP defines **avoided energy consumption and demand** as *“Reduction in Energy Consumption, demand, or cost that occurred in the reporting period, relative to the baseline period, as adjusted for the Reporting Period Conditions. Avoided Energy Consumption is determined by adjusting the Baseline Period Energy to the Reporting Period conditions by using Routine Adjustments and Non-Routine Adjustments”* (EVO, 2017:3).

The IPMVP defines a **baseline** as *“Referring to systems, time period, energy use, or conditions that provide a reference to which later performance of an Energy Conservation Measure (ECM) or measures can be compared”*. The protocol defines an independent variable as a *“parameter that is expected to change routinely and have a measurable impact on the energy use of a system or facility”* (EVO, 2017:3). Most studies evaluated in the previous sections of this research tried to relate electricity usage to production as an independent variable.

The IPMVP states that a baseline period should represent all operating modes of the facility from maximum energy use to minimum usage (EVO, 2017:10). A baseline period must represent the operating conditions of a normal operating cycle. The protocol specifies that sufficient knowledge of the energy governing factors in the historical period must be known when baselines are selected. The baseline period must also coincide with the period immediately before the implementation of the energy-conservation measure. This may be a challenge for this study, because the production stoppages cannot be classified as part of a normal operating cycle. The best comparison of a complete production stoppage at a deep-level mine could be the end-of-year Christmas break.

Energy savings are determined by subtracting the actual post-implementation demand from the demand before the implementation of the measure (EVO, 2017:9). The protocol states that it is necessary to evaluate possible routine or non-routine adjustments and that these effects must be added or subtracted from the savings if applicable (EVO, 2017:12). A literature survey was done to evaluate possible procedures and guidelines to handle non-routine events. Limited information was found that related to the specific challenge of quantifying the impact during medium-term production stoppages. Findings from other researchers who can assist with answering this research question will be discussed in more detail in the sections that follow.

Routine adjustments are usually quantified through mathematical models that correlate energy use with independent variables (EVO, 2017:12). The protocol defines energy-saving measures as avoided energy usage or normalised savings (EVO, 2017:12). Avoided energy use is used if the impact depends on the operating conditions. This is in contrast with the term normalised savings, which refers to an impact not affected by operating conditions. An example of a non-routine event in building-related energy interventions is a change in building occupancy levels or schedules (Granderson *et al.*, 2017:196). Available information from existing research that relates to baseline adjustment approaches will be discussed in the following sections. This will be preceded by a high-level overview of the four M&V options as suggested by the IPMVP to provide background information.

2.4.2 Typical M&V strategies

The IPMVP provides four measurement options for energy-saving measures (EVO, 2017:17). The four options are retrofit isolation with key measurement, retrofit isolation with all parameter measurement, whole facility, and calibrated simulation.

Option A: Retrofit isolation: Key parameter measurement

The baseline and reported period energy are calculated by using measurements from key operating performance parameters, estimated values and routine/non-routine adjustments. Measurements from field instruments are used. This option is typically used for lighting retrofit projects that replace old equipment with more efficient equipment (EVO, 2017:18).

Option A requires careful consideration of the measurement boundary to ensure that energy flows affected by the energy-saving measure are all accounted for. This option often requires installing additional meters to measure the impact of the saving measure. Meter calibration is an important consideration for retrofit isolation approaches (EVO, 2017:22).

Option B: Retrofit isolation: All parameter measurement

Savings are calculated based on field measurements of the energy usage of the specific system in which the energy-conservation measure is implemented. Engineering computations based on the measurement of energy proxies are used occasionally with this approach. This option is typically used for operations that alter the system (EVO, 2017:25).

Option B requires careful consideration of the measurement boundary. Additional meters along with calibration are necessary at times. Most energy-conservation measures can be evaluated by Option B (EVO, 2017:22).

Option C: Whole facility

Savings are determined by evaluating the change in energy usage of the entire facility where the energy-saving measure is implemented. Routine adjustments are typically done through a simple comparison or regression analysis. This approach is typically used where a multifaceted approach to energy management is followed. Utility level measurements are often used with this approach (EVO, 2017:26). Consumption measured by utility meters is generally considered to be 100% accurate because they define the payment for energy (EVO, 2017:129).

Option C involves using utility meters, whole facility meters or sub-meters to evaluate the impact of an energy-conservation measure (EVO, 2017:26). The protocol suggests that before this option is considered, expected savings must be more than 10% if only monthly billing data is available. This option can be used if the expected savings are less than 10% and if the logging interval is more frequent than monthly readings.

Typical independent variables include production volume, operating mode, weather and occupancy (EVO, 2017:28). The protocol cautions against using less data than a 12-month cycle (EVO, 2017:29). Typical statistical indices to be used for evaluating baseline models include the coefficient of variation of the root mean squared error [CV(RMSE)], mean bias error, and t-statistic (EVO, 2017:29). A primary challenge with Option C is savings quantifications that need non-routine adjustments due to operational changes at the facility (EVO, 2017:26).

Option D: Calibrated simulation

Savings are determined by estimating the energy usage of a system using a simulation model (EVO, 2017:31). Model accuracy and calibration of the model are major challenges when this option is used.

It is clear that the IPMVP was developed to accommodate a wide range of measurement options. Detail regarding the application of complex measurement problems is unfortunately limited. A wider literature review was conducted to identify academic studies that relate to M&V of energy-saving initiatives. Gallagher *et al.* (2018:649) conducted a literature review to identify the best performing M&V model. They found that no such an ideal solution exists and that each case must be analysed based on the circumstances surrounding the energy-saving measure. This is in line with the findings from Hamer *et al.* (2017:145).

Granderson and Fernandes (2017:15) determined that there are a limited number of calibrated simulation tools available for using Option D of the IPMVP. Adjustments to baseline models for non-routine events remain a major challenge to quantify the impact of energy-saving initiatives when these events occur (Granderson & Fernandes, 2017:15).

Maré (2017:3) discovered that manual measurements are needed for detailed simulation-based approaches on most South African mines. His study revealed that 560 highly skilled man-hours were needed to complete the simulation-based study. His study verified that the calibrated simulation approach as specified by the IPMVP cannot be used for the mining or industrial sector (Maré, 2017:188). Therefore, a simulation-based M&V approach will be time-consuming and the effort of M&V may outweigh the benefit of improved accuracy. This is especially true for a scenario in which the impact of energy management must be evaluated for relatively short periods, such as medium-term production stoppages.

Some researchers mentioned that M&V is typically done through a combination of engineering calculations and short-term measurements (Ke *et al.*, 2017:497). This process can be time and labour intensive (*ibid.*). It has been shown that time delays due to M&V processes lead to missed

opportunities since anomalies are only discovered after concluding these evaluations (*ibid.*). A further concern regarding M&V is the high costs associated with some accuracy requirements (Carstens, Xia, Yadavalli & Rajan, 2017:163). This goes against the spirit of the IPMVP, which states that M&V costs should be inexpensive compared with the savings impact (EVO, 2017:7)

The South African National Accreditation System (SANAS, 2017:11) standard standard suggests that sample sizes of at least 15 data points be used to evaluate savings. This is more than the IPMVP requirement that stipulates 12 data points (EVO, 2017:29). The industry standard for whole building M&V according to Granderson *et al.* (2017:193) requires 12-month data sets before and after implementation. Granderson *et al.* (2017:193) did, however, mention that the 12-month requirement is possibly the result of historical analysis for which only monthly billing values were available. They argued that nine-month data in hourly intervals would also suffice for baseline models developed using machine learning tools (*ibid.*). It is assumed that the sample size, which the SANAS standard references, refers to the M&V of replacement initiatives such as light replacements.

M&V guidelines that apply to equipment replacement such as lightbulb and energy-efficient motor replacements are well researched. Carstens, Xia, Yadavalli and Rajan (2017:163) researched M&V procedures for lighting retrofit projects. This M&V approach typically assumes a set energy-saving per lightbulb replacement based on the expected operation of a light, typically three hours per day during summer, combined with the rated power decrease per bulb (*ibid.*). The major focus of their study was evaluating the M&V frequency for light replacement projects. It is important to note that M&V for lamp retrofit projects is much simpler than most energy efficiency projects because of the independence of covariates such as temperature (Carstens, Xia & Yadavalli, 2017:431).

Other requirements for data analysis deal with the quality of the data and models. Gallagher *et al.* (2019:27) stated that the primary measures of M&V are accuracy, completeness, conservativeness, consistency, relevance, and transparency. Normal practice requires baseline models with independent variables not deviating by more than 110% from the maximum values and not less than 90% from the minimum values (Gallagher *et al.*, 2019:34). It has been noted that independent variables are selected based on their influence on power consumption (BPA, 2018:5). These variables cannot always be identified and isolated (*ibid.*). This creates M&V challenges because it can become challenging to differentiate the effect of energy efficiency interventions from other changes in energy usage.

The validity of baseline models is evaluated by considering statistical tests. A coefficient of determination (R^2) of 0.75 or better is generally regarded as good practice if monthly billing data

is used for regression analysis. This is based on the regression of the M&V guideline by the Bonneville Power Administration (BPA, 2018:24), a subsidiary of the United States of America Department of Energy. However, the R^2 value on its own is not enough to evaluate how well a regression model represents data. A low R^2 does not necessarily imply an inaccurate model, and a high R^2 does not always imply a good fit (BPA, 2018:24).

Best practice suggests that baseline models should only be accepted for a normalised mean bias error of less than 0.5%, an R^2 of at least 0.6, and a coefficient of variation of less than 25% (Granderson *et al.*, 2017:194). Other metrics include the CV(RMSE) standard deviation (Granderson & Fernandes, 2017:12). Granderson and Fernandes (2017:13) argued that transparency and consistency regarding the M&V process is a key requirement for energy-saving impact analysis. More information regarding the quantification of typical statistical measures is provided in Appendix A.

It was mentioned that annual data in 12-month increments is standard practice for evaluating the impact of energy-saving initiatives with regression models (EVO, 2017:29; Granderson *et al.*, 2017:193). Data is available in smaller increments due to the advent of smart metering technologies. One may be tempted to build data models that use data logged in smaller increments with the hope of improved models. Autocorrelation errors may, however, arise when using high-resolution metering data with daily or smaller increments (Touzani *et al.*, 2019:220). This was found to be of concern in commercial building M&V models that use occupancy as an independent variable. Touzani *et al.* (2019:226) stated that it is standard practice to use data for more than 12 months. Touzani *et al.* (2019:226) showed that guideline 14 of the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) is not sufficient for correcting autocorrelation errors in data sets with daily or smaller increments. The study by Touzani *et al.* (2019) serves as a word of caution to avoid using data in small increments.

M&V models related to projects on buildings are prone to be inaccurate if the energy consumption of a building varies in ways that are not distinguishable from outdoor air temperature, for example, the time of the week (Gallagher *et al.*, 2018:648). Gallagher *et al.* (2018:649) found that this is often the case with industrial buildings that use complex energy systems due to the number of independent variables that are prone to vary over time. The impact of the Covid-19 lockdown is similar in the sense that it is difficult to differentiate between the electricity usage reduction due to the production stoppage on its own and the reduction due to energy management.

Researchers in M&V fields are continuously investigating methods to improve the accuracy and repeatability of saving quantification. Some of the newer studies focused on machine learning methods. Machine learning approaches are used occasionally to evaluate the performance of

energy efficiency projects in the commercial building environment (Touzani *et al.*, 2019:218). Touzani *et al.* (2019) stated that outside temperature is typically used as an independent variable when modelling expected energy consumption for commercial buildings because of the influence of ambient temperatures on their heating and ventilation systems.

Machine learning algorithms need large quantities of training data to model accurately since the data must be spread across a wide range of multiple variables to ensure sufficient training data for the model (Gallagher *et al.*, 2019:29). Gallagher *et al.* (2019:28) specifically noted that industrial facilities present unique challenges due to the large number of variables that affect consumption. Gallagher *et al.* (2018:647) regarded uncertainty analysis as a necessity when evaluating energy savings. They stated that sampling, modelling and metering are the three sources of uncertainty. Multi-variable linear regression, decision tree regression, k-nearest neighbours, artificial neural networks and support vector machines are the most commonly used machine learning algorithms for M&V applications (Gallagher *et al.*, 2018:650).

It is tempting to consider modern evaluation techniques such as machine learning to evaluate the impact of focused energy management during medium-term production stoppages. This will unfortunately not be in the spirit of the IPMVP as M&V affordability remains a key requirement. The major advantage of machine learning approaches in the building sector is the repeatability of these initiatives. It may be easier to adopt machine learning techniques that are suitable for multiple applications. The diversity of the mining industry may prove to be a major challenge with this approach.

Granderson *et al.* (2017:194) evaluated the feasibility of automated M&V modelling using machine learning for buildings. Their research showed that automated modelling can be used for about 70% of buildings, provided that non-routine events are handled manually. These non-routine events must be evaluated by people with engineering expertise who know the extent of the event (Granderson *et al.*, 2017:196). It is clear from these research findings that machine learning is better suited to repeatable analysis. Granderson *et al.* (2017:196) specifically mentioned manual intervention in the event of non-routine adjustments. This proves that machine learning may not be suitable for M&V analysis during medium-term production stoppages.

Ke *et al.* (2017:497) developed a particle swarm optimisation cloud-based M&V model that was tested on the cold storage and freezer facilities of a hypermarket. The accuracy of their model was unfortunately not verified against previously proven approaches. They cautioned that their model could only predict project impact if it had the same operating range as the pre-implementation period (Ke *et al.*, 2017:507). The impact of energy improvements can, therefore, not be determined accurately in operating bounds outside the data set used to build the models.

A particle swarm optimisation cloud-based M&V model will not be feasible for evaluating the impact of energy management during medium-term production stoppages.

Other newer M&V methods such as M&V 2.0 tools are mostly used for M&V of commercial buildings (Granderson & Fernandes, 2017:15). Granderson and Fernandes (2017:15) found that data-driven techniques are the most frequently used approaches for M&V for continuous operational analysis. Simulation-based methods, as presented by Option D, are primarily used during design phases and for retrofit analysis (*ibid.*). They also identified the need for comprehensive methods for handling non-routine adjustments (*ibid.*). The study by Granderson and Fernandes (2017:15) highlighted the use of data-driven analyses for energy improvement evaluation. They further voiced their concern regarding the need for comprehensive methods to address non-routine events, which may include events such as the forced closure of a mine.

It was observed that academically published research relating to M&V is often focused on energy-saving initiatives that are implemented in the building industry. Wang *et al.* (2018:78) developed a macro evaluation model for ranking the performance of electricity production, transport and civil buildings based on their adoption of energy efficiency improvements. The model used evaluation factors along with a weighting ratio to rank the sectors. The consumption per unit of output was used to evaluate most energy and environmental factors when assessing electricity production.

Many evaluation factors used by Wang *et al.* (2018:69) compared the energy used by vehicles with the distance travelled. They also considered other factors such as punctuality, waste gas disposal, area occupied by roads, and floor space used for buildings related to transport. Wang *et al.* (2018:70) further considered the utilisation rate of renewable energy sources as one of the factors for evaluating the energy efficiency of the civil building sector. Other factors that were considered included recycling rates, indoor air quality, heat transfer rate, and policies regarding energy efficiency. The energy efficiency of air-conditioning systems was quantified based on the refrigeration capacity compared with the actual power input.

Thus, the energy efficiency evaluation strategy developed by Wang *et al.* (2018:78) focuses on a high-level approach for the electricity generation, transport and civil building sectors. This strategy cannot be applied directly to the mining industry. The evaluation factors for the electricity generation industry provides the closest relation and relies heavily on an output versus input quantification. Periods of no or low production are not specifically addressed.

Gallagher *et al.* (2019:28) argued that baseline modelling is much more complex for industrial buildings than commercial buildings due to the influence of production and process variables that are not evident in commercial buildings. The complexity of identifying the energy impact acts as

a barrier to energy efficiency investments in the industrial space. This is of concern since the discussions in previous sections of this document highlighted the significant electricity cost-saving opportunities in deep-level mining. Improved M&V guidelines with a focus on deep-level mine systems may increase the uptake of energy-saving measures. More research that focuses on the saving quantification of energy-saving measures on deep-level gold mines is needed.

Other research regarding the modelling of deep-level mine electricity consumption was consulted. Greyling (2014:49) evaluated the long-term electricity cost planning for a mining group that owns and operates deep-level gold mines. He identified the significance of baseload electricity usage at deep-level mines. Greyling (2014:49) defined baseload electricity usage in the mining industry as *“the minimum load that is required by the mine to sustain workable environmental conditions without production”*.

Figure 2-20 compares the baseload and the variable load for the major systems in a deep-level gold mine as provided by Greyling (2014:41). It is evident that rock hoisting has a small baseload and is, therefore, highly dependent on production volumes. Greyling (2014:49) found that baseload electricity consumption for his case study mining operation represented 70.2% of the total consumption. Thus, only 29.8% of the electricity consumption was variable load. Greyling (2014:49) further determined that refrigeration, pumping, ventilation, mining and compressed air combined contributed to 87% of the total electricity consumption. These systems also presented the highest base loads. The findings regarding the most significant electricity consumers in the study by Greyling (2014:41) are in line with the findings from other researchers, which were evaluated in previous sections of this document.

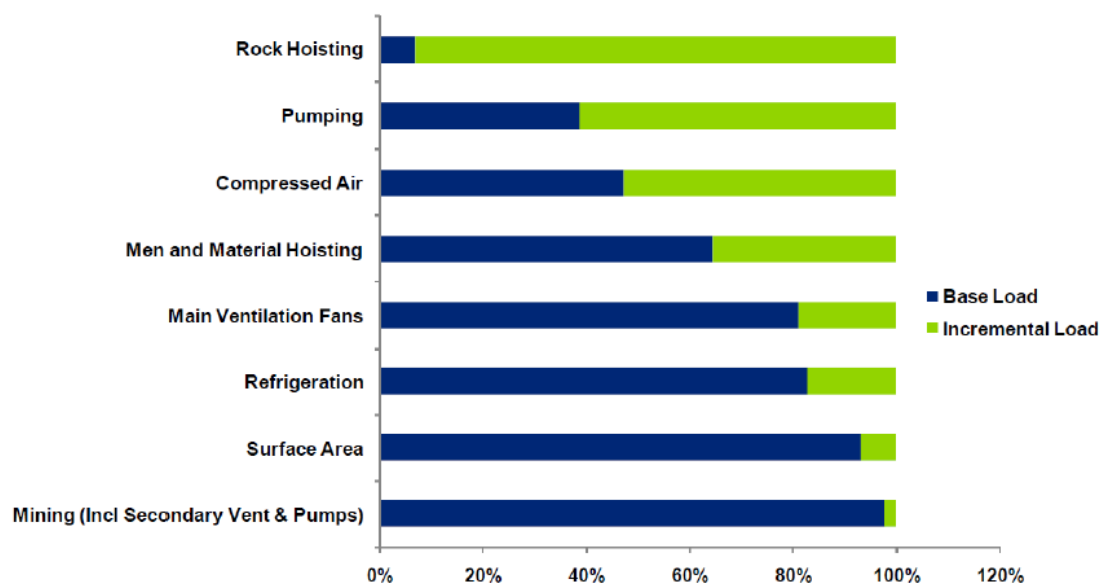


Figure 2-20: Deep-level gold mine baseload analysis

(Greyling, 2014:41)

Greyling (2014:52) found that mining depth shows the best correlation with total electricity consumption with an R^2 of only 0.42. He further established that total electricity usage correlates poorly with hoisting volumes with an R^2 of just 0.0144 (Greyling, 2014:51). He identified that a combination of hoisting volumes and mine age, which is representative of mine depth, may be the best indicators of expected electricity consumption. This finding makes sense considering the discussion of baseload operation in Section 2.2 that found that many large systems consume electricity with little regard for production.

Figure 2-21 shows the future electricity forecast for a deep-level gold mine as analysed by Greyling (2014). It is evident that if regression analysis is used, electricity consumption is forecasted to increase over time despite an expected decrease in production. The forecasted electricity usage with the Monte Carlo and the regression models does not present an observable peak when production volumes are expected to peak in 2017 and 2029. Electricity peaks are, however, predicted based on engineering calculations by the mine energy department.

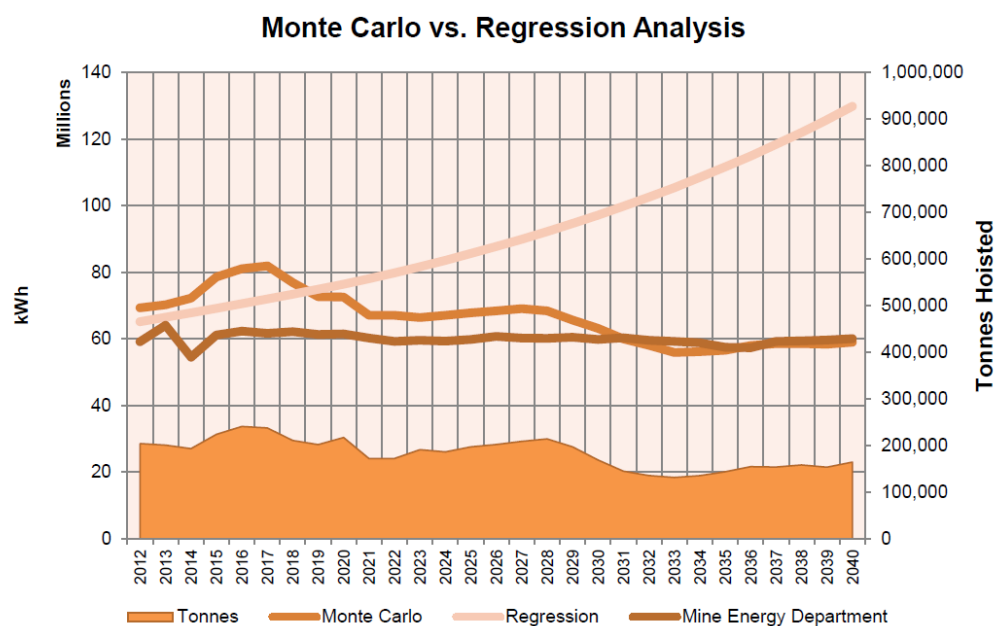


Figure 2-21: Forecasted electricity consumption for a deep-level gold mine

(Greyling, 2014:55)

Figure 2-22 compares the errors for the three methods investigated by Greyling (2014:57). Some prediction models had estimation errors of as high as 40% when evaluated at specific data points. Greyling (2014:57) reported the average errors as 20% for the Monte Carlo analysis, 13% for the regression model, and 6% for the model provided by the mine energy department. This suggests that it is preferable to use detailed calculations such as developed by the energy department at the mine rather than a Monte Carlo analysis. The regression analysis provided the second-best solution and could perhaps be used as a reality check for energy planning.

