Benchmarking electricity use of deep-level mines

C Cilliers

20667663

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Supervisor: Prof. M Kleingeld

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It all starts here ™

ABSTRACT

Title: Benchmarking electricity use of deep-level mines
Author: C Cilliers
Supervisor: Prof. M Kleingeld
Keywords: Energy consumption, Energy benchmarking, Deep-level mines, Compressed air system, Cooling system, Dewatering system, Ventilation system, Hoisting system, Energy efficiency initiatives, Energy budgeting

Electricity consumption, and the cost thereof, has become a large contributor to operating costs in deep-level mining in South Africa. Up to 60% of electricity used on deep-level mines can be attributed to five high power demand systems that continuously operate for maximum production output. Compressed air, cooling, dewatering, ventilation and hoisting systems form part of these high demand systems.

The need to reduce electricity consumption of high power demand systems is identified as a means to increase mining profit. Various initiatives that aim to increase energy efficiency of high power demand systems have been implemented. However, these initiatives are often driven by external parties with no stake in mining profitability. It is important to create awareness of system performance in terms of comparative energy consumption to start focusing on identifying possible energy efficiency initiatives for mines.

Numerous energy benchmarking studies have been conducted on systems ranging from commercial to industrial. The focus of these studies was on increasing energy consumption awareness and, in doing so, identifying the need to reduce energy consumption. The objective of this study is to benchmark the electricity use of deep-level mines in a new way that considers relevant external factors and variables.

New models were created using actual data obtained from South African deep-level mines. Models for both average and best practice benchmarking were developed. A novel technique for determining the priorities of energy efficiency initiatives on high demand systems was also developed. This study creates additional real-time awareness by developing a new method to determine operational energy budgets.

The developed models and techniques were verified by using external methods. The models were then validated by applying them to the high power demand systems of nine case study mines. The results showed that the benchmarking, prioritisation and dynamic energy budgeting models accurately distinguished between efficient and inefficient mine systems. With the knowledge obtained, awareness of system-specific and overall energy consumption was achieved and mitigating initiatives could be implemented.

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All information portrayed in this thesis was done acknowledging sources and referencing published work.

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NOMENCLATURE

Symbol	Unit	Description
°C	Celsius	Temperature
K	Kelvin	Temperature
kg/m^3	kg/m^3	Density per volume unit
kg/s	kg/s	Volume flow rate
kJ/kg	kJ/kg	Energy per mass unit
kJ/kg.K	kJ/kg.K	Gas constant
kPa	Kilopascal	Pressure
kt	Kilotonne	Weight
kW	Kilowatt	Power
kWh	Kilowatt-hour	Energy
ℓ/s	Litre per second	Flow rate
m	Metre	Head, depth or length
m^3	Cubic metre	Volume
m^3/kt	m^3/kt	Volume per unit mass
m^3/s	Cubic metre per second	Flow rate
mm	Millimetre	Length
MW	Megawatt	Power
MWh	Megawatt-hour	Energy
MWh/kt	Megawatt-hour per kilotonne	Energy per unit mass
MWh/m	Megawatt-hour per metre	Energy per unit depth
Pa	Pascal	Pressure

ABBREVIATIONS

BAC	Bulk Air Cooler
BEF	Benchmark Energy Factor
COLS	Corrected Ordinary Least Square
COP	Coefficient of Performance
DEA	Data Envelopment Analysis
DSM	Demand Side Management
EAF	Electric Arc Furnace
EUI	Energy Use Intensity
OLS	Ordinary Least Square
PRV	Pressure-reducing Valve
SCADA	Supervisory Control and Data Acquisition
SEC	Specific Energy Consumption
SFA	Stochastic Factor Analysis
VRT	Virgin Rock Temperature
VSD	Variable Speed Drive

CHAPTER 1 – Deep-level mines and energy benchmarking

[1]

[1] C. Cilliers, Personal photograph. "Winders", Carletonville, 2014.

1.1 PREAMBLE

The introductory chapter presents a brief overview of deep-level mines and their electricity consumption. Quantifying electricity use efficiency through benchmarking is presented as a viable method for electricity use awareness. Previous research on energy benchmarking for various commercial and industrial fields is reviewed and the findings are used to convey the research objective. From the research objective, original contributions to knowledge are formulated and presented.

1.2 DEEP-LEVEL MINES

The gold and platinum mining industry in South Africa contributes greatly towards employment, the gross domestic product and income via export [1], [2]. Constituting a third of the world's reserve, South Africa is one of the top contributing countries of these commodities [3], [4].

Although opencast mining is used in some instances, the bulk of gold and platinum is extracted via deep-level mining in South Africa. Deep-level mines in South Africa are the deepest mines in the world, and as of 2015, mines had depths of up to 4 000 m [5].

The goal of extracting gold or platinum ore from a mine can only be accomplished by a variety of intricate systems cooperating. These supporting systems, which include cooling, ventilation, dewatering, compressed air and hoisting systems, are in place to ensure that ore is extracted efficiently and safely [6].

Fridge plants, which form part of cooling systems, are typically found at a mine's surface but are present underground if a mine is deep enough. Ventilation fans are found throughout a mine – with large extraction fans at the surface and booster fans underground. Dewatering pumps are usually situated close to the deepest point in a mine, with additional pumping stations on shallower levels as required.

Numerous equipment on deep-level mines require compressed air to operate. Large centrifugal compressors are situated on the surface inside large compressor houses. The hoisting system of a mine always has at least one winder on surface to extract workers and mined ore. In a very deep mine where a subshaft is used, there will be another winder underground. Figure 1 shows the typical locations for all the supporting systems discussed.

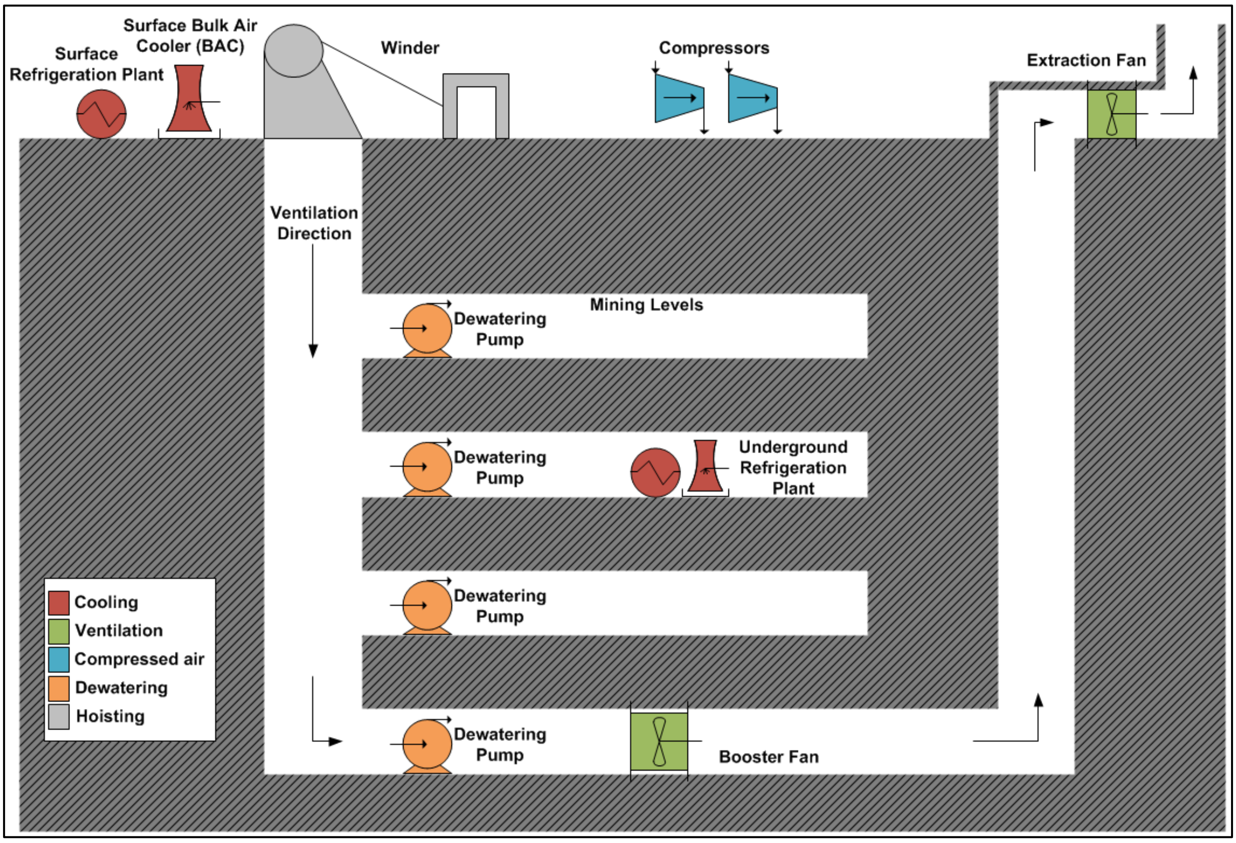


Figure 1: Deep-level mine supporting systems

The South African mining industry currently consumes up to 15% of all electrical energy in the country [7]. Of this, approximately half is used by gold mines and a third by platinum mines [8]. The majority of this electricity is needed to operate the supporting systems. High capacity industrial electric motors are the main mechanical motion providers for these systems.

In Figure 2 the electricity use of the supporting systems is shown as a percentage of the total electricity used by a typical deep-level mine in South Africa. It is seen that approximately 60% of the total electricity is consumed by these high power demand electric motor-based systems.

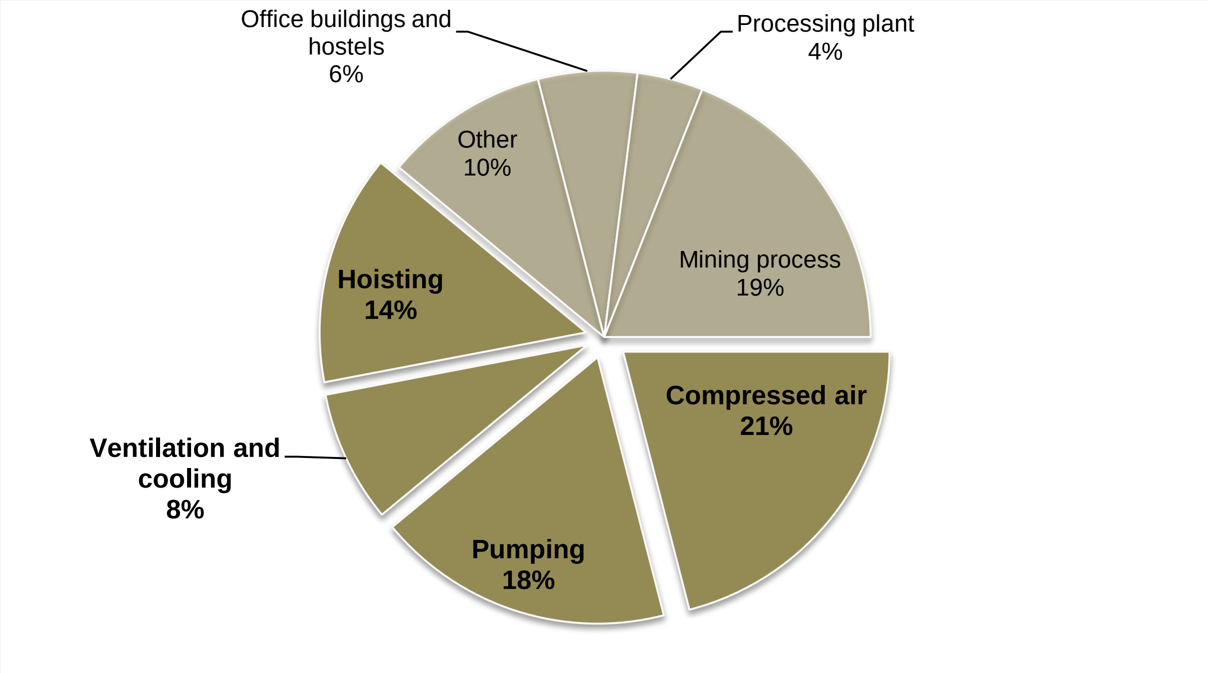


Figure 2: Electrical energy consumption per mining system (adapted from [6])

1.3 ELECTRICITY USAGE AWARENESS

Situational awareness is a vital part in preventing impending hardship [9]. Whether it is the early diagnosis of an illness, the increase in success rate due to statistical probability, or even just the preventative action taken after listening to a traffic report. Being aware of the future or present state of play may often encourage a more favourable outcome to the situation.

In 2015, Tsushima *et al.* proved that electricity use awareness could be greatly increased by an external motivator [10]. It was shown that after the 2011 Great East Japan earthquake that crippled nuclear power plants, a significant increase in electricity saving occurred due to people being aware of the reduced generation capacity. It was also shown that the awareness had a continuous electricity savings effect years after the earthquake [10].

Awareness is, however, not always a motivator for saving electricity. Brounen *et al.* showed in 2013 that being aware of household electricity use did not significantly reduce average electricity consumption [11]. It should be noted that the study was conducted only in the Netherlands. A year-on-year reduction of utility costs and the lack of incentive due to reduced electricity consumption might have greatly influenced this study's results [12].

As mentioned in previous sections, deep-level mines in South Africa use considerable amounts of electricity [7]. This makes the profitability of producing an ounce of precious metal directly proportional to the amount of energy needed to produce that ounce. Naturally, the less energy required to produce an ounce of precious metal, the higher the profit of a given mine will be. This may be calculated as an energy intensity of kWh/ounce of precious metal or kWh/tonne of ore mined.

Various methods for lowering electricity use on deep-level mines have been pursued. The main objectives of these methods are to aid in the ever-increasing problem of high demand versus low electricity supply that South Africa currently faces [13]. Apart from alleviating the effect of the strained electricity supply, a decrease of energy intensity is also realised through these methods.

As South Africa is experiencing a substantial increase in electricity costs each year, lowering a mine's intensity becomes an important motivator for the sake of profitability. Cost increases together with a declining energy generation capacity reserve margin show that the importance of energy efficiency industrial processes is becoming vital [14].

The twofold advantage of decreased intensity and a lower utility bill is a great motivator for South African deep-level mines to reduce electricity consumption. Increased awareness of a mine's system-level efficiency, and also of its overall efficiency with the abovementioned motivators, may reduce electricity consumption. A supply-side alleviation of constrained generation capacity and a demand side advantage of reduced intensity will be realised.

1.4 AWARENESS THROUGH BENCHMARKING

Evaluating performance against a reference performance is known as benchmarking [15]. In other words, a benchmark or target is set for an operational goal. By comparing the goal with present operations, a decision can be made to attempt to reach this goal [16].

Quantifiable performance indication is achieved by using specific indicators such as a cost per unit or production efficiency in terms of a measureable input. Comparing this performance with a similar indicator creates an understanding of shortfalls and/or achievements [17].

Using process benchmarking enables the evaluation of interfirm process efficiency as compared with best practices observed from firms specialising in benchmarking. Through this evaluation, process efficiency and output may be increased to the full achievable potential [17].

Various benchmarking models and methods exist with each approach being used for different purposes and outcomes. Two of the most commonly used methods are average benchmarking and frontier benchmarking [18].

Awareness of present system performance, i.e. efficiency, is increased after a benchmarking method has been applied at system and/or overall level on an entity such as a deep-level mine.

1.5 PREVIOUS STUDIES ON ENERGY BENCHMARKING

1.5.1 Preamble

Various studies in the field of energy benchmarking on either industrial or commercial level were investigated. This section focuses on some of these studies and identifies possible similarities and/or shortfalls when compared with the objective of benchmarking electricity use on deep-level mines.

1.5.2 Studies on commercial energy benchmarking

Chan, 2012 [19]

In 2012, Chan studied how to benchmark energy use for hotels in China [19]. Objectives of the study included developing a method for identifying benchmarking challenges, formulating hotel benchmark frameworks and recommending implementation strategies [19].

Information gathering for Chan's study consisted of interviewing relevant personnel and guests at various hotels. Chan found that an overall energy benchmark for hotels was not feasible due to various factors that influenced total energy use. These included different types and sizes of room, hotel building grade, hotel service level and external factors such as ambient outside temperature [19].

Chan developed a three-step methodology for determining energy use intensity (EUI) of, firstly, hotels as a whole; secondly, the subdivisions of hotels such as different facilities and star-rated levels; and thirdly, EUIs with reference to building standards, survey data and simulation results [19].

When reviewing Chan's study, it is clear that the need for benchmarking as a driver to reduce energy consumption is valid. Information regarding a hotel's performance in terms of energy use as compared with the industry is valuable information to hotel managers and owners. This information can lead to increased energy saving and better performance by management at hotel level. This subsequently reduces national energy use.

Filippín, 2000 [20]

Filippín conducted a study in 2000 on energy benchmarking of schools in Argentina [20]. The objective of this study was to determine the electricity use and greenhouse gas emissions per unit of similar factors at the schools. The units chosen were per pupil and per square metre of floor area covered [20].

The study found that the energy consumption and the number of pupils or floor space did not correlate well. External factors such as ambient temperatures, building orientation and school employee practices greatly affected the outcome [20]. These external factors were not normalised to get an accurate representation of energy use per unit. The study did, however, show that the schools in question had a high energy consumption [20].

Keirstead, 2013 [21]

A study by Keirstead was done in 2013 to benchmark urban energy use in the United Kingdom [21]. Keirstead calculated the energy use per capita (kWh/capita) for 198 urban areas. Due to large discrepancies in kWh/capita data when comparing industrial urban areas with commercial urban areas, various normalisation methods were applied [21].

One of Keirstead's methods was to group similar urban classes together [21]. This allowed for a relative accurate comparison between energy efficiency, as all urban areas per class would theoretically require the same energy per capita – not considering external factors. A second method used linear regression to control external factors such as climate. The third method used the data envelopment analysis (DEA) technique. This technique allowed energy efficiency to be defined in different ways depending on urban class.

When comparing these methods, Keirstead found that simply grouping similar classes together competed well with statistical methods of linear regression and data envelopment when determining urban energy efficiency rankings. It was, however, recommended that a more focused per-capita benchmarking study be conducted to increase accuracy [21]. The development of theoretical models could also assist in this benchmarking study. Keirstead's results successfully showed inefficient urban areas as compared with more efficient areas but did not address their potential inefficiency when compared with best practice models.

Mui *et al.* 2007 [22]

Mui *et al.* conducted a study in 2007 on benchmarking the energy consumption of air conditioning systems in Hong Kong offices [22]. Psychrometric analysis was used to develop the benchmarking model and showed that the carbon dioxide (CO_2) concentration in air correlated significantly with the energy consumption per unit floor area [22]. The conclusion to the study indicated that air temperature set point had less of a correlation to energy consumption [22].

High CO_2 concentrations could indicate that a high concentration of humans is present in an office. Increasing the human concentration will lead to an increased heat load, which will require higher energy consumption to maintain temperature set points. This verifies the correlation between CO_2 concentration and energy consumption.

A key omission from the study was the correlation between energy consumption and outdoor ambient air temperatures over a multiseason period. Hong Kong's average ambient temperature can vary between 12 °C and 32 °C from winter to summer [23]. A positive correlation between ambient temperature and energy consumption might have been found. This is something that must be taken into consideration when benchmarking mines.

1.5.3 Studies on industrial energy benchmarking

Ballantyne and Powell, 2014 [24]

A study for benchmarking the energy use of gold and copper comminution was done by Ballantyne and Powell in 2014 [24]. The results of the study allowed mines to determine rankings of energy efficiency when only considering comminution.

When only considering the gold mine benchmarking section of the study, it is seen that Ballantyne and Powell used reported data to determine energy intensity [24]. For this study, the energy intensity was calculated as energy unit per ounce of gold produced (kWh/oz). The results were displayed in a bar chart with the width of bars indicating annual production per mine and the height of bars indicating energy intensity per mine [24]. This is shown in Figure 3.

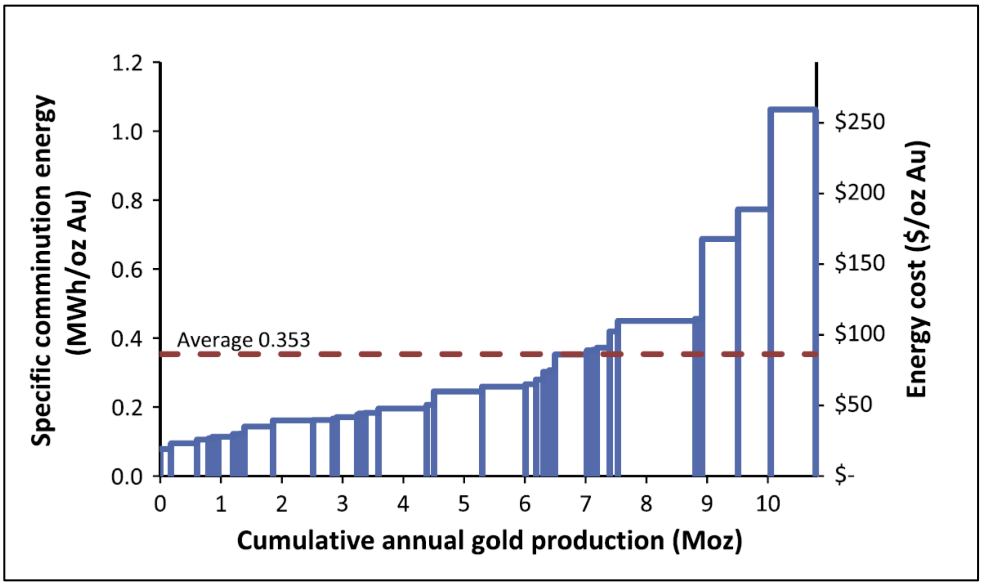


Figure 3: Benchmarking results of Ballantyne and Powell's study [24]

From Figure 3 it can be seen that a mine can determine its energy efficiency score when compared with other mines in the industry. It is seen that the majority of mines used in the study had a reasonably low intensity with the three least efficient mines drastically increasing the average. Using an average to separate efficient and inefficient mines in this study produced a distorted result. Due to very high intensities for the least efficient mines when compared with the rest, rather using a median would have shown that the benchmark intensity was lower.

Chan *et al.* 2014 [25]

Chan *et al.* conducted a study on energy benchmarking of industrial processes in Taiwan [25]. Industries including iron, steel, chemical, cement, textile, pulp and paper were selected for this study. Energy consumption data was collected and by using energy and mass balances of fuel and electricity, specific energy consumption (SEC) was determined for the various industries [25].

SEC calculated as gigajoule per ton (GJ/ton) was calculated for several years for each of the industries. This was to show changes of energy efficiency over time and to identify potential high or low energy efficient industries when compared with previous performance. The

SECs for blast furnace–basic oxygen furnace (BF–BOF) and electric arc furnace (EAF) steelmaking are shown in Figure 4 as determined by Chan *et al.*'s study.

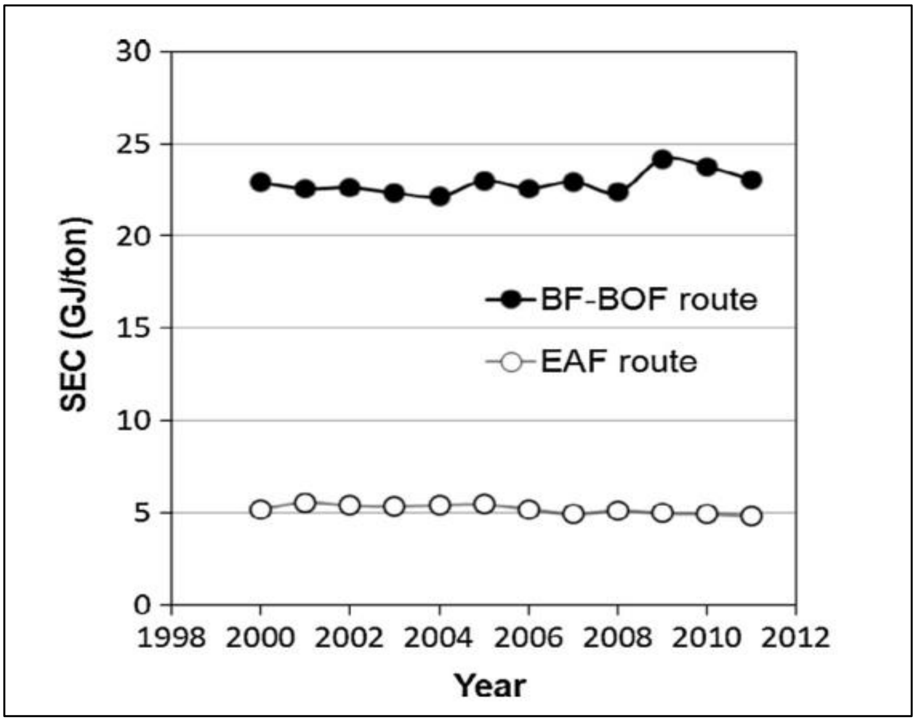


Figure 4: SEC for steelmaking [25]

By comparing the calculated SECs for the different industries with best practice technology, Chan *et al.* identified energy efficiency increase potential [25]. For steelmaking, an improvement of 28% in energy efficiency was identified when compared with best practice technology – it was recommended to apply energy saving actions.

Instead of only calculating SECs for benchmarking, Chan *et al.* also compared results with best practice technology. This allowed industries to not only determine efficiency in comparison with peers, but also to be educated in the potential of increased energy efficiency and lower SEC.

Sardeshpande *et al.* 2007 [26]

In 2007, Sardeshpande *et al.* used a different approach to energy benchmarking when compared with previously discussed studies. A simulation model for the energy consumption of a glass furnace was developed by using energy and mass balances [26]. The traditional benchmarking approach of using statistical analysis of actual data to compare performance was substituted by the simulation model for this study [26].

The simulation model predicted minimum energy consumption for different glass furnace configurations [26]. This predicted energy consumption was compared with real-time actual furnace energy consumption and showed potential energy inefficiencies. By varying parameters, the potential for increased energy efficiency could also be shown by the model before being implemented on an actual furnace [26].

The model-based benchmarking technique is a very informative method for determining energy efficiency. Assessing actual industrial process efficiency in comparison with a model can clearly show areas where improvements are possible. However, using a traditional statistical analysis of actual data is also recommended for benchmarking. Knowing actual capabilities within industry standards in combination with model-based capabilities, gives a better indication of overall energy consumption performance as compared with the industry.

Ke *et al.* 2013 [27]

The 2013 study done by Ke *et al.* focused on developing a process-based energy benchmarking method [27]. It was found that process-based benchmarking was able to evaluate the intricacies of complex system interconnections and through this, accurately identify energy savings potential [27].

Various difficulties were found by Ke *et al.* while developing process-based benchmarking. Firstly, it was problematic to break complex systems down into subsystems due to the disassociation found between subsystems. Secondly, actual industrial systems would never have exactly the same processes and energy consumption parameters. The third problem was the difficulty in obtaining accurate and exact system-specific data [27].

Mitigation of the abovementioned problems was discussed in the study. It was stated that traditional statistical analysis benchmarking methods could be applied. Approximation, linearization, mathematical transformation and normalisation could be used in instances where process-based benchmarking methods failed to compute accurately [27].

Process-based benchmarking was also compared with the more traditional product-based benchmarking. According to Ke *et al.*, product-based benchmarking is simpler to apply to industry and requires less data collection. However, the shortfall of product-based benchmarking is the inability to provide an explanation for identified inefficiencies. This is not the case with process-based benchmarking because individual processes are analysed [27].

Recommendations made by Ke *et al.* for wider application of process-based energy benchmarking included the following [27]:

- Acquisition of high quality data.
- Participation of knowledgeable staff in the industry when compiling benchmarking methods.
- Development of internal benchmarking methods or models to prevent the disclosing of sensitive data to third parties.

Nadolski *et al.* 2014 [28]

The objective of Nadolski *et al.*'s study in 2014 was to develop a method for determining minimum practical energy requirements for mineral comminution. This method was designed by experimentally determining the energy requirements for breaking ore into different particle sizes. Minimum practical energy intensity in kWh/tonne was determined for different comminution methods and compared with actual measured and collected data [28].

The results of the study displayed a benchmark energy factor (BEF) for each of the considered comminution methods. The BEF was calculated by dividing the actual intensity with the minimum practical energy (both in kWh/tonne). A lower BEF indicated a more energy efficient process and, consequently, the most efficient comminution process could be determined [28].

1.5.4 Studies on deep-level mine energy benchmarking

Van der Zee, 2013 [29]

A study conducted by Van der Zee in 2013 modelled electricity cost risks and opportunities on South African gold mines. Part of the study included the benchmarking of various gold mines according to electricity consumption of various high electricity-using systems. These systems included compressed air, water supply, water pumping and refrigeration systems [29].

Data elements that were selected to benchmark the electricity use of eight different mines are shown in Table 1 [29].

Table 1: Elements for benchmarking (adapted from [29])

Element	Description
Mine operation size	Number of production levels
	Number of mineshafts
	Number of employees
Mine profit contribution	Gold grade (g/t)
	Operating cost
	Reported profit
Mining technology	Conventional mining
	Mechanised mining
Mine depth	Shallow (<2 000 m)
	Deep (<3 000 m)
	Ultradeep (>3 000 m)
Production and electricity consumption	Tonnes produced
	Annual electricity consumption

After Van der Zee benchmarked mines according to the descriptive elements identified in Table 1, a consumption benchmark for each of the high electricity-using systems was investigated. Electricity consumption for these systems was linked to total mine electricity consumption and production. By comparing the system consumption benchmarks with the descriptive element benchmarks for each mine, Van der Zee identified electricity savings potential. These potential savings were validated by implementing the benchmarks on case studies [29].

Van der Zee touched on some of the factors that correlated with the electricity consumption of the three mining systems (compressed air; water supply and pumping; and refrigeration). However, when examining system-specific fundamentals (to be discussed in Section 2.2 to Section 2.6), additional deciding elements in electricity consumption were identified. The three high electricity-consuming systems from Van der Zee's study are discussed in the subsections that follow.

Compressed air

Additional factors that could have been considered because of their direct influence on compressor electricity use are:

- Ambient air temperature
- Ambient air pressure

These factors were derived from compressed air fundamentals (to be discussed in Section 2.2.3).

Refrigeration

An absent factor to consider when benchmarking refrigeration is the average ambient air temperature at the mine site. This is evident from refrigeration fundamentals (to be discussed in Section 2.3.3) as mining sites with higher average ambient temperatures require higher cooling capacity.

Water supply and pumping

For water supply and water removal via pumping, no additional energy consumption correlation factors could be identified when considering water removal fundamentals (to be discussed in Section 2.4). The main determining factors for energy required for water removal were addressed by Van der Zee. These factors included pumping system efficiency, water flow required and pumping head required.

Tshisekedi, 2009 [30]

Tshisekedi's study on energy consumption costs and standards on South African gold and platinum mines also benchmarked energy use. Data obtained by Tshisekedi comprised total annual energy consumption and ore production for various South African gold and platinum mines. From this data, energy intensity per mine was established in kWh/tonne as shown in Figure 5 [30]:

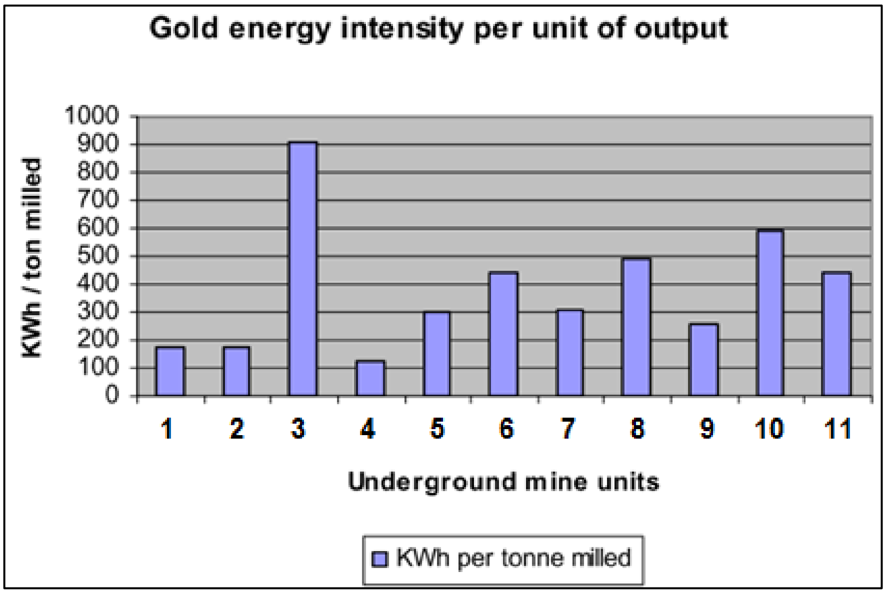


Figure 5: Energy intensity for various mines (adapted from [30])

Criteria selected by Tshisekedi for benchmarking included the following [30]:

- Mining depth
- Mine production
- Degree of mechanisation
- Productivity
- Environmental impact

By categorising the mines shown in Figure 5 according to the above criteria, Tshisekedi attempted to set kWh/tonne benchmarks corresponding to each of the criteria. When using average intensity and mining depth as the only criteria, the following results were found [30]:

Table 2: Average intensity with mining depth (adapted from [30])

Mine depth	Gold ore kWh/t	Platinum ore kWh/t
Shallow (<2 000 m)	262	290
Medium (<3 000 m)	484	114
Deep (<4 000 m)	245	–
Ultradeep (>4 000 m)	309	–

Analysing the results shown in Table 2 indicated that Tshisekedi's study found no correlation between mine depth and energy intensity. Due to Tshisekedi using total annual energy consumed by the mines and processing plants to calculate this intensity, the effect of depth on energy consumption cannot be seen. It could be that the mines used for Tshisekedi's study had very inefficient processing plants or other systems that greatly contributed to the total energy consumption.

If an approach was used to benchmark single systems on mines, especially by including systems that would undoubtedly show a correlation with depth, a clearer outcome would have been realised. Let us assume, for example, that all of the mines used in Tshisekedi's study had equally efficient systems that did not include those that correlated with depth. It would have been clear from the results in Table 2 that the medium-depth gold mines had a much lower system efficiency when correlated to depth than deep or ultradeep mines would have.

1.6 RESEARCH OBJECTIVES

Awareness of system and overall efficiency is vital to the South African deep-level mining sector. Chapter 1 showed the high electricity use of various systems in the mining industry. With these systems contributing to the bulk of electricity use on deep-level mines, any inefficient operation has a major impact on utility costs. This also directly correlates to an increased intensity (kWh/tonne) and lowered profits.

It was shown in Section 1.4 that benchmarking is an effective method for determining operational efficiency. Benchmarking clarifies the system and the overall level of efficiency of a deep-level mine and, in doing so, makes stakeholders aware of possible profit increases. This can be realised by either altering present operational practices or by implementing energy savings projects on the affected system.

Previous research in the field of energy benchmarking of various industries was reviewed in Section 1.5. Possible limitations of these studies as well as recommendations made by these studies are summarised below:

- Various factors influencing energy consumption were not considered independently for benchmarking. Categorising subsystems according to independent factors was not done (Chan, 2012 [19]), (Filippín, 2000 [20]).
- Normalisation of external factors was not attempted (Filippín, 2000 [20]).
- Categorisation was used to implement focused benchmarking on similar subsystems. Additional categorisation with external factors should have also been used to acquire more accurate results (Keirstead, 2013 [21]).
- Relevant external factors were not considered when the benchmarking method was applied (Mui *et al.* 2007 [22]).
- Not all comparison methods were used. Using multiple methods could have given a more accurate and/or different result (Ballantyne and Powell, 2014 [24]).
- Alternative benchmarking method was not verified by traditional methods (Sardeshpande *et al.* 2007 [26]).
- The use of company-owned benchmarking methods prevent disclosure of sensitive data to external parties (Ke *et al.* 2013 [27]).
- Subsystems and their fundamentals should be considered when attempting to benchmark accurately (Van der Zee, 2013 [29]), Tshisekedi, 2009 [30]).

- The use of best practice models allows benchmarking of systems with peers as well as with optimal operational procedures (Chan, 2012 [19]), (Filippín, 2000 [20]), (Keirstead, 2013 [21]). (Mui *et al.* 2007 [22]), (Ballantyne and Powell, 2014 [24]), (Ke *et al.* 2013 [27]), (Van der Zee, 2013 [29]), (Tshisekedi, 2009 [30]).

The first objective of this study is to benchmark high electricity-using systems on South African deep-level mines. These systems include compressed air, cooling, dewatering, ventilation and hoisting systems. Practical models based on actual data are produced for these systems and for the main operational mining system as a whole. The second objective is to develop best practice models for each of the high electricity-consuming systems and the main operational mining system as a whole.

Models created by achieving this study's objectives will enable South African deep-level mine energy managers to determine individual systems' efficiencies in terms of intensity easily. The intensity of each system will prove the efficiency or inefficiency of the system when compared with other mines in South Africa; and also to high efficiency or best practice systems in South Africa. Through this knowledge, mine energy managers will be aware of the areas in their mining operation that need energy optimisation and with this knowledge, attempt mitigation methods. Together with mitigation prioritisation, mine energy managers will also be able to use benchmarks to determine production targets or to calculate energy consumption budgets for specific targets.

1.7 ORIGINAL CONTRIBUTIONS OF STUDY

1.7.1 Original Contribution 1

New average benchmarking models for the energy use of deep-level mines' individual high demand systems based on actual data

What needs to be done?

An easy-to-use method for comparing the high-demand system-energy consumption requirements of different mines needs to be developed. These high demand systems include compressed air, cooling, dewatering, ventilation and hoisting systems. Using average benchmarking procedures will allow mines to determine efficiency scores in terms of energy consumption of specific systems compared with industry average.

How is the comparison currently done?

Mines use their own internal methods for comparing energy consumption or system intensity. However, there are no specific methods for comparing or benchmarking individual high-demand system-energy consumption across mine group borders on deep-level mines.

Why are the current methods insufficient?

Methods used by mines do not consider external factors when quantifying energy consumption comparisons. But, by comparing the high-demand system-energy use of different mines, individual mines would be made aware of their performance as compared with the average of peers.

How does this study solve the problem?

This study will use actual data from various deep-level mines situated in South Africa to formulate individual, accurate models for each of the high demand systems. Influential external factors will be taken into account to ensure that no preference is given to a mine based on operational efficiency alone.

1.7.2 Original Contribution 2

New best practice benchmarking models for the energy use of deep-level mines' individual high demand systems based on actual data

What needs to be done?

Mines must be compared using best practice benchmarking methods for high-demand system-energy consumption.

How is benchmarking currently done?

From literature reviews, it was found that no present best practice benchmarking procedures or models are available for specific high demand systems on deep-level mines.

Why are the models insufficient?

When comparing individual high-demand system-energy consumption with a best practice benchmark, a mine will be able to know how efficient a system is as opposed to the best in industry. This will assist a mine in deciding to take action toward more efficient operations if necessary. For this reason, best practice models need to be created.

How does this study solve the problem?

Best practice models will be developed by using actual data from existing mines in South Africa. These models will quantify the best practice energy consumption per high power demand system.

1.7.3 Original Contribution 3

A new method for prioritising energy efficiency interventions on deep-level mine high demand systems

What needs to be done?

The implementation of energy efficiency interventions on deep-level mine high power demand systems must be prioritised.

How is prioritisation currently done?

No specific prioritisation methods can currently be identified. However, there are external parties that may be able to conduct investigations on different systems to identify the need for energy efficiency initiatives.

Why are the prioritisation methods insufficient?

Possible present methods are insufficient when considering the amount of data and information required to determine system inefficiencies accurately. Not all mines have the necessary information available for this calculation. A new method needs to be developed to prioritise the focus on high-demand system-energy efficiency interventions that are easy to implement.

How does this study solve the problem?

A contribution of this study is to benchmark high demand systems with mine data that is generally available. Through the models developed for benchmarking the different high demand systems, mines will be assisted in deciding which of the high demand systems should be focused on when energy efficiency initiatives have to be implemented. The implementation of these initiatives can thus be prioritised.

1.7.4 Original Contribution 4

A new method for determining operational budgets of high demand systems on deep-level mines

What needs to be done?

Mines must create budgets for energy consumption of different individual high power demand systems.

How is it budgeting currently done?

Mines have different methods to budget for operational expenditure. These include using historical data as future budgets as well as predicting budgets according to production targets.

Why are the budgeting methods insufficient?

Standard methods are not used to determine operational budgets accurately. On many of the mines, budgets are allocated according to previous minimums, which may result in unreachable targets. Different mines from the same company might also use different budgeting methods. This can lead to budgets being misallocated to different mines.

How does this study solve the problem?

By using the benchmarking models developed for this study, electricity consumption budgets for different high demand systems can be determined. The average energy consumption per month for a specific system can be calculated according to a certain production target in tonnes of ore mined. This calculation can also be reversed by inserting fixed budgeted energy consumption into the models to obtain an approximate production yield relative to the budget.

1.8 THESIS LAYOUT

Chapter 1 – The introductory chapter consisted of several elements that needed to be discussed as a background to this study. Electricity use and the severity thereof on deep-level mines in South Africa were investigated firstly.

The method to create energy use awareness through benchmarking was discussed and previous studies on this topic were reviewed. From the evaluation of previous research, the need for this study and novel contributions were formulated.

Chapter 2 – This chapter researches various aspects relevant to the need of this study. This includes a specific study on high electricity-consuming systems of deep-level mines. Factors that directly influence the electricity consumption of these systems are reviewed, as well as previous studies on reducing electricity consumption of these systems.

The second part of this chapter consists of an in-depth look at various methods of energy benchmarking that are applicable to deep-level electricity use. Taking methods of energy benchmarking together with system-specific fundamentals into account, the tools needed for designing new methods are identified.

Chapter 3 – The methodology chapter develops a new method for benchmarking the energy use of high demand systems of mines – individually as well as combined.

The first phase of the methodology develops models using actual data obtained from different mines in South Africa. The second phase of the methodology develops a method for scoring individual system energy performance for different mines. This is done by using the models obtained during the first phase.

Chapter 4 – Verification procedures are conducted in Chapter 4. Developed models are verified and new techniques are accomplished by comparing hypothetical results with external methods. Both average and best practice benchmarking models are verified together with the new prioritisation methods for energy efficiency initiatives and energy budget forecasting.

Chapter 5 – Validation of new models and methods is accomplished in this chapter by using nine case study mines situated in South Africa. Applying the models and methods to these case studies produces quantifiable results.

Chapter 6 – This chapter concludes the study as well as recommends possible enhancements to the developed models. The recommendation to expand models to other industries is also discussed.

1.9 SUMMARY

Chapter 1 conveyed background information on deep-level mines in South Africa as well as their high energy consumption. Different studies conducted on energy benchmarking and the awareness they produced toward energy use and the possible saving thereof were also discussed. By reviewing previous research and information found on deep-level mines, the need for this study was identified and the novel contributions that the study produced were explained.

CHAPTER 2 – Energy intensive systems and benchmarking methods

[2]

[2] C. Cilliers, Personal photograph. "Fridge plant", Carletonville, 2014.

2.1 PREAMBLE

Important aspects of high electricity-using systems on South African deep-level mines and potential benchmarking methods are discussed in this chapter. An in-depth look at the parameters which determine high electricity use on various systems is presented. Factors affecting electricity use for each of the mining systems are analysed and classified for benchmarking.

2.2 COMPRESSED AIR SYSTEM

2.2.1 Background

A compressed air system of a deep-level mine is a critical part to all operations [31]. Due to the upgradability and alterability, ease of use and consistency of a compressed air system, it is still the preferred energy carrier in deep-level mines [32].

Industrial centrifugal compressors generate compressed air. These compressors have installed power capacities ranging between 1 MW and 15 MW [33]. Compressors feed compressed air directly into the compressed air system. This system comprises a network of steel pipes situated above ground and underground with a diameter ranging from 150 mm to 700 mm [34].

Applications for compressed air as an energy carrier are similar for different types of mine and include surface operations, underground operations and unregulated operations [35]. Any requirements from the compressed air system – be it pressure for using pneumatic cylinders or flow for fluid agitation – are tapped directly from the compressed air network. The whole network is thus always fully charged to deliver compressed air.

The compressed air system can be divided into a demand and supply side. The supply side includes physical compressors and pipe networks which produce compressed air at a certain pressure and flow. The demand side consists of various end users converting pressure and flow energy into mechanical energy.

2.2.2 Compressed air system supply

Multistage centrifugal compressors, which fall within the dynamic compressor category, are the preferred units for compressed air generation on South African deep-level mines [36]. These machines use multiple stages to increase pressure to the desired final output pressure of approximately 550 kPa [34]. Electric synchronous motors rotate compressor impellers using their installed power capacity of between 1 MW and 15 MW [36].

Two or more mines are frequently found within a few kilometres of each other. Instead of having one compressor with one network for each mine, a mutual compressed air ring is used to supply compressed air to all of the mineshafts. These compressed air networks can have a total length in excess of 40 km [34]. Figure 6 shows the typical layout of the surface section of a multishaft compressed air network.

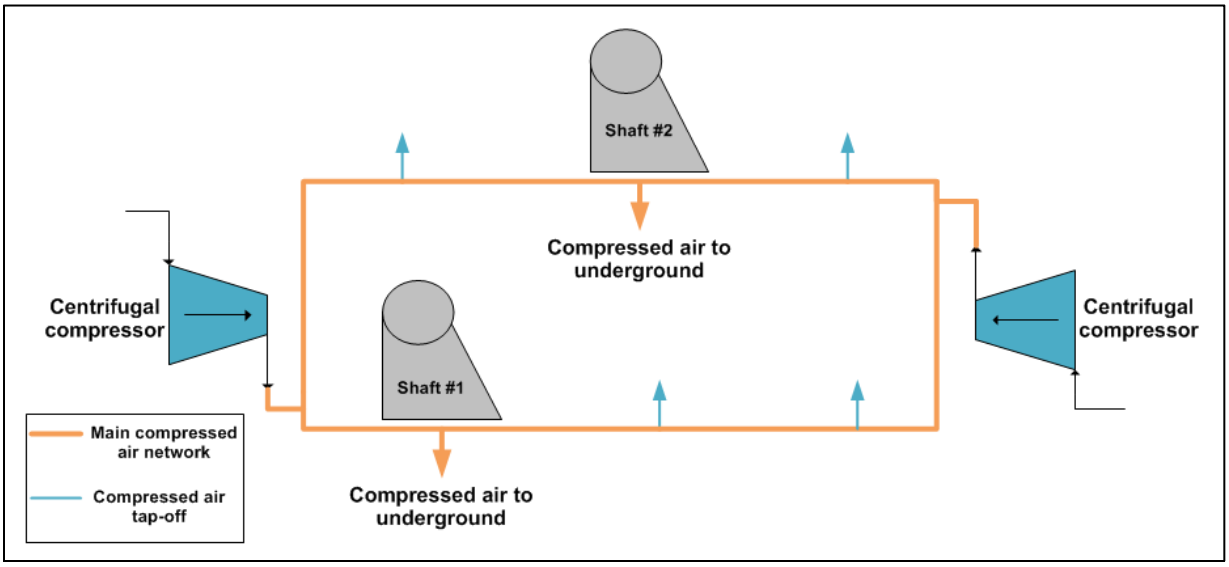


Figure 6: Surface compressed air network

Using compressed air underground ensures a robust and constant feed of energy to the mine. Large steel columns are usually installed within a mineshaft, with additional columns feeding from the main column on each mining level. This can be seen in Figure 7.

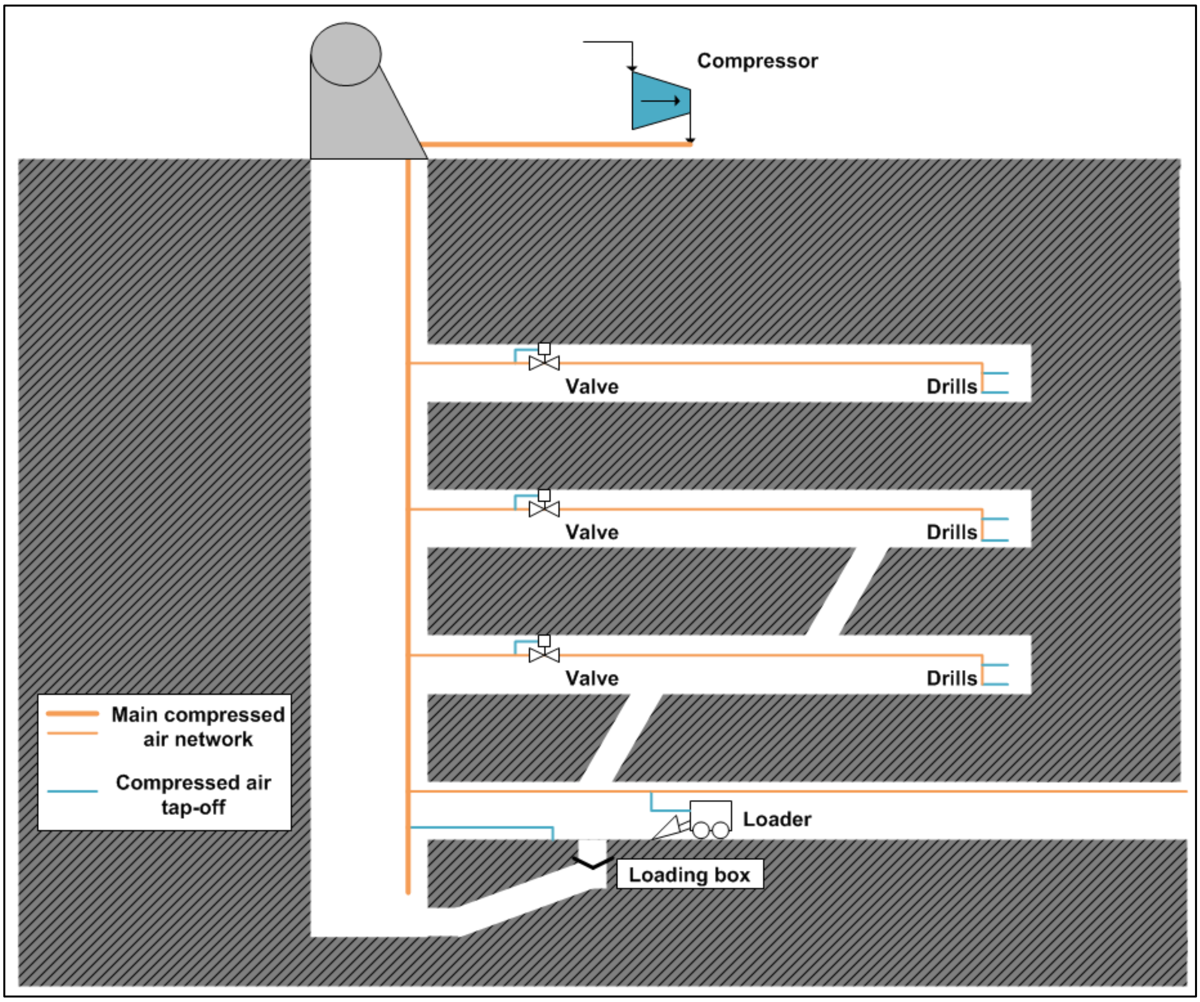


Figure 7: Underground compressed air network

2.2.3 Fundamentals of compressed air supply

Studies on mine compressed air energy management were done by Bredenkamp [35], Van Tonder [37] and Snyman [38]. Through these studies, substantial electricity cost savings were realised by implementing various energy reduction methods on mine compressed air systems.

Fundamental calculations for the power output necessary to compress air for certain system requirements were given by Bredenkamp, Van Tonder and Snyman as the following [35], [37], [38]:

Equation 1: Compressor motor power calculation

$$\boldsymbol{P_{motor}} = \frac{\boldsymbol{P_{comp}}}{\boldsymbol{\eta_{motor}}}$$

With: P_{motor} = Power required by motor (kW)

P_{comp} = Power required by compressor (kW)

η_{motor} = Motor efficiency

Equation 2: Compressor power calculation

$$\boldsymbol{P_{comp}} = \dot{\mathrm{m}}_{\boldsymbol{air}} \times \boldsymbol{W_{comp}}$$

With: P_{comp} = Power required by compressor (kW)

$\dot{\mathrm{m}}_{air}$ = Mass flow rate (kg/s)

W_{comp} = Mechanical energy per mass air unit (kJ/kg)

Equation 3: Compressor mechanical energy calculation

$$\boldsymbol{W_{comp}} = \frac{\boldsymbol{nRT_{in}}}{\boldsymbol{\eta_{comp}(n-1)}}\left(\left(\frac{\boldsymbol{p_2}}{\boldsymbol{p_1}}\right)^{\frac{\boldsymbol{n-1}}{\boldsymbol{n}}} - \mathbf{1}\right)$$

With: W_{comp} = Mechanical energy per mass unit (kJ/kg)

n = Polytropic constant for isentropic compression

R = Gas constant for air (kJ/kg.K)

T_{in} = Compressor inlet temperature (K)

η_{comp} = Compressor efficiency

p_2 = Compressor discharge pressure (kPa)

p_1 = Compressor inlet pressure (kPa)

It was shown in Section 2.2.2 that compressed air networks can have total lengths of 40 km or more. The age of the pipes and the moisture content in the compressed air contribute to pipe corrosion that increases friction within the pipes [32]. This friction encourages pressure loss which is directly proportional to the length of the pipe [39]. The isothermal calculation of compressed air pressure drops, due to pipe friction in compressed air networks, can be calculated with the Darcy–Weisbach equation [35]:

Equation 4: Darcy–Weisbach pressure loss calculation

$$\Delta P = \frac{f\rho L Q^2}{82.76D^5}$$

With: ΔP = Pressure loss (kPa)

f = Friction factor

ρ = Density of compressed air (kg/m^3)

L = Pipe length (m)

Q = Volume flow rate (m^3/s)

D = Inside diameter of pipe (m)

According to Joubert *et al.* in 2012, compressed airflow will be turbulent [39]. This corresponds to a Reynolds number (*Re*) of more than 4 000 which is calculated using Equation 5 [39]. Once the Reynolds number (*Re*) has been calculated, the Colebrook–White equation for determining the friction factor that corresponds to turbulent flow can be used (Equation 6).

Equation 5: Reynolds number calculation

$$Re = \frac{\rho v D}{\mu}$$

With: Re = Reynolds number

ρ = Density of compressed air (kg/m^3)

v = Airflow velocity (m/s)

D = Inside diameter of pipe (m)

μ = Dynamic viscosity of air (kg/m.s)

Equation 6: Colebrook–White friction factor calculation

$$\frac{1}{f} = -2log_{10}\left(\frac{e}{3.7D} + \frac{2.51}{Re\sqrt{f}}\right)$$

With: f = Friction factor

e = Pipe roughness (m)

D = Inside diameter of pipe (m)

Re = Reynolds number

Pipe roughness varies depending on the pipe material used during manufacturing. The following table shows pipe roughness for generally used pipe materials [35]:

Table 3: Compressed air pipe material roughness (adapted from [35])

Material	Roughness (m)
Wrought iron	0.000045
Commercial steel	0.000045
Galvanised iron	0.000150
Cast iron	0.000260
Riveted steel	0.0009–0.009

A study done by Garbers *et al.* in 2010 explained the benefits of a phenomenon known as autocompression [40]. Autocompression occurs when air is compressed by its own weight [40]. This generally happens on mines with depths in excess of 100 m and can realise a pressure increase of approximately 10.25 kPa per 1 000 m of depth [40].