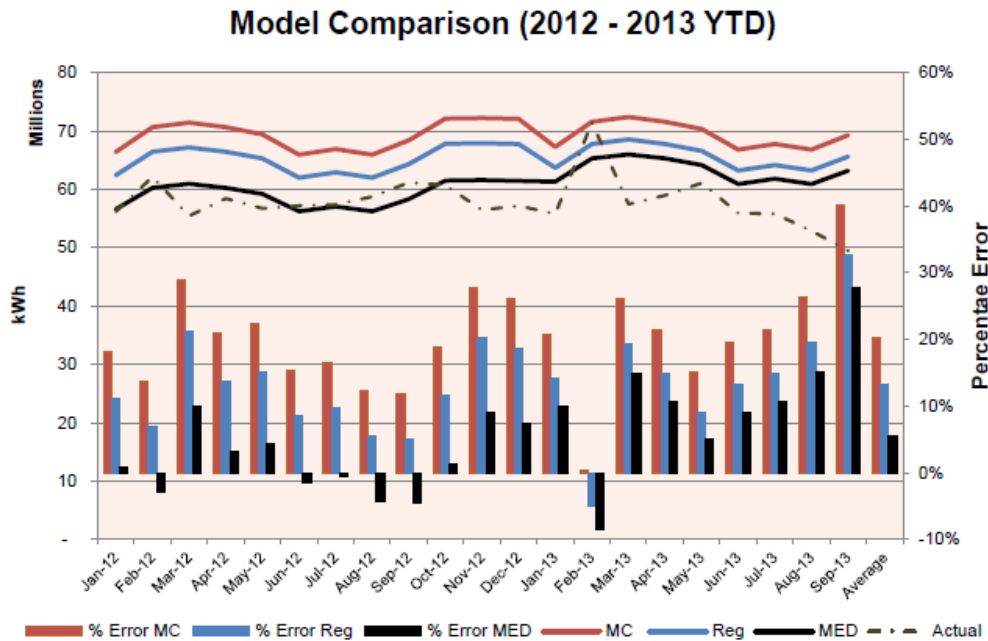


Figure 2-22: Deep-level gold mine electricity forecasting model comparison

(Greyling, 2014:57)

Greyling (2014:42) analysed the electricity intensity of a deep-level mine over time. A graphical representation of the electricity intensity over time for a deep gold mine is provided in Figure 2-23. It is clear from the graph that the intensity of a typical deep gold mine increases over time. This finding shows the extent to which deep-level mines become more inefficient over time. This finding is important for mine management since it highlights the need for continuous energy management to limit the electricity usage growth as mines get deeper and more complex.

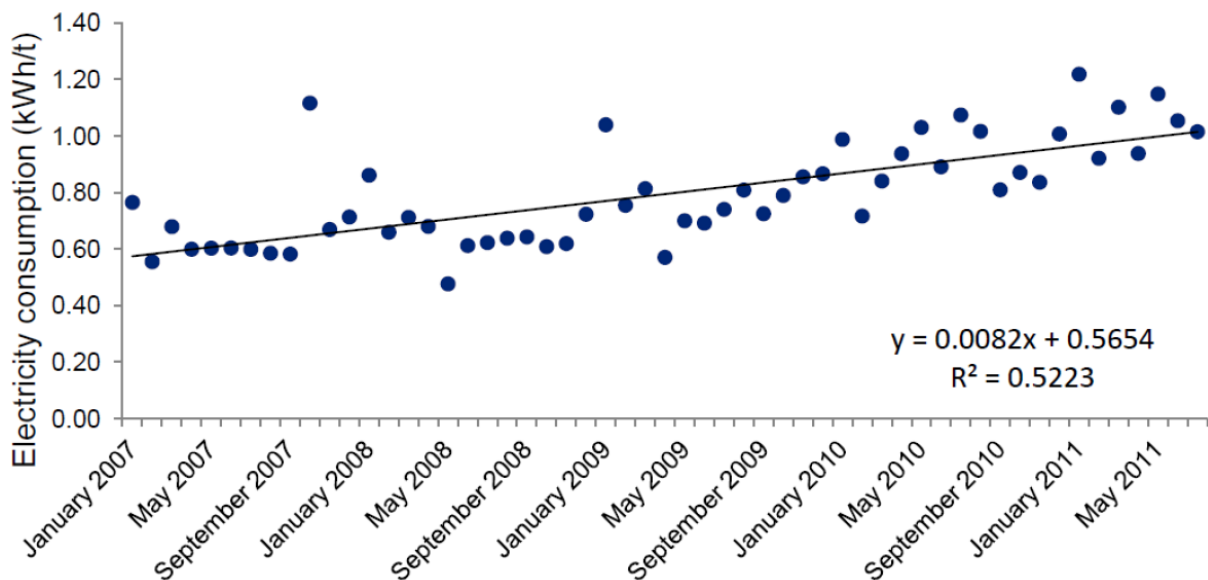


Figure 2-23: Deep-level gold mine electricity intensity

(Greyling, 2014:42)

The study by Greyling (2014:42) was aimed at mine electricity cost planning. His research highlighted a link between production and power consumption for the variable portion of electricity usage. This was also discovered by Bredenkamp (2016:126) who implemented a compressed air electricity-saving project at a deep-level mine. He used a production-based scaling approach to adjust a baseline according to production changes. Figure 2-24 provides a graphical representation of this approach. It is observed that multiple initiatives were implemented. Bredenkamp (2016:126) was able to isolate the impact of the various initiatives to show the impact of the initiatives separately.

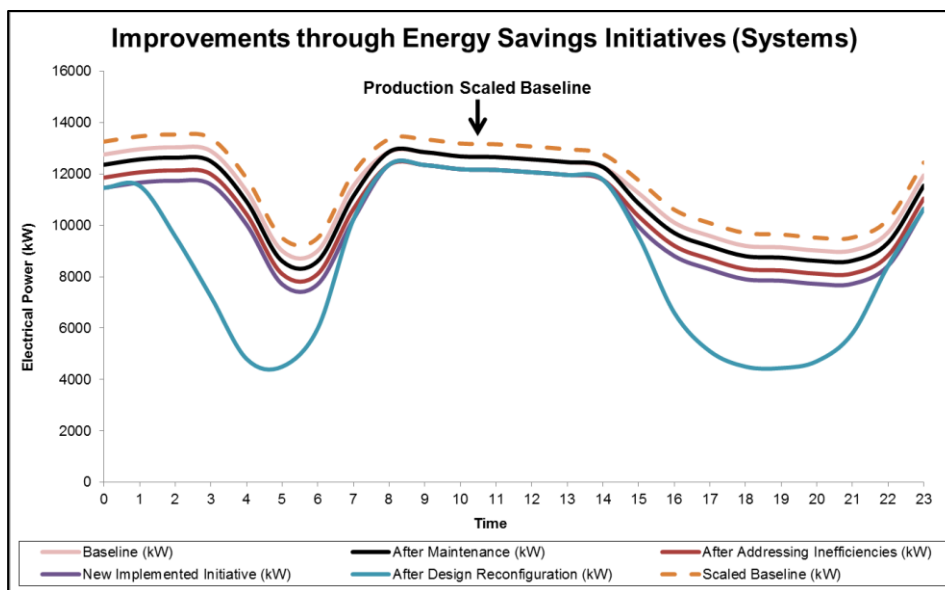


Figure 2-24: Production-based baseline adjustment

(Bredenkamp, 2016:126)

Section 2.2 mentioned that compressed air is used as an energy carrier for rock drills and loaders at deep-level mines and in refuge bays to supply respirable air as required by regulations. This complicates the electricity-saving analysis of these systems. Du Plooy *et al.* (2019:131) stated that many system efficiencies are due to neglect. Compressed air pipes are not closed when not in use, even in production areas. He observed these findings during extensive underground audits at a deep-level mine. Du Plooy *et al.* (2019:131) noted that such an audit takes three months to complete when done by four people. Thus, it is not practical for energy-saving companies to conduct detailed baseline audits for short-term production stoppages.

Regression models based on production and compressed air consumption were used by Du Plooy *et al.* (2019:130) to evaluate the impact of compressed air optimisation strategies. Du Plooy *et al.* (2019:130) argued that a linear correlation with an R^2 of more than 0.6 is indicative of a model that can be used to predict the compressed air demand if energy optimisation strategies have not been implemented. . Du Plooy *et al.* (2019:133) suggested that the impact of energy-

saving products could be calculated by comparing the actual compressed air consumption after the implementation of the strategies with the consumption values predicted by the linear regression model. This is in line with the suggested IPMVP procedures.

Figure 2-25 shows a regression analysis between compressed air and production as provided by Du Plooy *et al.* (2019:133). The data points are scattered with an R^2 of 0.36. This figure highlights a concern regarding a production-based analysis, especially if production comes to a complete halt. This confirms the findings by Du Plooy *et al.* (2019:131) that many system inefficiencies are due to mining personnel neglecting to close compressed air lines after production is stopped in a particular section. Similar problems can be expected for other equipment such as water supply and lighting.

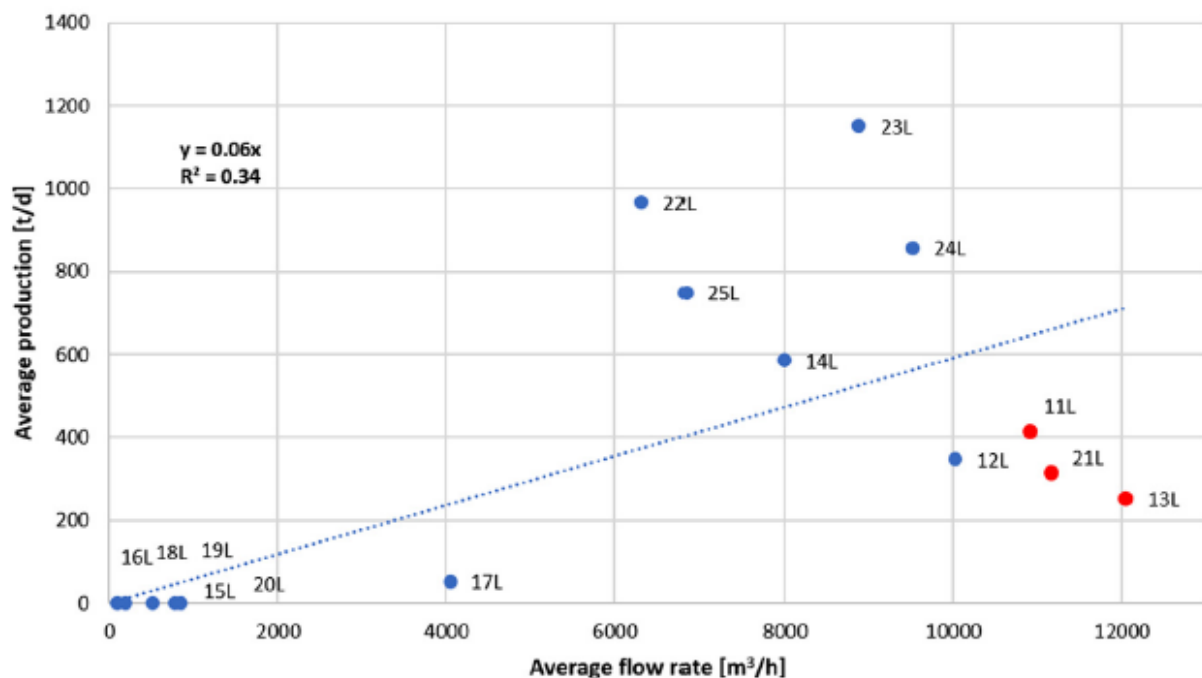


Figure 2-25: Compressed air regression analysis for a South African deep-level mine before optimisation

(Du Plooy *et al.*, 2019:133)

Du Plooy *et al.* (2019:133) repeated the regression analysis after implementing system improvements. The results are displayed in Figure 2-26. The figure shows that although the R^2 improved to 0.63 after the system improvements, the data points were still scattered widely apart. An observation from these figures suggests that an improvement in the R^2 is possible if energy-saving initiatives are implemented. An important observation from Figure 2-26 is that a production rate of zero will not necessarily result in zero usage.

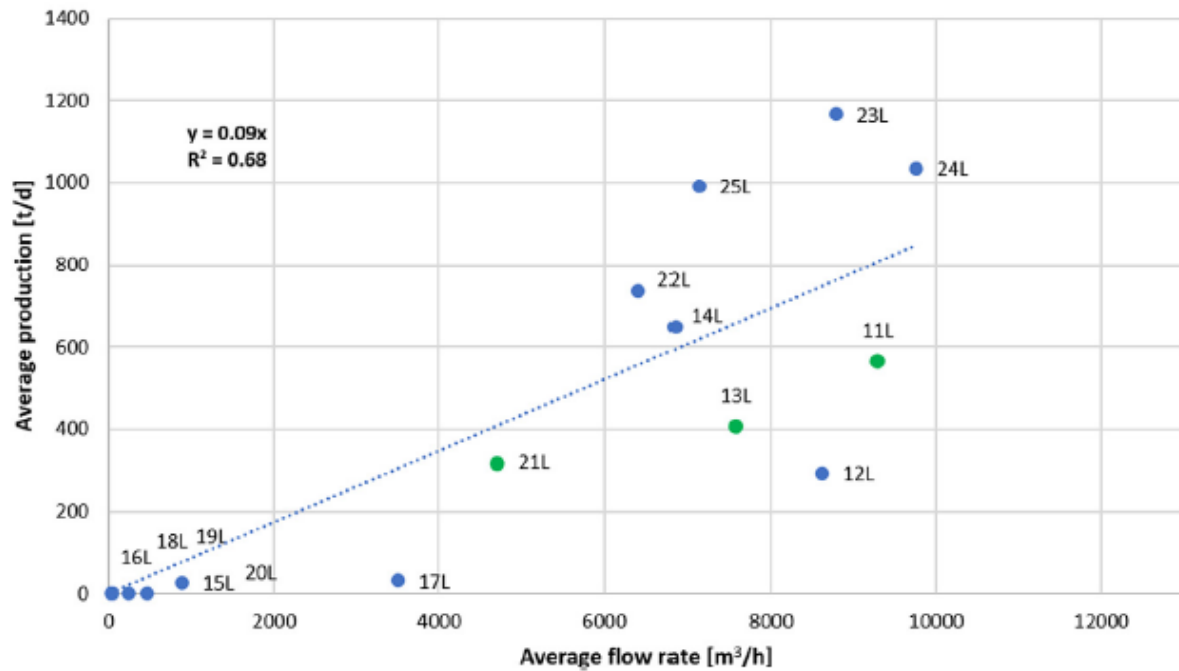


Figure 2-26: Compressed air regression analysis for a South African deep-level mine after optimisation

(Du Plooy et al., 2019:133)

Zietsman (2019:114) investigated several service level adjustment methods for evaluating the impact of energy-saving interventions on mine compressed air systems. He found that an increase in the number of active areas in the mine increased compressor electricity usage. The increase in active areas increased the total length of compressed air piping from 60.6 km to 72.8 km. This 20% increase in pipe length increased the compressor power consumption by 6% during peak production periods (Zietsman, 2019:107). The pipe lengths increased over time as the mine expanded.

Zietsman (2019:114) did a comparative analysis of various baseline adjustment methods for mine compressed air systems. The results of his study are shown in Figure 2-27. It is observed that the size of the compressed air network has a much higher impact on energy usage than production. Du Plooy (2019:12) stated that it would be time- and resource-intensive to patrol underground compressed air pipelines in deep-level mines due to the extent of these operations. Du Plooy (2019:57) mentioned that it took three auditors three months to audit the underground mining levels at a deep-level platinum mine.

The findings from Zietsman suggest that total pipe system length is a driver for compressor electricity consumption at deep-level mines. This ties in with the research from Greyling (2014:42) who found a gradual increase in electricity over time as mines expand. This suggests that a production-based regression approach for compressed air systems should consider the fixed baseload contribution carefully.

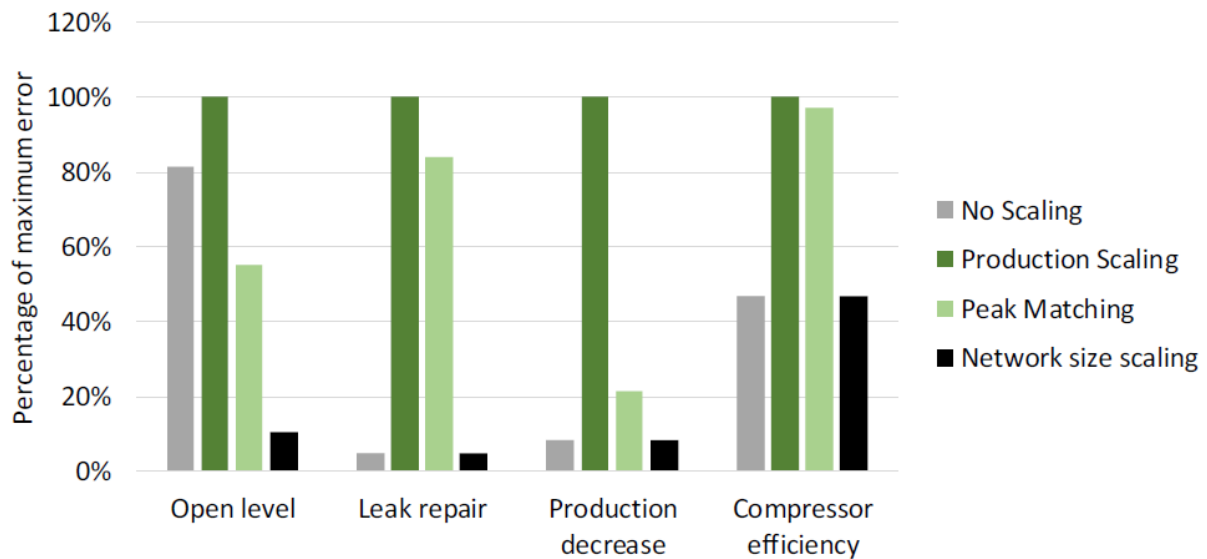


Figure 2-27: Error comparison between typical service level adjustment methods used on energy management projects on deep-level mine compressed air systems

(Zietsman, 2019:114)

2.4.3 Summary

Research suggests that performance evaluation is a key requirement for implementing energy management systems (Finnerty *et al.*, 2017:17). Baselines provide a reference point for evaluating the impact of energy-saving measures (EVO, 2017:3). The impact of an energy-saving measure is calculated by simply subtracting the actual use from the baseline usage.

Determining the correct baseline is the biggest challenge when evaluating savings. Researchers caution that M&V models can quickly become too costly and complex to implement (Carstens, Xia, Yadavalli & Rajan, 2017:163). Costly models increase M&V costs to the point at which energy efficiency projects are no longer viable if a balance between complexity and accuracy is not achieved (Ke *et al.*, 2017:497). Medium-term production stoppages are not supposed to occur frequently. The energy-saving impact during these periods is small compared with periods of the year that production is supposed to be normal and during which normal M&V calculations can be applied.

A baseline must be representative of what the savings would have been in the absence of any energy-saving measures (EVO, 2017:3). Baselines are sometimes created through a regression analysis that models energy consumption based on key energy drivers, which are also called independent variables (EVO, 2017:26). The IPMVP is a respected protocol used by many M&V practitioners and frequently referenced in scholarly articles.

IPMVP provides four measurement options for performing M&V of energy-saving measures (EVO, 2017:17). Option B can be considered for this study because the protocol states that most interventions can be evaluated with this approach. A concern regarding Option B is the protocol suggesting that calibrated metering be used. Although utility level power meters are regarded as 100% accurate (EVO, 2017:129), sub-level metering without calibration certificates cannot be treated as 100% accurate. The accuracy of sub-level metering can perhaps be evaluated by summing the values from all sub-level meters and by then comparing these summed sub-level measurements to utility level metering. The difference between these measurements can be used as a means of quantifying the accuracy of the meters.

IPMVP Option C can also be considered for this study because a holistic energy-saving approach is followed (EVO, 2017:26). The IPMVP cautions against instances in which non-routine events occur with significant operational changes. This study aimed to evaluate the impact during a prolonged shutdown such as Covid-19. This was a unique event, which is classified as a non-routine event. Various analysis techniques will be evaluated in Chapter 3 to identify a suitable solution for handling the non-routine event.

An extensive literature search was completed aimed at a quest for clear guidelines on how to handle non-routine events. A great deal of available research in the M&V field entails techniques that are used in residential and commercial buildings. Available methods related to building M&V include regression analysis (Gallagher *et al.*, 2018:651), machine learning (Gallagher *et al.*, 2018:654; Touzani *et al.*, 2019:2), simulations (EVO, 2017:17) and cloud-based swarm optimisation (Ke *et al.*, 2017). These studies cautioned against changes to the operation of the buildings that are outside the parameters used for developing the models.

A high-level approach was taken by Wang *et al.* (2018) who used evaluation factors to compare input with output to evaluate initiatives in the electricity generation, transport and buildings sectors. Their approach was tested in this mini-dissertation even though Wang *et al.* (2018) did not provide guidance on how to address low- to no-production situations.

Some researchers suggested detailed evaluation and engineering-based calculations for evaluating the impact of non-routine events (Granderson *et al.*, 2017). Engineering-based energy impact reports that were compiled and signed off at the case study will be compared with other saving analysis methods in Chapter 3. Greyling (2014) proved that regression models cannot be used to forecast mine electricity consumption without critical evaluations and engineering equations. He further confirmed that mines have very high baseloads and limited variable loads, especially on the extremely energy-intensive systems. The findings from the research by Greyling (2014) suggest that mine depth is a key driver for energy consumption. Production was not such

a significant contributor to total energy usage in the models used by Greyling (2014). This suggests that the impact of the Covid-19 event can be evaluated by using electricity usage during periods of no production, such as a December shutdown, as baseline electricity usage.

Research relating to mine compressed air systems showed R^2 s as low as 0.36 (Du Plooy *et al.*, 2019). The poor correlations were mostly attributed to the inefficiency of these systems. EVO (2017) provides a simulation-based M&V option. Du Plooy (2019) completed underground audits on underground mining areas to investigate energy efficiency improvements. It took 12 man-months to complete an audit on one shaft. Maré *et al.* (2017) used detailed calibrated simulation models to evaluate energy-intensive mining systems. They reported that it took highly skilled workers 560 hours to simulate the compressed air system at one shaft. Thus, a simulation-based approach is not a feasible solution for the mining industry due to the complexity and extent of these systems. The cost of such an M&V approach will most likely outweigh the benefit of the energy-saving initiative. This option will not be considered for this mini-dissertation because it will not be a cost-effective M&V option.

A production-based scaling approach was suggested by Bredenkamp (2016) to evaluate energy-saving projects. This approach will not be tested for a the Covid-19 production shutdown in Chapter 3. Zietsman (2019) found that compressed air consumption correlates strongly with the size of the compressed air network in terms of total pipe length. The total pipe length of a mine's compressed air system cannot be changed swiftly. The findings from his research suggest that energy usage of deep-level mine compressed air systems will be similar during non-productive periods and full production periods. The method proposed by Zietsman may not be applicable to a complete production stoppage and could perhaps overstate the savings realised.

The research relating to M&V procedures suggest several options for considering the impact of energy management during a medium-term production stoppage at a deep-level mine. The literature review revealed that production is a significant driver for electricity usage at deep-level mines. Researchers do caution that typical deep-level mine operations have high baseloads that are linked to mine age, depth and general size.