It is important to consider the effect of autocompression when focusing on the fundamentals of supplying compressed air on a deep-level mine. The increase of pressure as mining depth increases has a direct effect on compressed air usability [40]. The pressure gain due to autocompression can be calculated using Equation 7 [35]:

Equation 7: Autocompression calculation

$$\boldsymbol{p_2 = p_1 \left(1 - \frac{g(Z_1 - Z_2)}{T_1 C_p}\right)^{\frac{1}{k}}}$$

With:
- p_2 = Final pressure (kPa)
- p_1 = Initial pressure (kPa)
- g = Gravitational acceleration (m/s^2)
- Z_1 = Initial altitude (m)
- Z_2 = Final altitude (m)
- T_1 = Temperature of compressed air (K)
- C_p = Specific heat capacity of compressed air (kJ/kg.k)
- k = Specific heat ratio of compressed air

2.2.4 Compressed air system demand

There are various compressed air end users on a deep-level mine. Demand can range from surface to underground operations with processes requiring high pressure air, high flow air or a combination of both [41]. In 2012, Marais identified compressed air end users for surface and underground operations on deep-level mines [34]. Subsequently in 2013, Bredenkamp stated the compressed air volume flow and pressure requirements necessary for these operations to function [35].

Surface operations [34], [35]

Processing plants (0.08–0.7 m^3/s at 420–500 kPa)

Compressed air is released through large tanks containing an ore concentrate to facilitate gold recovery. This is known as agitation. Pneumatic instrumentation such as valve actuators use compressed air for mechanical movement.

Workshops (0.028 m^3/s at 200–250 kPa)

Mine workshops manufacture retrofitted parts and maintain worn or damaged parts. Pneumatic tools are used for this purpose.

Pneumatic cylinders (0.0006–0.14 m^3/s at 350–600 kPa)

After gold or platinum ore has reached the surface, ore-moving systems in the form of pneumatic doors and chutes are used to transport the ore to designated areas. These doors and chutes use pneumatic cylinders for operation.

Miscellaneous surface operations (~0 m^3/s at 350–600 kPa)

Pneumatic instrumentation is found on surface water and air columns. These include actuators on valves and guide vane control for compressors and fans. Pneumatic cylinders within the actuators and guide vane control systems convert pressure into movement. Pneumatic actuators are the most widely used type of actuator [42].

Underground operations [34], [35]

Rock drills (0.06–0.42 m^3/s at 400–620 kPa)

To extract gold- or platinum-bearing ore from a mine, the ore has to be released from the surrounding rock. Blasting of the rock by high power explosions is one of the most effective ways of releasing ore. To ensure that enough ore is released, explosive material has to be implanted within the rock to a certain depth. Pneumatic rock drills are used for creating deep blast holes wherein explosives are placed.

According to Fraser in 2010, between 12 kg and 24 kg of air is required to extract one tonne of ore [43]. This amount of air includes rock breakers, loaders, loading boxes and all other equipment needed to transport the ore to surface.

Rock breakers (0.28 m^3/s at 450 kPa)

Ore and waste rock that has been released by explosives has to be broken down to more manageable sizes. Large pneumatic rock breakers are used to decrease rock size and allow the broken rock to be transported by pneumatic loaders.

Pneumatic loaders (0.28 m^3/s at 550 kPa)

Trackbound pneumatic loaders have bulldozer-like front loaders used to load ore and waste rock into hoppers. These hoppers are pulled to loading bays when they are full and tipped using pneumatic cylinders thus triggering the ore and rock to fall into loading boxes.

Loading boxes (0.0006–0.14 m^3/s at 350–600 kPa)

Ore loaded into loading boxes accumulate until a certain weight is reached (measured with a loading cell) or when a hopper is moved underneath the loading box. When this happens, pneumatic cylinders open a door or chute beneath the loading box resulting in the ore falling into the hopper. Loading boxes are also used at the bottom of the mineshaft where all mined ore accumulates. Loading boxes are used to fill skips with ore before being hoisted to surface via a winder.

Agitators (0.47 m^3/s at 400 kPa)

Water used for cooling purposes and groundwater released from mining operations accumulate in underground dams. This water is usually very dirty and filled with mud and other small particles. In order to keep the mud and particles from settling at the bottom of underground dams, compressed air is released through the water. This is known as agitation and ensures that a homogenous solution of water and particles moves through pumps and water columns.

Refuge bays (0.0014 m^3/s per person at 200–300 kPa/person)

Refuge bays are chambers within mines that have positive atmospheric charges relative to the pressure outside the chambers. The main purpose of a refuge bay is to house mine employees in the case of a toxic or flammable gas leak. Gases are prevented from entering the chambers due to a higher in-chamber pressure.

Venturi blowers (0.019–0.091 m^3/s at 350–620 kPa)

Due to the ever-increasing depths of South African deep-level mines, ventilation of fresh air for mining personnel is necessary to ensure safety. Venturi blowers circulate fresh and cool air throughout the underground mining levels.

Open-ended pipes (0.2–1.6 m^3/s at 100–650 kPa)

Open-ended pipes connected to compressed air columns are used to blow dust from mining and newly developed areas. However effective this method for moving dust and small rocks may be, it is very inefficient and requires more work from compressors to maintain pressure set points throughout the compressed air system.

Miscellaneous underground operations (~0 m^3/s at 350–600 kPa)

Underground compressed air and water columns require valves to control or obstruct the flow of the medium within the columns. Pneumatic actuators are commonly found on these valves throughout the mining area and are operated by pneumatic cylinders within the actuators.

Unregulated operations

Unregulated operations are a common occurrence at South African gold and platinum mines. Due to the nature of these operations, unpredictable use of compressed air emerges. This increases the electrical energy required to maintain compressed air pressure and delivery volume [35]. Unregulated operations that use compressed air in South African mines include the following [37] , [44], [45]:

Leaks (0.008–23.67 m^3/s at 500 kPa)

It is inevitable that leaks form within the vast network of compressed air columns on the surface and underground. Leaks can occur at various different areas in the network, with the most common being column flanges where pipe sections are joined. Flange gaskets inserted between columns will perish after years of service and require replacement to stop leaks. Leaks in a compressed air network decrease the network pressure and force compressors to operate at increased loads to maintain pressure.

Figure 8 shows part of the intricate compressed air network. Flanges at every pipe joint are possible areas where compressed air can leak.

Figure 8: Compressed air network flange joints[3]

Illegal mining (up to 5.8 m^3/s at 560 kPa)

The process of using an existing mine and its services to extract gold or platinum ore for one's own gain, is known as illegal mining. Illegal miners use rock drills and open-ended pipes to obtain ore more easily. This additional use of compressed air can put substantial strain on compressors.

2.2.5 Research on compressed air system optimisation

As the outcome of this study aims to highlight individual deep-level mine system efficiency, this awareness or knowledge obtained by the mine will aid in determining potential energy optimisation areas. Commitment to the implementation of energy optimisation projects on any high demand system usually results in time-consuming investigation phases and great financial expenditure for the mines. By knowing the systems' efficiencies beforehand, the number of high demand systems on which optimisation projects must be implemented can be reduced, which could greatly reduce expenditure.

Various studies on the optimisation of compressed air networks, specifically focusing on the electricity consumption thereof, have been completed. Most of the studies aimed either to reduce total daily electricity consumption or to reduce electricity during evening high demand periods only. Table 4 shows a summary of previous studies towards reducing electricity consumption of compressed air networks on deep-level mines.

[3] R Deysel, Photograph. "Compressed air pipes", Northam, 2012.

Table 4: Previous work on compressed air system energy optimisation

Authors	Energy/cost saving per annum	Description	Ref.
Marais, J.	960 GWh	A new procedure for reducing compressed air network energy use	[34]
Bredenkamp, J.	R8.9 million	Compressed air network reconfiguration	[35]
Heyns, G.	R1.9 million	Challenges of implementing a compressed air network energy reduction project	[36]
Joubert, R.	2 GWh	Cost effective methods for implementing demand side management (DSM) on compressed air systems	[41]
De Coning, A.	R10.8 million	Compressed air network control for peak and overall energy reduction	[46]
Kriel, C.J.R.	R4.2 million	Modernising existing compressed air network energy savings projects	[47]
Schroeder, F.	R108 million	Compressed air system leak reduction and pressure control	[48]
Van Heerden, S.	15.8 GWh	Dynamic control system for compressor selection	[49]
Van der Linde, S.	R100 000	Underground valve control of compressed air networks	[50]
Van Niekerk, M.	R2 million	Implementation of dynamic compressor selector programs	[51]

2.3 COOLING AND AUXILIARIES

2.3.1 Background

With virgin rock temperature (VRT) increasing approximately 12 °C per kilometre of depth in deep-level mines, cooling is required to maintain a maximum allowable wet-bulb temperature of 27.5 °C [52]. Mining operations shallower than 700 m use circulated ambient air to replace warm air. When excavation continues past 700 m, alternative strategies are required to decrease temperatures effectively to acceptable levels [53].

Large refrigeration plants situated on mine surfaces are used for deep-level mine cooling purposes. These fridge plants use the vapour-compression cycle to attain a water temperature of approximately 2 °C [54].

At South African deep-level mines, the first step in the cooling process is to move “hot water” (approximately 27 °C) pumped from underground through precooling towers [55]. A precooling tower consists of a large chamber with ventilation fans forcing ambient air through the chamber. The hot water is sprayed into this chamber and rejects heat to the ambient air through direct-contact heat exchange. This process can be repeated various times until maximum cooling of the water is reached. Maximum available cooling is subjective to ambient wet-bulb temperatures [55]. When maximum cooling of the water is reached – the hot water is known as “warm water”.

Warm water exiting the precooling tower is forced via 50–300 kW pumps into a “warm dam”. This water is now near the designed water-inlet temperature required by the fridge plants for optimal cooling and is pumped directly to the evaporator heat exchanger inlet of the fridge plants.

2.3.2 Primary cooling

The vapour-compression cycle pictured in Figure 9 uses a liquid refrigerant such as ammonia. The refrigerant is compressed to a superheated vapour through the compressor (1 MW to 10 MW) and is forced into the condenser heat exchanger [6]. The refrigerant is condensed by rejecting heat to cold water circulating through the condenser. The condensate moves from the condenser and flashes over an expansion valve. A pressure reduction due to expansion promotes flash evaporation of the refrigerant to a supercooled state. This supercooled refrigerant moves through the evaporator heat exchanger and absorbs heat from circulating warm water [56].

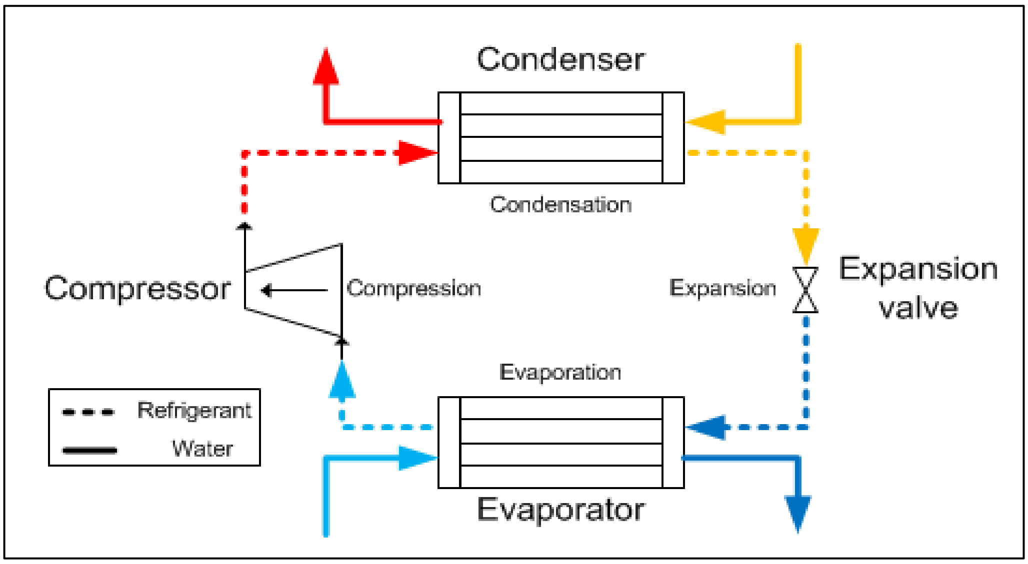


Figure 9: Vapour-compression cycle (adapted from [56])

Cooled water exiting the fridge plant evaporator heat exchanger is pumped to large surface storage dams known as “cold dams”. From these dams, water is either gravity-fed to underground mining operations or moved through bulk air coolers (BACs). The direct-contact heat exchange between cold water and ambient air within a BAC delivers cooled air of between 6 °C and 9 °C [57]. This cooled air is forced down the mineshaft to reduce high underground temperatures.

Figure 10 depicts a basic layout of a mine cooling system and shows the supply of cooled water to underground mining operations. Precooling tower (PCT), bulk air cooler (BAC) and pressure-reducing valve (PRV) are abbreviated in Figure 10.

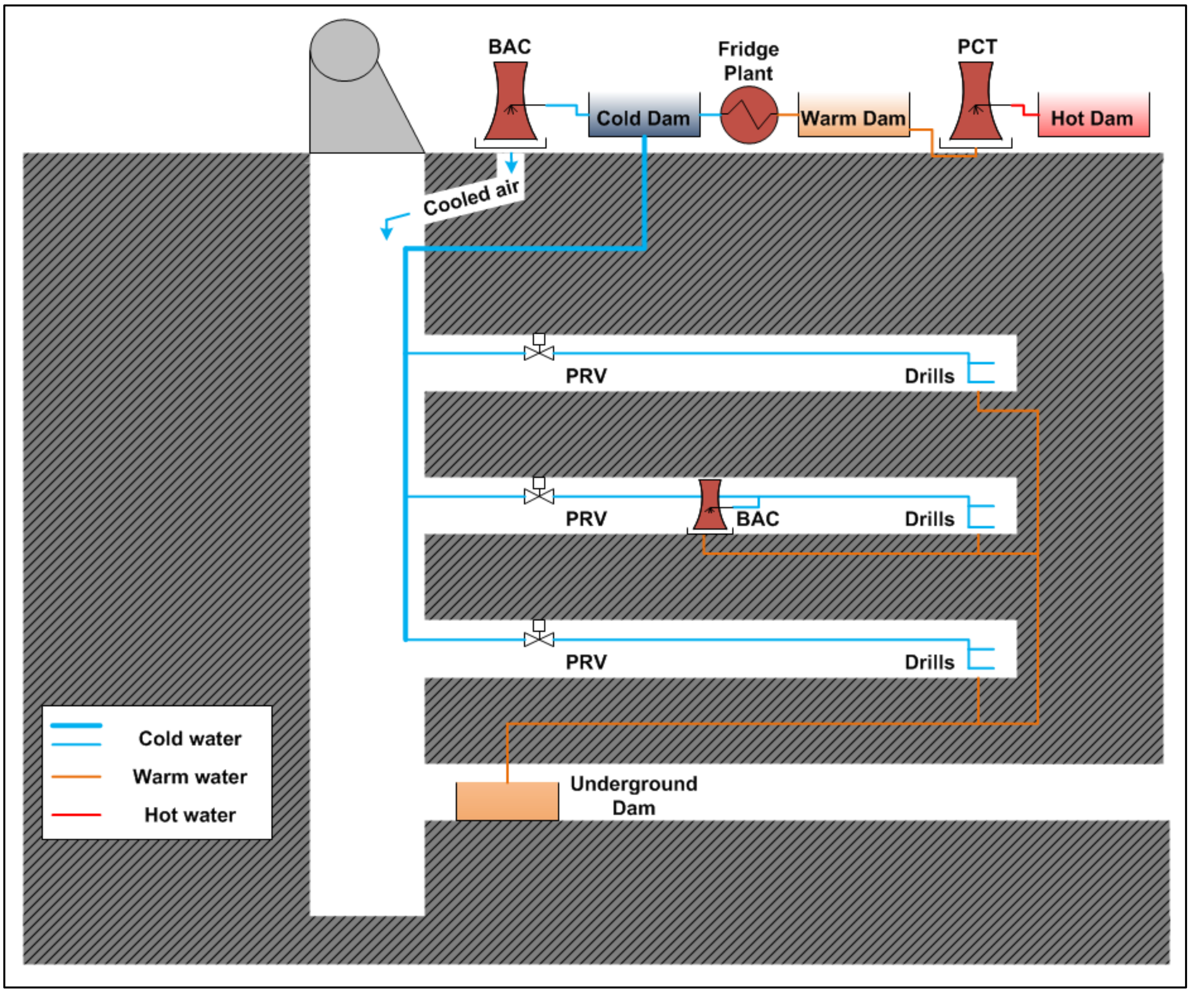


Figure 10: Cooling and water supply system

2.3.3 Refrigeration fundamental equations

In 2013, Schutte created a new strategy for reducing energy use of mine refrigeration and ventilation systems [6]. The following equations were used in this study to quantify heat absorbed by the evaporator, heat absorbed by the condenser, coefficient of performance (COP) of a single refrigeration machine, COP of the whole refrigeration system and efficiency of a fridge plant [6]:

Equation 8: Evaporator heat absorption

$$\boldsymbol{Q_{evap}} = \dot{\mathrm{m}}_{\boldsymbol{water}} \boldsymbol{C_{p_{water}}} (\boldsymbol{T_{out}} - \boldsymbol{T_{in}})$$

With:
Q_{evap} = Heat absorbed by evaporator (kW)
$\dot{m}_{water}$ = Mass flow of water (kg/s)
$C_{p_{water}}$ = Specific heat of water (kJ/kg.K)
T_{out} = Water temperature out of evaporator (K)
T_{in} = Water temperature into evaporator (K)

Equation 9: Condenser heat absorption

$$\boldsymbol{Q_{cond}} = \dot{\mathrm{m}}_{\boldsymbol{water}} \boldsymbol{C_{p_{water}}} (\boldsymbol{T_{out}} - \boldsymbol{T_{in}})$$

With:
Q_{cond} = Heat absorbed by condenser (kW)
$\dot{m}_{water}$ = Mass flow of water (kg/s)
$C_{p_{water}}$ = Specific heat of water (kJ/kg.K)
T_{out} = Water temperature out of condenser (K)
T_{in} = Water temperature into condenser (K)

Equation 10: Machine COP

$$\boldsymbol{COP_{machine}} = \frac{\boldsymbol{Q_{evap}}}{\boldsymbol{P_{motor}}}$$

With:
$COP_{machine}$ = Coefficient of performance of machine
Q_{evap} = Heat absorbed by evaporator (kW)
P_{motor} = Electric motor power (kW)

Equation 11: System COP

$$\boldsymbol{COP_{system}} = \frac{\boldsymbol{Q_{evap}}}{\boldsymbol{P_{motor}} + \boldsymbol{P_{aux}}}$$

With:
$COP_{machine}$ = Coefficient of performance of machine
Q_{evap} = Heat absorbed by evaporator (kW)
P_{motor} = Electric motor power (kW)
P_{aux} = Electric motor power of auxiliary equipment (kW)

Equation 12: Machine efficiency

$$\eta_{machine} = \frac{Q_{evap} + P_{motor}}{Q_{cond}}$$

With: $\eta_{machine}$ = Machine efficiency
Q_{evap} = Heat absorbed by evaporator (kW)
P_{motor} = Electric motor power (kW)
P_{aux} = Electric motor power of auxiliary equipment (kW)

2.3.4 Water supply and use

Water entering a mine from surface cold dams is distributed to all mining areas needing water through a water supply system. This system consists of a large network of steel pipes similar to the underground compressed air network. A main steel column is situated within the mineshaft and taps off to different mining levels. Due to the considerable depths of South African mines, the pressure must be reduced in the main water column. This is accomplished by pressure-reducing valves (PRVs) on each level [52].

Cold water supplied to production mining levels can serve a multitude of purposes. The three typical uses of water on any given production level are rock drilling, dust suppression and cooling [58]. It is thus found that water consumption in a mine is proportional to the ore production rate [5].

To sustain an average rock-face advance rate of 5 m per month on production levels, pneumatic rock drills must be used optimally [59]. Cold water feeds through pneumatic drills and cools the drill bits. This also suppresses dust released by the drilling action [60]. After blasting has occurred, ore and waste rock can be moved to loading stations using high pressure water jets. Water used for drill-cooling and for operating water jets accumulates to roughly 185 l/tonne of ore mined [43]. All of the water used in production areas ultimately accumulates in canals and gravity-feeds to lower levels [52].

When production areas are situated at great distances from the main mineshaft, secondary and tertiary cooling systems are required over and above the primary cooling system found on the surface [61]. Underground BACs ensure that mining levels are supplied with cool air. Spot coolers, situated close to the production rock face, safeguard mining employees against the harsh temperatures found at great distances from the main shaft [53]. Both the secondary and tertiary systems receive cooled water directly from the water supply pipes in each level.

According to Buys in 2014, cooling cars require cold water flow of 7 l/s to operate optimally [62]. Underground BAC water use can vary greatly and is dependent on the capacity of the BAC. On South African deep-level mines, the average flow required by an underground BAC can range between 200 l/s and 250 l/s [63].

2.3.5 Research on cooling system optimisation

As was the case with compressed air systems on deep-level mines, several studies have previously been completed on energy optimisation of cooling systems. Studies ranging from reducing overall energy by optimised variable flow to simply switching off systems during high demand periods have been conducted. A number of these studies are summarised in Table 5 below.

Table 5: Previous work on cooling system energy optimisation

Authors	Energy/cost saving per annum	Description	Ref.
Schutte, A.	R30 million	Integrating energy efficiency strategies on mine cooling systems	[6]
Buys, L.	R12.5 million	Platinum mine cooling system optimisation	[62]
Bornman, W.	20.15 GWh	Auxiliary cooling system optimisation	[64]
Holman, A.M.	52.13 GWh	Improved performance monitoring of a mine cooling system	[65]
Van der Bijl, J.	66.57 GWh	Sustainable DSM on mine cooling systems	[66]
Van Greunen, D.	20.15 GWh	Variable speed drive control of mine cooling auxiliary systems	[67]
Van Jaarsveld, S.	R1.2 million	Control system for efficient operation of BACs	[68]
Maré, P.	20.94 GWh	Improving strategies used to reduce cooling system energy use	[69]
Strydom-Bouwer, E.	R5.7 million	Load management on underground cooling systems	[70]
Swart, C.	21.02 GWh	Optimising underground cooling systems	[71]
Uys, D.C.	13.14 GWh	Ice storage to chilled water system conversion	[72]

2.4 DEWATERING SYSTEMS

2.4.1 Background and infrastructure

Flooding of underground mining areas is one of the greatest risks faced by mine management. Every litre of water sent down a mine as well as water released from subsurface fractures (fissure water) has to be pumped to the surface on a continuous basis [73]. Water used for cooling, mining and fissure water accumulates in canals and gravity-feeds to collection areas.

Water used in the mining process is usually filled with microscopic dirt particles and ore. This water needs to be cleaned to a certain extent before it can be removed from underground. Settlers are used to separate water and particles [74]. Flocculant, a chemical that reacts with solid particles in water, encourages particles to clump together [75]. The larger particles called “floc”, which is formed by flocculation, settle at the bottom of the settler (sedimentation) and allow “clear water” to overflow into underground storage dams [76].

Water accumulating in underground dams needs to be pumped to the surface. Dewatering via pumping is the most widely used method and is most commonly achieved using multistage centrifugal pumps [77], [78]. A centrifugal pump converts electrical energy to kinetic energy via an electric motor-to-pump shaft connection. The rotation of the pump shaft causes kinetic energy to be converted to pressure energy by an impeller that forces water centrifugally against a diffuser. The pressure energy within the water allows the water to be forced out through the pump’s discharge [79].

Pump stations are situated in close proximity to underground dams and can house anywhere from two to more than ten pumps with installed power capacities of as high as 20 MW per station [80]. Water is transported from one pump station to the next via a cascading method. Each consecutive pump station is situated on a shallower level in the mine, until the surface is reached. The average distance between pump station instances is 600 m but can reach up to 1 000 m [60].

The head pressure needed by centrifugal pumps to attain a positive flow for up to 1 000 m requires multistage pumps. Multiple stages allow a cumulative increase of water pressure until finally being discharged.

Dewatering pumps are typically installed in a parallel configuration rather than a series configuration. This allows maximum flow delivery when discharging into a common manifold [81]. An increase in flow may be achieved by installing additional pumps in parallel. This is evident up to a certain maximum discharge pressure experienced in the common manifold. When this pressure threshold is exceeded, system efficiency reduces and flow no longer increases [80].

A simplified layout of the dewatering system on a deep-level mine is portrayed by Figure 11.

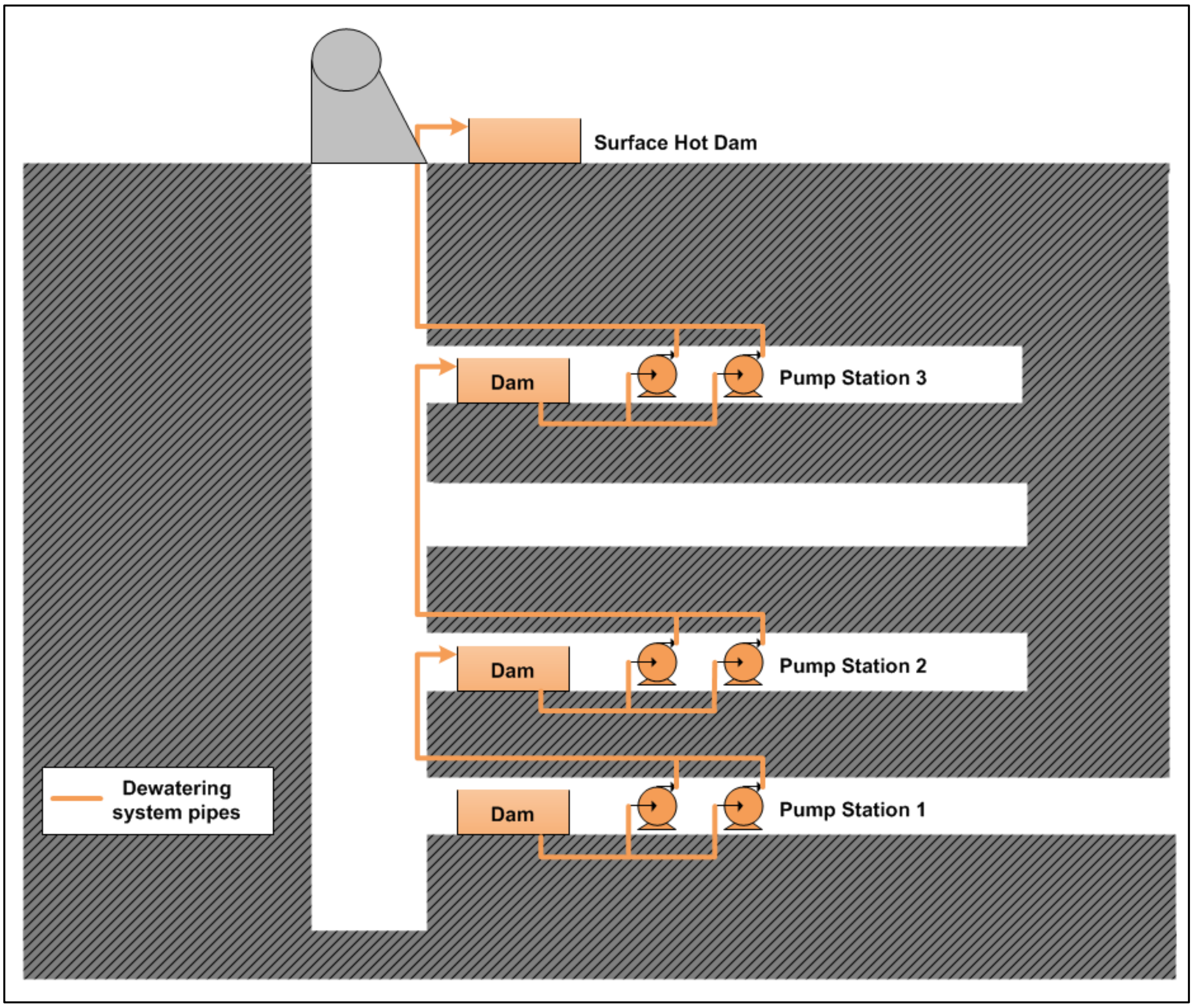


Figure 11: Dewatering system

2.4.2 Fundamentals of dewatering

According to Cilliers in 2013, the power required by a pump to remove water from a deep-level mine can be calculated by considering the power needed to move water at a certain volume flow for a certain vertical distance. This is calculated by using Equation 13 [80]:

Equation 13: Pump power required

$$P_{pump} = \frac{\rho g Q h}{\eta_{pump}}$$

With: P_{pump} = Power required (kW)

ρ = Density of fluid (kg/m^3)

g = Gravitational acceleration (m/s^2)

Q = Volume flow (m^3/s)

h = Head (m)

η_{pump} = Pump efficiency

It is apparent from Equation 13 that the power required (P_{pump}) by a dewatering pump is directly proportional to the density (ρ) of the fluid, gravitational acceleration (g), volume flow rate (Q) of the fluid and the static head (h) of the fluid that needs to be moved. Seeing as ρ and g will stay relatively constant for the purpose of dewatering, Q and h may be seen as the only two factors needed to determine P_{pump}.