A regression analysis can be done should production be used as an independent variable. The literature review also revealed that engineering-based calculations were also suggested by a few researchers. The significant impact of baseloads suggests that power usage when production is stopped for the December break may provide a feasible baseline for a medium-term production stoppage. This will be investigated in the empirical analysis section in Chapter 3. Benchmarking will be considered as an option for evaluating a medium-term production stoppage.

2.5 Benchmarking

The challenges associated with typical M&V strategies were discussed in the preceding sections. Energy management performance is often quantified based on numerically quantifiable indicators such as kWh/m² and \$/ft². Performance metrics are typically normalised to account for site-specific differences such as building type (Finnerty *et al.*, 2017:18). These metrics are used for evaluating improvements to heating, ventilation and air-conditioning systems. Energy management studies often involve benchmarking studies (Du Plooy *et al.*, 2019:126).

Du Plooy *et al.* (2019:126) stated that benchmarking studies regularly use KPIs for comparing different operations with one another. These KPI measures include comparisons between production and energy consumption for various mining systems such as compressed air systems. Available benchmarking research will be evaluated to look for an alternative approach for determining the impact of an energy-saving project during prolonged production stoppages.

Jank (2017:529) evaluated the energy performance of buildings in Germany by using guidelines provided by the IEA. The energy performance of buildings was evaluated based on the energy consumption per square meter of floor space (Jank, 2017:534). Jank (2017:536) evaluated the impact of different energy conversion technologies on energy performance. He was able to evaluate the impact of using more energy-efficient technologies using floor space as the driver for energy consumption (Jank, 2017:536). This approach did not consider other factors such as occupancy or temperature, which is possibly due to a significant baseload electricity usage similar to what is experienced in the mining industry.

There is, therefore, a distinct possibility that most buildings as evaluated by Jank (2017:534) would only have shown a decrease in consumption during a period such as Covid-19 if it would have been possible to stop systems such as air conditioning and to switch lights off. This would, however, only have been possible if the building was used as an office. Nonetheless, support and maintenance staff would most likely still have visited the offices to perform essential maintenance. This would affect the total electricity usage in the system.

Sucic *et al.* (2016:63) developed a context-sensitive energy management approach for energy-intensive operations. They used an energy modelling approach to compare the energy performance of different shifts. Thereafter, the data was compared with factory benchmarks, which allowed managers to identify opportunities for improving energy efficiency (Sucic *et al.*, 2016:71). Nonetheless, this energy management approach will not be suitable for evaluating a medium-term production stoppage because the benchmarks are highly reliant on normal production levels.

Cai, Liu, Xie, Liu et al. (2017:345) developed a benchmarking strategy for component machining. The developed strategy benchmarked energy on a component level. A benchmarking rating system was used to develop benchmark energy consumption for the manufacturing of a specific component. They proposed that this approach be used to compare the energy consumptions of machining systems with one another. A concern is that high production volumes dilute the baseload electricity consumption of support systems. The effect of baseload usage per unit manufactured will increase drastically if low or no units are produced.

Benchmarking studies in the mechanical manufacturing industry showed energy-saving potential of as much as 21% (Cai, Liu, Xie & Zhou, 2017:370). The approach by Cai, Liu, Xie and Zhou (2017:370) entailed developing energy consumption databases to manufacture different components. They developed a multi-objective benchmark that divided energy consumption into the various stages of product manufacturing. Their evaluation strategy included the evaluation of energy usage during standby and idling (Cai, Liu, Xie & Zhou, 2017:364). They found that a small fraction of savings, compared with total usage, is possible by eliminating standby energy use in their case study (Cai, Liu, Xie & Zhou, 2017:370). This reveals that electricity savings are not always significant should standby energy usage be reduced in industrial systems.

Awuah-Offei (2016:93) defined the energy efficiency for mine loading operations as *“the ratio of production per unit time to energy input (or volume of fuel, for non-electric excavators)”*. Awuah-Offei (2016:93) stated that production per unit time for excavators depends on the specifications of the system and the operating conditions. He further noted that energy input is influenced by various operation-related factors, including the human operator. He found that a ‘poor’ operator can use up to 40% more energy than the ‘best’ operator (Awuah-Offei, 2016:93). This study proved that mine personnel have a significant impact on electricity usage, which make it difficult to find correlations between production and energy usage in mining operations.

Cilliers (2016:92) developed a benchmarking technique for comparing electrical energy usage of deep-level mines with one another. According to Cilliers, the formula for calculating the power demand for summer months is as follows:

$$E_{total_summer} = -2129.95 + 5.38(Z) + 131.6T + 49.38(f) \quad (1)$$

Where

E_{total_summer} :	Total high demand system energy requirement during summer periods	(MWh)
Z :	Depth of mine	(metre)

T :	Tonnes of ore mined	(kiloton)
f :	Fissure water flow rate	(litre/second)

Cilliers (2016:93) developed a similar formula for winter:

$$E_{total_winter} = -2353.63 + 5.31(Z) + 114.28T + 49.38(f) \quad (2)$$

Where

E_{total_winter} :	Total high demand system energy requirement during winter periods	(MWh)
Z :	Depth of mine	(metre)
T :	Tonnes of ore mined	(kiloton)
f :	Fissure water flow rate	(litre/second)

These formulas can be used to predict typical energy consumption with a standard error of 5343 MWh for summer and 5457 MWh for winter (Cilliers, 2016:92). Cilliers (2016:102) proved that his approach was not valid for periods of zero production. Therefore, he used a minimum production value of 20 000 tonnes of ore mined. The best practice formulas as determined by Cilliers are as follows:

$$E_{total_summer} = -6040.38 + 5.38(Z) + 131.6T + 49.38(f) \quad (3)$$

$$E_{total_winter} = -6512.45 + 5.31(Z) + 114.28T + 49.38(f) \quad (4)$$

An important finding from the research by Cilliers (2016:102) is the baseloads due to mine depth and fissure water volumes. This is in line with the information presented in Section 2.2. These baseload energy drivers will not vary during medium-term production stoppages since fissure water influx and mine depth do not change quickly. Thus, production will be the main variable energy driver during a medium production stoppage when the models by Cilliers (2016:102) are used.

Du Plooy *et al.* (2019:128) argued that it is necessary to conduct benchmarking for each underground level at deep-level mines and not on a shaft level. He proposed a strategy for improving the total system efficiency by focusing on optimisation strategies based on individual KPIs per underground level as well as a level's contribution to the total system load. This strategy is aimed at identifying poor performing production levels to ensure a focused leak identification

and system optimisation approach. Levels without production will, therefore, not necessarily be targeted provided that their contribution to total consumption is not high.

A section indicator was calculated by using the following formula (Du Plooy *et al.*, 2019:128):

$$Section_{indicator} = KPI \times \left(\frac{C_{factor} + P_{factor}}{2} \right) \quad (5)$$

Where

$$KPI = \frac{\text{Compressed air consumption by section}}{\text{Ore produced by section}} \quad (6)$$

$$C_{factor} = \frac{\text{Compressed air consumption by section}}{\text{Total compressed air consumption for shaft}} \quad (7)$$

$$P_{factor} = \frac{\text{Ore produced by section}}{\text{Ore produced by entire shaft}} \quad (8)$$

The compressed air flow rates are typically measured in cubic metre per hour and the ore production in tonnes. The C_{factor} and P_{factor} are used to normalise the levelised KPI value to identify the area of biggest concern. A big concern with this approach is the dependency on ore production. Results from a benchmarking case study by Du Plooy *et al.* (2019:131) are shown in Figure 2-28. It is evident that there is no clear distinction between the daily production and average compressed air flow rates. Du Plooy (2019:4) discovered that older levels that extend between 6 km and 8 km from the shaft barrel used more compressed air flow per tonne of production than newer levels that extend between 1 km and 3 km from the shaft barrel. This is further proof of a link between mine size and compressed air wastage.

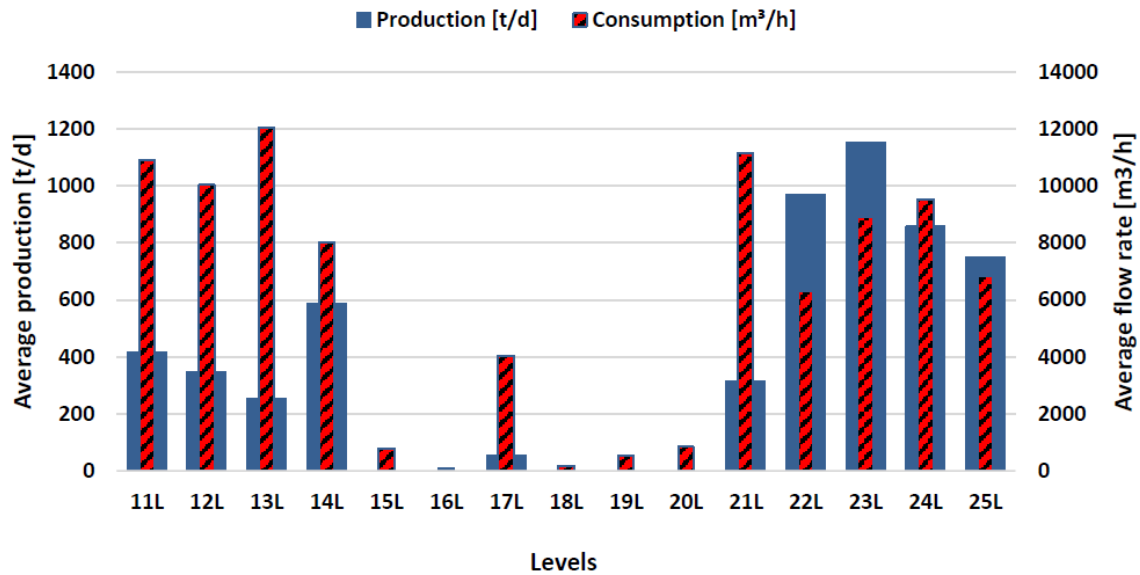


Figure 2-28: Results from a benchmarking study on a deep-level mine compressed air system

(Du Plooy *et al.*, 2019:131)

The localised benchmarking strategy by Du Plooy *et al.* (2019:131) highlighted that older levels with longer pipe lengths used more compressed air per unit of production than newer levels with shorter pipe lengths. His findings correspond with the results from Zietsman (2019:114) that demonstrated that pipe length and mine age show higher correlations with compressed air usage than production. It is clear that benchmarking studies are suited to typical production scenarios due to the impact of high baseload electricity usage. Therefore, it is concluded that benchmarking studies will not be suitable for investigating the impact of medium-term production stoppages.

2.6 Summary

South African deep-level mines are amongst some of the deepest mines in the world (Sibanye Stillwater, 2019:165). This creates several unique challenges not found at opencast mines. Deep-level mining operations are extremely energy-intensive with electricity costs as high as R3.2 billion per annum for a South African mining company (Harmony Gold, 2019:7). Electricity costs contribute to more than 20% of all operational expenses (Sibanye Stillwater, 2019:22). These high costs create significant challenges for mining companies. Some South African deep-level mining companies caution that electricity prices increase the risk of mine closure for operations with marginal profit margins (Harmony Gold, 2019:29; Sibanye Stillwater, 2019:22).

Mining complexes are typically quite complex with underground areas that span up to 100 km² (Du Plooy, 2019:5). Complex energy-intensive pumping systems are used at deep-level mines to pump large volumes of fissure water and used service water to surface to prevent flooding

(Greyling, 2014:44; Maré, 2017:129). These pumping systems contribute significantly to baseload electricity usage and operating costs. This has a significant effect on mining profitability if mines need to stop production completely. Mine pumping systems are typically targeted to realise electricity cost savings. Annual electricity cost savings in excess of R31 million have been reported for a single deep-level mining operation (Conradie, 2018:118).

Large energy-intensive cooling systems are needed to cool underground working areas since rock temperatures can be as high as 80°C (Sasmito *et al.*, 2015:1145). Integrated mine cooling systems contribute as much as 41% to a mine's total electricity consumption (Maré, 2017:4). Various energy management studies have been completed on mine cooling systems and savings of as much as R31 million per annum have been reported (Maré, 2017:181). These large cooling systems must normally be operated continuously regardless of production levels. The electricity costs of these systems have a noteworthy impact on the operating expenses of deep-level mines.

Compressed air is used as an energy source at underground mining operations to power rock drills and other ancillary systems such as loading systems (Zietsman, 2019:43). Compressed air is further used to supply fresh air to refuge bays and to supplement inadequate ventilation (Zietsman, 2019:103). The extent of system losses is linked to the sizes of these compressed air networks. Deep-level mine compressed air systems have total pipe lengths of as long as 105 km (Zietsman, 2019:113). This results in large baseload electricity demands. Peak power consumption on mine compressed air systems is estimated at close to 467 MW (Vermeulen *et al.*, 2018:124). Mine compressed air systems are regarded as hugely inefficient and a savings potential of R620 million has been identified (Zietsman, 2019:99).

Large fans with installed capacities of up to 4.1 MW per fan are used to provide ventilation and cooling to underground operations (Nel *et al.*, 2019:384). These ventilation systems contribute to approximately 12% of a mine's total electricity consumption (Nel *et al.*, 2019:384). Mine ventilation systems with efficiencies of as low as 15% have been reported (Nel *et al.*, 2019:384). These ventilation systems must be operated even when production levels are low.

The impact of the high electricity costs at deep-level mines affects a mine's bottom-line profit and ways to reduce these costs must be investigated. This may be why energy management is seen as essential to ensure sustainable competitiveness (Trianni *et al.*, 2019:1614). It has also been shown that energy-saving initiatives have the potential to mitigate rising electricity costs (McKinsey Global Institute, 2017:6). Lack of funding is a barrier to the implementation of energy efficiency improvements (Finnerty *et al.*, 2018:924, 925). Escos sometimes enter into performance agreements with clients because it bridges the funding problem and savings are guaranteed (Newsham, 2019:2). The performance of Escos that are contracted by performance

agreements is usually measured by comparing actual usage with the expected usage in the absence of energy-saving measures. The value that represents the energy usage in the absence of energy-saving initiatives is often referred to as the baseline. It is obvious that the quality of baselines has a significant effect on the savings that are reported (Hamer *et al.*, 2017:131). It is important to develop a baseline prior to implementing an energy-saving measure (Bredenkamp, 2016:105). This ensures that all parties agree to the quantification methodology beforehand to prevent conflict after the implementation of the project.

M&V research focuses on quantifying energy-saving measure during production-as-normal situations (EVO, 2017:10). Non-routine adjustments are needed if a system is operated outside normal production parameters (EVO, 2017:9). This is typically done through intensive analysis that includes engineering calculations on occasion (Ke *et al.*, 2017:497). Non-routine adjustments are regarded as a time- and labour-intensive process (Ke *et al.*, 2017:497). This may result in a situation in which Escos and their customers find it difficult to find the balance between the cost implications for accurate saving quantification and the benefit of energy management.

No clear guidelines were found in the available research on how to evaluate the impact of energy-saving interventions during medium-term production stoppages. Available research related to deep-level mining proved high baseload electricity usage linked to mine age, depth and the amount of fissure water entering the system (Greyling, 2014:49). These factors are static during medium-term production stoppages. It can thus be expected that it may be a challenging task to differentiate between energy reduction due to production stoppages and the impact of energy management initiatives during a medium-term production stoppage.

Regression analysis with production as an independent variable seems to be the most feasible option. It may be beneficial to use a whole facility approach (Option C of the IPMVP) due to the advantage of utility-grade power meters. A comparison of electricity usage during shorter production stoppages, such as during the annual December break, may be suitable and will be analysed in the empirical analysis in Chapter 3.

Benchmarking was considered as an option for evaluating the impact of energy efficiency initiatives. Typical benchmark initiatives use a quantifiable indicator such as kWh/m² to evaluate system performance (Finnerty *et al.*, 2017:18). The impact of mine depth and fissure water volumes makes it difficult to use a benchmarking methodology. Localised compressed air benchmarking models were also evaluated (Du Plooy *et al.*, 2019:126). Research showed that compressed air electricity consumption is linked to system size. Benchmarking techniques are more suitable for normal production situations and will not be used to evaluate medium-term production stoppages.

CHAPTER 3: EMPIRICAL STUDY

3.1 Introduction

The literature review revealed that energy-saving initiatives in the deep-level mining environment focus on dewatering systems, cooling systems, compressed air systems, and ventilation systems. The IPMVP (EVO, 2017) and the ASHRAE 14 guideline (ASHRAE, 2014) are often used to evaluate the impact of energy-saving projects. This mini-dissertation refers to the ASHRAE 14 guideline when the notion is made of 'ASHRAE'. Research surrounding the use of the protocol or guideline cautions against using baseline models in situations that are not within normal operating conditions.

A case study was identified where an Esco implemented energy management initiatives on a South African deep-level mine during normal production periods. Mine management had to reduce operating costs during the complete mining production shutdown period of the Covid-19 lockdown to curb the financial impact of production losses. The Esco actively assisted with measures to reduce electricity usage during this period. An understandable concern from the management of the mining company was that the effect of the shutdown had to be seen as a non-routine event. The biggest challenge with a non-routine adjustment is differentiating between the electricity reduction that occurred because production was halted and the additional reduction due to energy management.

Mine management must ensure that they minimise potential financial losses to protect their shareholders by minimising operational costs during a production shutdown. They are further required to place a hold on the contracts of all sub-contractors during such periods to limit expenses. The research in Chapter 2 proved that it is beneficial for deep-level mining companies to appoint Escos to assist with energy management. It was also observed that a suitable approach is using a performance-based contracting method.

A challenge during the Covid-19 lockdown period was that mine management were required to minimise sub-contractor spend while reducing electricity costs. The Esco decided to take a risk by continuing with dedicated energy management despite their contract being placed on hold for the lockdown period. They did this to investigate the business case for Esco involvement during medium-term production stoppages. The empirical analysis aimed to investigate whether it is worthwhile for Escos to take the risk of continuing with performance-based energy management contracts during medium-term production stoppages. The results can further be used by deep-level mining companies to evaluate their business case for dedicated energy management during medium-term production stoppages.

3.2 Research design

Operational verification serves as an initial step for reviewing the impact of energy-saving measures (EVO, 2017:15). The IPMVP suggests that visual inspection, sample spot measurements, short-term performance testing, or data trending and control logic review be used as operational verification that energy-saving measures have been implemented (EVO, 2017:16). The data collected for this case study was examined to check for data loss and other possible measurement errors. Gathered data was compared with other verified sources, such as the annual report of the mining company where the case study was implemented, to confirm that the correct data was used. This provided high-level data verification. Documentation relating to initiatives that were implemented was reviewed as operational verification that savings measures have been implemented.

The IPMVP states that a baseline period should represent all operating modes of the facility from maximum energy use to minimum usage (EVO, 2017:10). A baseline period must represent the operating conditions of a normal operating cycle. The protocol specifies that sufficient knowledge of the energy governing factors in the historical period must be known to select baselines. The baseline must further coincide with the period immediately before the implementation of the energy-conservation measure.

The mine contracted the services of an Esco from January 2019 onwards. The data from the inception of the energy management services at the case study already contains energy-saving measures implemented by the Esco. However, data from before January 2019 will be more suitable for the analysis to provide a better representation of energy usage without dedicated energy management.

The Covid-19 lockdown regulations required a hard lockdown for the largest part of April 2020. The mine started with a gradual ramp-up phase by the end of April 2020. Very limited production occurred during this period. The impact of energy management during medium-term production stoppages was evaluated by using available system data from 1 April 2020 to 30 April 2020 since it provided the best reference point for the study.

The literature review revealed that regression models are often used for estimating baseline electricity consumption. Regression models for the M&V of energy-saving projects typically model the impact of independent variables, such as production, on electricity consumption (EVO, 2017:29). Ordinary least-squares regression is regarded as the preferred approach for quantifying the impact of energy-saving projects (BPA, 2018). It was decided to use the Microsoft Excel data analysis tool because it uses the least-squares method and simplifies the analysis (Microsoft,

2020). The data analysis tool further provides descriptive statistics that are typically used to evaluate the quality of baseline models (*ibid.*).

The guidelines provided by the IPMVP committee were followed to evaluate the impact of Esco involvement at the case study mine. It is important to note that quantifying the impact of energy-saving measures is subject to errors that originate from meter inaccuracy, adjustment procedures and sampling procedures (EVO, 2018:1). The protocol further states that the rationale behind the modelling and sampling approach must be considered carefully.

Measurement errors from instruments that measure independent variables (i.e. temperature, occupancy and production) contribute more to the inaccuracy of regression models than the dependent variable, for example, electricity (Carstens *et al.*, 2018:2797). Carstens *et al.* (2018:2797) argued that these errors make it difficult to distinguish between variances in the drivers of electricity. This can make it challenging to model the impact of the independent driver on electricity usage. Carstens *et al.* (2018:2797) wrote that this problem is typically mitigated by using larger sample sizes.

The suitability of using regression models was evaluated based on the information provided by leading M&V protocols such as the IPMVP (EVO, 2017) and ASHRAE guideline 14 (ASHRAE, 2014:17). Additional information was sourced from other industry bodies such as SANAS (2017). ASHRAE (2014:17) provides helpful guidelines for evaluating model uncertainty. The IPMVP and ASHRAE formulas used for evaluating the suitability of the regression-based baseline models for this mini-dissertation are summarised in Appendix A.

One of the specific requirements from ASHRAE (2014:99) is a CV(RMSE) of less than 25% when using pre-implementation data of between 12 and 60 months. A CV(RMSE) of less than 20% is suggested for pre-implementation data of less than 12 months (*ibid.*). The CV(RMSE) requirements will be less stringent if data from more than a 12-month period is used. Regression-based models can be accepted if they have a CV(RMSE) of less than 25%.

Energy usage of complex systems is influenced by many explanatory variables (EVO, 2018:18). The IPMVP states that it is not feasible to include all independent variables in regression models (EVO, 2018:18). Zietsman (2019:114) investigated the relationship between compressor electricity consumption and the production volumes of several deep-level mines in South Africa. He found that compressor electricity consumption correlates poorly with mine production volumes. Zietsman (2019:137) showed that the baseload consumption of a deep-level mine compressed air system has a baseload leakage of as much as 82% of total consumption.

Zietsman (2019:114) found a good correlation between compressed air consumption and total compressed air network lengths for deep-level platinum mine compressed air systems. Compressed air consumption at deep-level gold mines did, however, not correlate as well with total network length. This suggests that compressed air systems at deep-level gold mines may be less efficient than at deep-level platinum mines. A contributing factor may very well be that the gold mines that formed part of the study by Zietsman were older than the platinum mines. This ties in with the findings from Greyling (2014:51) who found that mine age plays a significant role in energy consumption. An approach to use total network length as the driver for energy consumption is not relevant to this study since network length will not change during medium-term production stoppages.

Greyling (2014:72) evaluated electricity forecasting models for the deep-level gold mines based on a Monte Carlo process. He proposed the following formula:

$$y_i = \beta_0 \left(\frac{\text{Production days}}{\text{Calendar days}} \right) (\text{Seasonal adjustment}) \quad (9)$$

$$+ (\beta_1 X + (Y + BY)X) \left(\frac{\text{Production days}}{\text{Calendar days}} \right)$$

$$+ \text{New energy equipment}$$

$$- \text{Energy efficiency projects}$$

Where

y_i :	Electricity required	(kWh)
β_0 :	Baseload electricity constant	(kWh)
β_1 :	Variable portion of electricity usage	(kWh)
X :	Production	(tonne)
Y :	Future year	
BY :	Base year	
<i>Seasonal adjustment</i> :	Seasonal adjustment factor to account for variability in seasonal ambient conditions	
<i>Production days</i> :	Actual number of production days expected	
<i>Calendar days</i> :	Actual number of calendar days	

It is noteworthy from the formula by Greyling (2014:72), as shown above, that baseload electricity plays a significant role in the total electricity usage at a deep-level gold mine. Greyling (2014:72) found that electricity usage is a function of production as well as mine age. His modelling techniques were used to do forecasting for life-of-mine planning that spanned a few years into

the future. This mini-dissertation aims to evaluate the impact of medium-term production stoppages. The impact of mine age is already part of the baseload of the mine since the production stoppages only lasted for a few weeks.

The detailed literature review in Chapter 2 revealed that mine age, depth, size and production are the predominant energy drivers for electricity usage at deep-level mines. The Covid-19 lockdown during April 2020 was not long enough to have a significant impact on mine depth, age or size. This suggests that electricity usage and production values will provide the best proxy for the analysis.

This section describes how electricity and production data will be used to compile various baseline models. The baseline models will be used to estimate what the electricity usage would have been if no energy management interventions took place. The impact of energy management during the medium-term production stoppage will be determined by subtracting the actual post-implementation usage from the baseline models.

Production data will be retrieved from spreadsheets that are distributed frequently, typically daily. These values will be compared with the production figures that were published in integrated annual reports. The accuracy of these values will be considered by assuming that the data in the integrated annual report were checked and audited since this data was reported to shareholders.

Historical electricity usage and production data are available from January 2016 to date on the Esco database. The most suitable baseline training data for an electricity and production-based model could be for the periods from January 2016 to December 2018. Greyling (2014:77) found that electricity forecasting is the most accurate when forecasted monthly. Utility level invoices provide electricity usage at monthly intervals. This allows the development of regression models using monthly data. The summated annual Eskom invoice values will be compared with the electricity usage reported in the annual report of the case study mine to verify that the correct data is used.

The accuracy of electricity meters used for billing purposes is generally regarded to be 100% accurate. This approach is supported by ASHRAE (2014:30) and EVO (2018:29). The approach for evaluating the impact of an Esco during prolonged production stoppages will be evaluated based on electricity meters. The usage of non-mining consumers that falls within the utility measurement boundary at the case study is monitored and managed by a third-party metering company. The impact of increased or reduced usage of these consumers can be excluded from the analysis if the correct measurement boundary is used. Carstens *et al.* (2018:2794) argued

that lower accuracy sub-meters, which are more affordable than revenue-grade meters, can be used to provide insight into main electricity usage drivers.

Additional sub-level electricity meters are also used at the case study mine to recoup electricity costs from the different business units based on their consumption. It can perhaps be argued that these sub-level meters are also utility meters even though they are not Eskom-owned power meters. This could simplify the process of saving quantification since the measurement boundary will be much smaller. An attempt will be made to quantify the accuracy of the sub-level metering by comparing their measurements with the Eskom billing values. Various baseline models can be developed based on the measurement boundary chosen. A possible challenge may present itself if a subdivision of electricity is not possible between sub-systems where the Esco has little control, for example, hoisting systems.

The literature review revealed a few studies that attempted regression analysis on deep-level mining systems. It was evident from most studies that production-based regression models for deep-level mines often have high levels of uncertainty. It is important to balance the cost of M&V with the level of certainty required (SANAS, 2017:4). An alternative approach that does not use regression analysis can also be considered.

Electricity consumption data during the Covid-19 lockdown period can be compared with electricity usage during non-production periods such as the annual December break. Electricity and production data can be collected for an annual shutdown period before the mine contracted an Esco to provide a holistic energy management service. This option can be tested for different measurement boundaries. It may also be possible to use an evaluation similar to Option B (Retrofit isolation: All parameter measurement) of the EVO (2017:23).

It is observed that there are several options available for measuring the impact of energy savings during medium-term production stoppages. A recurring topic throughout the literature review is the challenge regarding the establishment of a baseline. Standard M&V practice is focused on energy-saving interventions that realise savings during business-as-usual conditions. The need for this study was identified from the challenge that the standard M&V procedure for energy management service at the case study did not provide clear guidelines for a prolonged complete shutdown.

Botes (2018:85) developed a methodology for addressing concerns for scenarios in which it is not straightforward to select a baseline model. The study by Botes (2018:85) was aimed at tax incentives that require rigorous M&V practices. It is important to realise that the cost and intricacy of an M&V model must be considered when deciding on a specific methodology (SANAS, 2017:4).

Campbell *et al.* (2017:26) found that up to 80% of energy-saving initiatives in the South African industrial sector do not comply with the requirements of section 12L of the Income Tax Act 58 of 1962. They determined that this is due to data and measurement management strategies that do not comply with these stringent requirements. It is not feasible to evaluate the involvement of an Esco during medium-term production stoppages based on these stringent requirements.

The idea to use more than one model to evaluate the savings as proposed by Botes (2018:85) was used for this study. The aim was, however, not to provide savings that are on par with the stringent requirements of section 12L of the South African Income Tax Act 58 of 1962. The impact of documented interventions was evaluated. The results from the regression analysis, the December break comparison, and the individual intervention-based approach were compared. Thereafter, the impact band between the minimum and maximum values was compared with the expected service fee of an Esco. The ratio between the energy-saving impact and the service indicated the financial feasibility of Esco involvement during prolonged production stoppages.

A high-level flow diagram of the research design followed is summarised in Figure 3-1. This figure shows that the historical Eskom invoice values were entered into Excel spreadsheets and compared with other available data such as the electricity reported in the annual integrated report of the mining company. Eskom invoice values were compared with electricity usage data available on the electronic database of the Esco.

Production data was retrieved from spreadsheets that are emailed frequently, typically daily. These values were compared with the production figures published in integrated annual reports. The accuracy of these values was considered by assuming that the data in the integrated annual report was checked and audited since this data was reported to shareholders.

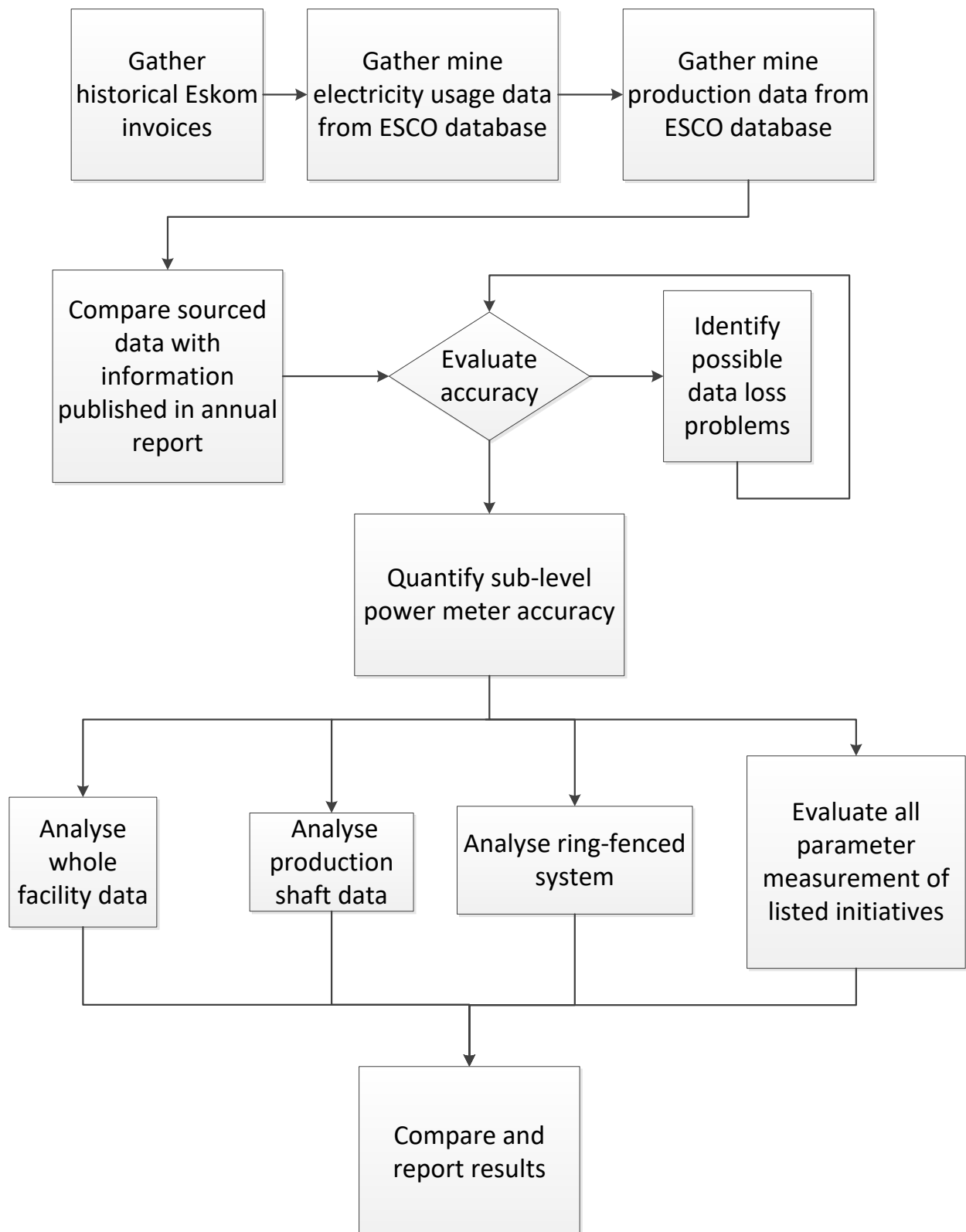


Figure 3-1: Research design process

Large deviations from reported electricity and production values were investigated in further detail to identify possible gaps in the data retrieved from the Esco database. Alternative approaches to gathering the data were investigated as and when they were discovered. Sub-level metering data was obtained from the database of the Esco and used for a more detailed analysis of a system and/or shaft level. The accuracy of these meters was evaluated by comparing the data with the Eskom invoice values and the various levels of metering.

Several evaluation options were considered once the accuracy of the meters had been identified. The impact was investigated by using four different analysis options. The first approach was to evaluate the impact on the whole facility level. Regression and a December shutdown comparison was used for this analysis. The impact of using different boundaries was investigated by considering the electricity usage on a shaft as well as a system level.

The system-level approach considered the impact on the major electricity consumers such as the compressed air, dewatering, cooling, and ventilation systems. The Esco documented specific initiatives in an attempt to minimise electricity usage during the lockdown period. These reports provided the estimated impact of the specific initiatives.

3.3 Data collection

3.3.1 Preamble

The data used in this study was gathered from the databases of an Esco that has active energy management contracts in place. Access was provided to the study with the agreement that no client information would be made available since the data is protected by confidentiality agreements. Thus, to ensure the privacy of the data, not all information will be shared in this document. Actual mine names will not be used to protect the information of the mine. Reference to specific mining groups in this document is provided based on information in annual reports that are publicly available. It does not imply that the case study was implemented at any of the mining groups that are referred to.

3.3.2 Electricity consumption

The case study mine purchases all electricity from Eskom. The Eskom invoice values were compared with the electricity consumption values published in the integrated annual report of the mining company. This ensured that the correct source documentation was used for the analysis. Eskom invoice values were available from Jan 2016 onwards. The case study mine had additional power metering for monitoring electricity distribution throughout the operation. A high-level

overview of the electricity distribution system is provided in Figure 3-2. The mining operation receives electricity from several points of delivery. Electricity is distributed to several main incomer units, also referred to as meter panels. Each incomer has a power meter that is used by the mine to monitor the electricity distribution on that level. Each meter panel supplies power to several sub-level distribution points, which are also referred to as feeders. The electricity consumption supplied to each feeder connection is also metered.

The electricity consumption on both the incomer level and feeder level was measured and stored in 30-minute intervals. Incomer and feeder level data were available on the Eskom databases from 2018 onwards. The Eskom invoice values were used to evaluate the impact using IPMVP Option C (whole facility). Incomer and feeder level meters would be more suitable for IPMVP Option B (all parameter).

The mine has a contract with a third-party metering company to manage the integrity of the metering network. The metering company is also responsible to allocate electricity usage to the different business units as well as other consumers that are supplied from the mine electricity network. The mine uses metering equipment to split the electricity consumption to lower levels. Electricity usage is also sometimes split into lower levels based on ratios that are determined from a more detailed analysis of system operation. Some of these sub-level split ratios are only updated when it is suspected that the system operation is no longer representative.

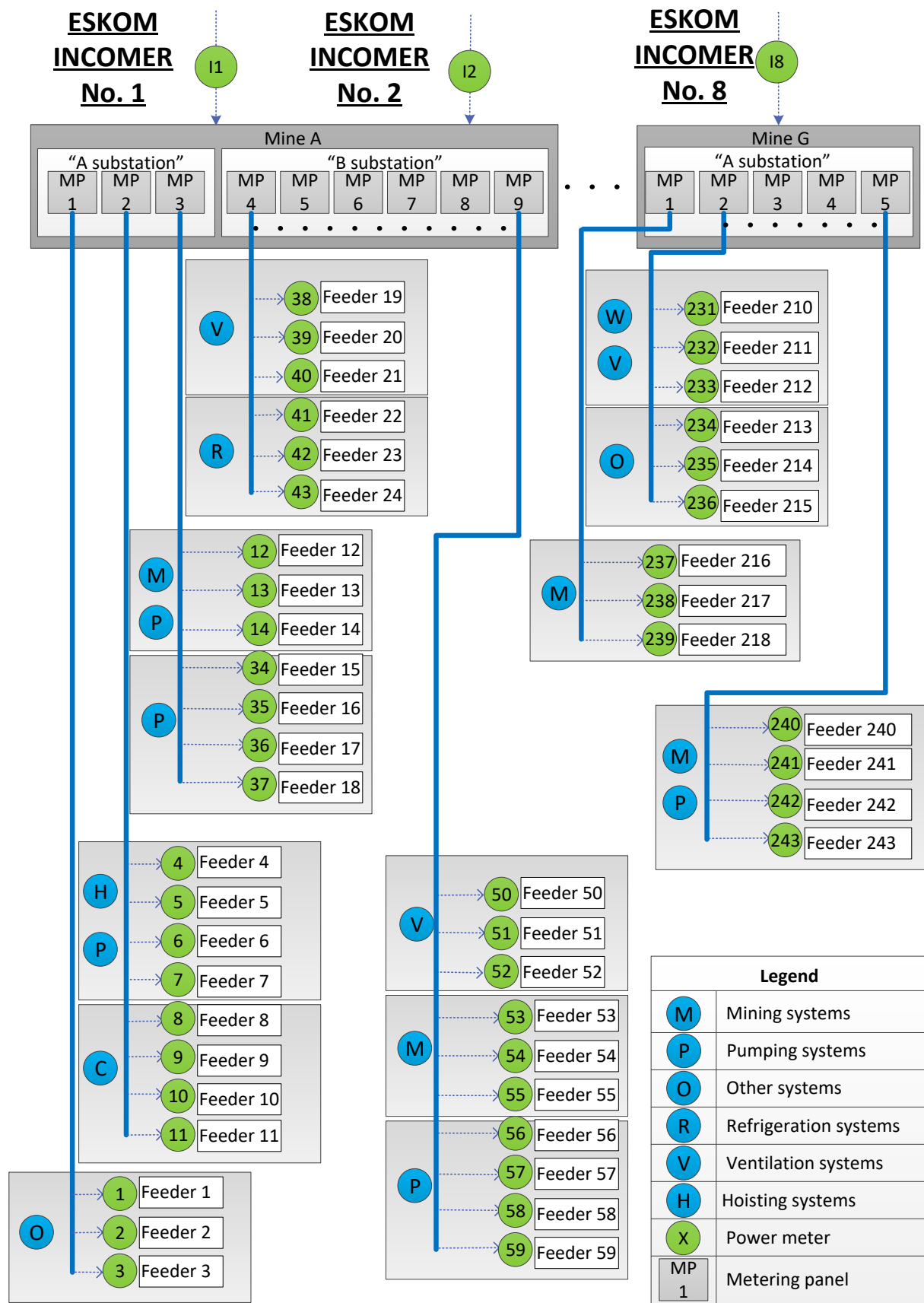


Figure 3-2: High-level electricity distribution at case study mine

Electricity consumption is grouped according to the biggest mining systems being compressors, dewatering pumps, ventilation fans, refrigeration systems, hoisting systems, processing plants, underground mining feeders, change houses, hostels, offices, and outside companies. The mining operation has measurement instrumentation in place to split energy usage for shared systems between different mining systems and per shaft. This is done by using flow measurement instrumentation to split the proportion of energy used from utilities such as compressed air and water according to actual usage. The accuracy of sub-billing using flow meters could not be confirmed and may lead to incorrect analysis. The impact quantification aimed to remain at metering levels where there were sufficient confidence that the metering equipment was suitably accurate.

3.3.3 Production data

Daily production data was gathered from reports that are distributed to mining personnel frequently, typically once a day. These reports provide production figures for the amount of reef and waste that was hoisted by each shaft per day. The annual total production values were compared with the annual integrated reports for the mining company. The integrated report provides production figures per operation per year.

It is important to note that this mine operates on a mining schedule similar to the mining schedule provided by Zietsman (2019:5) as shown in Figure 3-3. The drilling shift is known as the period when most of the energy is consumed and the largest number of people is underground. The cleaning shift is used to reclaim the blasted rock from the stopping areas to ensure that drilling can take place the following day. It is important to note that typical deep-level mines operate according to a schedule. There is a lag between the drilling shift and when the mined rock is removed from the mine.

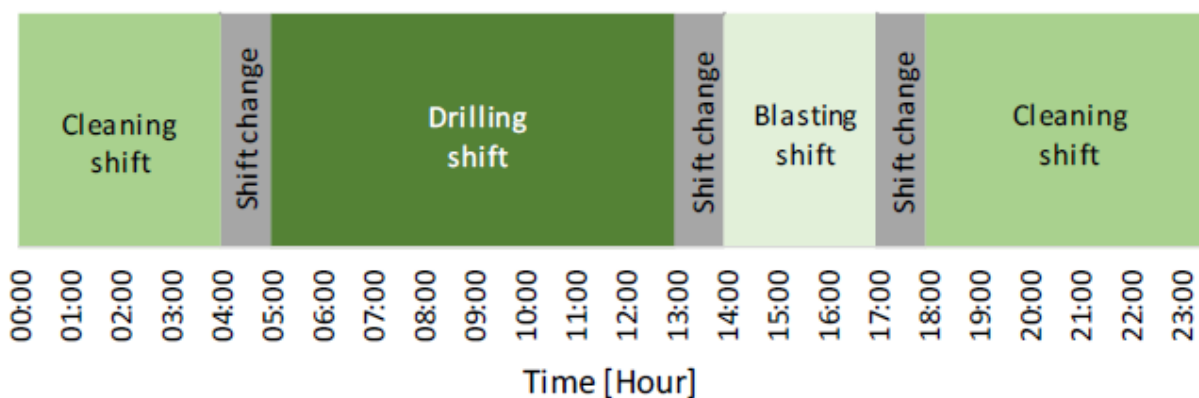


Figure 3-3: Typical deep-level mining cycle

(Zietsman, 2019:5)

It can also not be stated with certainty that all of the rock mined during a day is removed during the next cleaning shift. This is due to the large extent of a typical deep-level mine and the time that it takes to move the blasted rock to the main hoisting systems. The time delay from when the bulk of the electricity is consumed and when the blasted rock is hoisted to the surface must be considered if regression analysis is used.

3.4 Data analysis

3.4.1 Introduction

A high-level analysis of the electricity usage and daily hoisted material compared with the period just before the lockdown as a base is provided in Figure 3-4. The influence on production is prominent in the graph. A sharp decrease in electricity usage is observed from the start of the lockdown period. An increase in electricity usage is observed towards the end of April 2020 when the mine started with preparations to start production. The uncertainty regarding when production would have been permitted under the different Covid-19 alert levels is visible on 13 April 2020 when an increase in electricity usage is observed. This was the result of the start-up of some mining equipment in preparation for production. Electricity usage reduced again for a few days because of the uncertainty regarding permission to start with production.

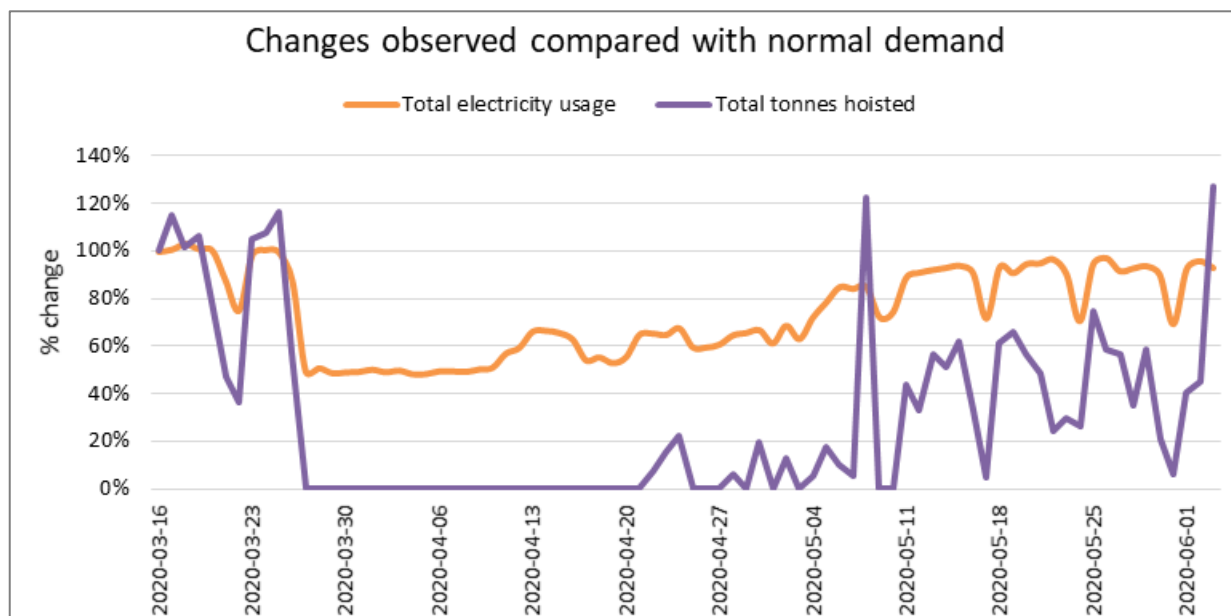


Figure 3-4: High-level analysis of electricity usage and mining production

Figure 3-4 shows a gradual start-up of mining systems from 21 April 2020. It is observed that electricity consumption stabilised at close to 100% load during May even though production levels were far from normal production. This is indicative of the large electrical baseload of this mining operation. Very low hoisting volumes were observed from 21 April 2020 while electricity demand was still at low levels. The rock hoisted during the period was probably material that was mined, but not removed before the lockdown.