2.4.3 Research on dewatering system optimisation

Most of the previous studies completed on dewatering system energy management have come to the same conclusion – that the shifting of power load from high demand periods to lower demand periods is viable. Using storage capacity in the form of dams enables dewatering pumps to "prepare" for a high demand shutdown period. Removing as much water as possible before high demand periods allows dewatering pumps to be shut down until underground dam levels again rise to their upper limits.

Table 6 shows a number of studies conducted on the shifting of power load from high demand periods to lower demand periods. As the shifted load has to be recovered at later stages, a physical reduction in energy is not accomplished. However, moving load from high demand periods with a high electricity tariff to low demand periods, which are less expensive, benefits both mines and utility companies.

Table 6: Previous work on dewatering system energy optimisation

Authors	Energy/cost saving per annum	Description	Ref.
Cilliers, C.	R1.6 million	Optimised load shifting strategies for reduced electricity costs	[80]
Oberholzer, P.	R6 million	Best practice methods of dewatering pump automation and load management	[82]
Oosthuizen, N.	R39 million	Multishaft mine dewatering system optimisation	[83]
Prinsloo, A.	R1.6 million	Automation of mine dewatering pumps and load management	[84]
Rautenbach, J.W.	R5.7 million	Developing new mine dewatering pump control system for load management	[85]
Smith, T.	R5.6 million	Automated control of mine dewatering pumps for load management	[86]
Janse van Vuuren, A.	R1.4 million	Optimisation of a mine three-pipe system for dewatering	[87]

2.5 VENTILATION

2.5.1 Background

Flammable gases such as methane commonly occur in underground excavation areas [88]. The need to create breathable air by diluting these gases is paramount to the safety of mining personnel working in underground areas. This is achieved by using a complex ventilations system that consists of various fans [89]. Deep-mine ventilation systems also displace hot air from virgin rock radiation, reduce humidity and remove dust [90].

The most common ventilation system on South African deep-level mines consists of main extraction fans situated above a ventilation shaft with smaller booster and auxiliary fans in underground ventilation areas [91]. These fans have an installed power capacity ranging between 100 kW and 3 MW and usually run uninterruptedly to ensure continuous circulation of air through the mine [88].

The use of pneumatically operated ventilation doors and a strategically branched layout of underground mining areas assist in directionality of airflow. This is necessary to introduce additional clean air to high priority areas and to decrease disproportionate air motion in populace zones that may cause discomfort [92]. Figure 12 shows a basic layout of the underground ventilation system of a typical South African deep-level mine.

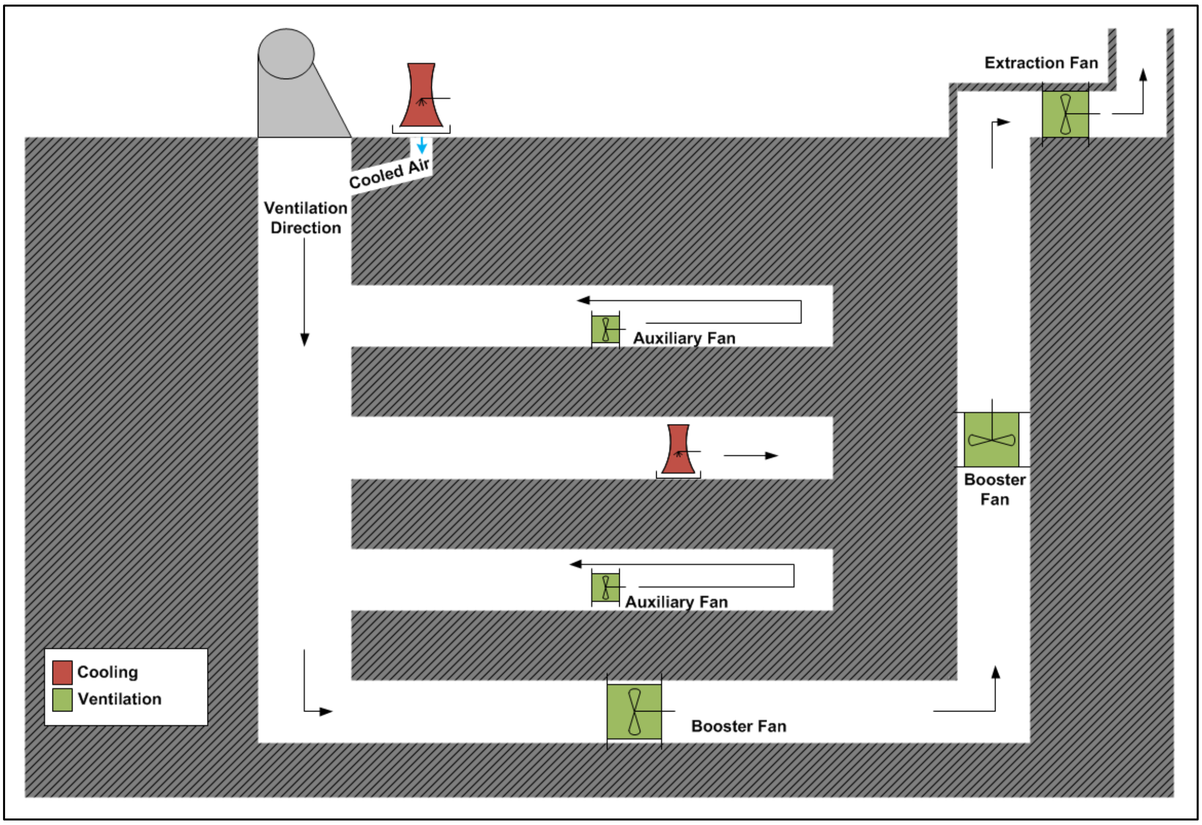


Figure 12: Ventilation system

2.5.2 Surface fans

The large extraction fans situated on surface and above ventilation shafts are the main drivers of the deep-level mine ventilation system. Two or more fans are usually installed in parallel to allow a backup unit to be ready to start. This is necessary in case of an elevated air extraction requirement due to a sudden increase of gas concentration, or when a primary fan fails [91].

According to Schutte in 2013, surface fans can extract between 0.05 m^3/s and 0.09 m^3/s of air at a constant rate [6]. The reduction in pressure of underground areas due to extraction assists in the downcast of cold air through BACs, as described in Section 2.3.2. This cool air is drawn underground and dispersed to all needed areas by auxiliary fans.

2.5.3 Auxiliary and booster fans

The use of auxiliary and booster fans in a mine ventilation system are mainly due to excessive depths and intricate layout of underground mining areas. The larger booster fans are situated at strategic locations to "boost" or maintain the overall airflow through the underground system. Auxiliary fans are positioned inside ducts that direct the airflow to areas located further away from the main air movement induced by booster fans. These fans ventilate new development areas [91].

Depending on the layout of a specific mine, hundreds of auxiliary fans may be installed to ensure that overall ventilation is achieved efficiently at all times. This is naturally a very dynamic system and will constantly need changes to manage sufficient airflow as underground mining areas are enlarged or sealed off.

A study done by Kukard in 2006 focused on increasing the efficiency of underground auxiliary and booster fans [91]. It was found that both an overall energy consumption reduction and a power load shift from high demand periods could be accomplished.

2.5.4 Ventilation fan fundamentals

Kukard's study showed that the electrical power input required by an axial fan is highly dependent on a number of factors included in the whole ventilation fan system [91]. Low impeller efficiencies result in a very high electrical input power to fan power ratio. Equations for calculating electrical input power required for axial ventilations fans are as follows [91]:

Equation 14: Fan power required

$$\boldsymbol{P_{fan} = QP}$$

With: P_{fan} = Fan power required (kW)

Q = Air volume flow (m^3/s)

P = Static pressure (Pa)

After fan power (P_{fan}) has been calculated, the next step is to determine the shaft power (P_{shaft}).

Equation 15: Shaft power required

$$\boldsymbol{P_{shaft} = \frac{P_{fan}}{\eta_{impeller}}}$$

With: P_{shaft} = Shaft power required (kW)

P_{fan} = Fan power required (kW)

$\eta_{impeller}$ = Impeller efficiency

With the shaft power (P_{shaft}) calculated, the final step is to determine the electrical input power (P_{input}) required.

Equation 16: Electrical input power required

$$\boldsymbol{P_{input} = \frac{P_{shaft}}{\eta_{motor}}}$$

With: P_{input} = Electrical input power required (kW)

P_{shaft} = Shaft power required (kW)

η_{motor} = Motor efficiency

2.6 HOISTING

2.6.1 Background

One of the most important systems in a deep-level mine is the hoisting system [93]. If the hoisting system does not work efficiently and as intended, final production figures of a mine can be very low. This is irrespective of the amount of precious metal ore being released from underground mining activities.

Hoist or winder systems are usually classified as either "rock" winders, which sole purpose is to transport reef and waste from underground, or "man" winders, which transport personnel to and from underground working areas [94]. Depending on the mine depth or hoisting system used, single and multiple shaft winding systems might be used. For a mine deeper than 3 000 m, a multiple shaft system is typically needed to reach deeper ore [94].

2.6.2 Hoisting system components and structure

A mine hoisting system consists of various components needed for operation [93], [94], [95], [96]:

- **Headframe –** This is the large, most recognised steel structure at a deep-level mine. The headframe is situated directly over the main shaft of a mine and houses one or multiple sheaves.
- **Sheave** – Situated at the top of the headframe. The sheave guides the winder cable down the shaft.

- **Skip –** Also known as a conveyance or cage, the skip is a container filled with either rock (reef and waste) or mine personnel.
- **Winder motor** – An electric motor with a drum attached to the motor shaft. The winder cable is fixed to this drum. Motor capacity is between 1 MW and 4 MW.
- **Buntons –** Steel beam grid that forms part of the in-shaft hoisting structure. Guide wheels attached to the skip roll against the buntons for smooth manoeuvring.
- **Cable** – Steel cable attached to the winder motor on one end and to the skip at the other end.
- **Winder house** – Houses winder motors and winder operators.

Winder systems in South Africa will typically fall into one of three varieties [94]:

- Double drum system
- Blair multirope system
- Friction (Koepe) system

The double drum system, which is the most commonly used winding system in South Africa, operates by winding and unwinding cables onto two drums connected to two motor shafts [97]. The cables are guided from the drums to two sheaves situated on a headframe and down the mineshaft to two skips. To balance the skips, the cables are winded in opposite directions on the drums while lifting one skip and lowering the other. [94]

Similar to the double drum system, the Blair multirope system uses two drums connected to two motor shafts. However, the difference between the two systems is that the Blair multirope system (as the name suggests) uses more than one cable per skip. The drums are split into two separate containers with two separate cables. Each of the cables is guided by separate sheaves onto one skip. Due to a reduced winding load per cable, smaller drums and lighter cables can be used to obtain the same winding capacity as a double drum system. For deeper and heavier winding, the Blair multirope system is preferred [94].

The friction winding system uses a single cable from a drum attached to a skip. This is known as the head rope. At the bottom of the skip, another cable is attached to the first skip and to the bottom of the second skip or counterweight – this is known as the tail rope. The excess cable hangs in a loop underneath both of the skips. The advantage of this system is that the weight of the tail rope reduces the initial load required to start hoisting.

The three hoisting systems are shown in Figure 13.

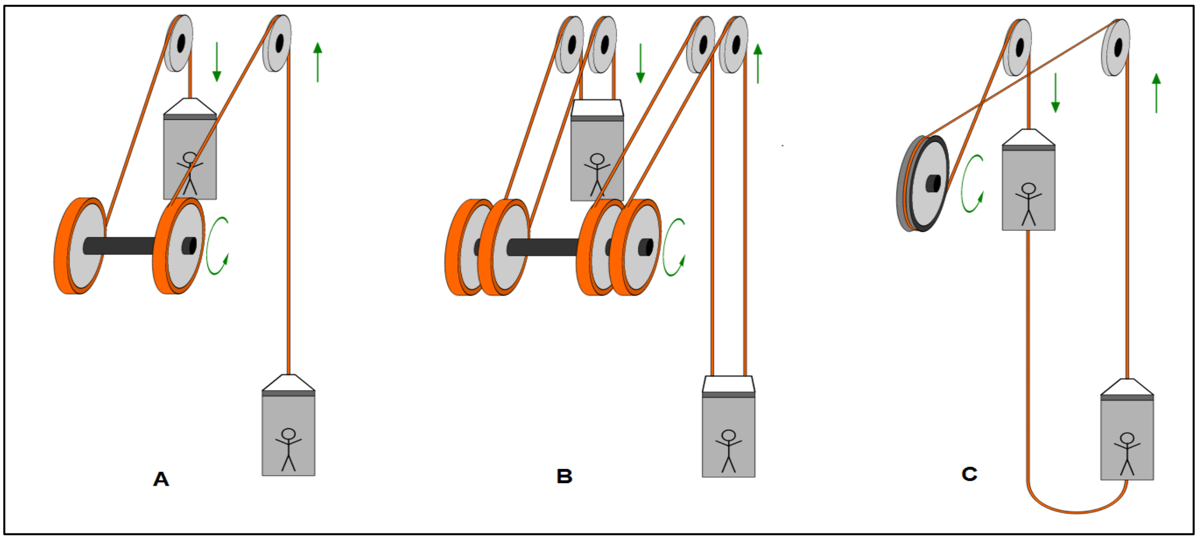


Figure 13: Double drum system (A)[4], Blair multirope system (B)[5], Friction system (C)[6]

2.6.3 Hoisting system power requirements

Vosloo's study in 2006 on mine rock winders showed that the gravitational potential energy law could be used to calculate the amount of energy required by a hoisting system [94]. The following equation is derived from Vosloo's study with a factor of $2.78{\times}10^{-7}$ used to convert joule to kWh [94]:

Equation 17: Hoisting energy calculation

$$E_{hoist} = \frac{(2.78 \times 10^{-7})mgh}{\eta_{system}}$$

With: E_{hoist} = Energy required (kWh)

m = Hoisted mass (kg)

g = Gravitational acceleration (m/s^2)

h = Vertical distance hoisted (m)

η_{system} = Hoisting system efficiency

4 Biezl, "File:Doppel-trommelförderung.svg," Wikimedia Commons, 31 August 2014. [Online]. Available: http://commons.wikimedia.org/wiki/File:Doppel-trommelf%C3%B6rderung.svg. [Accessed 12 March 2015].

5 Biezl, "File:Blair-trommelförderung.svg," Wikimedia Commons, 28 May 2014. [Online]. Available: http://commons.wikimedia.org/wiki/File:Blair-trommelf%C3%B6rderung.svg. [Accessed 12 March 2015].

6 Biezl, "File:Treibscheiben-Förderung.svg," Wikimedia Commons, 26 February 2015. [Online]. Available: http://commons.wikimedia.org/wiki/File:Treibscheiben-F%C3%B6rderung.svg. [Accessed 12 March 2015].

2.6.4 Previous studies on hoisting system efficiency

Two previous studies on energy optimisation were found for deep-level mine hoisting systems. Both of these studies incorporated similar to dewatering system load management approaches. Shutdown of the rock winder system during high power demand periods was accomplished by increased hoisting during low demand periods. Thus, the peak demand hoisting load was shifted to times of the day with less demand. Table 7 shows the details of the two studies.

Table 7: Previous work on hoisting system energy optimisation

Authors	Energy/cost saving per annum	Description	Ref.
Vosloo, J.	R1.4 million	Optimised control of mine rock winders	[94]
Buthelezi, M.A.	R600 000	Automation of mine rock winders for load management	[98]

2.7 BENCHMARKING METHODS

2.7.1 Average benchmarking

When the purpose of benchmarking is to compare the average performance of multiple companies with similar costs, average benchmarking could be used [99]. One of the most widely used methods for average benchmarking is the Ordinary Least Square (OLS) method [99]. OLS is a regression-based technique used to approximate an average function. This function represents production, cost or any other performance indicator applicable to the benchmarked entity.

Applying the OLS method on a normal regression analysis yields an estimated function [100]. In the following example (Figure 14), the function is estimated as the average linear regression line found by the correlation between input and output [16]. The estimate obtained from using only one input and one output is in the form of a straight-line equation shown as Equation 18.

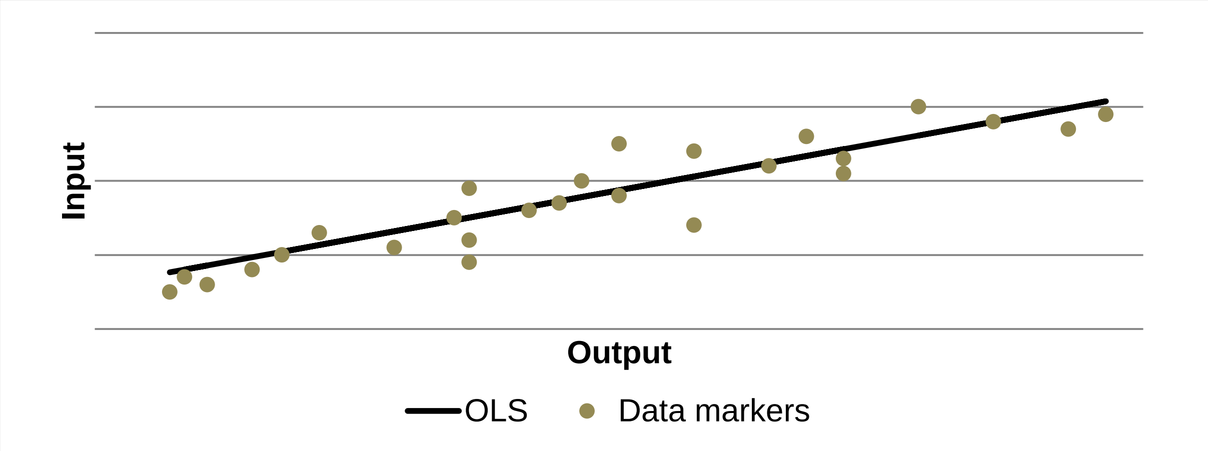


Figure 14: OLS method (adapted from [16])

Equation 18: Straight-line equation

$$\boldsymbol{y = mx + c}$$

With: y = Y-axis variable

m = Gradient

x = X-axis variable

c = Y-axis intercept

By using third-party software such as Microsoft Excel®, statistical information regarding the regression analysis can be obtained. This information is displayed in an array by using Excel's LINEST function and is shown in Table 8.

Each of the numbers returned within the LINEST array aids in determining statistical information for the specific regression analysis. The most important numbers are shown in Row 1 of the array presented as Table 8. These numbers represent the slope coefficients for each of the variables of the regression analysis except for number "b" found in Row 1 of Column F. This constant is also known as the y-intercept [101].

Table 8: LINEST function array (adapted from [101])

	A	B	C	D	E	F
1	m_n	m_{n-1}	…	m_2	m_1	b
2	se_n	se_{n-1}	…	se_2	se_1	se_b
3	R^2	se_y				
4	F	d_f				
5	ss_{reg}	ss_{resid}				

To determine if the relationship between the variables used in the regression analysis is valid, the coefficient of determination (R^2) is the first value to consider. The value of R^2 will be between 0 and 1, with a value of 1 showing a perfect linear relationship between the two variables and 0 showing no linear relationship. To establish if the value of R^2 was determined by chance, the F-statistic (F) and degrees of freedom (d_f) have to be considered. By using Excel's FDIST function, the probability of R^2 occurring by chance can be calculated [101].

Finally the value of $\mathrm{se_y}$ is considered. This value represents the standard error of the y-estimate and is useful in determining the significance of the error of the y-estimate found from using the regression function. If the relationship of more than one output is compared with a single input, a multivariable regression analysis is done. The format of the LINEST function for multivariable regression is exactly the same as when using a single variable, with the only difference being the number of slope coefficients found within the LINEST array. Equation 19 is an example of the regression function obtained from multivariable linear regression.

Equation 19: Multivariable regression function

$$\boldsymbol{y = a + m_1x_1 + m_2x_2 + m_3x_3 + \ldots + m_nx_n}$$

With: y = Y-axis variable
a = Constant or intercept
m_n = Gradient for x_n
x_n = n$^{\text{th}}$ independent variable

2.7.2 Frontier benchmarking

The choice of benchmarking methods is highly dependent on availability and size of data, and whether a representative or best practice measurement of performance is required [102]. To estimate the best practice performance efficiency of an entity, frontier-benchmarking methods are used. The primary frontier-benchmarking methods include the Corrected Ordinary Least Square (COLS), Stochastic Frontier Analysis (SFA) and DEA methods [99].

Although a representative analysis is achieved by the previously described OLS method, a focus on performance variation is often essential for a benchmarked entity. Seeing as the

OLS method delivers an average function on a regression analysis, data markers beneath the regression line are either representative of best practice (frontier) indicators or of errors [16].

To establish frontier benchmarks, the OLS method is modified to become the COLS method [99]. Using the regression analysis example again, the average regression function found by the OLS method is lowered while maintaining its gradient until no data markers are located beneath the function [16]. The function will now represent the measurement of best practice. This function is shown in Figure 15 as COLS.

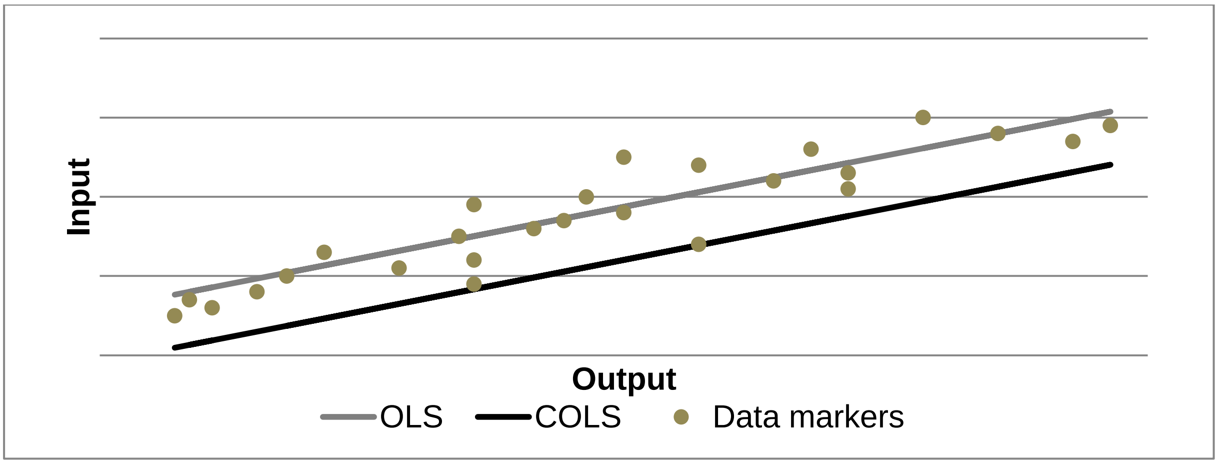


Figure 15: COLS method (adapted from [16])

Due to the possibility of errors in the data, the above example of COLS might produce an inaccurate function for benchmarking. The outlier responsible for modifying OLS creates an overcorrected function. Thus, the COLS method does not consider stochastic factors. The SFA technique is used to consider these factors [103]. Outliers as errors and "noise" in data must be identified and excluded for an increase in function estimation accuracy. It is, however, a challenging task to recognise an absolute error pattern in data, which brands the SFA technique as estimation [99]. An example of the SFA method as implemented on a linear regression model is shown in Figure 16. The data marker located beneath the SFA function is recognised as an error through estimation [16].

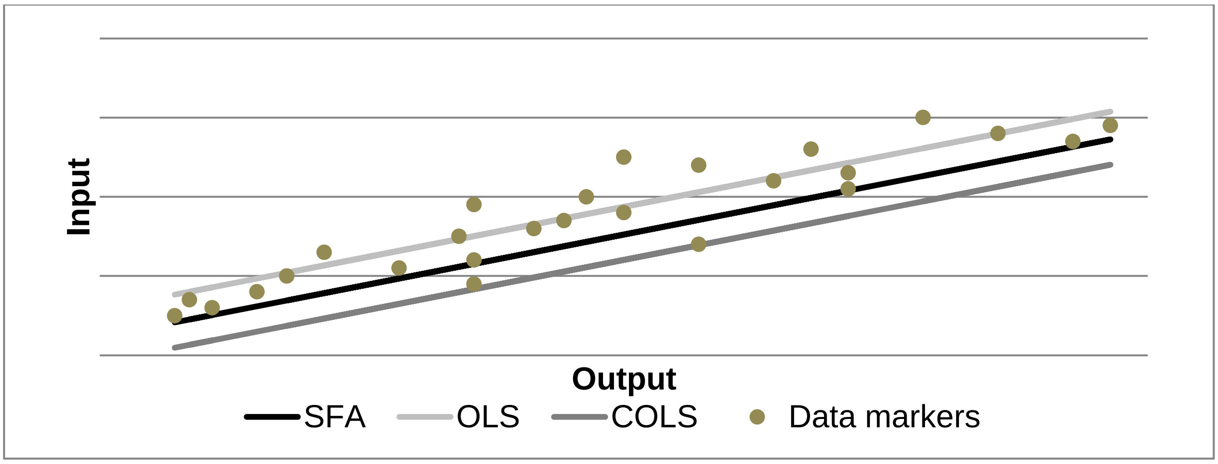


Figure 16: SFA method (adapted from [16])

The DEA technique is a computational benchmarking method rather than an estimation method such as OLS, COLS and SFA. Using linear programming, DEA strives to solve the most efficient input-to-output data markers [104]. In contrast with OLS, COLS and SFA, DEA draws an "envelope" around all data markers to intersect the highest intput-to-output data markers [105]. The markers intersected by this envelope are considered the most efficient. Figure 17 displays the DEA method on the same example used to depict previously discussed benchmarking methods.

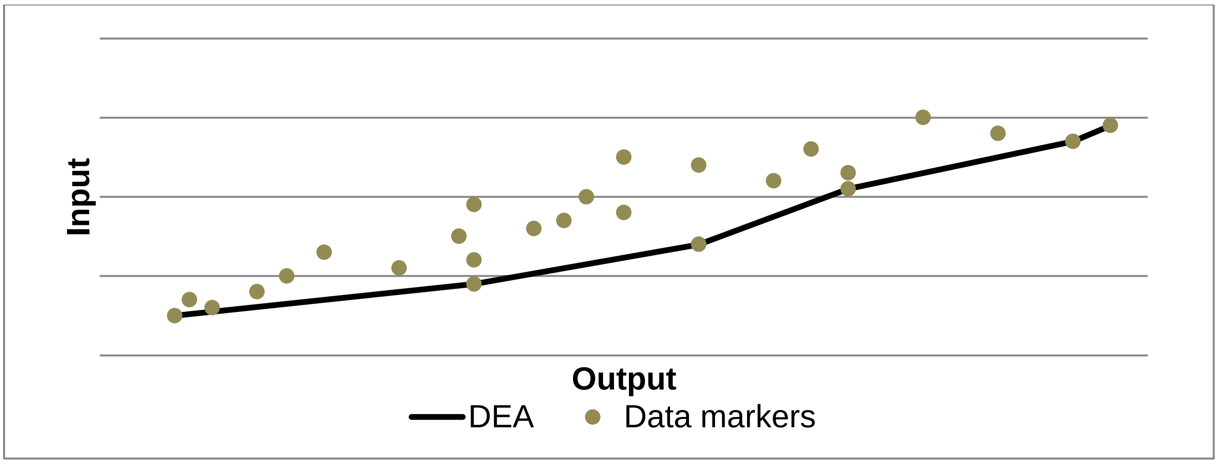


Figure 17: DEA method (adapted from [16])

2.8 METHODS FOR MINE ENERGY BENCHMARKING

2.8.1 Previous methods

Tshisekedi's 2009 study [30] was discussed in Section 1.5.4. His methods included the calculation of total mine intensity. For each of the mines used in the study, a different kWh/t value was determined. In doing so, Tshisekedi could compare the energy efficiency of the mines. This is a very unassuming way of benchmarking mines according to total energy intensity as no external factors were taken into account.

Using Tshisekedi's method on actual monthly data obtained from various deep-level mines in South Africa, the regression model shown in Figure 18 of energy in MWh and ore mined in kilotonne (kt) is drawn.

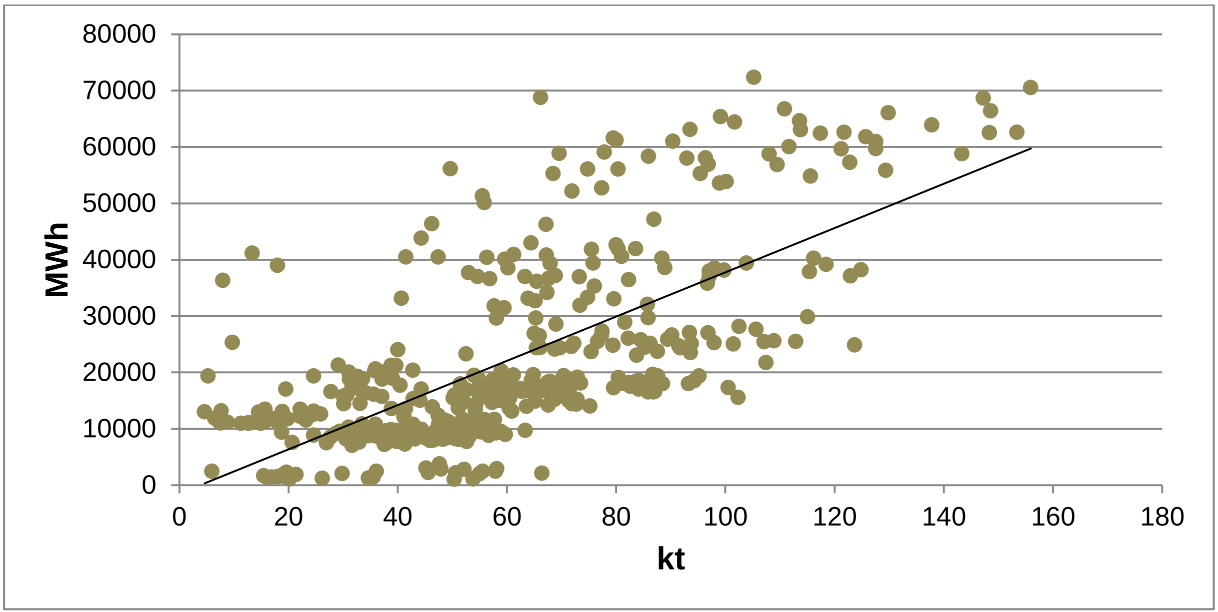


Figure 18: Regression model of MWh versus kt per month

Analysing the regression model found in Figure 18 reveals that although a linear correlation is found, a high number of data points are scattered outside of the acceptable range. Table 9 shows the calculated intensity, i.e. the total mine average energy use per month per tonne of ore mined per month, from the data in Figure 18. The erraticism of intensities proves the observation that a good correlation was not found.

Table 9: Energy intensity of various mines per month

Mine	Average MWh	Average kt	MWh/kt
Mine A	18 576	34	546
Mine B	37 470	98	381
Mine C	34 061	69	496
Mine D	64 825	125	517
Mine E	38 412	65	592
Mine F	9 543	16	580
Mine G	12 823	65	198
Mine H	8 275	47	177

Mine	Average MWh	Average kt	MWh/kt
Mine I	53 340	81	661
Mine J	16 552	64	258
Mine K	16 527	62	266
Mine L	25 517	86	297
Mine M	8 306	35	238
Average:	**26 479**	**65**	**406**

Due to the varying intensities found in Table 9, the high and low energy efficient mines can undoubtedly be singled out for the purpose of benchmarking. In this case, the unassuming conclusion is made when using Tshisekedi's method that Mine I is the least efficient with an intensity of 661 MWh/kt. Mine H is the most efficient with an intensity of 177 MWh/kt. This will be true if no external factors are taken into account as the total input (MWh) is directly compared with the total output (kt).

Mine depth is one of the external factors that Tshisekedi did take into account. By categorising mines by depth and calculating the average intensity of each of the depth categories, the efficiency of a mine within its depth category can be determined [30]. Tshisekedi added this necessary addition to the primary method, which only determines and compares the total intensity for any mine depth.

By applying Tshisekedi's depth categories to the mines shown in Table 9, the average intensity for each category can be determined. The average intensity is recognised as the benchmark energy intensity (from actual data) for each of the depth categories. This allows for each of the mines in a depth category to be compared with the benchmark. Table 10 shows the results of depth categorisation of mines.

Table 10: Depth categorisation of mines for benchmarking

Depth	Mines	Intensity (MWh/kt)	Average intensity (MWh/kt)
Shallow (<2 000 m)	Mine H	177	208
	Mine M	238	
Medium (<3 000 m)	Mine B	381	330
	Mine F	580	
	Mine G	198	
	Mine J	258	
	Mine K	266	
	Mine L	297	
Deep (<4 000 m)	Mine A	546	567
	Mine C	496	
	Mine I	661	

Depth	Mines	Intensity (MWh/kt)	Average intensity (MWh/kt)
Ultradeep (>4 000 m)	Mine D	517	554
	Mine E	592	

From Table 10, it can now be seen that high and low energy efficient mines exist for each of the depth categories. Mine I and Mine H from the previous example are still the least and the most efficient mines in their respective depth categories but can no longer be seen as the least and most efficient when considering all of the mines.

Tshisekedi is moving into the right direction by applying depth categorisation before obtaining intensity benchmarks. However, additional external factors over which mines have no control are still not being addressed. Other aspects not considered by Tshisekedi are the reasons behind high or low energy efficiency.

2.8.2 Mitigation of previous methods' inadequacy

Different high electricity-using systems on deep-level mines in South Africa were discussed within the first parts of Chapter 1 and 2. By examining the fundamentals of each system during the course of Section 2.2 to Section 2.6, multiple variables that influence power demand or total energy consumption are identified. By considering these variables when attempting to benchmark the electricity use of mines, the focus can be shifted to each system independently.

Compressed air system

Table 11 displays the results of analyses using Equation 1 to Equation 7. These results specify the variables that contribute to the power demand of compressed air systems on deep-level mines.

Table 11: Compressed air system – variables affecting power demand

From equation	Dependent variable	Independent variable	Dependent variable will increase when
Equation 1	Motor power (P_{motor})	Motor efficiency (η_{motor})	Efficiency is lower
		Compressor power (P_{comp})	Power is higher
Equation 2	Compressor power (P_{comp})	Mass flow rate ($\dot{m}_{air}$)	Flow rate is higher
		Compressor energy (W_{comp})	Energy is higher

From equation	Dependent variable	Independent variable	Dependent variable will increase when
Equation 3	Compressor energy (W_{comp})	Inlet temperature (T_{in})	Temperature is higher
		Compressor efficiency (η_{comp})	Efficiency is lower
		Discharge pressure (p_2)	Pressure is higher
		Inlet pressure (p_1)	Pressure is lower
Equation 4	Pressure loss (ΔP)	Friction factor (f)	Friction factor is higher
		Density of compressed air (ρ)	Density is higher
		Pipe length (L)	Length is higher
		Volume flow rate (Q)	Flow rate is higher
		Diameter of pipe (D)	Diameter is lower
Equation 5	Reynolds number (Re)	Density of air (ρ)	Density is higher
		Airflow velocity (v)	Velocity is higher
		Diameter of pipe (D)	Diameter is higher
		Dynamic viscosity of air (μ)	Viscosity is lower
Equation 6	Friction factor (f)	Pipe roughness (e)	Roughness is higher
		Diameter of pipe (D)	Diameter is lower
		Reynolds number (Re)	Number is lower
Equation 7	Final pressure (p_2)	Final altitude (Z_2)	Altitude is higher
		Air temperature (T_1)	Temperature is lower

In Section 1.6, one of the objectives was to design a model that could be used to benchmark energy use of deep-level mines easily. The importance in this statement is that it has to be easy. To ensure that the model can effortlessly be implemented on any South African deep-level mine, the data needed as inputs to the model need to be readily available.

Supervisory control and data acquisition (SCADA) systems on mines are used for monitoring and logging of necessary parameters of all systems [106]. Usually set up in custom configurations for specific mines, SCADA systems can vary greatly between mines regarding the amount of information given. Some mines might not even have SCADA systems. Thus, relying on SCADA systems to supply all the required information needed as inputs for a benchmarking model will render the effortless use and ease thereof doubtful.

The challenge now is to identify readily available information on any or most of the deep-level mines in South Africa. When considering a mine's monthly profit calculations, several factors have to be available for this to happen. Mine turnover is directly proportional to the amount of tonnes of ore mined and is, thus, an important figure to have. One of the highest contributors to operational expenditures for each month is electricity [107]. These expenditures are crucial in determining profit and are thus important to calculate.

Power metering equipment is installed on most, if not all, incomers and feeders on mines. This is needed to determine the monthly electricity use for electricity cost calculations. The two most crucial elements, which are electricity use per system and total tonnes of ore mined per month, are thus readily available for energy benchmarking.

Earlier in this section, the importance of categorisation was discussed for accurate energy benchmarking. When considering the compressed air system fundamentals as summarised in Table 11, it is clear that some of the variables may not be readily available at all mines. It is thus necessary to identify external factors that correspond with these variables and to determine the changeability thereof; these must also be readily available to perform easy-to-use benchmarking.

Firstly, mass flow rate ($\dot{m}_{air}$) is evaluated. According to Table 11, the power demand of a compressor increases when mass flow rate increases. This, together with the discussion of compressed air demand in Section 2.2.4, tells us that the amount of ore mined and the amount of compressed air used (mass flow) should be directly proportional. The same can be assumed for volume flow rate (Q) and discharge pressure (p_2).

A study regarding baseline scaling of compressed air energy consumption was conducted by Barnard and Grobler in 2012 [108]. The study established that no correlation can be found between compressed air energy consumption and amount of ore mined. This is contradictory to what is assumed for this study of benchmarking energy use. It must be noted that Barnard and Grobler's study focussed on a single mine and not multiple mines as with this specific study. Further research on the matter will be conducted in Chapter 3 [108].

Inlet pressure (p_1), which is the same as ambient pressure, may be determined by the ambient conditions of where the compressor is situated. The factor that correlates with final altitude (Z_2) – as found in Equation 7 – is the depth of the mine. The rest of the independent variables for different compressed air systems may be regarded as the same. External factors will not have a significant effect on these variables.

Readily available external factors that directly influence compressed air system energy use and that should be considered when developing an energy benchmarking model for compressed air systems may thus be summarised as follows:

Dependent variable:

- Compressed air system energy use

Independent variables:

- Amount of tonnes mined
- Mine depth
- Ambient conditions (winter or summer)

Cooling system

Equation 8 to Equation 12 are summarised in Table 12. The equations are found in the discussion of cooling system fundamentals in Section 2.3.3.

Table 12: Cooling system – variables affecting power demand

From equation	Dependent variable	Independent variable	Dependent variable will increase when
Equation 8	Evaporator heat absorbed (Q_{evap})	Mass flow of water ($\dot{m}_{water}$)	Mass flow is higher
		Water temperature out of evaporator (T_{out})	Temperature is higher
		Water temperature into evaporator (T_{in})	Temperature is lower
Equation 9	Condenser heat absorbed (Q_{cond})	Mass flow of water ($\dot{m}_{water}$)	Mass flow is higher
		Water temperature out of condenser (T_{out})	Temperature is higher
		Water temperature into condenser (T_{in})	Temperature is lower
Equation 10	Machine COP ($COP_{machine}$)	Evaporator heat absorbed (Q_{evap})	Heat is higher
		Electrical motor power (P_{motor})	Power is lower
Equation 11	System COP (COP_{system})	Heat absorbed by evaporator (Q_{evap})	Heat is higher
		Motor electrical power (P_{motor})	Power is lower
		Auxiliary electrical power (P_{aux})	Power is lower

From equation	Dependent variable	Independent variable	Dependent variable will increase when
Equation 12	Machine efficiency ($\boldsymbol{\eta_{machine}}$)	Evaporator heat absorbed (Q_{evap})	Heat is higher
		Motor electrical power (P_{motor})	Power is higher
		Condenser heat absorbed (P_{motor})	Heat is lower

Once again, the external factors affecting power demand have to be found as was attempted for the compressed air system fundamentals. From Section 2.3.4 onwards, it was shown that cooled water sent to underground mining areas is mainly used for drill-bit cooling, dust suppression and overall cooling. Cooled water use is also directly proportional to production (tonnes). From this, it can be assumed that production rate or tonnes mined have a direct positive relation to the amount of energy required by the cooling system of a deep-level mine. Looking at Table 12, this will result in mass flow ($\dot{m}_{water}$) correlating to tonnes mined.

In fact, the installed power capacity of the whole cooling system and its auxiliaries, which include precooling towers, pumps from precooling towers to warm dams, evaporator pumps, BAC pumps and condenser cooling towers and pumps, would have had to be designed with mine expansion and high production in mind. From this it is accepted that the power demand from all auxiliaries (P_{aux}) correlates to tonnes mined as well.

Secondary and tertiary cooling are of great importance and are often found in deep-level mines. The depth of South African mines exposes underground air to high virgin rock temperatures (VRT) [62]. A study done by Buys in 2014 indicated that different geographical areas in South Africa have different VRT gradients for mine depth [62]. This can be seen in Figure 19.

Cooling through secondary and tertiary methods due to mine depth and VRT requires cooled water from surface. Thus, an increase in VRT will result in an increase in cooling water ($\dot{m}_{water}$). This supports an assumed correlation between geographical area and mine depth to cooling demand requirements.

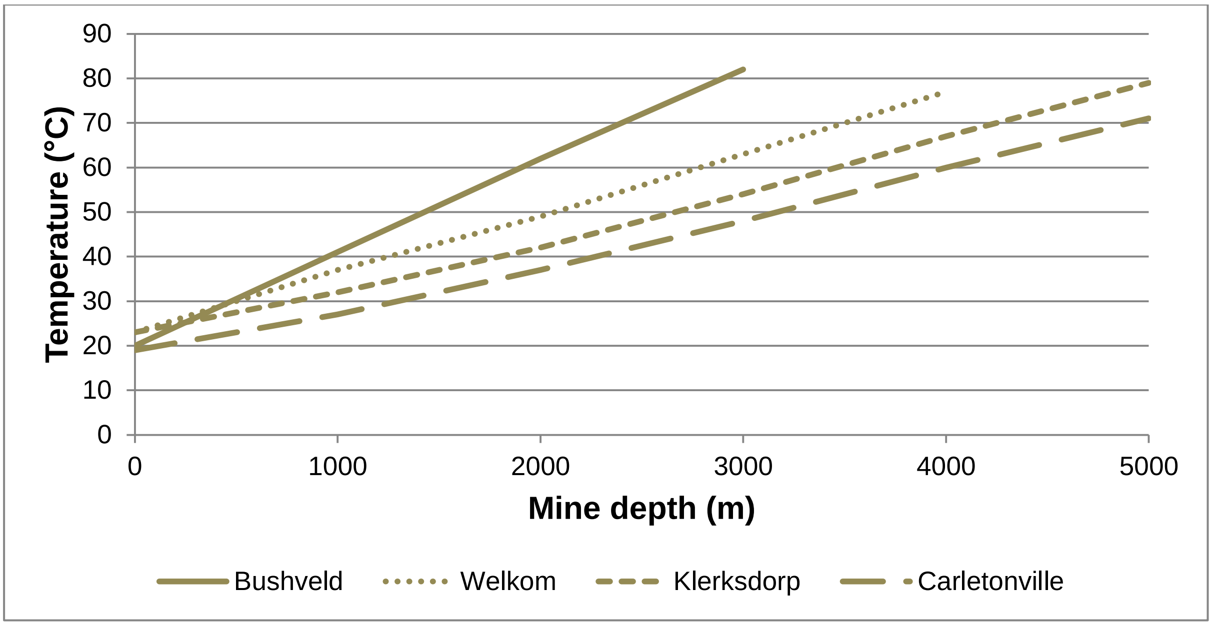


Figure 19: VRT for South African geographical areas (adapted from [62])

Ambient temperature variation at different geographical areas also affects the heat load experienced at surface. Due to evaporative cooling, the effectiveness of precooling towers and condenser cooling towers associated with the surface cooling system is determined by ambient conditions such as dry- and wet-bulb temperatures [109]. Recirculation of water through cooling towers is required when set-point temperatures are not met and additional pump power demand is required.

Readily available external factors to be used for cooling system energy benchmarking can thus be summarised as follows:

Dependent variable:

- Cooling system energy use

Independent variables:

- Amount of tonnes mined
- Mine depth
- Ambient conditions (winter or summer)
- Geographical area

Dewatering system

Equation 13 was shown in Section 2.4.2 to determine the power demand for removing water from a mine. The interpretation of Equation 13 shown in Table 13 reveals that power demand will be affected by the volume of water pumped (Q) and the static head that needs to be overcome (h) negating the effect of fluid density (ρ) and pump efficiency (η_{pump}).

Table 13: Dewatering system – variables affecting power demand

From equation	Dependent variable	Independent variable	Dependent variable will increase when
Equation 13	Pump power (P_{pump})	Density of fluid (ρ)	Density is higher
		Volume flow (Q)	Volume flow is higher
		Head (h)	Head is higher
		Pump efficiency (η_{pump})	Efficiency is lower

The total volume of water pumped from a mine includes cooled water sent down the mine and fissure water, as described in Section 2.4.1. Cooled water (as shown for cooling systems) is affected by the tonnes of ore mined. The amount of fissure water for any given mine can vary greatly and is totally dependent on groundwater quantities at or near developed mining areas. This is an important factor for mines to take into account to ensure that the water sent down a mine and the water pumped from a mine are balanced. Fissure water can thus be seen as an external factor directly contributing to the amount of energy required to remove water from a deep-level mine.

The mine depth corresponds to the static head (h) to be overcome by the dewatering system. This can be assumed due to dewatering pumps being situated at or near a mine's deepest areas where most of the water accumulates before being pumped to surface [80]. The readily available external factors to be used for dewatering system energy benchmarking can thus be summarised as follows:

Dependent variable:

- Dewatering system energy use

Independent variables:

- Amount of tonnes mined
- Mine depth
- Amount of fissure water

Ventilation system

As described in Section 2.5.4, the electrical input power required by an axial ventilation fan (often found on deep-level mines) may be calculated by using a number of equations consecutively. Table 14 summarises these equations.

Table 14: Ventilation system – variables affecting power demand

From equation	Dependent variable	Independent variable	Dependent variable will increase when
Equation 14	Fan power (P_{fan})	Air volume flow (Q)	Volume flow is higher
		Static pressure (P)	Static pressure is higher
Equation 15	Shaft power (P_{shaft})	Fan power (P_{fan})	Power is higher
		Impeller efficiency ($\eta_{impeller}$)	Efficiency is lower
Equation 16	Input power (P_{input})	Shaft power (P_{shaft})	Power is higher
		Motor efficiency (η_{motor})	Efficiency is lower

The purpose of ventilation and extraction fans was discussed in Section 2.5. It was concluded that the main drives of ventilation in the deep-mining environment are to circulate air for reduced methane concentrations and to replace hot air with cooler fresh air. Radiation from exposed rocks due to high VRT is the main contributor to hot air within a deep-level mine [6]. Therefore, the assumption is made that hotter air will need increased circulation to keep underground working areas within acceptable temperature ranges. Increased circulation will thus result in an increase in air volume flow (Q).

High VRT has already been shown to relate to mine depth and geographical areas in South Africa. Using this knowledge, the following readily available external factors may thus be used for energy benchmarking of ventilation systems on deep-level mines. These are summarised as follows:

Dependent variable:

- Ventilation system energy use

Independent variables:

- Amount of tonnes mined
- Mine depth
- Ambient conditions (winter or summer)
- Geographical area

Hoisting system

Similar to the dewatering system, the hoisting system energy consumption requirements are proportional to mass (m) and vertical distance (h), shown in Table 15.

Table 15: Hoisting system – variables affecting energy consumption

From equation	Dependent variable	Independent variable	Dependent variable will increase when
Equation 17	Hoisting energy (E_{hoist})	Hoisted mass (m)	Mass is higher
		Vertical distance (h)	Distance is higher
		System efficiency (η_{system})	Efficiency is lower

From a fundamental point of view, no additional external factors would influence the energy consumption of a hoisting system. If both man and rock winders were included in the study, the hoisted mass of man winders might have been affected by the number of mining personnel transported and indirectly by the amount of tonnes mined. As this study only includes rock winders, it is assumed that only tonnes of ore mined will show a correlation together with vertical distance hoisted.

Readily available external factors to be used for hoisting system energy benchmarking can thus be summarised as follows:

Dependent variable:

- Hoisting system energy use

Independent variables:

- Amount of tonnes mined
- Mine depth

2.9 SUMMARY

Throughout this chapter, the various high electricity-using systems on deep-level mines were discussed in depth. Fundamental analyses of these systems highlighted the main electricity demand-affecting variables. The identified variables were compared with readily available external factors in order to obtain a positive correlation.

It was shown that various external factors directly influence the electricity consumption of different systems on deep-level mines and could be used for further development towards the objective of this study. The next chapter will further develop benchmarking models by using information gathered during the course of Chapter 2.

CHAPTER 3 – A new benchmarking model for deep-level mines

[7]

[7] C. Cilliers, Personal photograph. "Dewatering pumps", Welkom, 2012.

3.1 PREAMBLE

The objective of this study is to benchmark the electricity use of deep-level mines. Chapter 3 focuses on developing methods for reaching this objective. Using the knowledge obtained in Chapter 1 and Chapter 2 regarding high energy-using systems, previous methods for energy benchmarking and different benchmarking methods, three new methods are developed.

The first phase is to develop benchmarking functions by analysing actual energy consumption data of a number of deep-level mines in South Africa. Chapter 2 proposed that actual data and fundamental variables be compared with easily obtainable external factors. The aim is to create a quantifiable method for benchmarking the electricity use of the individual identified high demand systems on deep-level mines and for mines as a whole.

The second phase is to develop a step-by-step technique to be used by mines or mine energy managers to obtain an accurate benchmarking score. Functions obtained from the initial development (first) phase are used together with statistical information retrieved from the second phase to develop the procedure of obtaining the benchmark score.

Finally, a frontier-benchmarking method is developed to determine the best practice energy consumption on South African deep-level mines for each high demand system. The best practice benchmark allows mines to determine the level of efficiency for a specific system compared with the best performing system on South African mines.

3.2 DEVELOPMENT OF ACTUAL DATA MODEL

3.2.1 Methodology

It was stated in Chapter 2 that readily available external factors have to be identified to aid the energy benchmarking objective of this study. A number of factors directly affecting the energy use of high demand systems were also proposed. It was needed to validate these factors using data analysis to affirm their roles in the process of developing a benchmarking model. Thus, this study needs a step-by-step method to be developed that would result in a quantifiable model for benchmarking of high demand systems and mines as a whole.

As this model is based on actual data from different deep-level mines in South Africa, it is thus important to obtain the required data. Step 1 is, therefore, to identify which external factors will be used for a specific high demand system of a mine and to categorise these factors. Not all mines will have all the required data available. It is also needed to identify “model mines” where all the required data for the development of the models are available and accessible.

Step 2 is to acquire data from the model mines identified in Step 1. This data may be in any readable form with preference given to digital data for easy and quick processing. In this technological day and age, it should not be difficult to procure digital data. As the goal of this study is to benchmark electricity use, the obvious primary data needed is electricity consumption.

An effective benchmarking method is to compare input with output as was shown in the previous chapters. Electricity consumption is the input needed for energy benchmarking and would thus require a suitable output for benchmarking results. The primary output of deep-level mines is the amount of tonnes of ore mined or ounces of precious metal extracted from the ore. This was also shown to be true in previous work on energy benchmarking of mines.

Step 3 is to validate assumed correlations between external factors and electricity data for the different high demand systems on mines. Methods discussed in Section 2.7 are used for this purpose. Step 4, which is the final step in the model development phase, is to obtain functions from regression and/or other analyses of electricity use as input and ore mined or metal extracted as output.

The functions obtained from Step 4 enable any mine to insert readily available variables as inputs and have the functions return the average needed electricity consumption for those specific variables. A mine’s electricity use is, therefore, benchmarked by comparing the actual measured data with the returned value from the developed functions.

The method for developing different models for various high demand systems on deep-level mines can, therefore, be summarised in Figure 20.