EVO (2017:29) states that utility invoices can be regarded as 100% accurate. The historical Eskom invoice values were used as a starting point for investigating data reliability for electricity consumption. Daily production figures were used to calculate yearly production from underground operations at the case study. Independent variables, production in this case, with measurement errors of higher than 5% result in significant regression errors (SANAS, 2017:11). Both the production and the power consumption values were compared with the values published in the integrated annual reports to evaluate measurement accuracy.

A summary of this comparison is provided in Table 3-1. Daily production values deviated between 1% and 4% compared with the values in the annual reports. This provided confidence that a good data source was selected as a measure of production since it was lower than the 5% requirement from the SANAS (2017:11) standard. The published electricity data compared remarkably well with the values obtained from the Eskom invoices with a maximum deviation of 1% from reported values. The electricity values from the invoices were deemed as correct in line with the recommendation by EVO (2017:29).

Table 3-1: Comparison between annual report values and available data

	Underground production daily values vs published values	Electricity purchased from Eskom vs published values
2016	101%	100%
2017	97%	100%
2018	102%	101%
2019	104%	100%

3.4.2 Analysis 1: whole facility

Figure 3-5 shows a scatter plot of monthly production versus monthly energy usage for the three years before Esco involvement. A linear regression line is also fitted to the data. This model will be referred to as Analysis 1. It is observed from the graph that most data points were indicative of production higher than 140 kt/month with monthly electricity consumption of more than 100 GWh. It is observed that the second-lowest monthly production of 109 kt used more electricity than some monthly production figures above 130 kt. This is in line with the findings of the research

presented in Section 2 in which previous researchers suggested that deep-level mines have large baseload demands.

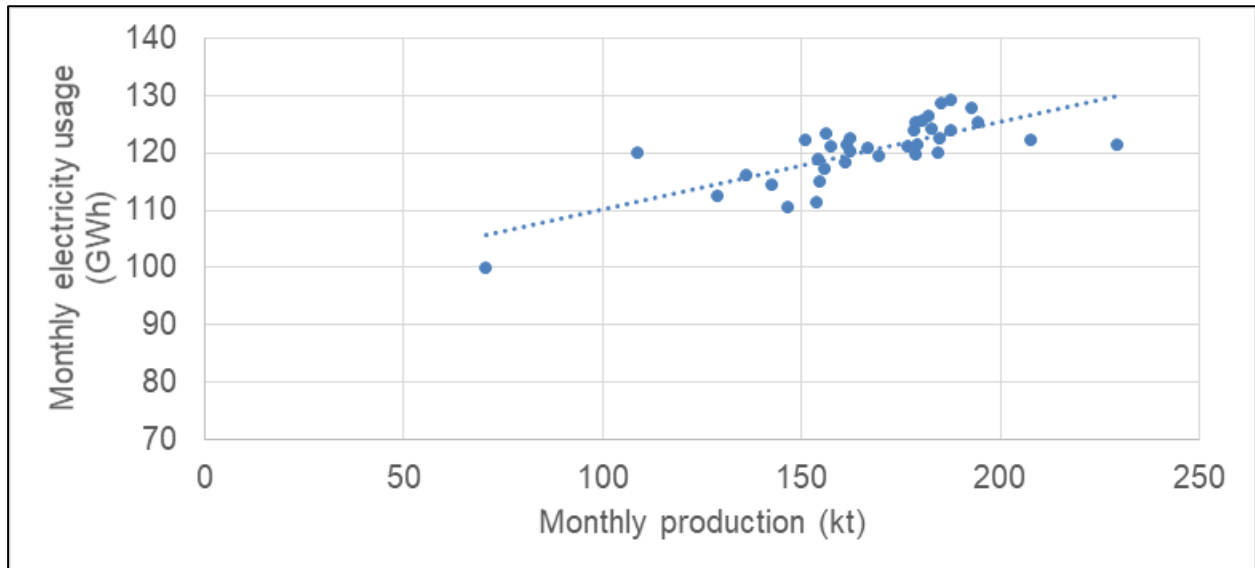


Figure 3-5: Analysis 1: Eskom level linear regression

SANAS (2017:12) suggests that outliers must not be removed if they form part of normal operating conditions. The challenge with the data presented in Figure 3-5 is that there is a clear indication of two data points that stand out. These points are indicative of the lowest production and energy consumption over the sample period. The main aim of this study was to identify the impact of Escos during such conditions. These points were therefore not removed since they provided the best indication of expected electricity consumption during low production periods. It is important to note that the data represented by this model was for the period from January 2016 to December 2018. The data from January 2019 onwards could not be used because an active energy management contract with an Esco started in January 2019. The period before 2019 is, therefore, representative of electricity usage without Esco involvement.

Some statistical parameters from the regression are summarised in Table 3-2. The model has an R^2 of 0.558. This suggests 55.8% of the variance in electricity consumption is explained by production. The IPMVP states that regression models must not be accepted or rejected purely based on the R^2 value (EVO, 2018:15). They also mention that there is no universal standard for a minimum acceptable standard. Table 3-2 indicates that the intercept and slope variable are statistically significantly different from zero with P-values of less than 0.05. This suggests that production has a notable effect on energy usage and that energy usage will not be zero if production output is zero.

Table 3-2: Summary of statistical parameters for Analysis 1

Parameter	Value
Standard error of the regression estimate (GWh)	3.84
R ²	0.558
CV(RMSE)	3%
Absolute precision at a 90% confidence level (GWh)	6.50
Relative precision of sample mean at 90% confidence level	5%
Absolute precision at an 80% confidence level (GWh)	5.02
Relative precision of sample mean at 80% confidence level	155.80
Absolute precision at a 68% confidence level (GWh)	3.88
Relative precision of sample mean at 68% confidence level	3%
P-value for the intercept	4.95×10^{-23}
P-value for independent variable	1.65×10^{-7}
Total uncertainty as per ASHRAE at 68% confidence level	5%

Carstens *et al.* (2018:2792) stated that a 90% confidence interval and a 10% precision is regarded as common practice for energy-saving M&V concerning clean development for mechanism type of projects. The aim of this mini-dissertation was not to verify savings applicable to clean development mechanism savings since the case study was only concerned with a one-month impact. The SANAS (2017:5) standard states that an 80% confidence level with a precision of 20% is regarded as acceptable for most M&V applications. ASHRAE (2014:19) specifies a maximum level of uncertainty of 50% at a confidence level of 68% (ASHRAE, 2014:19). Table 3-2 summarises the savings that were reported at the various confidence levels. It is observed that the whole facility model was within this requirement since a 5% precision was obtained at the 90% confidence level.

The ASHRAE (2014:19) standard proposes CV(RMSE) values of 25% or better when data from more than 12 months is available in a monthly format compared with a value of 20% for models with data for less than 12 months. A CV(RMSE) of 3%, as provided by this model, is well within this requirement. ASHRAE (2014:19) specifies a maximum level of uncertainty of 50% at a confidence level of 68%. This model achieved a relative uncertainty of 3% at the 68% confidence level and, therefore, exceeded this requirement. It is important to remember that the model did not have data points in a range similar to the actual April 2020 values since such a prolonged production shutdown did not occur from 2016 to April 2020.

Actual energy usage during April 2020, as measured by Eskom while the Esco assisted with energy savings, was 76 GWh. The whole facility baseline model that was developed suggests

that the actual electricity usage during April 2020 would have been 96 GWh based on historical operations.

A summary of the predicted energy-saving impact at the various confidence levels is shown in Table 3-3. The table clearly shows that it can be stated with 90% confidence that a saving of at least 14 GWh was achieved. This translated to an electricity cost benefit of R14 million for the month when the effective electricity rate of R1.04 per kWh was used. This rate was obtained by dividing the total monetary value on the Eskom invoice by the total active energy consumed by the mining operation during April 2020. This rate was used for all electricity rate calculations for April 2020.

Table 3-3: Summary of saving estimations on whole facility level

Confidence level	90%	80%	68%
Upper band baseline (GWh)	102	101	100
Predicted baseline (GWh)	96	96	96
Lower band baseline (GWh)	89	91	92
Upper band saving (GWh)	27	25	24
Predicted saving (GWh)	20	20	20
Lower band saving (GWh)	14	15	16
Lower band cost saving (R million)	14	16	17

A concern regarding the available data set is that the actual production during the Covid-19 lockdown deviated by more than 10% from the lowest reported production figure of the model. Gallagher *et al.* (2019:34) stated that it is common practice to only use baseline models if the independent variable during the reporting period is not less than 90% of the lowest data point used for developing the model. The model did not comply with these criteria. An alternative approach will be investigated in Analysis 2.

3.4.3 Analysis 2: whole facility annual shutdown

The previous section mentioned that the model input data did not have data points for stopping production for an entire month. A way around this was to work with available data when the mine stopped for a shorter period. The case study mining operation stops production from about 24 December to 1 January every year to allow workers to enjoy the festive period. Data from this period was analysed to evaluate the feasibility of using the annual shutdown period as a baseline for investigating the impact of the Esco.

Although Eskom invoices provide electricity usage for a calendar month, it only differentiates between the standard, off-peak and peak electricity usage. Electricity usage is not broken down into any smaller increments than monthly values. Production takes place for the largest part of December during normal operation. Comparing a saving analysis for an entire month of no production, as was the case in April 2020, with a typical December would not provide the correct answers.

Electricity usage data in shorter increments must be used to conduct such an analysis. The electricity consumption values as provided on invoices can be regarded as 100% accurate according to the IPMVP (EVO, 2017:29). The accuracy of sub-level electricity meters was considered by comparing the values with the invoices supplied by Eskom. A high-level comparison between the different data sources is provided in Table 3-4. It is evident from the comparison that incomer level data differed by less than 0.5% from Eskom values. Feeder level data showed a slightly higher deviation with a maximum difference of 0.77%. The small difference between these values suggested that the sub-level meters could be used to evaluate electricity usage in smaller increments than a monthly analysis.

Table 3-4: Comparison between different levels of metering

Date	Absolute difference between Eskom and incomer level	Absolute difference between Eskom and feeder level
Jan-18	0.14%	0.51%
Feb-18	0.06%	0.77%
Mar-18	0.28%	0.55%
Apr-18	0.31%	0.52%
May-18	0.33%	0.46%
Jun-18	0.26%	0.26%
Jul-18	0.11%	0.12%
Aug-18	0.18%	0.62%
Sep-18	0.31%	0.67%
Oct-18	0.45%	0.43%
Nov-18	0.19%	0.30%
Dec-18	0.05%	0.11%
Jan-19	0.17%	0.41%
Feb-19	0.25%	0.51%
Mar-19	0.35%	0.32%
Apr-19	0.37%	0.49%
May-19	0.16%	0.19%
Jun-19	0.29%	0.12%
Jul-19	0.36%	0.17%

Date	Absolute difference between Eskom and inco level	Absolute difference between Eskom and feeder level
Aug-19	0.17%	0.26%
Sep-19	0.16%	0.04%
Oct-19	0.14%	0.61%
Nov-19	0.24%	0.73%
Dec-19	0.48%	0.56%
Jan-20	0.37%	0.55%
Feb-20	0.18%	0.19%
Mar-20	0.15%	0.48%
Apr-20	0.22%	0.16%
May-20	0.09%	0.01%
Jun-20	0.10%	0.07%
Jul-20	0.09%	0.44%
Aug-20	0.06%	0.46%
Sep-20	0.02%	0.39%

The sub-level metering data provided electricity consumption in 30-minute intervals. This enabled an analysis that compared the December consumption on specific days with the usage during April 2020. Data on this level was only available from January 2018 onwards. The only available data for a December analysis before Esco involvement was thus December 2018.

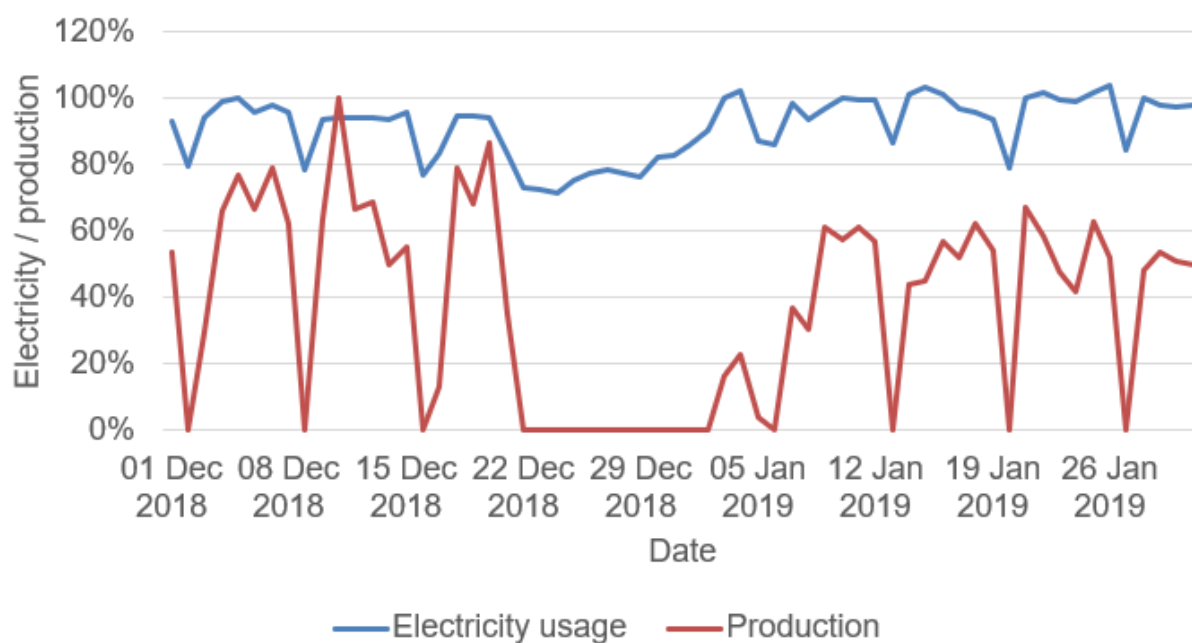


Figure 3-6 shows a graph that represents production and electricity usage as a percentage of the maximum December 2018 values. Electricity usage dropped to 71% of the maximum December usage on 24 December 2018. Production stopped on 21 December 2018 and limited production started on 3 January 2019. A ramp-up in electricity usage is noted from 29 December 2018 until

3 January 2019 when electricity consumption reached 100% of maximum December usage. Electricity consumption jumped to 102% of the maximum December value on 4 January 2019.

Figure 3-7 shows a zoomed-in view of the electricity usage and production from 18 December 2018 to 6 January 2019. A breakdown between the different electricity usage periods is highlighted on the graph. The shutdown period from 22 December 2018 to 2 January 2019 represents electricity usage when no mining took place. It is observed from the graph that most activities started from 3 January 2019 with some material already being hoisted on 3 January 2019. The average daily electricity consumption during the December 2018 shutdown period was 2.91 GWh compared with 3.47 GWh during the production start-up.

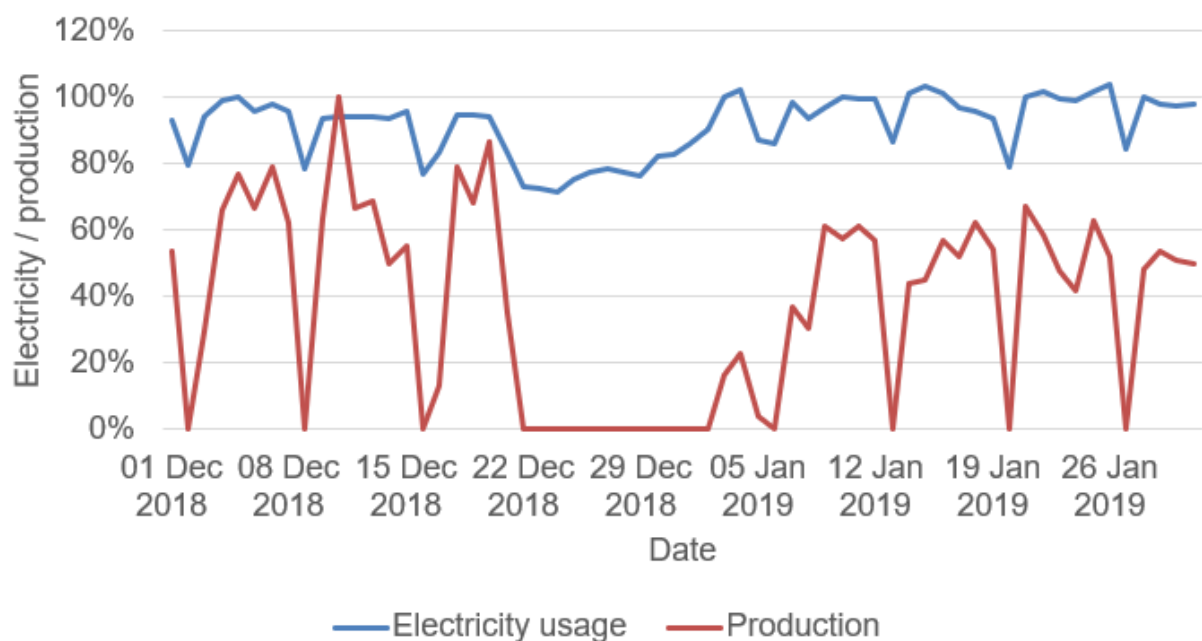


Figure 3-6: December 2018 and January 2019 electricity vs production

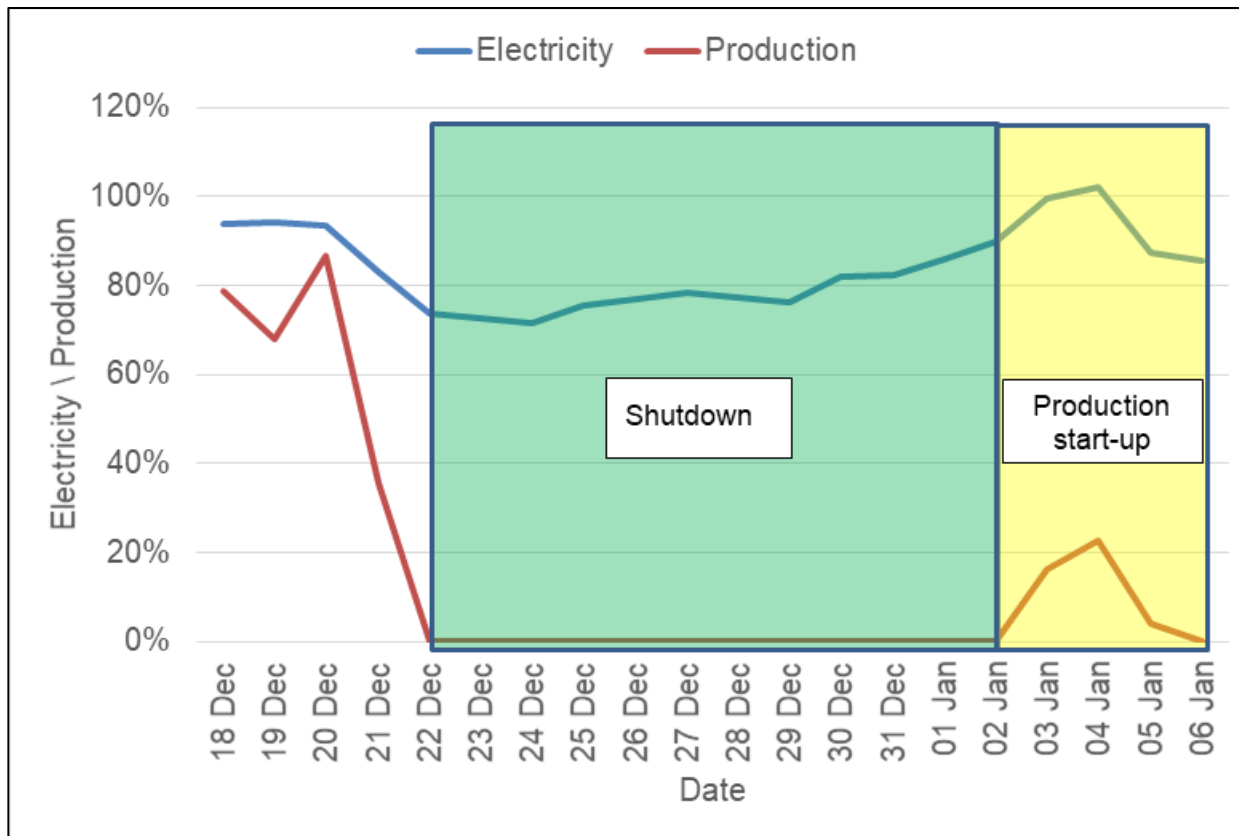


Figure 3-7: Electricity usage and production from 18 December 2018 to 6 January 2019

A similar analysis was done for the Covid-19 lockdown period, which is shown in Figure 3-8. The reference point for the percentage base in Figure 3-8 is the same base as used for Figure 3-6 and Figure 3-7. It is observed from the graph that the electricity consumption and the production figures before the Covid-19 lockdown were higher than the highest December 2018 values. Greyling (2014:42) stated that mine electricity consumption is dependent on the age of the mine due to increased size. The observed difference between the 2018 and the 2020 values may be due to the increase in mine size from 2018 to 2020 as well as increased production. Therefore, this analysis had to be conservative because the impact of the Covid-19 lockdown was based on a low base.