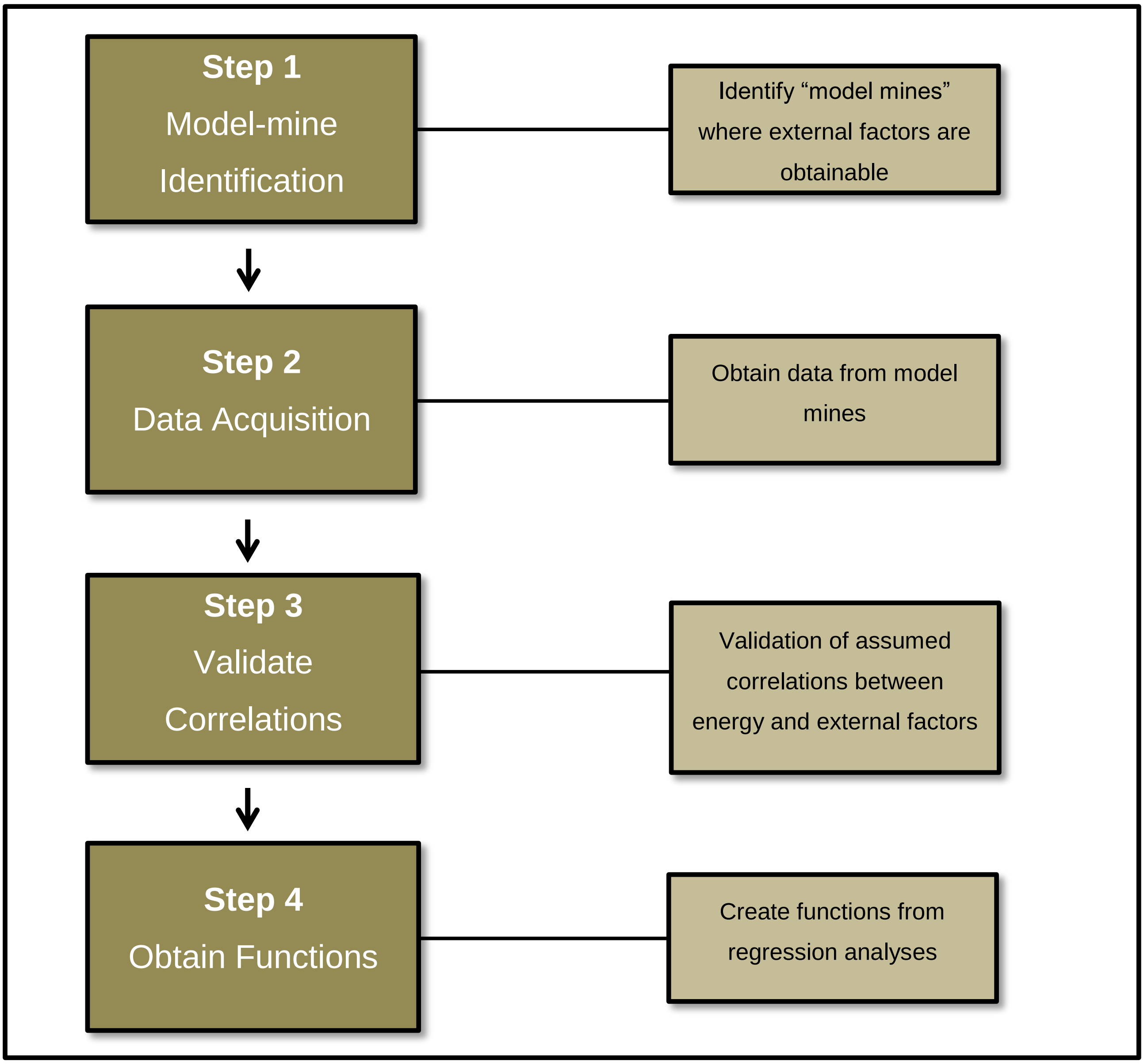


Figure 20: Model development methodology flow diagram

3.2.2 Steps 1 and 2 – Model mine identification and data acquisition

Previous chapters discussed high demand systems encountered at deep-level mines. A separate model is needed for each of these systems. Therefore, each system has to be evaluated individually. Analysing the fundamentals for each of the high demand systems on mines was done in Section 2.8.2. Possible external factors that influence electricity consumption were listed and are summarised in Table 16.

Table 16: Summary of system independent variables

High demand system	Dependent variable	Independent variables
Compressed air	Electricity consumption	Tonnes mined
		Mine depth
		Ambient conditions
Cooling	Electricity consumption	Tonnes mined
		Mine depth
		Ambient conditions
		Geographical location
Dewatering	Electricity consumption	Tonnes mined
		Mine depth
		Fissure water
Ventilation	Electricity consumption	Tonnes mined
		Mine depth
		Ambient conditions
		Geographical location
Hoisting	Electricity consumption	Tonnes mined
		Mine depth

As South Africa has numerous deep-level mines, only local mines were considered. Model mines were identified that fitted the criteria shown in Table 16. Additionally, these mines had to have the data shown in the Dependent Variable and the Independent Variable columns of Table 16 available.

Most of the model mines had digital real-time data available from SCADA systems and other large data collection and historian systems. Monthly data spanning several years was collected for each of the identified variables where available. Data from various previous years were obtained to ensure accuracy when determining averages. It was also important to ensure that data for both summer and winter months was included. This was especially necessary for high demand mining systems where seasonal changes could have affected energy consumption.

The model mines are not named to protect their privacy and sensitive data. The names Mine A to Mine O are used to distinguish between the model mines. The data is shown in Table 64 in Appendix A. Available data for each mine is shown with a checkmark. The same mines were used for the example shown in Section 2.8.1. After the model mines were identified, each high demand system was analysed separately. Data for the independent variables (shown in Table 16) was collected for each mine. The data for each of the high demand systems is summarised in Table 17 to Table 24. All of the data shown in these tables is for monthly averages over a number of years.

Compressed air system

Independent variables for the compressed air system include mine depth, amount of ore mined and ambient conditions. Table 17 shows the variables for summer months (September–April). Table 18 shows the variables for the winter months (May–August). Data for summer and winter months were processed separately to accommodate ambient conditions.

Table 17: Compressed air variables (summer)

Mine	Depth (m)	Ore mined (kt)	Energy use (MWh)
B	2 600	81	5 211
C	3 045	78	6 387
D	4 000	126	9 981
E	1 200	12	3 123
F	2 000	62	5 632
G	1 400	34	2 269
H	3 300	55	8 700
I	2 180	48	4 604
L	2 300	62	6 794
M	1 800	26	3 520

Table 18: Compressed air variables (winter)

Mine	Depth (m)	Ore mined (kt)	Energy use (MWh)
B	2 600	102	8 285
C	3 045	74	6 169
D	4 000	149	10 358
E	1 200	11	2 445
F	2 000	61	6 365
G	1 400	41	1 864
H	3 300	88	9 520
I	2 180	56	4 880
L	2 300	68	6 920
M	1 800	28	3 479

Cooling system

The independent variables identified for cooling systems were the same as for compressed air systems except for geographic area that also came into play. Once again, data was processed separately for summer and winter months. The data for mines with available information on cooling systems is shown in Table 19 and Table 20.

Table 19: Cooling system variables (summer)

Mine	Geographical area	Depth (m)	Ore mined (kt)	Energy use (MWh)
C	Klerksdorp	3 045	78	9 747
D	Carletonville	4 000	126	11 605
E	Welkom	1 200	12	2 781
H	Carletonville	3 300	54	7 794
J	Welkom	2 350	48	7 364
L	Welkom	2 300	63	4 849
M	Welkom	1 800	27	964

Table 20: Cooling system variables (winter)

Mine	Geographical area	Depth (m)	Ore mined (kt)	Energy use (MWh)
C	Klerksdorp	3 045	74	6 517
D	Carletonville	4 000	149	8 335
E	Welkom	1 200	11	1 838
H	Carletonville	3 300	87	7 527
J	Welkom	2 350	50	7 253
L	Welkom	2 300	68	3 523
M	Welkom	1 800	28	128

Dewatering system

Fissure water was identified as an additional independent variable for the dewatering system. Fissure water data was obtained from each mining site by analysing water balance data where available. For mines where no water balance data was available, fissure water data was obtained by interviewing mining personnel. As ambient conditions do not affect the amount of water that has to be removed from a mine (shown in Section 2.8.2), summer and winter months were not processed separately. Table 21 shows the variables for dewatering systems with fissure water flow representing a constant average.

Table 21: Dewatering system variables

Mine	Depth (m)	Fissure water (ℓ/s)	Ore mined (kt)	Energy use (MWh)
B	2 600	21	89	4 097
C	3 045	42	77	6 528
E	1 200	4	10	690
G	1 400	6	36	1 236
I	2 180	10	51	2 017
H	3 300	35	71	5 259
L	2 300	18	64	3 362
M	1 800	3	27	681

Ventilation system

Independent variables for the ventilation system of a deep-level mine were the same as for cooling systems. Table 22 shows the processed data for summer months and Table 23 for winter months.

Table 22: Ventilation system variables (summer)

Mine	Geographical area	Depth (m)	Ore mined (kt)	Energy use (MWh)
B	Klerksdorp	2 600	81	2 646
C	Klerksdorp	3 045	78	5 632
D	Carletonville	4 000	126	6 930
E	Welkom	1 200	12	1 538
F	Carletonville	2 000	53	2 726
G	Welkom	1 400	34	1 266
I	Welkom	2 180	47	3 515
K	Welkom	2 350	20	1 025
L	Welkom	2 300	62	4 104
M	Welkom	1 800	26	1 648
O	Welkom	2 200	36	1 104

Table 23: Ventilation system variables (winter)

Mine	Geographical area	Depth (m)	Ore mined (kt)	Energy use (MWh)
B	Klerksdorp	2 600	102	3 685
C	Klerksdorp	3 045	74	5 767
D	Carletonville	4 000	149	7 402
E	Welkom	1 200	11	1 539
F	Carletonville	2 000	58	2 689
G	Welkom	1 400	41	1 301
I	Welkom	2 180	55	3 890
K	Welkom	2 350	21	1 122
L	Welkom	2 300	68	4 094
M	Welkom	1 800	28	1 637
O	Welkom	2 200	39	1 577

Hoisting system

Tonnes of ore mined and mine depth were the only identified independent variables for the hoisting system. The data from mines with available information is shown in Table 24.

Table 24: Hoisting system variables

Mine	Depth (m)	Ore mined (kt)	Energy use (MWh)
B	2 600	89	1 229
C	3 045	77	1 215
D	4 000	136	2 323
F	2 000	58	1 492
G	1 400	36	423
I	2 180	51	1 057
K	2 350	20	656
M	1 800	27	550

3.2.3 Step 3 – Validate correlations

The next step is to validate correlations between dependent and independent data as shown in the previous section. This is to confirm that the selected external factors for each of the high demand systems influence electricity consumption as was assumed in Section 2.8.2.

Using the OLS average benchmarking method (described in Section 2.7) on each of the independent variables – with electricity consumption as the dependent variable – a regression analysis was done for each high demand system. Seeing as different mines have vastly different efficiencies when it comes to their high demand systems, very good correlations in the form of R^2 values close to 1 were not expected. A wide scattering of data confirms the need for this study as quantifying the scatter is valuable to mines and energy managers (as was discussed in Section 1.6).

Compressed air

The first regression analysis for compressed air is on electricity consumption as dependent variable and amount of ore mined as independent variable. Figure 21 shows the data for summer months and Figure 22 shows the data for winter months. When reviewing the two figures, it is clear that a correlation exists between compressed air energy use and amount of ore mined. The validity of the regression is supported by relatively high R^2 numbers of 0.646 for summer data and 0.827 for winter data.

It was mentioned in Section 2.8.2 that a study conducted by Barnard and Grobler in 2012 disproved a correlation between compressed air energy and amount of ore mined [108]. A significant difference is found when comparing the data scatter of the previous study to this study. This study compares monthly average data from various mines which means that a single data point in this study represents the total scatter from the previous study.

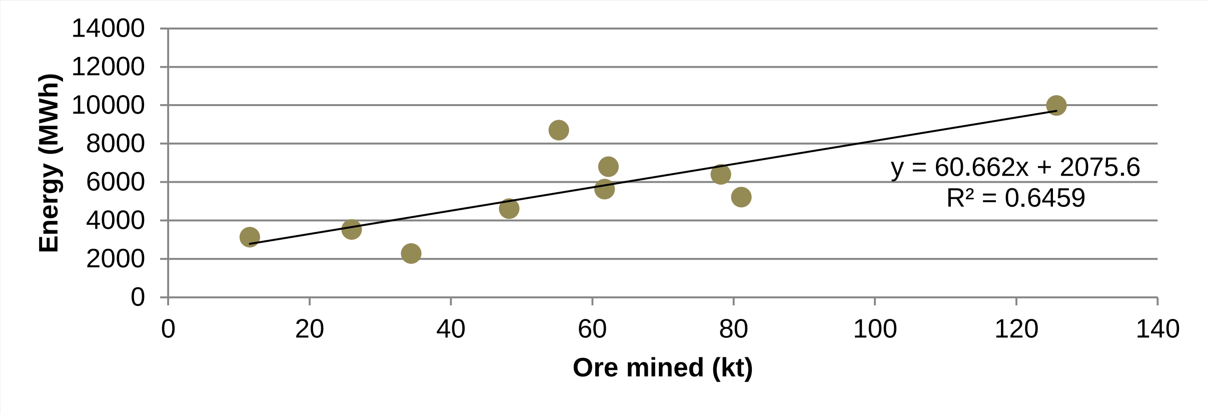


Figure 21: Compressed air – MWh versus ore mined (summer)

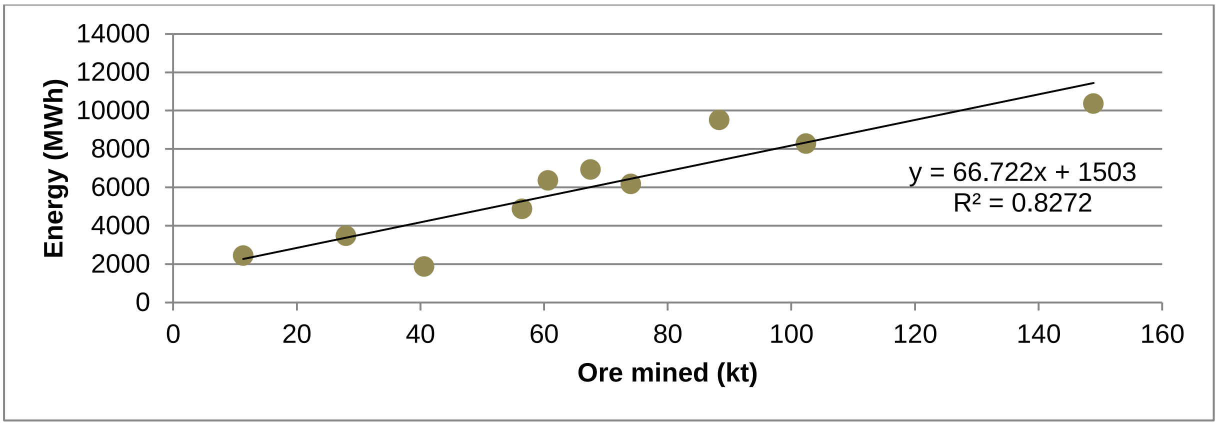


Figure 22: Compressed air – MWh versus ore mined (winter)

The next external factor (or independent variable) that was considered was mine depth. Figure 23 represents data from summer months and Figure 24 data for winter months. With R^2 values of 0.872 and 0.830 respectively, both the summer and winter months' correlation between compressed air energy use and mine depth were verified.

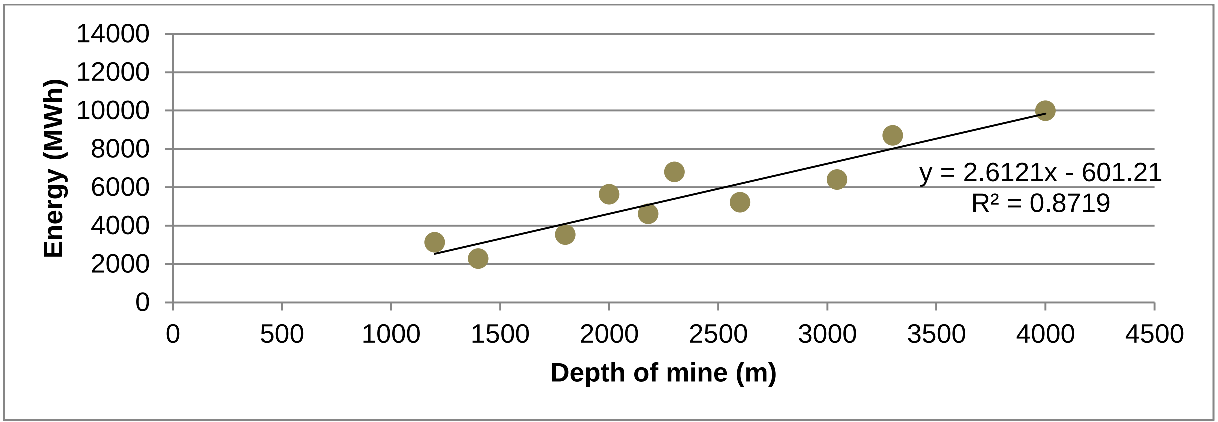


Figure 23: Compressed air – MWh versus mine depth (summer)

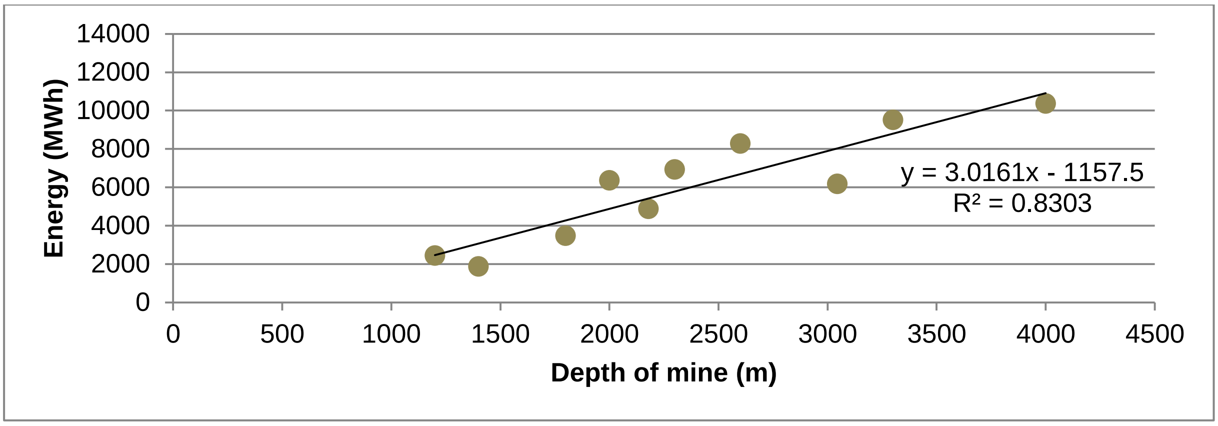


Figure 24: Compressed air – MWh versus mine depth (winter)

Cooling system

As was mentioned previously in 3.2.2, the independent variables identified for the mine cooling system were the same as for compressed air systems with the exception of geographical area. Therefore, Figure 25 represents the correlation between cooling system energy consumption and tonnes of ore mined for summer months and Figure 26 for winter months.

When reviewing the regression analysis of cooling energy versus tonnes of ore mined during summer months (Figure 25), it is seen that a relatively good R^2 value of 0.757 was obtained. The correlation between cooling energy and ore mined during winter months (shown in Figure 26) results in an R^2 value of 0.598. This indicated that the correlation was less than ideal. Very low energy consumption during winter months, which is visible on Figure 26, was most likely responsible for delivering a lower R^2 value.

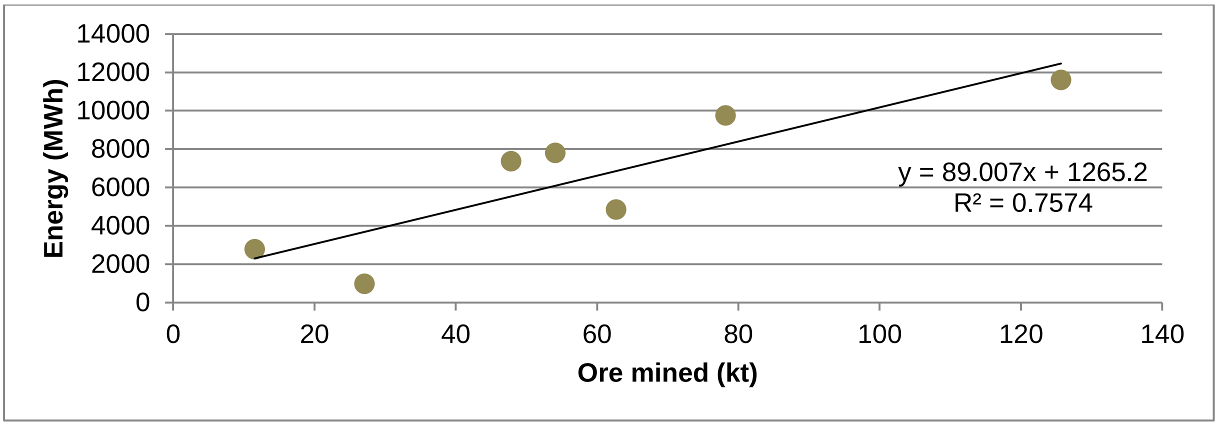


Figure 25: Cooling system – MWh versus ore mined (summer)

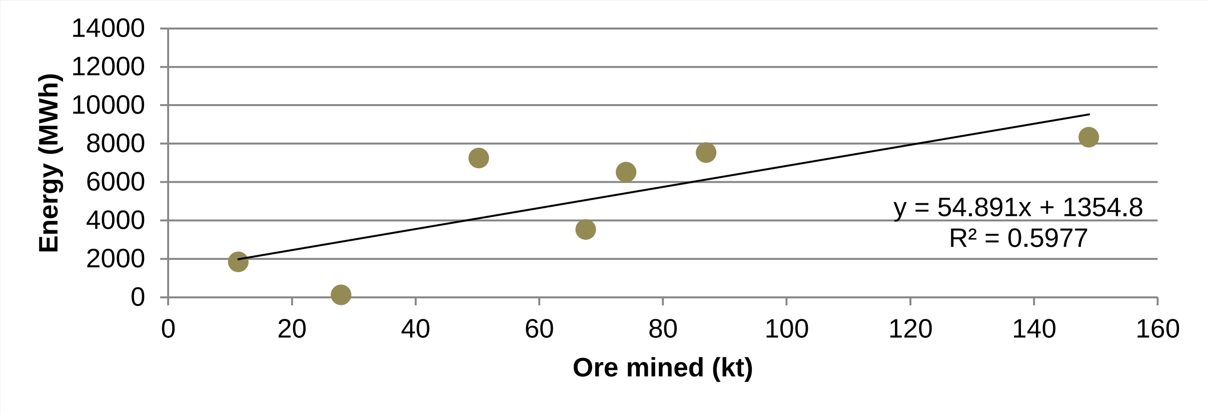


Figure 26: Cooling system – MWh versus ore mined (winter)

The correlation between cooling energy and mine depth for both summer and winter months are shown in Figure 27 and Figure 28 respectively. Both the summer and winter data for cooling systems on deep-level mines showed a good correlation between energy used for cooling and mine depth. This was shown by R^2 values of 0.809 for summer and 0.716 for winter months.

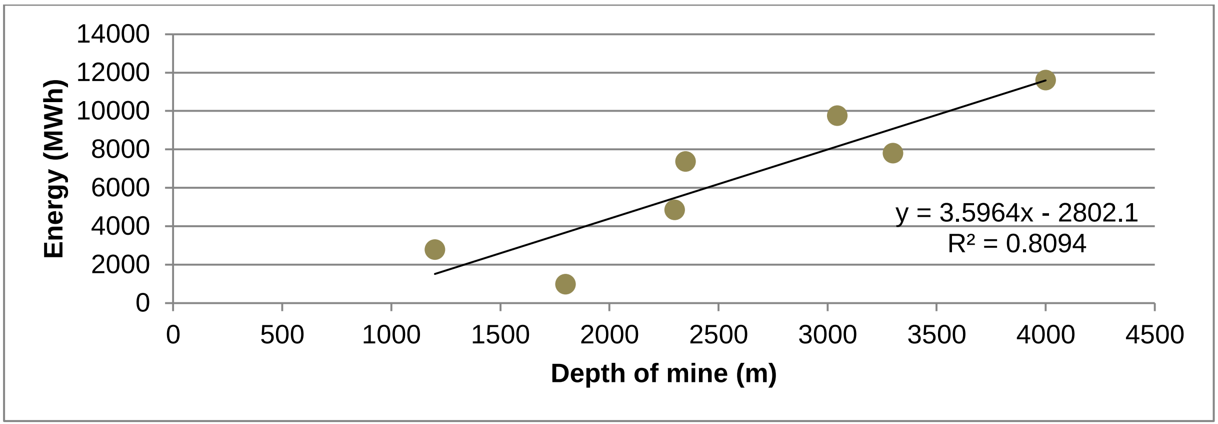


Figure 27: Cooling system – MWh versus mine depth (summer)

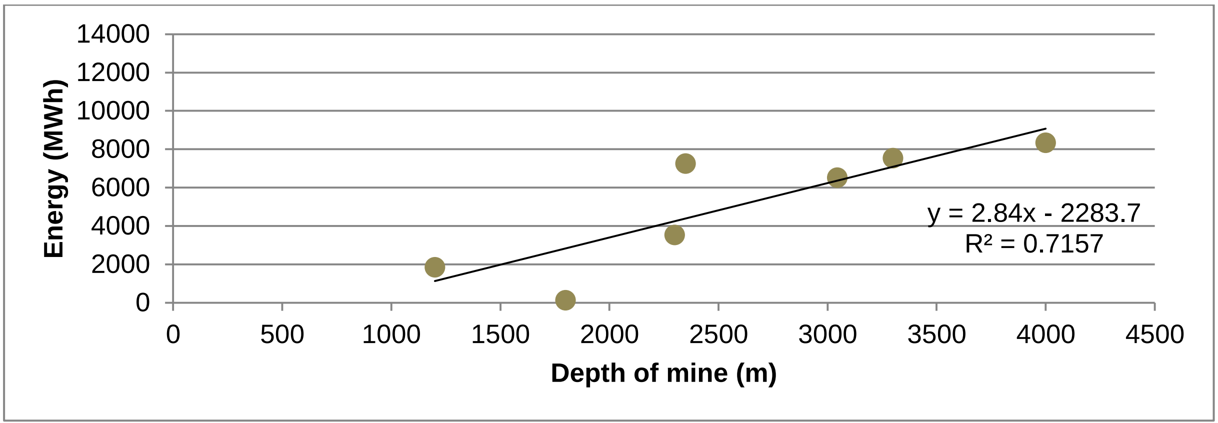


Figure 28: Cooling system – MWh versus mine depth (winter)

Section 2.8.2 showed that a mine's geographical location affects the gradient of the underground VRT. Figure 19 shows that Bushveld locations have the steepest increase in VRT as depth increases followed by the Welkom area in the Free State, the Klerksdorp area in the North West province and, lastly, the Carletonville area near the Gauteng–North West border.

Geographical location was, therefore, assumed a valid independent variable for cooling energy requirements. However, upon processing available data for cooling systems, it was found that not enough data was available to prove the assumed correlation. It was found that mines in the Carletonville area were much deeper than mines in the rest of South Africa. These excessive depths resulted in mines in the Carletonville area using the most cooling energy.

Figure 29 shows the average cooling energy versus mine location for:

1 = Klerksdorp
2 = Carletonville
3 = Welkom

It is seen that not enough data was available with only one Klerksdorp mine being present. The trend line obtained from Figure 29 indicates that an opposite correlation was found to what was assumed. Once again, this proves that mine depth plays an important role in cooling energy requirement. Mine location does not necessarily play an important role.

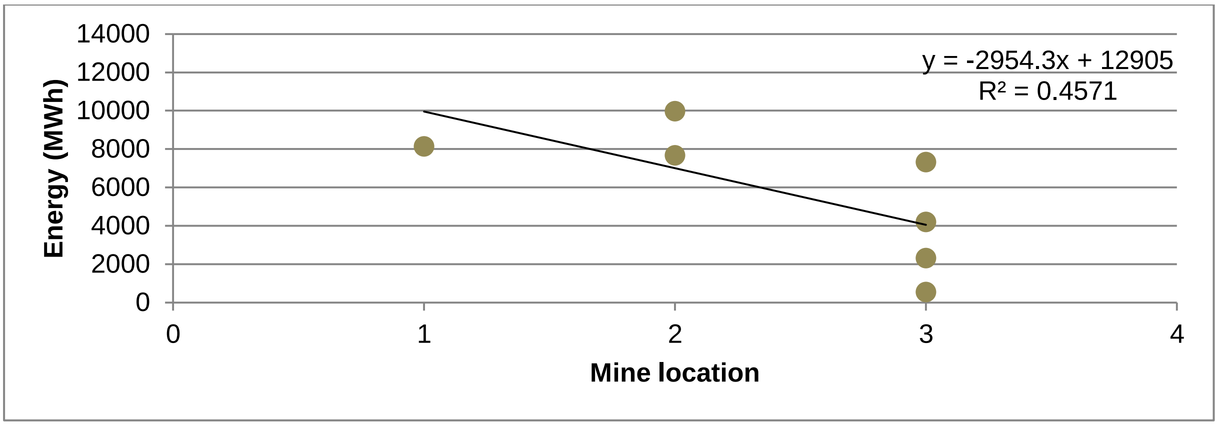


Figure 29: Cooling system – MWh versus location

Dewatering system

As was shown in Table 16 and Table 21, the dewatering system energy consumption is assumed to be proportional to tonnes of ore mined, mine depth and amount of fissure water. Figure 30, Figure 31 and Figure 32 show the regression models for dewatering system energy consumption versus each of these independent variables respectively. As dewatering energy consumption has no assumed correlation with ambient conditions, the total average values for both summer and winter months were used.