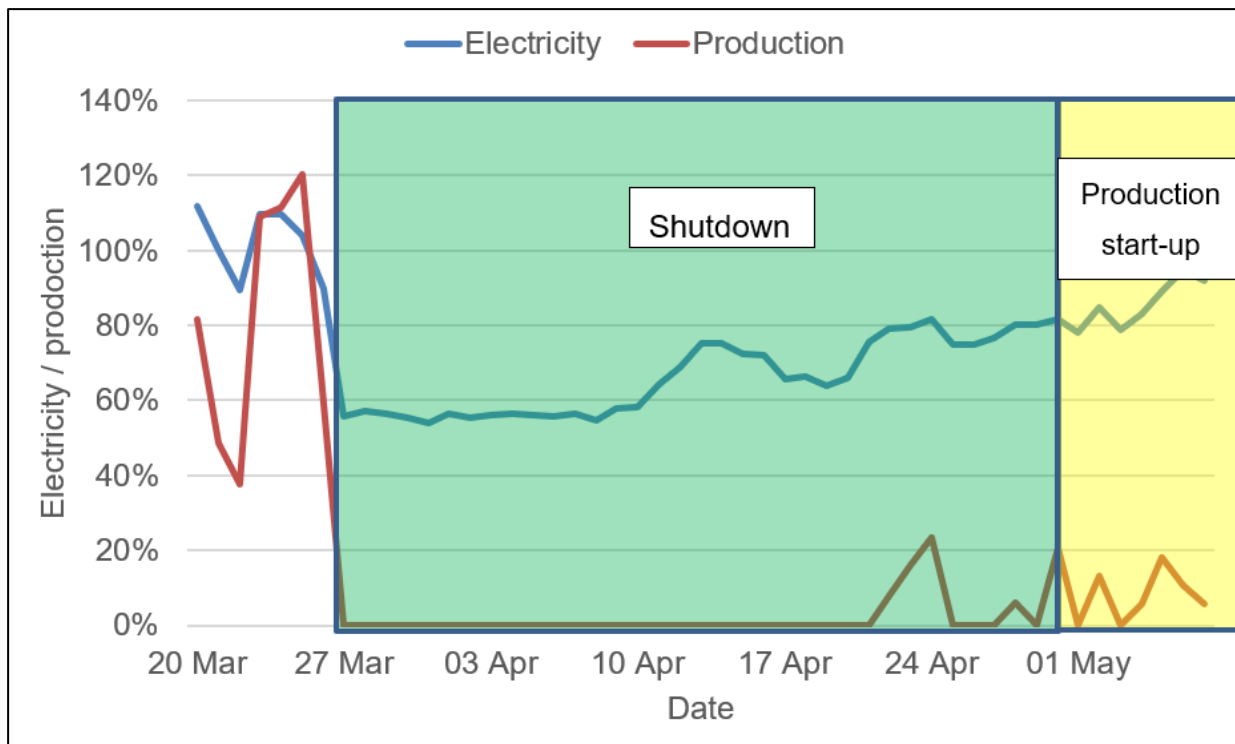


Figure 3-8: Electricity usage and production from 20 March 2020 to 7 May 2020

The electricity demand during April 2020 fluctuated between 55% and 81% of the December 2018 load. An increase in electricity usage was observed from 11 April 2020. This was due to speculation that the mining industry would be allowed to continue with mining shortly after 11 April 2020. A downwards slope in electricity usage was noted from 17 April 2020 due to confusion regarding Covid-19 regulations at that time. Mining managers were unable to get a clear direction of whether mines would be allowed to operate. A small amount of rock ore was hoisted between 22 April and 24 April 2020. Low levels of production continued until 30 April 2020. The impact of the Esco was only evaluated for April 2020 for the benefit of uniformity between the different modelling options.

The average daily electricity usage during the Covid-19 shutdown period (1–30 April 2020) was 2.52 GWh compared with the baseline usage of 2.91 GWh. A comparison between the electricity consumption during the December 2018 break and the Covid-19 lockdown during April 2020 is provided in Table 3-5. It is observed that the quantified impact, which was evaluated on a whole facility level using the annual December shutdown as a baseline, suggests a financial impact of R12.14 million during April 2020. This value is in the same range as the reported impact of R14.17 million from Analysis 1. A concern with Analysis 1 and Analysis 2 is that many external factors influenced power consumption at the mine during the Covid-19 April lockdown. It was expected that the electricity usage would reduce due to the decreased use from other consumers such as the processing plants, change houses and offices. This reduction in usage at these facilities was not due to active energy management and was excluded from the analysis.

Table 3-5: Whole facility annual shutdown analysis results

	Value	Unit
Baseline (22 December 2018 to 2 January 2019)	2.91	GWh per day
Performance period (1 to 30 April 2020)	2.52	GWh per day
Energy saving	0.39	GWh per day
No. of performance period days	30	Days
Total energy saving	11.68	GWh
Monetary impact	12.14	R million

3.4.4 Analysis 3: production shaft linear regression

The aim of the energy-saving contract at the case study mine was to realise energy saving on the production shafts. The literature review in Section 2.3.2 highlighted that most Escos focus on the dewatering, cooling, compressed air and ventilation systems of deep-level mines. The mine allocated electricity usage to the various shafts, processing plants, offices, housing and outside companies through various sub-level meters. This made it possible to ring-fence the production shafts to analyse the energy management impact where it was implemented.

It was expected that this would provide a better representation of the impact achieved by the Esco since the Esco was not involved in any initiatives to reduce usage at the other systems. The only exception is the compressed air system. The mine has two centralised compressed air networks that supply compressed air to the shafts as well as the processing plants. The processing plant was billed for compressed air consumption based on flow meter readings. Energy efficiency initiatives on the compressed air system would influence the effective rate at which the plant is billed for compressed air. The compressed air consumption at the plant was regarded as the responsibility of the Esco at the case study operation.

Figure 3-9 provides a scatter plot of monthly shaft production values plotted against monthly electricity usage. Electricity usage, in this case, represents the total usage allocated by the mining operation to production shafts as well as the compressed air supplied to the processing plants. It was mentioned previously that sub-level metering was used to split the electricity bill between different business units based on consumption. The uncertainty of this approach would be higher than the full facility analysis since there was room for error in the internal bill splitting between the shafts.

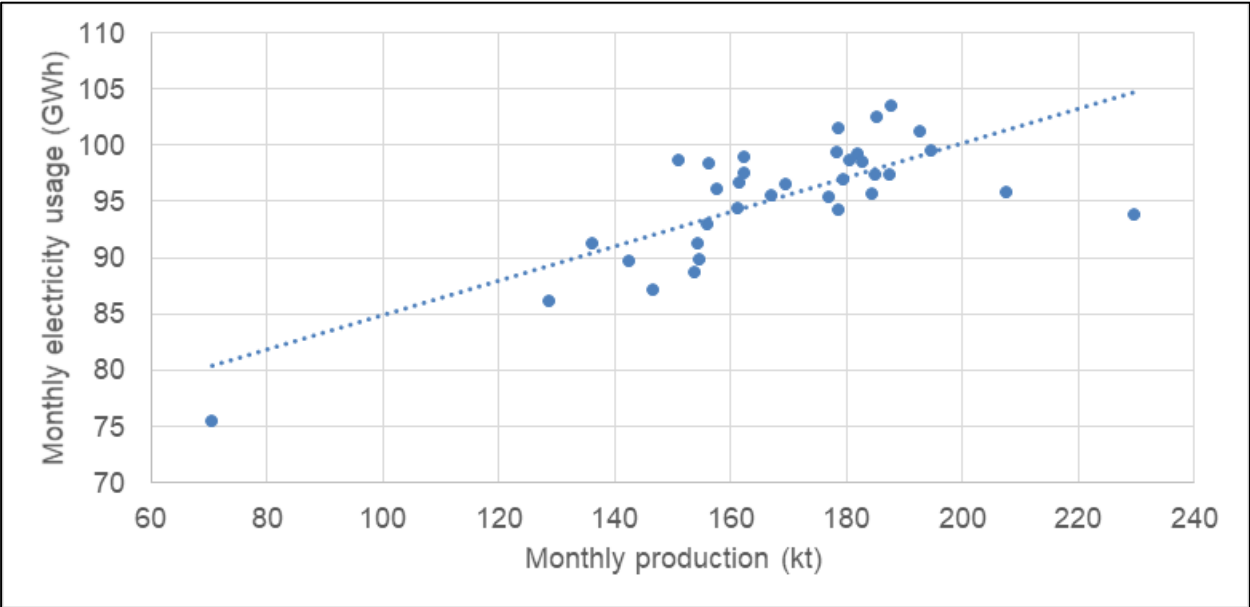


Figure 3-9: Analysis 3: Production shaft level linear regression (whole facility)

A summary of the statistical parameters is provided in

Table 3-6. The most notable change from Analysis 1 to this analysis is the deterioration of the total uncertainty calculated based on the ASHRAE (2014:19) method. This was due to the introduction of a sub-level metering error because it was no longer assumed to be 0% as with utility-grade metering. The model had an R^2 of 0.556 compared with an R^2 of 0.558 for the whole facility model. This suggested that this model explained 55.6% of the variance in the electricity consumption with production. The table further indicates that the intercept and slope variable were statistically significantly different from zero with P-values of less than 0.05. This suggests that production has a notable effect on energy usage and that energy usage will not be zero if production output is zero.

Table 3-6: Summary of statistical parameters for Analysis 3

Parameter	Value
Standard error of the regression estimate (GWh)	3.69
R ²	0.556
CV(RMSE)	3.9%
Absolute precision at a 90% confidence level (GWh)	6.24
Relative precision of sample mean at 90% confidence level	7%
Absolute precision at an 80% confidence level (GWh)	4.82
Relative precision of sample mean at 80% confidence level	5%
Absolute precision at a 68% confidence level (GWh)	3.72
Relative precision of sample mean at 68% confidence level	4%
P-value for the intercept	5.30×10^{-18}
P-value for independent variable	2.7×10^{-7}
Total uncertainty as per ASHRAE at 68% confidence level	10%

ASHRAE (2014:19) specifies a maximum level of uncertainty of 50% at a confidence level of 68%. The model was therefore still within acceptable limits based on the ASHRAE requirements. A 90% confidence interval and a 10% precision are regarded as common practice as previously discussed. The 7% relative precision of this model at the 90% confidence level was within these requirements.

This model predicted that energy consumption at the production shafts would have been 70 GWh without the intervention of dedicated energy management. This was compared with the actual energy usage of 55 GWh if measured at the same metering level. A summary of the predicted energy-saving impact at the various confidence levels is shown in Table 3-7. It is observed from the table that the most conservative impact was estimated at R9 million for the month.

Table 3-7: Summary of saving estimations on production shaft level with regression analysis

Confidence level	90%	80%	68%
Upper band baseline (GWh)	76	75	74
Predicted baseline (GWh)	70	70	70
Lower band baseline (GWh)	64	65	66
Upper band saving (GWh)	21	20	18
Predicted saving (GWh)	15	15	15
Lower band saving (GWh)	8	10	11
Lower band cost saving (R million)	9	10	11

This reported saving was lower than the value proposed by Analysis 1 and Analysis 2 due to the exclusion of the impact at the processing plant where the Esco had limited influence. The major electricity users at the processing plant are mills, which are only operated when the plant is in production. It was thus expected that the plant electricity consumption would be lower during a

complete production stoppage. It is important to remember that the model did not have data points in a range similar to the actual April 2020 values since such a prolonged production shutdown did not occur between 2016 and April 2020.

A concern regarding Analysis 1 (whole facility level) was that the independent variable, in this case, production, deviated by more than 10% from the lowest available data point. Analysis 3 had the same shortcoming. An annual shutdown evaluation on a production shaft level will be discussed in the next section to evaluate the impact of Esco involvement during the Covid-19 shutdown.

3.4.5 Analysis 4: production shaft annual shutdown

It was mentioned in the previous section and in Section 3.4.2 that the regression model input data did not have data points that showed production stopping for an entire month. A way around this was using data from the annual shutdown period as discussed in Section 3.4.3. Analysis 2, discussed in Section 3.4.3, was done on a whole facility level. Analysis 3, discussed in the previous section, used lower-level data by evaluating only the change in electricity at production shafts.

Analysis 4 was similar to Analysis 2 but only focused on the production shaft electricity usage. It included all compressed air power consumption as was done in Analysis 3. A comparison between production and the electricity consumption of the production shafts is shown in Figure 3-10. It is observed that the graph follows the same trend as a similar graph for the whole facility level in Analysis 2.

A comparison between mine production and production shaft electricity usage is shown in Figure 3-11. This graph follows a similar trend as the whole facility analysis. The reference point for the 100% production and the electricity usage were taken as the highest values in the December 2018 period. It is observed that the electricity consumption on a production shaft level was higher before the Covid-19 lockdown 2020 than 2018. This was also observed in the whole facility analysis. This is possibly due to the continued expansion of the mine. This effect was also evident in the study by Greyling (2014:42). This analysis would therefore be conservative because the impact of the Covid-19 lockdown was based on a low base.

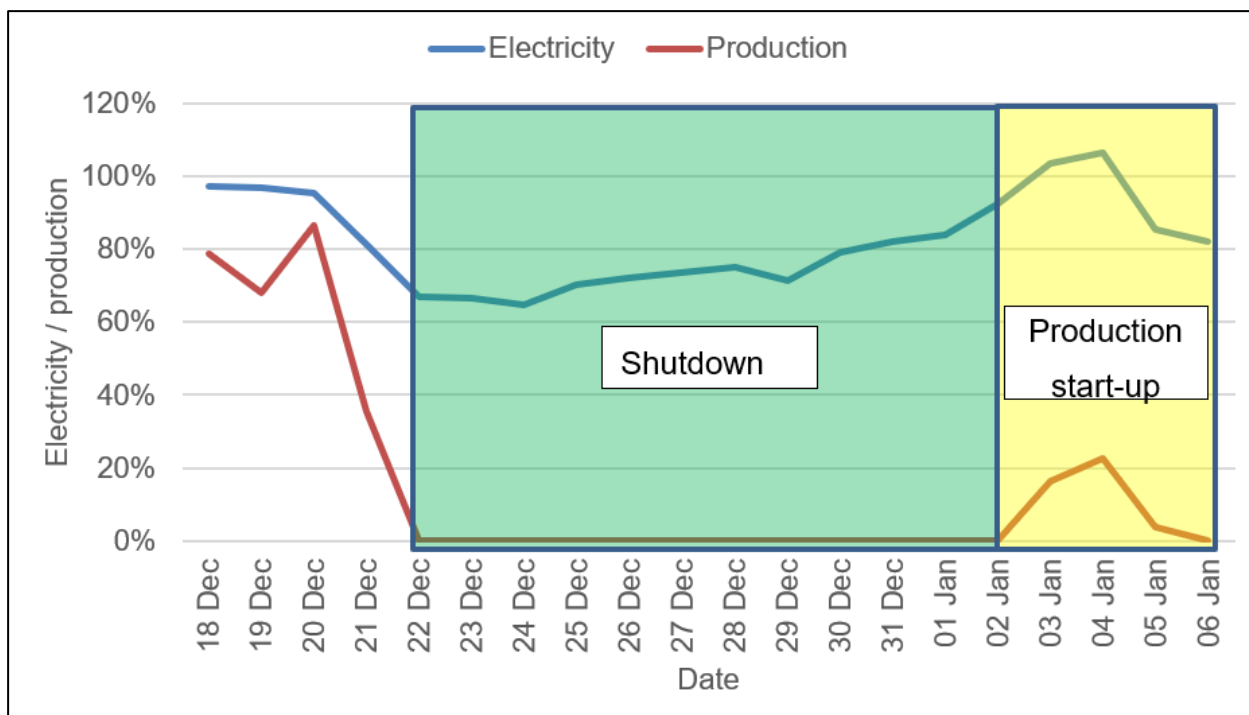


Figure 3-10: Electricity usage and production from 18 December 2018 to 6 January 2019 for production shafts

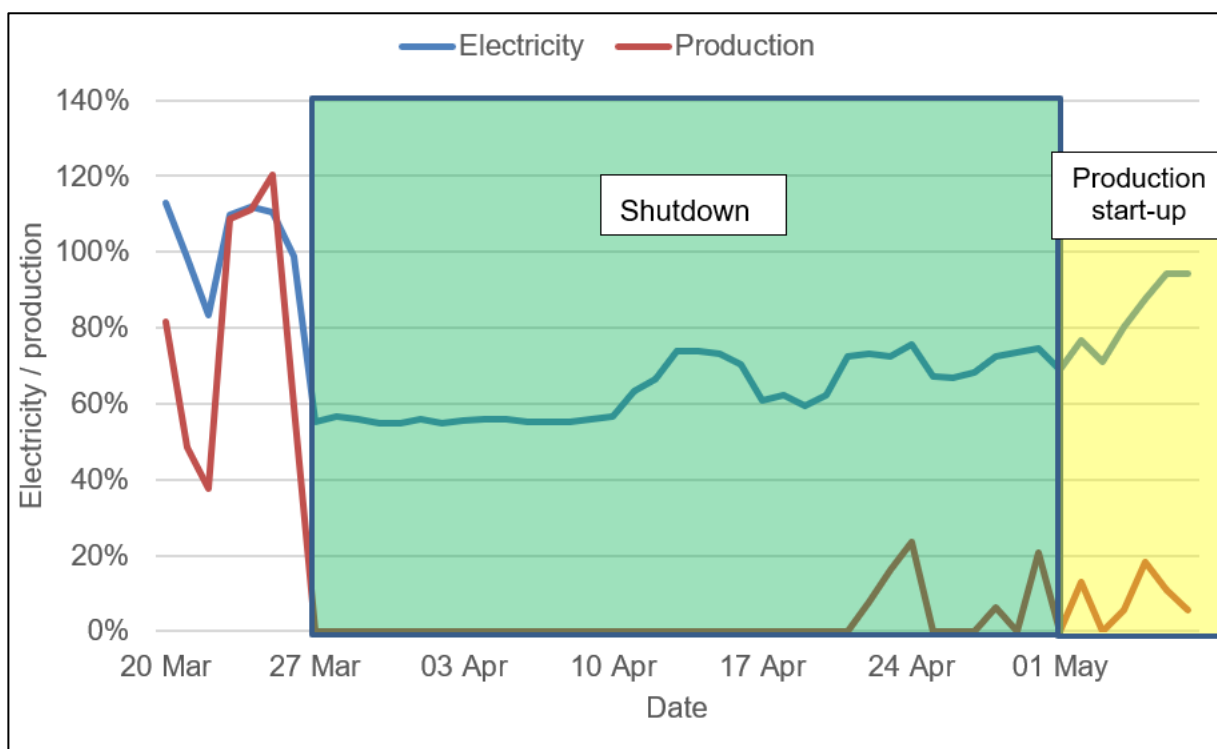


Figure 3-11: Production shaft electricity usage and production from 20 March 2020 to 7 May 2020

Table 3-8 summarises the results of the annual shutdown analysis done on a production shaft level. It is observed that the baseline and performance values were lower than the corresponding values in the whole facility analysis. This was due to the exclusion of the processing plants and other consumers not related to the production shafts. The impact was in the same order as the saving of R9 million that was evaluated through a regression analysis on the production plants.

Table 3-8: Production shaft annual shutdown analysis results

	Value	Unit
Baseline (22 December 2018 to 2 January 2019)	2.18	GWh per day
Performance period (1 to 30 April 2020)	1.88	GWh per day
Energy saving	0.30	GWh per day
No. of performance period days	30	Days
Total energy saving	8.89	GWh
Monetary impact	9.24	R million

3.4.6 Analysis 5: ring-fenced linear regression

It was identified in the literature review that Escos typically target the dewatering, cooling, compressed air and ventilation systems of deep-level mines. The energy management focus at the case study mine was also to reduce electricity usage on these systems. Internal electricity billing at the case study mine was done through multiple measurement instruments that included electricity, compressed air flow and water flow meters. Most measurements were time-stamped. Spot readings were used in the event of time-stamped readings not being available.

A major drawback to the analysis at this point is that it was not possible to check the accuracy of all metering equipment. The summation of the internal bill splitting values were compared with the Eskom invoice values. The summated internal billing values deviated by 0.7% from the Eskom billing values. Calibration certificates were not available for the flow meters used for the internal billing system. This made it impossible to identify the correct accuracy of the internally split electricity consumption.

ASHRAE (2014:72) states that typical fluid flow meters have errors that vary between 0.25% and 5%. Airflow meters have errors that vary between 2% and 5% (ASHRAE, 2014:77). An upper-value error of 5% was assumed for this study because it provided the most conservative total uncertainty for the analysis. This analysis was further aimed at rolling usage up to the highest level possible to avoid possible metering inaccuracies. The following systems were excluded from this analysis:

- Hoisting systems;

- Processing plants;
- Dedicated fissure pumping systems;
- Change houses;
- Hostels and other housing;
- Office;
- Change houses; and
- Outside companies.

A scatter plot of the ring-fenced systems is provided in Figure 3-12. A larger deviation from the linear regression line and the actual values was observed in the graph compared with the whole facility and the production shaft analysis. This suggested that linear regression would have a lower R^2 value. The lowest electricity usage for a month on this level was recorded at 71 GWh. This was much higher than the usage of 52 GWh during April 2020.

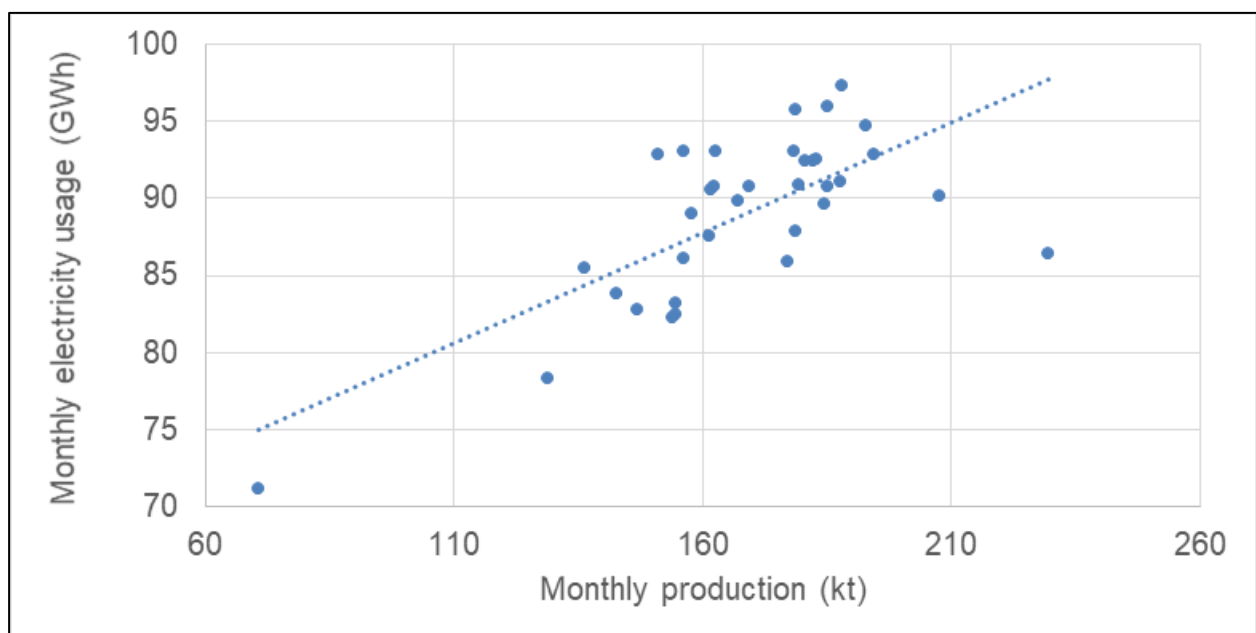


Figure 3-12: Analysis 5: Ring-fenced linear regression

A summary of the model parameters is provided in Table 3-9. The R^2 was slightly worse than for the Eskom level and production level analysis. The model had an R^2 of 0.491 compared with an R^2 of 0.558 for the whole facility model. This suggested that 49.1% of the variance in the electricity consumption was explained by production with this model. The CV(RMSE) was still significantly better than the 25% maximum value required by ASHRAE (2014:19).

The total uncertainty was well below the maximum ASHRAE requirement of 50%. Table 3-9 indicates that the intercept and slope variable were statistically significantly different from zero

with P-values of less than 0.05. This suggested that production had a notable effect on energy usage and that energy usage would not be zero if production output was zero. This suggested that the model could be used to provide an estimation of the impact. This model was within the 10% uncertainty at the 90% confidence level requirement.

Table 3-9: Summary of statistical parameters for Analysis 5

Parameter	Value
Standard error of the regression estimate (GWh)	3.90
R ²	0.491
CV(RMSE)	4.4%
Absolute precision at a 90% confidence level (GWh)	6.60
Relative precision of sample mean at 90% confidence level	7%
Absolute precision at an 80% confidence level (GWh)	5.10
Relative precision of sample mean at 80% confidence level	6%
Absolute precision at a 68% confidence level (GWh)	3.94
Relative precision of sample mean at 68% confidence level	4%
P-value for the intercept	2×10^{-16}
P-value for independent variable	2.7×10^{-6}
Total uncertainty as per ASHRAE at 68% confidence level	12%

This model predicted that energy consumption at the production shafts would have been 66 GWh without the intervention of dedicated energy management. This was compared with the actual energy usage of 52 GWh measured at the same metering level. A summary of the predicted energy-saving impact at the various confidence levels is shown in Table 3-10. It is observed that the most conservative impact was estimated at R7 million for the month.

Table 3-10: Summary of saving estimations on production shaft level

Confidence level	90%	80%	68%
Upper band baseline (GWh)	72	71	70
Predicted baseline (GWh)	66	66	66
Lower band baseline (GWh)	59	61	62
Upper band saving (GWh)	20	18	17
Predicted saving (GWh)	13	13	13
Lower band saving (GWh)	7	8	9
Lower band cost saving (R million)	7	9	10

This reported saving was substantially lower than the value proposed by Analysis 1 and more in line with the saving reported by Analysis 2. It is important to remember that the model did not have data points in a range similar to the actual April 2020 values since such a prolonged production shutdown did not occur between 2016 and April 2020.

A concern regarding Analysis 1 and Analysis 2 was that the independent variable, in this case, production, deviated by more than 10% from the lowest available data point. This analysis had the same shortcoming as the whole facility level. An annual shutdown evaluation on a production shaft level will be discussed in the next section to evaluate the impact of Esco involvement during the Covid-19 shutdown.

3.4.7 Analysis 6: ring-fenced annual shutdown

The major drawback to the regression analysis is that monthly data was not available for production being as low as in April 2020. A regression model with daily values would also not be suited since production volumes were reported when hoisting ore. The ore was not necessarily hoisted on the same day as when the bulk of the electricity was used to mine the rock. Furthermore, there was not a very strong correlation between production and electricity consumption monthly due to the large baseload electricity usage.

Analysis 2 and Analysis 4 compared consumption with the lowest values before procuring the services of an Esco. The lowest values in the available database were for the December 2018 Christmas break. Analysis 2 was done on an Eskom level. All electricity consumers including all shaft power, processing plants, housing, offices and outside companies were included.

Analysis 4 focused on electricity usage at all production shafts, but processing plants, housing, offices, fissure pumping systems and outside companies were excluded. Analysis 4 only considered the electric systems where the Esco had active energy-saving initiatives in place. Similar to Analysis 5, it excluded the hoisting systems, change houses, processing plants, housing, offices and outside companies.

Figure 3-13 compares the electricity consumption and production during the annual Christmas break. It is observed that the electricity usage and production profiles followed a similar trend than the whole facility and production shaft analyses. The electricity consumption of the ring-fenced system during the April 2020 lockdown period is shown in Figure 3-14. The trends were similar to the trends observed on the Eskom level and when production shafts were considered.

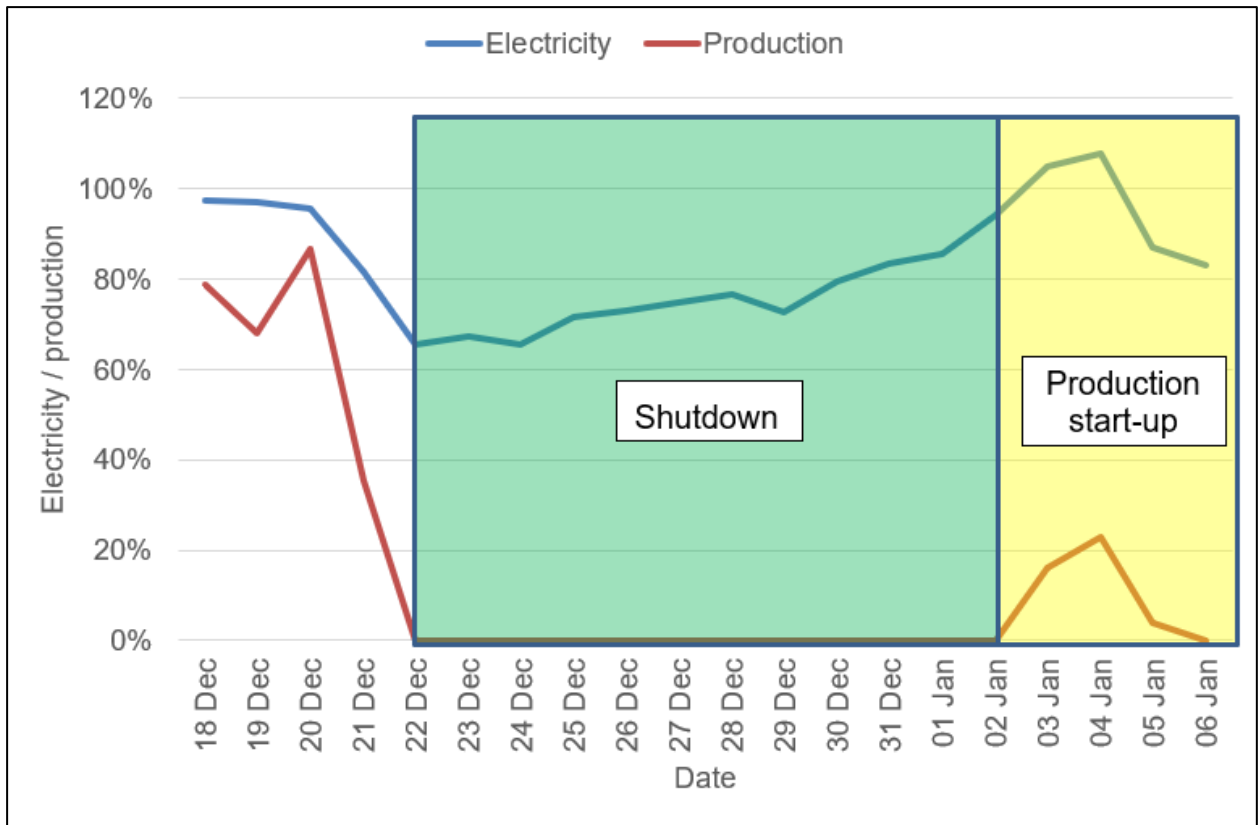


Figure 3-13: Electricity usage and production from 18 December 2018 to 6 January 2019 for specific systems

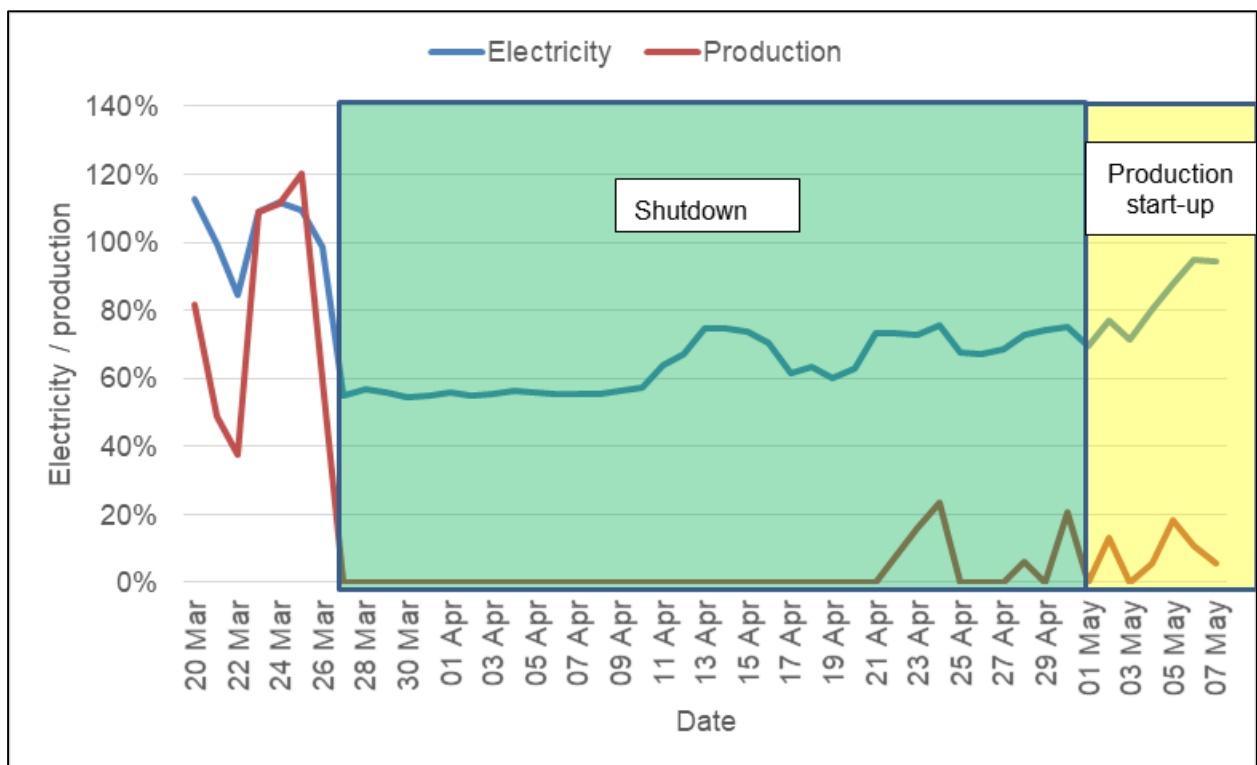


Figure 3-14: Electricity usage and production from 20 March 2020 to 7 May 2020 for specific systems

The results from the ring-fenced annual shutdown analysis are summarised in Table 3-11. This analysis suggested an energy-saving benefit of R9.11 million for April 2020. This saving is in line with the saving impact of R9.24 million that was calculated with the production shaft level December breakdown analysis. A saving impact of R6.96 million was suggested by the regression analysis done on the ring-fenced systems.

Table 3-11: Ring-fenced systems annual shutdown analysis results

	Value	Unit
Baseline (22 December 2018 to 2 January 2019)	2.04	GWh per day
Performance period (1 to 30 April)	1.74	GWh per day
Energy saving	0.29	GWh per day
No. of performance period days	30	Days
Total energy saving	8.77	GWh
Monetary impact	9.11	R million

3.4.8 Analysis 7: individual intervention

Analysis 1 to Analysis 6 used a modelling approach to calculate the savings compared with a previous baseline. All methods focused on a high-level approach since it was more aligned with the contractual requirements of the performance contract that was in place at the case study mining operation. There was, however, uncertainty regarding which process to use and the correct baseline period and data.

Specific initiatives that took place during the lockdown period were documented by the Esco site engineers who used engineering calculations to quantify the impact of the individual methods. These methods were discussed in detail with the case study site personnel. Some methods went through multiple iterations to ensure mutual agreement on the savings quantification methods and the Esco's actual involvement to reduce electricity consumption during the Covid-19 lockdown period. These individual impact reports were signed off by the relevant Esco site engineer and the responsible client personnel.

The initiatives focused on the compressed air, ventilation, refrigeration and pumping systems. The compressed air electricity reduction measure included changing the compressed air set-point schedules of underground control valves. The literature review revealed that mine compressed air projects often involve valve control. These control valves must be monitored regularly to identify system malfunction. A few instances occurred during the lockdown period and the system malfunctions resulted in unnecessary compressed air consumption. The equipment failures were promptly reported to the mine personnel who worked on-site because they were classified as essential staff.

Esco-appointed engineers monitored the operation of the compressors. These engineers were specialised energy managers who were able to identify alternative compressor combinations that were able to deliver the compressed air requirements for underground refuge bays while using less electricity. The Esco instated alternative compressed air supply configurations just before the lockdown that interconnected the compressed air supply from different shafts. The Esco arranged that a 4 MW compressor, which would have been in constant operation during the lockdown, be stopped.

The Esco engineers monitored the systems throughout the day and noticed that a mine control room operator started this machine again because he was used to it being in operation. The Esco was alerted about the start-up. This was quickly reported to the responsible site personnel who then acted quickly to stop the compressor. The impact of all these compressed air improvements was documented and signed off by both Esco engineers and the responsible person at the mine.

Esco engineers further evaluated the ventilation requirements. The analysis by the Esco engineers proved that it would be possible to stop several main ventilation fans. A faulty VSD was detected and reported quickly. Previous experience has shown that malfunction of the particular VSD goes unnoticed for many weeks before site personnel realise that it is not working. The impact of the reduced ventilation fans and the possible lost saving from the broken VSD were approved by mining personnel.

The refrigeration systems operation and water demands were monitored by the Esco. Cold water was required by some shafts to ensure that the workplaces did not heat up during the lockdown period. The Esco did several investigations to identify demand reductions in the system that would not affect the safety of workers. Mine control room operators started a refrigeration plant during the lockdown period because they were used to certain system temperatures. The Esco received notification of this via their monitoring systems and contacted site personnel to enquire about the start-up. It was concluded that the start-up was not needed, whereafter the system was stopped.

Various tests were arranged with site personnel to identify additional room for improvement. These tests further reduced electricity consumption. Unauthorised water consumption was reported that led to the closure of several supply points. Some initiatives resulted in savings on the dewatering pumping systems.

More detail regarding the specific initiatives that were implemented may not be provided due to confidentiality requirements. A summary of the impacts of individual initiatives is provided in Table 3-12. It is observed that a total saving of R7.67 million was signed off by site personnel. Most of the savings were realised on the compressed air system.

Table 3-12: Summary of benefit based on specifically quantified initiatives

Commodity	Energy saving (MWh)	Cost saving (R million)
Compressed air	4798	4.99
Pumping	131	0.14
Refrigeration	752	0.78
Ventilation	1040	1.08
Total	6721	6.99

3.4.9 Guidelines to evaluate energy-saving interventions during production stoppages

Clear guidelines for evaluating energy-saving interventions during medium-term production stoppages were not available in the literature. A few lessons were learned during this study that may assist other energy-intensive businesses to evaluate the feasibility of energy-saving initiatives during medium-term production stoppages. Highlights from this study are summarised in the remainder of this section.

The employees at the mining operation who were involved on a shop floor level with the practical implementation of the energy-saving interventions were hesitant to sign off interventions reports that included financial values. Initiative impact reports that only mentioned the specific actions that were take were signed off by shop floor employees if they agreed that the interventions had been implemented.

This suggests that many employees do not always take cognisance of the financial implication of energy wastage. Higher-level employees such as supervisors and managers did not want to sign off energy impact intervention reports if lower-level employees had not signed off first. The signature of a lower-level employee provides reassurance to the managers that the intervention was implemented.

Managers were less hesitant to sign off reports that included financial information since they are more aware of the cost implications of electricity usage. A multilevel documentation approach is, therefore, best suited for such interventions. Initiative reports that provide clear actions that were taken to reduce electricity usage must be signed off by shop floor level employees if specific actions have been taken by Esco employees. These documents must be used as supporting documentation for higher-level reports that must be approved by managers.

The analysis showed that there are many ways of evaluating the impact of energy-saving interventions. The operating conditions of the mine during baseline conditions had a significant effect on the evaluation strategy. It was not possible to use the electricity usage data without a detailed analysis of system conditions during the baseline period. The analysis showed that a

quantification approach on the whole facility level suggested savings that were much higher than the models using smaller measurement boundaries. The selection of the correct measurement boundary is, therefore, of great importance.

Performance contracts for energy management interventions typically only cater for normal production. An M&V strategy must be developed for contracts for normal production periods and other operating scenarios. This will minimise the uncertainty for both the energy-intensive company and the Esco.

3.5 Results and discussion

3.5.1 Technical implications

Energy-saving initiatives are often implemented by Escos working under performance contracts. The Escos are typically reimbursed for proven energy savings. The impact of energy management interventions is typically evaluated by comparing actual energy usage with a baseline value. The baseline value must provide a representation of what the energy consumption would have been if the energy management initiative had not been implemented.

It is common practice to develop baseline models that assume the performance assessment periods will have operating conditions similar to the baseline period. These models are normally valid within a set operating range. However, it is challenging when there is no clear indication of what the baseline power consumption would have been during medium-term production stoppages. This challenge is generally not experienced in the event that production stops for a short while since the baseline data normally has representative days of a complete production shutdown. A major difference during a medium-term production stoppage is the possibility of stopping more baseload equipment than during shorter stoppages.

The Covid-19 lockdown event has been the longest production shutdown at the case study mine in many years. The problem with such a medium-term production stoppage is to find a representative baseline for such a prolonged period. It was challenging choosing the correct baseline model and measurement boundary. This study used seven different analysis methods to evaluate the impact of contracted energy management based on typical M&V procedures.

Three of the methods used regression analyses to calculate the impact. A further three methods identified the lowest prolonged production period for three years before the implementation of dedicated energy management. The last approach used an approach similar to Option B of the EVO (2017) protocol. This approach used reports to evaluate saving initiatives based on engineering calculations.

Table 3-13 summarises the quantified impacts as evaluated in the seven options. The values from the regression-based methods are stated with their precisions at the 68% confidence level as required by ASHRAE (2014:19).

Table 3-13: Summary of different quantification methods

Comparison	Saving (R million)
Analysis 1 (whole facility regression)	20±4 @ 68% confidence level
Analysis 2 (whole facility annual shutdown)	12
Analysis 3 (production shaft regression)	15±4 @ 68% confidence level
Analysis 4 (production shaft annual shutdown)	9
Analysis 5 (ring-fenced system regression)	13±4 @ 68% confidence level
Analysis 6 (ring-fenced annual shutdown)	9
Analysis 7 (individual intervention)	7

The regression values are shown at their lower limits and rounded at the 90% confidence level for simplicity in Table 3-14. The highest reported impact of R14 million was obtained by doing a whole facility regression analysis. The individual intervention saving, which was based on the specific initiatives that have been documented and accepted by the Esco personnel and the client personnel, was estimated at R7 million. This is the same value as the ring-fenced regression analysis. It can, therefore, be stated with a high level of confidence that the Esco realised an energy-saving impact of R7 million during the April 2020 Covid-19 lockdown period.

Table 3-14: Summary of different quantification methods at lower precision values

Comparison	Saving impact from 1 April to 30 April (R million)
Analysis 1 (whole facility regression)	14
Analysis 2 (whole facility annual shutdown)	12
Analysis 3 (production shaft regression)	9
Analysis 4 (production shaft annual shutdown)	9
Analysis 5 (ring-fenced system regression)	7
Analysis 6 (ring-fenced annual shutdown)	9
Analysis 7 (individual intervention)	7

Bredenkamp (2016:150) proved an 18.5% reduction in electricity usage by implementing a continuous improvement approach at deep-level mines in South Africa that realised annual electricity cost savings of R75 million. This is equivalent to an average monthly cost reduction of R6 million. The savings summarised in Table 3-14 are in line with the savings achieved by Bredenkamp (2016:150).

3.5.2 Business implications

The minimum project impact of the existing contract between the Esco and the client at the case study may not be disclosed due to confidentiality agreements. The cost of an Esco team may also not be divulged and was thus estimated by using the consultancy fees effective from July 2020 as proposed by the Department of Public Service and Administration of South Africa (DPSA, 2020). The consultancy fees from DPSA are based on the annual salary band of a consultant.

A high-level view of the Esco team in the case study is provided in Figure 3-15. All personnel, except for the control room attendant, had a bachelor's degree in engineering as a minimum qualification. The salary for an engineer varied between R30 862 and R77 031 per month in 2015 (Fin24, 2015). These salaries were adjusted to 2020 values by using the consumer price inflation index as published by Stats SA (2020a:5). The salaries adjusted to 2020 values were equivalent to R451 819 per year on the lower level and R1 127 732 on the higher level. The more junior engineers fell in salary band 9 of the DPSA consultancy fee structure and the senior engineers fell in salary band 13 (DPSA, 2020).

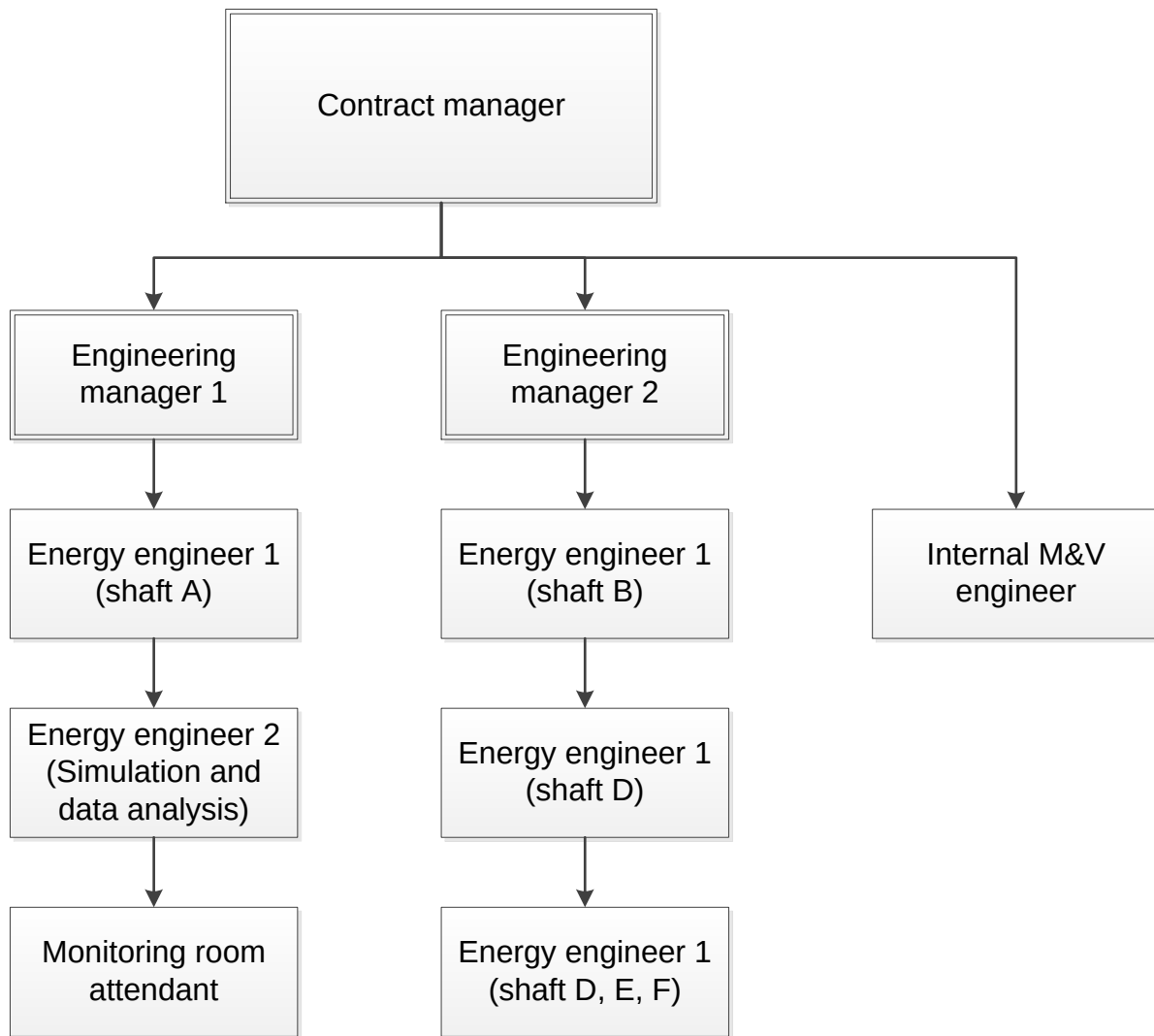


Figure 3-15: Esko organogram

The Esko used a control room attendant with an engineering diploma. The salary of this attendant was expected to be similar to an electrician with a higher limit earnings potential of R23 121 per month (Fin24, 2015). The salary adjusted to a 2020 value was equivalent to R338 491 per year and fell within the 6 to 8 salary band of the DPSA (2020) consultancy fee structure.