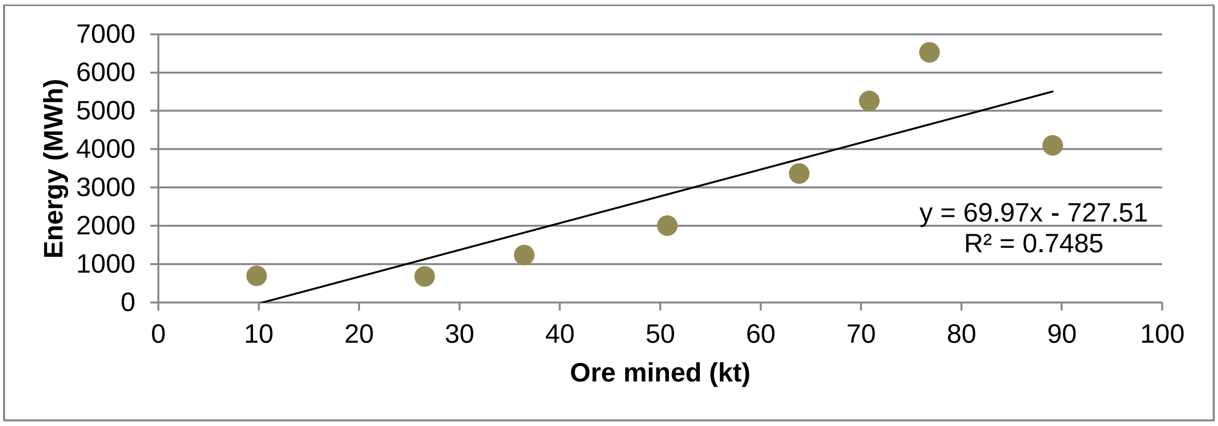


Figure 30: Dewatering system – MWh versus ore mined

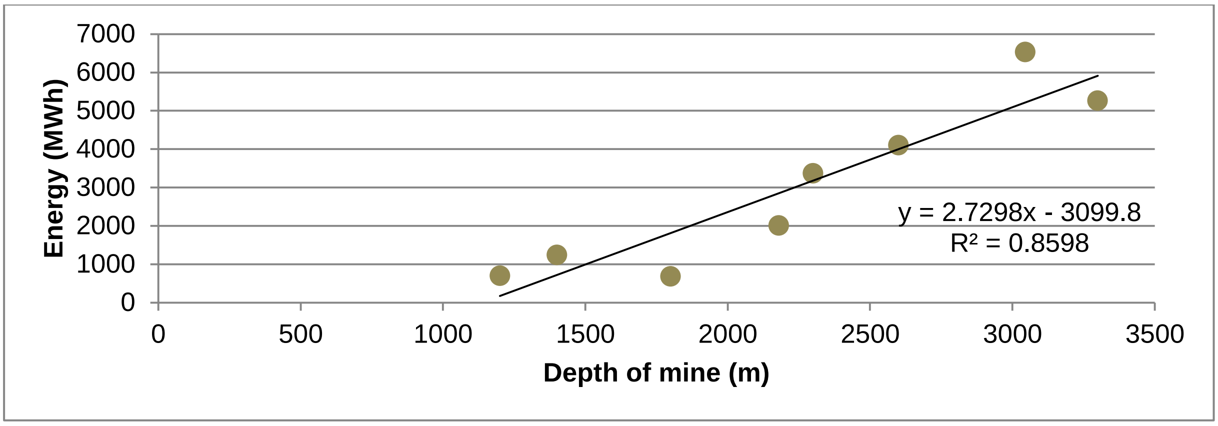


Figure 31: Dewatering system – MWh versus mine depth

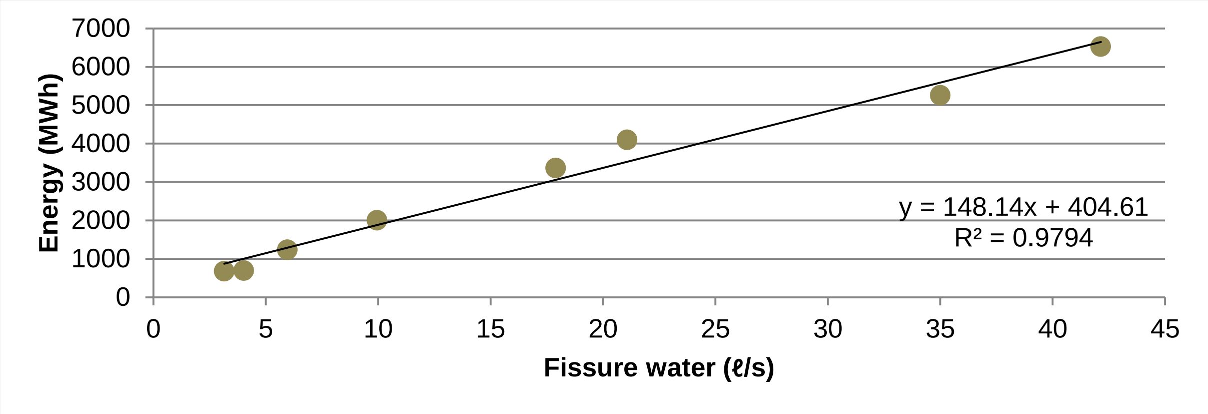


Figure 32: Dewatering system – MWh versus fissure water

Good correlations for dewatering system energy consumption with all of the external factors were found. R^2 values of 0.749, 0.859 and 0.979 were obtained for each of the independent variables respectively and confirm the assumption that these factors directly affect the energy consumption of a dewatering system of a deep-level mine.

Ventilation system

For the ventilation system of a deep-level mine, the possible external factors identified in Section 2.8.2 were tonnes of ore mined, mine depth, ambient conditions and the mine location. Therefore, the following figures represent the correlation between the ventilation system energy use and the ore mined for both summer and winter months.

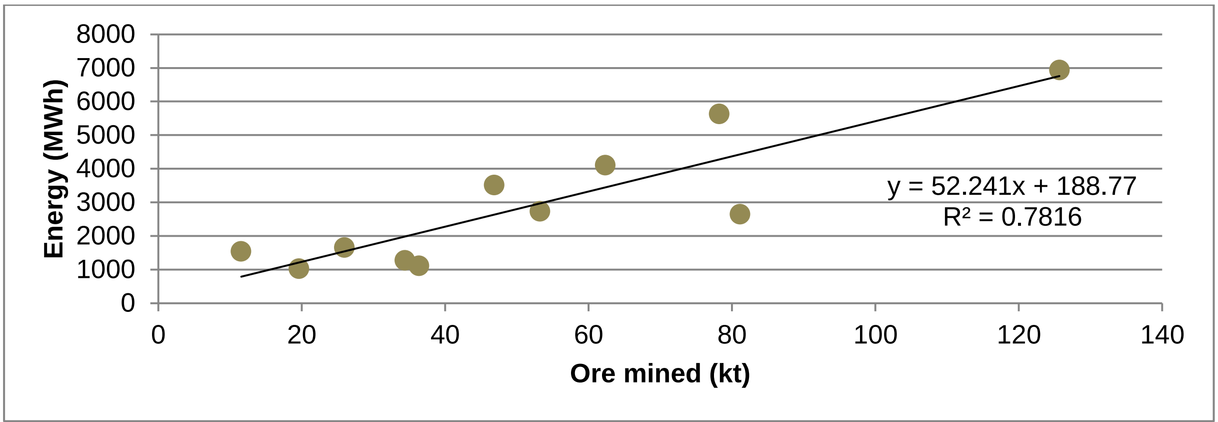


Figure 33: Ventilation system – MWh versus ore mined (summer)

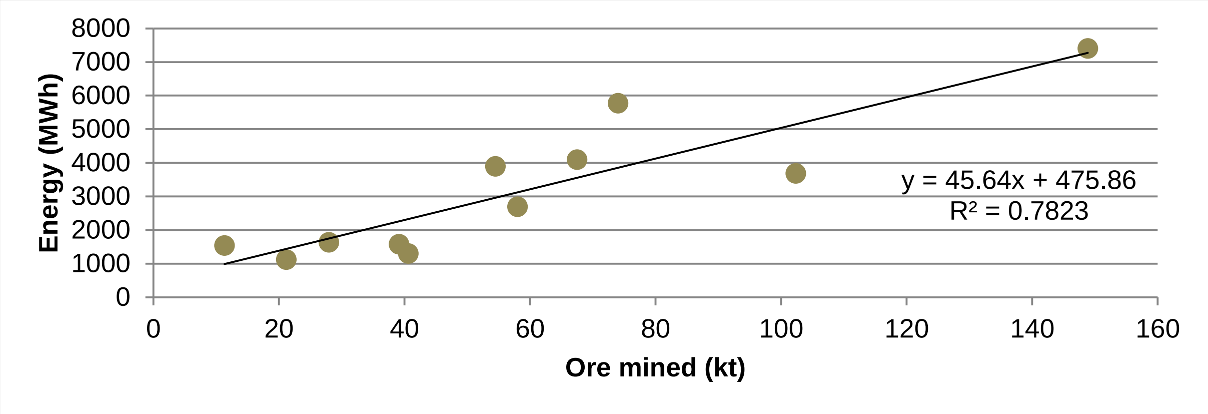


Figure 34: Ventilation system – MWh versus ore mined (winter)

The scattering of data in Figure 33 and Figure 34 results in R^2 values of 0.782 for both models respectively. Figure 35 and Figure 36 present the correlation of energy use with mine depth for both summer and winter months. An R^2 value of 0.684 and 0.753 for both summer and winter months are respectively seen.

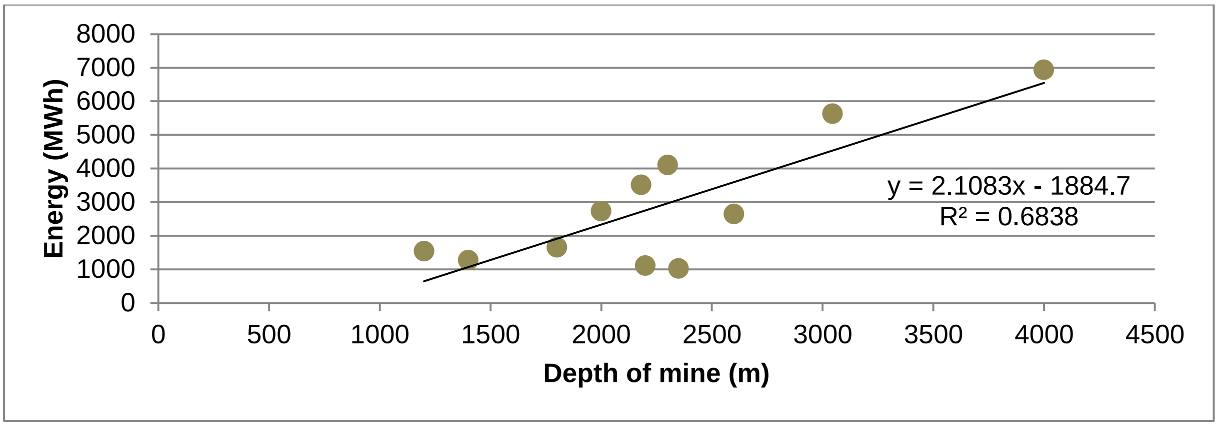


Figure 35: Ventilation system – MWh versus mine depth (summer)

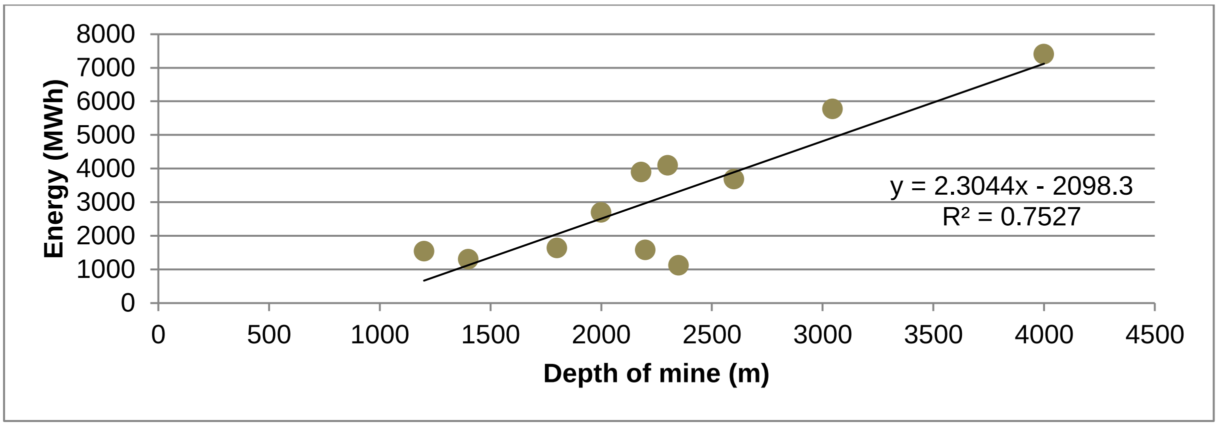


Figure 36: Ventilation system – MWh versus mine depth (winter)

Similar to the cooling system, higher underground VRT was assumed to influence the amount of ventilation system energy consumption. This was expected due to higher heat radiation from underground rock surfaces. The same geographical areas where most deep-level mines in South Africa are concentrated were studied.

Figure 37 shows the average ventilation system energy versus mine location for:

1 = Klerksdorp
2 = Carletonville
3 = Welkom

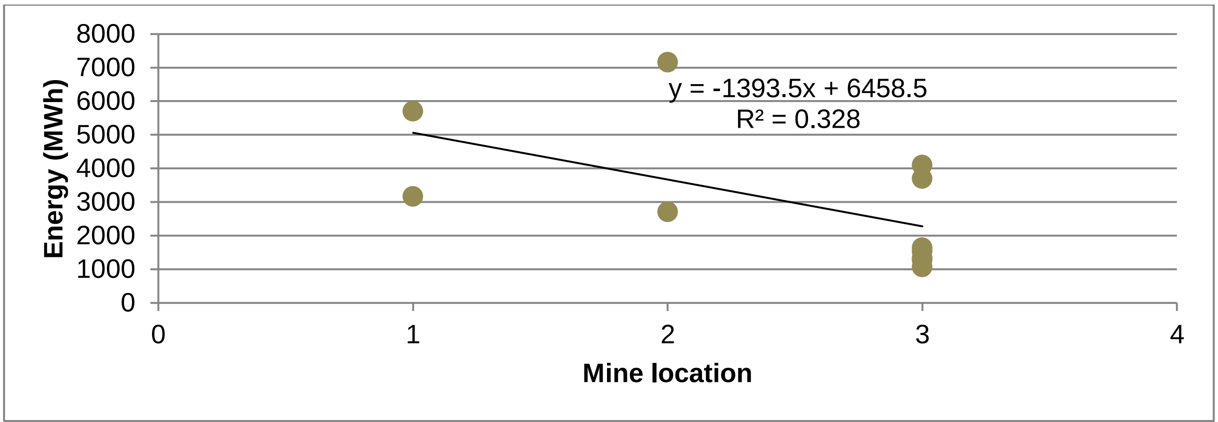


Figure 37: Ventilation system – MWh versus location

Figure 37 produces the same conclusion as was found by Figure 29 for the cooling system. An opposite correlation was found to what was assumed. The higher average ventilation system energy consumption at deeper mines near Klerskdorp and Carletonville once again proves that mine depth plays a more important role in ventilation energy requirement.

Hoisting system

It was mentioned that the independent variables identified for hoisting systems were the same as for most of the other high demand systems – tonnes of ore mined and mine depth. Figure 38 and Figure 39 represent the correlation between hoisting energy consumption and the abovementioned variables.

The result of the abovementioned correlations for Figure 38 shows a good R^2 value of 0.836. However, the R^2 value obtained from the correlation between energy and mine depth (Figure 39) is surprisingly low at 0.714 when keeping in mind that mine depth should have a significant impact on hoisting system energy consumption.

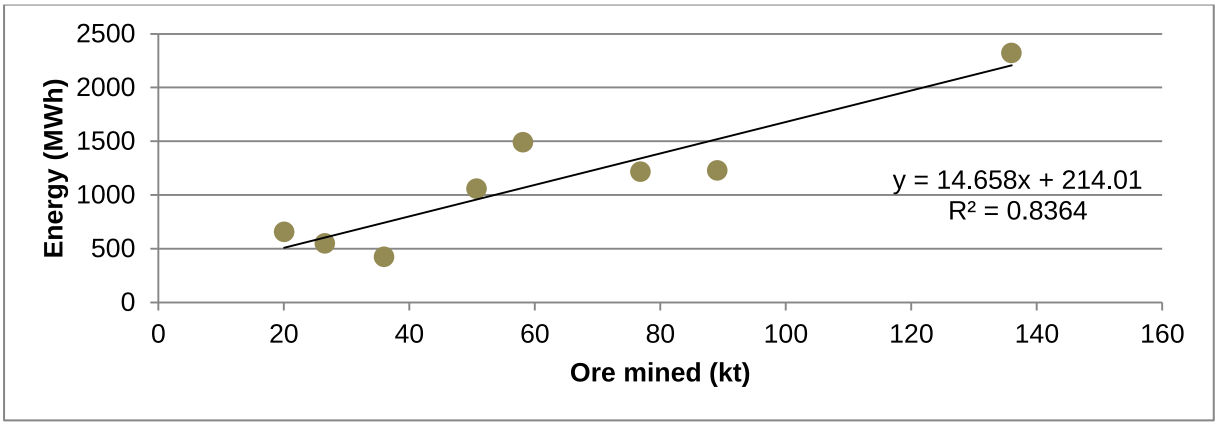


Figure 38: Hoisting system – MWh versus ore mined

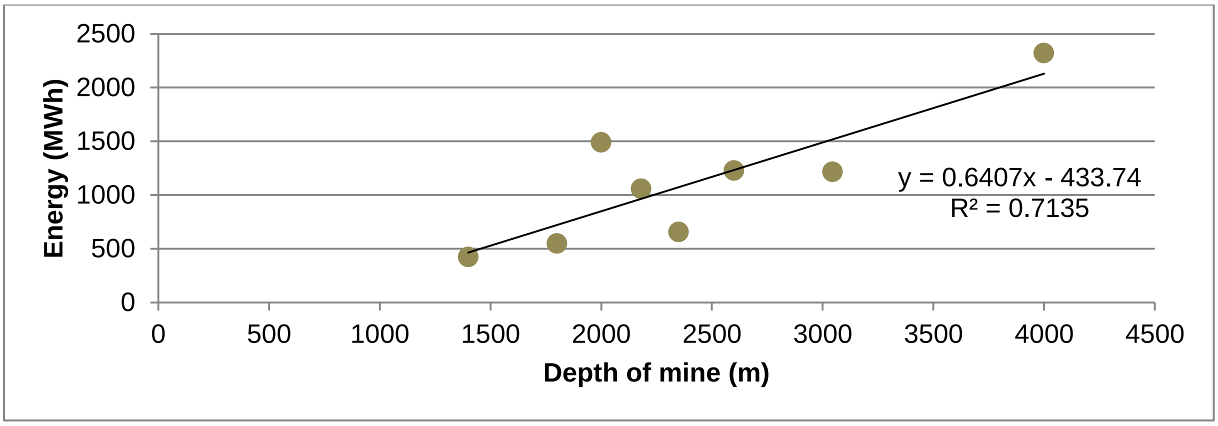


Figure 39: Hoisting system – MWh versus mine depth

It is still clear from Figure 39 that a positive correlation between energy and mine depth exists for hoisting systems. The lower than expected R^2 value can be attributed to a number of possibilities. The most likely cause for the R^2 value not being closer to 1 is because different mines use different hoisting systems (as described in Section 2.6.2). This should, however, not significantly affect the outcome of the study, as mine depth forms only a part of the overall hoisting system energy consumption calculation.

At the start of this section, it was mentioned that it was not expected that the R^2 values would be very close to 1. Values very close to 1 would have shown that most of the mines were equally efficient as calculated intensities would have been roughly the same. Due to the variance in R^2 found for each of the high demand systems, the assumption of efficiency differences between mines was confirmed. It is also important to note that the R^2 values – although not very close to 1 – were still high enough to validate the positive correlations between the independent and dependent variables.

3.2.4 Step 4 – Obtain functions

During the explanation of Step 3 (Section 3.2.3), the independent variables identified in Section 2.8.2 were verified by the OLS method. It is important to note that the identified variables are most likely not the only variables affecting electricity consumption. However, as the variables were selected by analysing system fundamentals, it is assumed that adequate information was used. Using these variables also ensured simplicity.

Individual variable verification (as was done during Step 3) already supplied OLS functions. Each variable provided a function of energy use for a specific system. The high demand systems specifically targeted for this study were highly intricate and dynamic thus the effect of individual variables could not solely be used to determine average energy use. It was, therefore, required that a combining function, which tied all identified variables for each system together, be determined.

Functions obtained from the single variable OLS method used in Step 3 resulted in a simple straight-line equation. The format for straight-line functions with single variables was discussed and shown in Section 2.7. When combining the different variables for each high demand system, the statistical multivariable regression method can be used. This method was explained in Section 2.7.

Using the multivariable method ensured that each variable – be it tonnes of ore mined, mine depth or any other variable included in the construction of the function – accurately reflected the calculation of energy. Equation 19 (shown in Section 2.7) indicates the format of the multivariable regression function. It is seen that this function was also for a straight line but with additional variables projected into more than two dimensions.

Compressed air system

Variables for the compressed air system were energy requirement for one month as the dependent variable, and tonnes of ore mined and mine depth as independent variables. Using the same summer and winter data shown in Section 3.2.2 for compressed air systems, the arrays shown in Table 65 and Table 66 in Appendix A were found. These arrays were obtained using the multivariable calculation method known as the LINEST function in Microsoft Excel®.

Compressed air system data retrieved from the arrays in both Table 65 and Table 66 is shown in Table 25 with R^2prob showing the probability of the R^2 values occurring by chance.

An R^2prob value that approaches1 indicates that the R^2 occurred completely by chance and have no statistical merit. The two multivariable regression functions obtained for both summer and winter months are shown in Equation 20 and Equation 21.

Table 25: Compressed air system array data from LINEST

	Summer	Winter
R^2	0.792	0.861
F	15.22	24.72
d_f	8	8
se_y	1 282.57	1 229.84
R^2prob	0.001879	0.000376

Equation 20: Compressed air energy requirement from LINEST (summer)

$$\boldsymbol{E_{comp} = -269.82 + 1.69(Z) + 28.55(T)}$$

With: E_{comp} = Compressor energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

Equation 21: Compressed air energy requirement from LINEST (winter)

$$\boldsymbol{E_{comp} = 406.76 + 0.78(Z) + 54.16(T)}$$

With: E_{comp} = Compressor energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

In order to verify the accuracy of the functions obtained from the LINEST method, it was decided that the value retrieved from Equation 20 had to be compared with the value found when using a function created manually from the regression models (shown in Section 3.2.3). By using the average of the functions from Figure 21 and Figure 23, the following function for compressed air energy requirement for summer months was found (Equation 22):

Equation 22: Compressed air energy requirement (summer)

$$\boldsymbol{E_{comp} = 737.21 + 1.31(Z) + 30.33(T)}$$

With: E_{comp} = Compressor energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

In order to compare the compressed air energy requirement values calculated from Equation 20 and Equation 22, the available data used for compressed air systems was inserted into both equations. Table 26 displays the actual measured energy consumption as was shown in Section 3.2.3, together with the energy consumption obtained from both Equation 20 and Equation 22.

Table 26: Compressed air system energy consumption

Mine	Actual MWh	Equation 20 (MWh)	Equation 22 (MWh)
B	5 211	6 415	6 604
C	6 387	7 079	7 099
D	9 981	10 038	9 789
E	3 123	2 076	2 660
F	5 632	4 854	5 231
G	2 269	3 065	3 615
H	8 700	6 852	6 737
I	4 604	4 771	5 057
L	6 794	5 374	5 641
M	3 520	3 496	3 883

Upon first inspection, both Equation 20 and Equation 22 delivered relatively similar energy consumption requirements. However, when the values were analysed in more detail, it was seen that Mine D's energy requirement (as was determined by both equations) delivered a different result when compared with the actual data. To illustrate this better, the data points found in Figure 21 and Figure 23 for Mine D were considered.

Figure 40 shows that Mine D used slightly more energy than the average regression line obtained from Figure 21 and Figure 23. Thus, Mine D was slightly less efficient than the benchmark energy consumption for compressed air systems. Looking at the results shown in Table 26 again, it is seen that Mine D's actual energy consumption was 9 981 MWh. The implementation of Equation 20 shows that Mine D was allowed to use up to 10 038 MWh and Equation 22 allowed up to 9 789 MWh. As the actual data retrieved from the mine indicated that Mine D was less efficient than the benchmark, it is clear that the value obtained from Equation 22 was more accurate, albeit marginally.

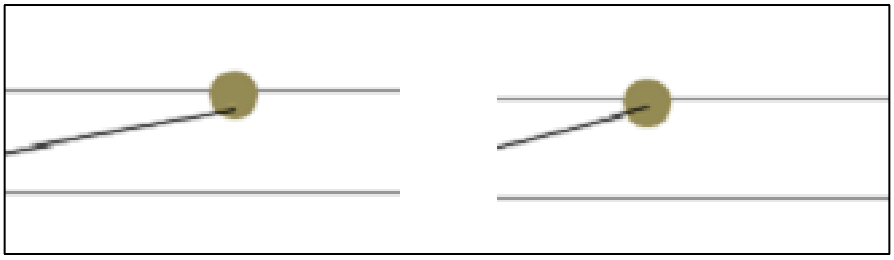


Figure 40: Mine D – compressed air energy use (magnified)

It was, therefore, decided that the method for manually obtaining an average regression function from the models shown in Section 3.2.3 be used instead of multivariable regression analysis. Table 27 presents the data retrieved from the linear regression functions for compressed air systems in Section 3.2.3. The arrays for this data are shown in Appendix A as Table 67 and Table 68. Equation 22 was determined for summer months found by combining the regression functions. Equation 23 represents the winter months.

Table 27: Compressed air system array data

	Summer	Winter
R^2	0.759	0.829
F	34.52	38.72
d_f	8	8
se_y	1 232.64	1 266.60
$R^2 prob$	0.00037	0.00025

Equation 23: Compressed air energy requirement (winter)

$$\boldsymbol{E_{comp}} = \mathbf{172.78} + \mathbf{1.51}(\boldsymbol{Z}) + \mathbf{33.36}(\boldsymbol{T})$$

With: E_{comp} = Compressor energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

Cooling system

The variables for the cooling system were the same as for the compressed air system. The dependent variable was cooling energy requirement for one month and the two independent variables were tonnes of ore mined per month and mine depth. The combined regression functions for both summer and winter months are shown in Appendix A as Table 69 and Table 70. Cooling system regression information retrieved from the arrays in both these tables is shown in Table 28 with R^2prob showing the probability of the R^2 values occurring by chance. The two combined regression functions obtained for both summer and winter months are shown in Equation 24 and Equation 25.