The monthly consultancy fee was R2 million, which was based on the above salary bands according to the DPSA schedules for long-term contracts. The contractor was responsible for overheads and charged a mark-up fee. This monthly consultancy fee was compared with an expected salary expense of R545 000 per month. A saving impact of R7 million was proven at a high confidence level through a rigorous process. The mining group, therefore, received a minimum nett benefit of R5 million by contracting the services of an Esko during a medium-term production stoppage.

The results of this study prove a business case for using a dedicated energy management approach. It is important to note that the Esco engineers were able to act quickly to reduce electricity usage at the case study mine because they were actively involved with energy management at the operations before the production stoppage.

The literature review revealed that deep-level mining is complex and has extensive operations with unique challenges. The successful implementation of the energy-saving measure during the Covid-19 lockdown was as a direct result of the experienced Esco engineers. The possibility to realise such quick results is highly unlikely if an active energy management approach is not already in place before a production stoppage.

3.6 Summary

The literature showed that energy-saving initiatives at deep-level mining operations often entail improvements on dewatering, cooling, compressed air and ventilation systems. Existing research evaluates the impact of energy interventions by comparing the interventions with business-as-usual conditions. The impact of a prolonged production shutdown during the Covid-19 lockdown period caused great uncertainty for Escos due to shortcomings in the measurement of the impact during these times. The research design followed was based on IPMVP and ASHRAE guidelines. Electricity usage and production data were gathered for a case study from the database of an Esco that was actively involved with energy management in the deep-level mining industry in South Africa. Baseline data was retrieved for the period before any Esco involvement.

The impact of the saving interventions was evaluated by using seven evaluation models. Three baseline analysis models were developed using regression analysis with baseline data that spanned from 2016 to 2018. Data from 2019 was not included in the baseline analysis because dedicated energy management was started in 2019 at the case study mine. The first model evaluated the savings on the entire facility at the same level as which Eskom metering was installed. This major advantage of this model is that Eskom invoices are generally regarded as 100% accurate, which provided a good reference point.

The second regression model narrowed the measurement boundary to only consider electricity usage by the production shafts. Although metering discrepancies increased the model error, it increased the validity of the model since the measurement boundary was closer to the location of the interventions. The third approach evaluated impact by only considering the electricity usage on the systems where energy-saving measures were implemented. A drawback to this approach was the unavailability of meter accuracy on the individual systems. An estimated meter error of 5% as provided by ASHRAE was used to determine the total uncertainty of the savings.

A major drawback to the regression models is the lack of baseline data for an entire month when production came to a complete standstill. It was not practical to develop regression models in shorter than monthly intervals due to the phase shift from measuring electricity used to measuring production output. This challenge was mitigated by comparing the electricity usage during the Covid-19 lockdown with the electricity usage during a December break that spanned between 22 December 2018 and 2 January 2019. Three different models were considered for this evaluation and measurement boundaries similar to the regression analysis were selected.

Individual impact reports based on a combination of engineering calculations and actual system data approved by mining personnel were used as a final verification of the impact of the saving interventions. These reports only contained the electrical energy saved. The monetary impact of the reports was quantified by using the average electricity tariff paid by the mine. A saving impact of R7 million was proven for April 2020 at a high confidence level. This was compared with an expected monthly contract cost of R2 million, which provided a benefit-to-cost ratio of 3.5:1 to the mining company. It will be beneficial for the mining company to enter into a performance agreement with an Esco to implement dedicated energy management.

The lessons learned may be helpful to other industrial energy-intensive operations and Escos with similar M&V challenges. It is important to involve all stakeholders from employees working on the shop floor to mine management. Continuous and transparent reporting of initiatives ensures mutual trust by all parties. It is suggested that M&V processes be developed to account for normal production and production stoppages to avoid any doubt for future scenarios.

CHAPTER 4: CONCLUSIONS AND RECOMMENDATIONS

4.1 Introduction

The South African mining industry contributes to just more than 7% of the country's GDP and employs about 450 000 people (Stats SA, 2020b:8; 2020d). Mining companies that operate in South Africa have shown a downwards production trend from 1994 to date (McKinsey Global Institute, 2017:4). This is partially due to high operating costs, such as electricity, that contribute to as much as 20% of the total operating costs of a deep-level mine (Sibanye Stillwater, 2019:22). The World Energy Council (2020) stated that energy affordability is one of the critical uncertainties in terms of South Africa's energy situation. Some mining companies that own and operate deep-level mines in South Africa have shared their concern regarding the impact of these high costs with their shareholders (Harmony Gold, 2019:29).

International research shows that energy efficiency measures have the potential of realising savings that are comparable to the expected increase in worldwide energy usage over the next 20 years (IEA, 2018:332). Research further proves that the implementation of energy management interventions can realise significant improvements in the financial performance of companies (Martí-Ballester, 2017:S35). The effect of these interventions is only realised over the long term if energy management interventions are aimed at continuous improvement.

Research focusing on the influence of environmental performance on 996 businesses based in the United States shows that good environmental performance can affect the returns on assets and equity positively (Bassetti *et al.*, 2020:9-11). It was further shown that the financial performance of companies is influenced by their environmental performance. Eskom-generated electricity results in particulate emissions of 40% more than targeted emissions due to the generation fleet being dominated by coal-fired plants (Eskom, 2020a:86). This suggests that the financial performance of energy-intensive companies that operate in South Africa can be improved significantly if electricity cost-saving measures are implemented.

This has been proven in the South African mining industry where energy management strategies implemented on deep-level gold mines realised electricity cost savings worth approximately R75 million per annum (Bredenkamp *et al.*, 2016:138). Research proves that industrial energy consumers are not always keen to invest in research and development to implement energy efficiency improvements (Bukarica & Tomšić, 2017:970). Internal factors such as company culture, evaluation processes, fiscal rules such as payback periods, and investment parameters influence the uptake of energy efficiency measures (Finnerty *et al.*, 2018:916).

The predominant barriers to the implementation of energy efficiency projects are lack of capital, low priority of energy efficiency, risk of production disruptions and a lack of awareness (Finnerty *et al.*, 2018:925). Escos often enter into performance agreements and are only paid for proven savings. These contracts are used to overcome these implementation barriers (Newsham, 2019:2). Escos are contracted by mining companies to implement energy-saving interventions (Harmony Gold, 2019:136; Implats, 2019:45; Sibanye Stillwater, 2019:209). The impact of energy-saving interventions is typically evaluated by comparing the actual electricity usage after implementation with the usage for comparable conditions before the intervention (EVO, 2017:3).

The electricity usage before the implementation of the intervention is known as the baseline usage. Baseline electricity usage is based on business-as-usual operating conditions and is adjusted if system conditions in the assessment stage of the interventions differ from the baseline conditions. These adjustments aim to ensure an accurate reference point to what the electricity consumption would have been in the absence of any saving interventions. The impact of the saving measure is quantified by comparing the actual usage after the intervention with the predicted usage without the saving interventions (EVO, 2017:3).

A challenge arises when mines are forced to halt production since these events are not considered to be normal operating conditions. Mining companies face significant financial challenges when production is stopped (AngloGold Ashanti, 2019:19; Harmony Gold, 2020; Sibanye Stillwater, 2019:21). Expenses must be minimised during production stoppages to limit its financial impact. Research has shown that employees are not always highly motivated to implement energy-saving initiatives (Finnerty *et al.*, 2018:916, 924, 925).

It may be difficult for mining employees to justify energy management contracts with Escos during production stoppages. The services of Escos can potentially be placed on hold during medium-term production stoppages due to the uncertainty of the Esco's impact. This significantly increases the business risk to Escos that are contracted under performance agreements. Escos are already exposed to financial risk during normal operations if they enter into performance agreements and are only paid for proven savings.

Existing research related to deep-level mine energy management is directed towards interventions that reduce electricity costs during business-as-normal operating conditions. Research on impact evaluation techniques in the energy efficiency environment focuses on quantifying energy savings during business-as-usual scenarios. No research was found that provided guidelines on quantification techniques to evaluate the impact of electricity-saving initiatives during medium-term production stoppages.

A need was identified to evaluate the financial feasibility of dedicated energy management by specialised Escos. An in-depth literature review was conducted to understand the typical electricity cost-saving interventions at deep-level mines. Literature related to the quantification of the impact of energy-saving measures was also evaluated. Most literature related to M&V of energy-saving interventions uses the guidelines provided by the IPMVP as published by the EVO (2017). Many studies use the guidelines supplied by the ASHRAE.

It is common practice to use mathematical models to evaluate the impact of energy-saving interventions (EVO, 2017:13). It is difficult, if not impossible, to develop a model that can state the impact of energy-saving interventions with 100% certainty (SANAS, 2017:5). It is challenging to select the correct saving calculation model from many available options. Some research suggests that more than one model should be developed and compared with one another to evaluate the saving impact (Botes, 2018:85).

This study evaluated seven baseline models to quantify the impact of dedicated energy management by an Esco at a South African deep-level mine during a medium-term production stoppage. The baseline models differed in the evaluation approaches and measurement boundaries that were used.

4.2 Results

Three baseline analysis models were developed using regression analysis. Baseline data spanned from 2016 to 2018. Data from 2019 was not included in the baseline analysis because dedicated energy management was started in 2019. The first model evaluated the savings on the entire facility at the same level as where metering was installed by Eskom. The second regression model narrowed the measurement boundary to only consider electricity usage by the production shafts. The third approach evaluated the impact by only considering the electricity usage on the systems that had energy-saving measures implemented.

A major drawback to the regression models is the lack of baseline data for the period when production came to a complete standstill for an entire month. It was not practical to develop regression models in shorter than monthly intervals due to the phase shift from measuring electricity used to measuring production output. This challenge was mitigated by comparing the electricity usage during the Covid-19 lockdown with the usage during a December break that spanned between 22 December 2018 and 2 January 2019. Three different models were considered for this evaluation and measurement boundaries similar to the regression analysis were selected.

This final analysis was done by comparing the results with the individual energy-saving interventions that were quantified based on engineering calculations. The impact and validity of these interventions were approved and signed off by mining employees, which served as a final validation of the results. It was not possible to use these impact reports in isolation since the impact for the performance contract at the case study mine required an evaluation on a whole facility level.

The savings impact quantified through the various models is summarised in Table 4-1. It is observed that the individual intervention quantification provided the lowest saving estimation. This was expected since mining personnel were not burdened with requests from the Esco to sign off each initiative. The initiatives that were signed off were only the actions that had significant effects and that could prove without a doubt that the savings were realised due to the involvement of the Esco.

Table 4-1: Summary of different quantification methods at lower precision values

Comparison	Saving impact from 1 April to 30 April (R million)
Analysis 1 (whole facility regression)	14
Analysis 2 (whole facility annual shutdown)	12
Analysis 3 (production shaft regression)	9
Analysis 4 (production shaft annual shutdown)	9
Analysis 5 (ring-fenced system regression)	7
Analysis 6 (ring-fenced annual shutdown)	9
Analysis 7 (individual intervention)	7

The estimated contract fee for the Esco was quantified by considering the consultancy fees as published by the DPSA (2020). The salary bands for the Esco personnel were approximated based on the typical salaries for South African engineers. This approach estimated a service fee of R2 million per month. The expected monthly salary bill for the Esco was estimated at R545 000. This provided an Esco fee versus salary fee ratio of 3.7:1. The client benefit versus cost ratio is a minimum of 3.5:1 when the minimum saving value is used. It can be concluded that there is enough electricity-saving potential at deep-level mining operations to justify dedicated energy management.

4.3 Conclusions

This study proved that dedicated energy management at deep-level mines is beneficial to the deep-level mining industry during medium-term production stoppages. It is also beneficial for Escos to enter into performance agreements during such stoppages. The correct measurement of the impact during such shutdown periods is a significant challenge. It was not possible to develop an M&V strategy in time for Covid-19 lockdown. This left Escos and their clients in the dark regarding their benefit during such periods. It is therefore suggested that baselines procedures be developed together with the normal production baselines. This will minimise the uncertainty during production stoppage events.

4.4 Achievement of the objectives of the study

The primary objective of this study was to evaluate the financial impact of dedicated energy management on deep-level mines during medium-term production stoppages. This required a detailed literature review of the typical systems used at deep-level mining operations. The research was further needed to understand why the energy for deep-level mines is much more intensive than for surface mining operations. This research was presented in Section 2.2.

A thorough review of available research was conducted to gain insight into the typical energy-saving interventions implemented at deep-level mining operations. This research helped to identify typical strategies and the typical savings that they realise. The literature review further provided information regarding the approaches used by researchers to measure the impact of the interventions.

A detailed literature review was conducted to evaluate the typical procedures used to quantify the impact of energy-saving initiatives. This literature review was not limited to the deep-level mining industry. Research findings provided valuable insight to solve the primary research objective of this study.

The detailed empirical analysis discussed in Chapter 3 used a multimodel approach to quantify the impact of energy savings. A minimum benefit-to-cost ratio of 3.5:1 proved that it is beneficial for deep-level mining companies to implement dedicated energy management strategies at deep-level mining companies during medium-term production stoppages. A conservative approach was followed and the saving impact may be more than the stated benefit. This reported benefit was estimated at a great level of confidence. Therefore, the primary research objective was achieved.

The secondary objective of the study was to provide high-level guidelines for evaluating the impact of energy-saving initiatives at other energy-intensive operations. The most important

finding from the research was the proper documentation of all interventions. It was observed that a multilevel sign-off approach was the best-suited approach. This approach requires that shop floor level employees must sign off intervention reports that only state the specific actions taken to reduce energy usage. Thereafter, higher-level employees sign off reports that summarise the actions taken and the related monetary impact. The results from the analysis showed that the correct selection of the measurement boundary was the most important consideration for the baseline models. It is suggested that the measurement boundary be defined clearly at the onset of the interventions.

4.5 Recommendations for further research

This study did not evaluate other newer M&V strategies such as machine learning and more modern M&V 2.0 techniques, which are typically based on existing operating conditions and are focused on the building sector. Research relating to the use of these and other modern M&V techniques focused on industrial energy users can add significant value to the field of energy management and measurement.

This study provided guidelines regarding the evaluation techniques to be followed to quantify the impact of energy-saving initiatives during medium-term production stoppages. Case study information was not available to evaluate the feasibility of implementing energy-saving strategies during medium-term production stoppages at non-mining energy-intensive industries.

Research regarding energy management during short-term production stoppages, such as Sundays and public holidays, is very limited. Energy management potential during these short-term periods may realise additional energy-saving potential. The energy impact during the medium-term production stoppage in this study was compared with the electricity usage during a typical December break. The interventions realised a significant impact compared with the December break. This suggests that there is perhaps energy-saving potential during the December break. More research regarding possible saving strategies during this period may be beneficial.

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APPENDIX A – STATISTICAL FORMULAS

Appendix A provides an overview of the formulas used to complete data analysis in Chapter 3. The sample mean indicates the central tendency of the data, and was calculated according to the following formula as provided by the EVO (2018:5):

$$\bar{Y} = \frac{\sum Y_i}{n} \quad (10)$$

Where

$\bar{Y}$:	Sample mean
Y_i :	Individual data point
n :	Number of data points

Sample variance indicates the variability or dispersion between individual data points (EVO, 2018:5). High variability is indicative of high uncertainty in the mean of the sample (EVO, 2018:5). The sample variance was calculated according to the following formula as provided by the EVO (2018:5):

$$s^2 = \frac{\sum (Y_i - \bar{Y})^2}{n} \quad (11)$$

Where

s^2 :	Sample variance
$\bar{Y}$:	Sample mean
Y_i :	Individual data point
n :	Number of data points

The sample standard deviation converts the variability measure (sample variance) back to the unit of the data that was sampled (EVO, 2018:5) (EVO (2018:5). This measure indicates the variability of the data among the observations of the data (EVO, 2018:5). About 68% of observations of normally distributed data will be within $\pm 1S$ of the mean and 95% will be within $\pm 2S$ of the mean (EVO, 2018:5). A large standard deviation is evidence of a great dispersion about the mean (EVO, 2018:5).

The sample standard deviation was calculated according to the following formula as provided by the EVO (2018:5):

$$s = \sqrt{s^2} \quad (12)$$

Where

s : Sample standard deviation

s^2 : Sample variance

The standard error of the mean is used to estimate the precision of the estimated mean (EVO, 2018:5). It is a measure of the accuracy at which the sample represents the population. The standard error of the mean is estimated through a sample, and was calculated according to the following formula as provided by the EVO (2018:6):

$$SE_{\bar{Y}} = \frac{s}{\sqrt{n}} \quad (13)$$

Where

$SE_{\bar{Y}}$: Standard error of the mean

s : Sample standard deviation

n : Number of data points

The coefficient of variation is the standard deviation of a distribution expressed as a percentage of the mean. It was calculated according to the following formula as provided by the EVO (2018:6):

$$cv = \frac{s}{\bar{Y}} \quad (14)$$

Where

cv : Coefficient of variation

s : Sample standard deviation

$\bar{Y}$: Sample mean

The standard error of the regression estimate or the regression or root mean square error (RMSE) is a measure for quantifying the extent of the variation for the regression model (EVO, 2018:6). The standard error of the estimate was calculated according to the following formula as provided by the EVO (2018:7):

$$SE_{\hat{y}} = \sqrt{\frac{\sum(\hat{Y}_i - Y_i)^2}{n - k - 1}} \quad (15)$$

Where

$SE_{\hat{y}}$:	Standard error of the regression estimate also known as the RMSE
$\hat{Y}_i$:	Predicted energy value of Y_i
Y_i :	Individual data point
n :	Number of data points
k :	Number of explanatory variables in the regression equation

The range of the possible values from a regression model was obtained using the following equation (EVO, 2018:20):

$$\hat{Y} \pm t \cdot SE_{\hat{y}} \quad (16)$$

Where

$SE_{\hat{y}}$:	Standard error of the regression estimate also known as the RMSE
$\hat{Y}_i$:	Predicted energy value of Y_i
t :	Value from t-tables

The coefficient of variation of the root mean squared error [CV(RMSE)] is a measure of the variability between the predicted and the actual values (Gallagher *et al.*, 2018:650). SANAS (2017:20) regards this measure as the most reliable measure for energy data. The CV(RMSE) was obtained with the following equation (EVO, 2018:21):

$$CV(RMSE) = \frac{SE_{\hat{y}}}{\bar{Y}} \quad (17)$$

Where

$SE_{\hat{y}}$:	Standard error of the regression estimate also known as the RMSE
$\bar{Y}$:	Sample mean

The adjusted r^2 value is used if more than one explanatory variable is used. The formula for adjusted r^2 was as follows (EVO, 2018:16):

$$Adjusted R^2 = 1 - \frac{(1 - R^2) \times (n - 1)}{n - P - 1} \quad (18)$$

Where

R^2 :	Coefficient of determination
n :	Number of data points
P :	Number of explanatory variables

The SANAS (2017:29) guideline provides a formula for determining the relative uncertainty when considering the accuracy of the regression model, sampling error, and instrument measurement error. The formula is based on the formula from the ASHRAE (2002) and ASHRAE (2014) standard. The ASHRAE (2014:14) standard states that it is not necessary to include measurement errors for measurements in the baseline period since these errors will be measured by the coefficient of determination (R^2).

The formula for relative uncertainty when considering regression and meter errors as provided by ASHRAE (2014:17) is as follows:

$$U = \frac{t}{F} \sqrt{\frac{CV(RMSE)^2}{m} \times \left[\frac{n}{n'} \left(1.6 + \frac{3.2}{n'} \right) \right] + U_s^2 + RE_{instrument}^2 + U_{iv}^2} \quad (19)$$

Where

U :	Relative uncertainty in reported savings expressed as a percentage
$CV(RMSE)$:	Coefficient of variation on the root mean square error
t :	T-statistic
F :	Fractional savings percentage (approximate savings relative to baseline)
U_s :	Sampling uncertainty
m :	Number of periods (months, weeks, days, hours) in the post-retrofit savings reporting period
n :	Number of post-retrofit reporting periods
n' :	Number of independent observations in a total of n observations during the baseline period

$RE_{instrument}$: The relative error of energy instrument expressed as a percentage

U_{iv} : Post-retrofit energy-saving uncertainty

The sampling uncertainty was calculated as follows (SANAS, 2017:30):

$$U_s = \frac{100}{\bar{y}} \sqrt{\frac{\left(1 - \frac{q}{Q}\right) \left[\sum_{i=1}^m \frac{(y_i - \bar{y})^2}{(q-1)}\right]}{q}} \quad (20)$$

Where

U_s : Sampling uncertainty
 Q : Population size
 m : Number of periods in baseline (months, weeks, days)
 $\bar{y}$: Arithmetic mean of sampling observations
 y_i : Predicted value at i
 n : Number of post-retrofit reporting periods
 q : Size of the random sample

The number of independent observations in a total of n observations during baseline period was calculated as follows (SANAS, 2017:30):

$$n' = n \times \frac{1 - \rho}{1 + \rho} \quad (21)$$

Where

n' : Number of independent observations in a total of n observations during the baseline period
 n : Number of post-retrofit reporting periods
 ρ : Autocorrelation coefficient of a series of n observations at lag 1

The autocorrelation coefficient of a series of n observations at lag 1 was calculated as follows (SANAS, 2017:30):

$$\rho = \sqrt{1 - \frac{\sum_{i=1}^p (y_i - \hat{y})^2}{\sum_{i=1}^p (y_i - \bar{y})^2}} \quad (22)$$

Where

- ρ : Autocorrelation coefficient of a series of n observations at lag 1
- p : Number of parameters or terms in the baseline regression model
- y_i : Actual energy at data point i
- $\bar{y}$: Arithmetic mean of sampling observations
- $\hat{y}_i$: Predicted energy value of Y_i

The ASHRAE (2014:13) standard states that p can be set to zero if monthly data is used. This causes n' to be equal to n . The post-retrofit energy-saving uncertainty due to independent variable measurement error was calculated as follows (SANAS, 2017:31):

$$U_{iv} = \frac{t}{F} \sqrt{\frac{CV(STD)^2}{m} + U_s^2 + RE_{instrument}^2} \quad (23)$$

Where

$$CV(STD) = \frac{\sqrt{\frac{\sum (y_i - \bar{y})^2}{n-1}}}{\bar{y}} \quad (24)$$