Table 28: Cooling system array data

	Summer	Winter
R^2	0.78	0.66
F	18.42	10.00
d_f	5	5
se_y	1 928.96	2 035.49
R^2prob	0.0077	0.0249

Equation 24: Cooling system energy requirement (summer)

$$\boldsymbol{E_{cool}} = -\mathbf{768.44} + \mathbf{1.79}(\boldsymbol{Z}) + \mathbf{44.50}(\boldsymbol{T})$$

With: E_{cool} = Cooling energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

Equation 25: Cooling system energy requirement (winter)

$$\boldsymbol{E_{cool}} = -\mathbf{464.44} + \mathbf{1.42}(\boldsymbol{Z}) + \mathbf{27.45}(\boldsymbol{T})$$

With: E_{cool} = Cooling energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

Dewatering system

The dewatering system had an additional variable in the form of fissure water. The dependent variable was thus dewatering energy required per month and the independent variables were tonnes of ore mined per month, mine depth and average fissure-water flow rate. The combined regression array for the variables is shown in Table 71 in Appendix A.

Dewatering system regression information retrieved from the array in Table 71 is shown in Table 29. Equation 26 shows the function to calculate average monthly dewatering energy requirement as a function of the independent variables.

Table 29: Dewatering system array data

	Summer and winter
R^2	0.86
F	113.09
d_f	6
se_y	805.39
$R^2 prob$	0.00004

Equation 26: Dewatering system energy requriement

$$\boldsymbol{E_{pump} = -1140.91 + 49.38(f) + 0.91(Z) + 23.32(T)}$$

With: E_{pump} = Dewatering energy requirement (MWh)

f = Average fissure water flow (ℓ/s)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

Ventilation system

To formulate the monthly energy requirement function for the ventilation system, the independent variables of tonnes of ore mined per month and mine depth were again used for both summer and winter months. Table 72 and Table 73 in Appendix A show the combined regression arrays for monthly energy consumption as a function of the independent variables for both summer and winter months respectively.

Ventilation system regression information retrieved from the arrays in both Table 72 and Table 73 is shown in Table 30 with $R^2 prob$ showing the probability of the R^2 values occurring by chance. The average monthly ventilation energy requirement could thus be calculated by the functions derived from Table 72 and Table 73. These functions are shown as Equation 27 for summer months and Equation 28 for winter months.

Table 30: Ventilation system array data

	Summer	Winter
R^2	0.73	0.77
F	25.84	29.87
d_f	9	9
se_y	1 064.21	1 037.95
$R^2 prob$	0.0006	0.0004

Equation 27: Ventilation system energy requirement (summer)

$$\boldsymbol{E_{vent} = -847.94 + 1.05(Z) + 26.12(T)}$$

With: E_{vent} = Ventilation energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

Equation 28: Ventilation system energy requirement (winter)

$$\boldsymbol{E_{vent} = -811.19 + 1.15(Z) + 22.82(T)}$$

With: E_{vent} = Ventilation energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

Hoisting system

Independent variables for the hoisting system again only included the tonnes of ore mined and mine depth. The combined regression function array for hoisting systems with average monthly hoisting energy use as dependent variable is shown in Appendix A as Table 74. Hoisting system regression information retrieved from the array in Table 74 with R^2prob showing the probability of the R^2 value occurring by chance is shown in Table 31. The equation derived from this function is shown as Equation 29. The average monthly hoisting system energy requirement as a function of ore mined and mine depth is obtained from this equation.

Table 31: Hoisting system array data

	Summer and winter
R^2	0.77
F	22.80
d_f	6
se_y	311.53
R^2prob	0.0015

Equation 29: Hoisting system energy requirement

$$\boldsymbol{E_{hoist}} = \mathbf{-109.87 + 0.32(Z) + 7.33(T)}$$

With: E_{hoist} = Hoisting energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

High demand systems combined

The objective of this study stated that a method is required to benchmark the energy use of each of the high demand systems on a deep-level mine separately, as well as benchmark all of the systems as a whole. The need for separate benchmarking was explained to enable the user (mine energy manager) to understand the efficiency of each system as compared with peer mines, and to be aware of shortfalls in the energy efficiency of the systems.

Using Equation 22 to Equation 28 enables the user to determine the average monthly energy required for each of the high demand systems. Therefore, by comparing or benchmarking the actual energy use measured by a mine with the answers obtained from these equations, the user can determine the efficiency of each system. It is important to note that because Equation 22 to Equation 28 were developed by using actual historical data of South African deep-level mines, the answers obtained are a true reflection of the average energy use of these systems.

Each of the separate system functions from Equation 22 to Equation 28 is summarised into one table for summer (Table 32) and one table for winter (Table 33). It is seen that mine depth and tonnes of ore mined are common independent variables for all high demand systems. The only exception is fissure water flow – which is an independent variable – that is added for the dewatering system function.

Table 32: High demand system function summary (summer)

			Gradient		
System	**Dependent variable**	**Constant**	**Mine depth**	**Ore mined**	**Fissure water**
Comp. air	$\boldsymbol{E_{comp}}$	737.21	1.31	30.33	0
Cooling	$\boldsymbol{E_{cool}}$	-768.44	1.79	44.5	0
Dewatering	$\boldsymbol{E_{pump}}$	-1 140.91	0.91	23.32	49.38
Ventilation	$\boldsymbol{E_{vent}}$	-847.94	1.05	26.12	0
Hoisting	$\boldsymbol{E_{hoist}}$	-109.87	0.32	7.33	0
Total		**-2 129.95**	**5.38**	**131.60**	**49.38**

Table 33: High demand system function summary (winter)

System	Dependent variable	Constant	Gradient		
			Mine depth	Ore mined	Fissure water
Comp. air	E_{comp}	172.78	1.51	33.36	0
Cooling	E_{cool}	-464.44	1.42	27.45	0
Dewatering	E_{pump}	-1 140.91	0.91	23.32	49.38
Ventilation	E_{vent}	-811.19	1.15	22.82	0
Hoisting	E_{hoist}	-109.87	0.32	7.33	0
Total		**-2 353.63**	**5.31**	**114.28**	**49.38**

Two new equations can be formulated using the totals of each of the gradients of common independent variables shown in Table 32 and Table 33. These equations represent the calculation of total high demand system energy requirement as a whole. The first equation (Equation 30), which is for summer months, is applied by a user to benchmark energy consumption during the months of September to April. The second equation (Equation 31) is applied for energy benchmarking during the winter months of May to August.

The two total high demand system energy requirement functions were formulated from the separate functions of each system. For this reason, not all of the statistical information acquired from the combined regression arrays is present for total system functions. However, an important factor that is quantifiable from separate system arrays for the total system functions is the standard error of the y-estimate or se_y. As was used to determine the total system function gradients for each independent variable, the sum of separate system se_y values can be used to determine the overall total high demand system value of se_y. The values for both summer and winter months are shown in Table 34.

Table 34: Standard error of the y-estimate for high demand systems

	Summer	Winter
se_y	5 342.73	5 456.96

Equation 30: Total high demand system energy requirement (summer)

$$\boldsymbol{E_{tot} = -2129.95 + 5.38(Z) + 131.60(T) + 49.38(f)}$$

With: E_{tot} = Total high demand system energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

f = Fissure water flow rate (ℓ/s)

Equation 31: Total high demand system energy requirement (winter)

$$E_{tot} = -2353.63 + 5.31(Z) + 114.28(T) + 49.38(f)$$

With: E_{tot} = Total high demand system energy requirement (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

f = Fissure water flow rate (ℓ/s)

3.3 DEVELOPMENT OF SCORING TECHNIQUE

3.3.1 Methodology

This section focuses on developing the technique to be used by mines to obtain a benchmarking score for each of the high demand systems and for all the systems as a whole. It is important to quantify the score, as it will give a direct indication of specific system efficiency and will enable a mine to observe this instantly. The technique for scoring high demand systems or benchmarking high demand system energy consumption will be broken down into a few steps.

The simplest method would be to use just the system-specific functions obtained from Section 3.2.4. However, it is important to consider some of the statistical factors retrieved from the regression arrays during the development of these functions. Due to the varied scattering of data, which implies differences in efficiencies from different mines, standard errors of the y-estimate (se_y) – in other words, standard errors in the estimation of energy consumption required – cannot be ignored. It is thus necessary to normalise the score to reflect the standard error and not penalise a mine for scoring in the lower regions but still within the error range.

3.3.2 Development of normalisation functions

Normalisation can only be done after an initial score, which does not consider the standard error, has been obtained. This will be known as the initial score or $\%_{initial}$. In order to obtain the normalised score (known as the corrected score or $\%_{corrected}$), each of the high demand systems' se_y will be used to determine normalisation functions. The $\%_{initial}$ obtained from each system for a specific mine being tested will fall into one of three categories: underperformance, normal performance or overperformance. Each of these categories will be related to a categorical function used to calculate $\%_{corrected}$.

As was previously mentioned, the standard error of the y-estimate will be used to determine the normalisation functions for each of the high demand systems' three categories. The calculation of $\%_{initial}$ used to determine the category that has to be used is shown by Equation 32.

Equation 32: Calculation of initial percentage

$$\%_{\boldsymbol{initial}} = \frac{\boldsymbol{E_{model}}}{\boldsymbol{E_{actual}}}$$

With: $\%_{\boldsymbol{initial}}$ = Initial benchmarking score (%)

E_{model} = Required energy obtained from system functions (MWh)

E_{actual} = Actual energy consumption measured (MWh)

Converting each of the high demand systems' standard error to a percentage error is required for further use in determining the performance category that a system's score will fall into. By using the averages of all independent variables used to obtain system-specific functions in Section 3.2.4, the average energy required for each system is found. This is compared with the standard error to determine the percentage error ($\%_{error}$) and is shown in Equation 33.

Equation 33: Calculation of percentage error

$$\%_{\boldsymbol{error}} = \frac{\boldsymbol{se_y}}{\boldsymbol{E_{model_{ave}}}}$$

With: $\%_{error}$ = Percentage error of se_y (%)

se_y = Standard error of the y-estimate (MWh)

$E_{model_{ave}}$ = Average required energy obtained from system functions (MWh)

Using the value of $\%_{error}$ from Equation 33, the three performance categories can be obtained: underperformance, normal performance and overperformance. The range of each of these categories is a function of $\%_{error}$ and a specific category is selected by using $\%_{initial}$ (shown in Table 35). The overperformance category goes up to 200 to obtain the same gradient as the underperformance category.

Table 35: Normalisation category ranges

Category	$\%_{initial}$ range
Underperformance	0 to (100 – $\%_{error}$)
Normal performance	(100 – $\%_{error}$) to (100 + $\%_{error}$)
Overperformance	(100 + $\%_{error}$) to 200

Now that the performance category can be selected from $\%_{initial}$, the final normalisation to $\%_{corrected}$ can be achieved. In order to do this a function for each of the categories has to be obtained. This is done by drawing a regression plot between $\%_{corrected}$ as dependent variable and $\%_{initial}$ as independent variable. To draw a regression plot, $\%_{corrected}$ values corresponding with the $\%_{initial}$ values obtained from Table 35 have to be selected. A value of 100% is selected as the score obtained for systems with performances equal to the benchmark. A variance of 10% in both directions is selected as the range for the normal performance category. This is to normalise $\%_{initial}$ scores that exist within the $\%_{error}$ range to within 10% of the benchmark.

The dependent variable ranges selected for both underperformance and overperformance categories are related to the 10% variance selected for normal performance. Therefore, the ranges for both dependent variables of underperformance and overperformance are 0– 90%, and 110– 200% respectively. This is made clear by Table 36 and the regression plot shown in Figure 41.

Table 36: Variable ranges for regression of each performance categories

Underperformance (f1)		Normal performance (f2)		Overperformance (f3)	
$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$
0	0	100 – $\%_{error}$	90	100 + $\%_{error}$	110
100 – $\%_{error}$	90	100 + $\%_{error}$	110	200	200

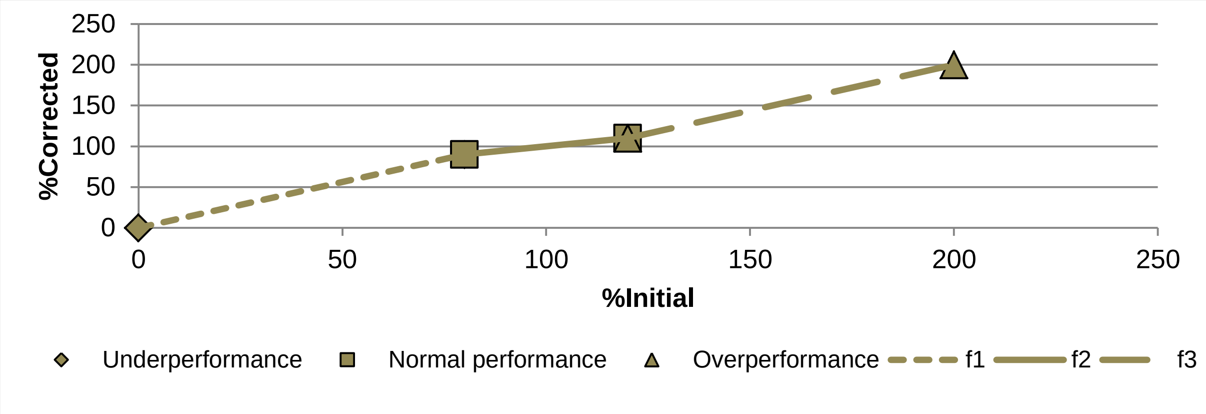


Figure 41: Corrected score versus initial score

Using functions obtained from Figure 41, the $\%_{corrected}$ can be calculated. The criteria used to determine which of the three functions to use are shown in the "Criteria" column of Table 37. The corresponding function to be used is shown in the "Equation used" column.

Table 37: Calculation of percentage corrected

Category	Criteria	Equation used
Underperformance	$\%_{initial}$ < (100 – $\%_{error}$)	f_1
Normal performance	(100 – $\%_{error}$) < $\%_{initial}$ < (100 + $\%_{error}$)	f_2
Overperformance	$\%_{initial}$ > (100 + $\%_{error}$)	f_3

For each of the high demand systems it is now necessary to determine the three functions that will be used to calculate $\%_{corrected}$. These functions will be named f_1 for the underperformance category, f_2 for the normal performance category and f_3 for the overperformance category. The value of $\%_{error}$ was calculated using Equation 33. Thereafter, the values for dependent ($\%_{corrected}$) and independent ($\%_{initial}$) variables were found. Table 75 to Table 85 found in Appendix B show these values. Regression plots of these variables are shown in Appendix C for each of the high demand systems.

Calculating the high demand systems' $\%_{\mathrm{corrected}}$ is done using the equations obtained from the functions of Figure 86 to Figure 92. The criteria for each category are derived from the corresponding tables found in Appendix B. The equations and criteria are shown in Table 38 below.

Table 38: Calculation of percentage corrected for each high demand system

Category	Criteria	Equation used
Compressed air system – summer		
Underperformance	$\%_{initial}$ < 78.07	$\%_{corrected} = 1.1528 \times \%_{initial}$
Normal performance	78.07 < $\%_{initial}$ < 121.93	$\%_{corrected} = (0.456 \times \%_{initial}) + 54.399$
Overperformance	$\%_{initial}$ > 121.93	$\%_{corrected} = (1.1528 \times \%_{initial}) - 30.561$
Compressed air system – winter		
Underperformance	$\%_{initial}$ < 78.99	$\%_{corrected} = 1.1394 \times \%_{initial}$
Normal performance	78.99 < $\%_{initial}$ < 121.01	$\%_{corrected} = (0.476 \times \%_{initial}) + 52.405$
Overperformance	$\%_{initial}$ > 121.01	$\%_{corrected} = (1.1394 \times \%_{initial}) - 27.878$
Cooling system – summer		
Underperformance	$\%_{initial}$ < 70.06	$\%_{corrected} = 1.2846 \times \%_{initial}$
Normal performance	70.06 < $\%_{initial}$ < 129.94	$\%_{corrected} = (0.334 \times \%_{initial}) + 66.597$
Overperformance	$\%_{initial}$ > 129.94	$\%_{corrected} = (1.2846 \times \%_{initial}) - 56.193$
Cooling system – winter		
Underperformance	$\%_{initial}$ < 59.43	$\%_{corrected} = 1.5144 \times \%_{initial}$
Normal performance	59.43 < $\%_{initial}$ < 140.57	$\%_{corrected} = (0.2465 \times \%_{initial}) + 75.352$
Overperformance	$\%_{initial}$ > 140.57	$\%_{corrected} = (1.5144 \times \%_{initial}) - 102.88$
Dewatering system		
Underperformance	$\%_{initial}$ < 73	$\%_{corrected} = 1.2329 \times \%_{initial}$
Normal performance	723 < $\%_{initial}$ < 127	$\%_{corrected} = (0.3703 \times \%_{initial}) + 62.968$
Overperformance	$\%_{initial}$ > 127	$\%_{corrected} = (1.2329 \times \%_{initial}) - 46.589$
Ventilation system – summer		
Underperformance	$\%_{initial}$ < 63.57	$\%_{corrected} = 1.4158 \times \%_{initial}$
Normal performance	63.57 < $\%_{initial}$ < 136.43	$\%_{corrected} = (0.2745 \times \%_{initial}) + 72.55$
Overperformance	$\%_{initial}$ > 136.43	$\%_{corrected} = (1.4158 \times \%_{initial}) - 83.152$
Ventilation system – winter		
Underperformance	$\%_{initial}$ < 67.10	$\%_{corrected} = 1.3413 \times \%_{initial}$
Normal performance	67.10 < $\%_{initial}$ < 132.9	$\%_{corrected} = (0.3039 \times \%_{initial}) + 69.606$
Overperformance	$\%_{initial}$ > 132.9	$\%_{corrected} = (1.3413 \times \%_{initial}) - 68.259$
Hoisting system		
Underperformance	$\%_{initial}$ < 69.86	$\%_{corrected} = 1.2882 \times \%_{initial}$
Normal performance	69.86 < $\%_{initial}$ < 130.14	$\%_{corrected} = (0.3318 \times \%_{initial}) + 66.819$
Overperformance	$\%_{initial}$ > 130.14	$\%_{corrected} = (1.2882 \times \%_{initial}) - 57.65$

By considering the sum of all se_y for each of the high demand system arrays (as was found in Table 34), the functions to obtain $\%_{corrected}$ for all the systems as a whole can be determined. These functions are shown in Figure 42 and Figure 43 for summer and winter months. The performance category criteria and equations to use to calculate $\%_{\mathrm{corrected}}$ when specific criteria are met are shown in Table 39.

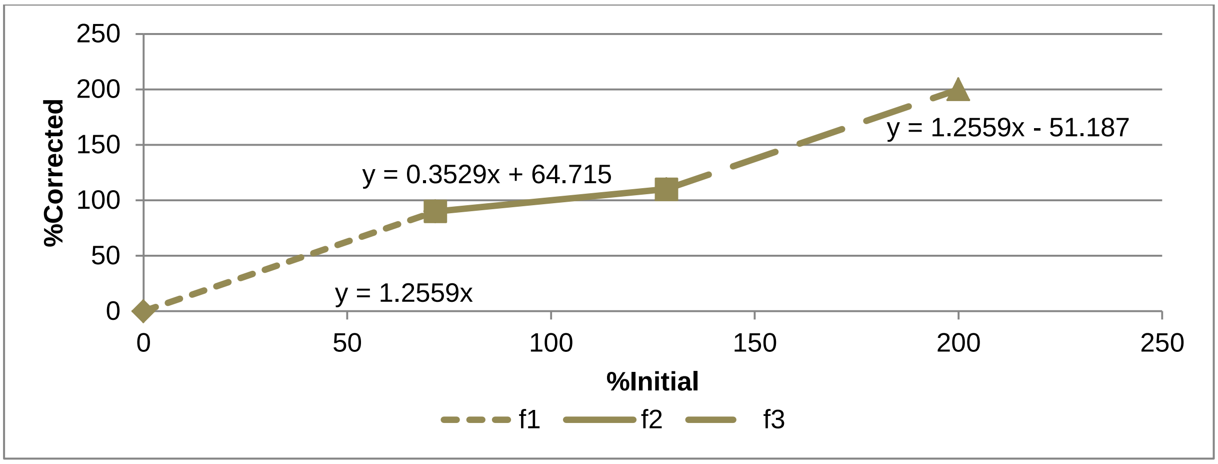


Figure 42: All high demand systems – percentage corrected versus initial percentage (summer)

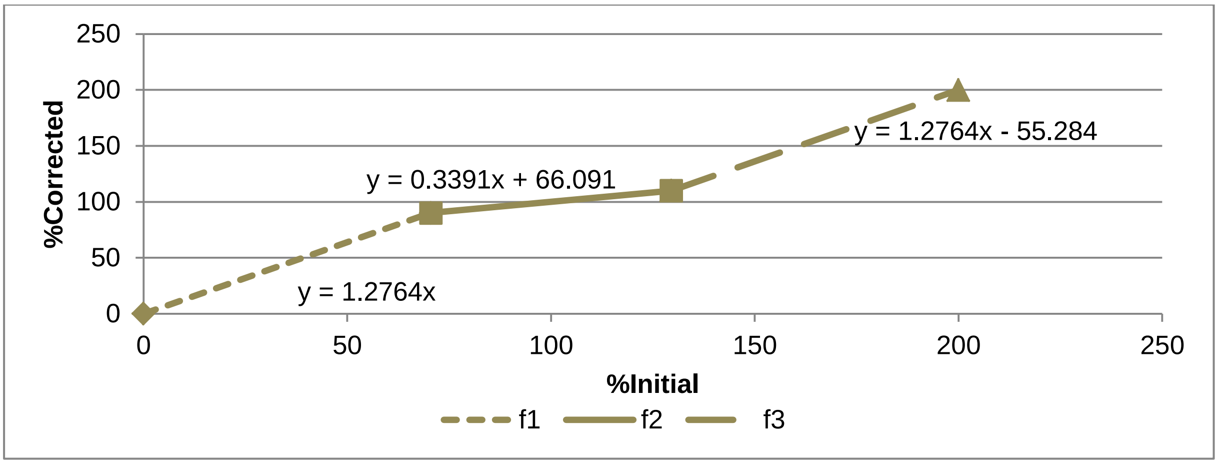


Figure 43: All high demand systems – percentage corrected versus initial percentage (winter)

Table 39: Calculation of percentage corrected for all high demand systems

Category	Criteria	Equation used
All high demand systems – summer		
Underperformance	$\%_{initial} < 71.66$	$\%_{corrected} = 1.2743 \times \%_{initial}$
Normal performance	$71.66 < \%_{initial} < 128.34$	$\%_{corrected} = (0.3529 \times \%_{initial}) + 64.715$
Overperformance	$\%_{initial} > 128.34$	$\%_{corrected} = (1.2743 \times \%_{initial}) - 51.187$
All high demand systems – winter		
Underperformance	$\%_{initial} < 70.51$	$\%_{corrected} = 1.3068 \times \%_{initial}$
Normal performance	$70.51 < \%_{initial} < 129.49$	$\%_{corrected} = (0.3391 \times \%_{initial}) + 66.091$
Overperformance	$\%_{initial} > 129.49$	$\%_{corrected} = (1.3068 \times \%_{initial}) - 55.284$

3.4 DEVELOPMENT OF BEST PRACTICE BENCHMARKS

3.4.1 Frontier benchmarking

Frontier benchmarking was explained in Section 2.7.2 as a method for determining the best practice benchmark. The three frontier-benchmarking methods (COLS, SFA and DEA) were explained and the usability of each method was discussed. COLS and SFA produce similar functions to the OLS method used, to determine the average benchmarks for each high demand system (Section 3.2). In order to achieve frontier-benchmarking functions, the gradient of the functions obtained from average benchmarking will be used and the functions will be scaled down sufficiently to represent either a COLS or an SFA function.

The SFA method is designed to eliminate noise from a large number of data points. It was decided that due to the relatively low number of data points available for each function, the COLS method would firstly be used to determine the best practice benchmarks. The OLS average benchmarking functions from Section 3.2 will thus be scaled down while maintaining the same gradient, until the most efficient data points intersect.

3.4.2 High demand system individual best practice benchmarks

Similar to what was done in Section 3.2.3, correlations between each of the dependent and independent variables were found for each of the high demand systems. Instead of average linear regression functions (OLS) used in Section 3.2.3, the COLS best practice benchmarking method was used on the same data. Each of these regressions is displayed in graph form in Appendix D (Figure 94 to Figure 110). As was mentioned in Section 3.4.1, the trend lines of these regressions intersect the most efficient data points.

Using the functions obtained from each of the regression models for best practice benchmarking (COLS method), the best practice energy consumption for each of the high demand systems can be calculated. The separate regression models between energy consumption and the different independent variables are once again combined to create an overall function representing the overall energy consumption of each high demand system.

The independent variables for the newly created best practice functions are exactly the same as for the average benchmarking functions; namely kilotonnes of ore mined, mine depth and amount of fissure water flow into the system. Equation 34 to Equation 41 are derived from the functions found in Figure 94 to Figure 110 with:

- T representing kilotonnes of ore mined
- Z representing mine depth
- f representing amount of fissure water flow into the system

Equation 34: Compressed air system – COLS best practice energy (summer)

$$E_{bp_{comp}} = -699.28 + 1.31(Z) + 30.33(T)$$

With: $E_{bp_{comp}}$ = Best practice benchmark for compressed air energy consumption (MWh)

Equation 35: Compressed air system – COLS best practice energy (winter)

$$E_{bp_{comp}} = -1930.21 + 1.51(Z) + 33.36(T)$$

With: $E_{bp_{comp}}$ = Best practice benchmark for compressed air energy consumption (MWh)

Equation 36: Cooling system – COLS best practice energy (summer)

$$E_{bp_{comp}} = -3478.35 + 1.79(Z) + 44.50(T)$$

With: $E_{bp_{cool}}$ = Best practice benchmark for cooling energy consumption (MWh)

Equation 37: Cooling system – COLS best practice energy (winter)

$$E_{bp_{comp}} = -3195.6 + 1.42(Z) + 27.45(T)$$

With: $E_{bp_{cool}}$ = Best practice benchmark for cooling energy consumption (MWh)

Equation 38: Dewatering system – COLS best practice energy

$$E_{bp_{comp}} = -2098.73 + 0.91(Z) + 23.32(T) + 49.38(f)$$

With: $E_{bp_{pump}}$ = Best practice benchmark for dewatering energy consumption (MWh)

Equation 39: Ventilation system – COLS best practice energy (summer)

$$E_{bp_{vent}} = -2760.95 + 1.05(Z) + 26.12(T)$$

With: $E_{bp_{vent}}$ = Best practice benchmark for dewatering energy consumption (MWh)

Equation 40: Ventilation system – COLS best practice energy (winter)

$$E_{bp_{vent}} = -2640.70 + 1.15(Z) + 22.82(T)$$

With: $E_{bp_{vent}}$ = Best practice benchmark for dewatering energy consumption (MWh)

Equation 41: Hoisting system – COLS best practice energy

$$E_{bp_{hoist}} = -477.07 + 0.32(Z) + 7.33(T)$$

With: $E_{bp_{hoist}}$ = Best practice benchmark for dewatering energy consumption (MWh)

Analysing the functions obtained from the COLS method showed that some of the functions were lowered to such an extent that tonnes of ore mined and mine depth variables commonly found on actual mines would result in negative best practice energy consumption. In order to mitigate this, the SFA method had to be applied to some of the high demand system functions. To adjust the COLS function in question to SFA functions, certain targets for the independent variables had to be set. For tonnes of ore mined the target was 0 and for mine depth the target was 1 200 m (the shallowest model mine).

With these targets in mind, the COLS functions were altered at a constant gradient to ensure a best practice benchmark energy consumption of 0 MWh would equate to 0 tonnes of ore mined and a mine depth of 1 200 m. To convert COLS to SFA for the energy versus tonnes functions, the y-intercept was equalled to 0. Conversion of the energy versus depth functions was done by applying certain steps shown in Figure 44 and numbered below.

1. Find the absolute value of the COLS function y-intercept.
2. Find the value of the COLS function gradient.
3. Determine SFA y-intercept by multiplying target depth with COLS function gradient.

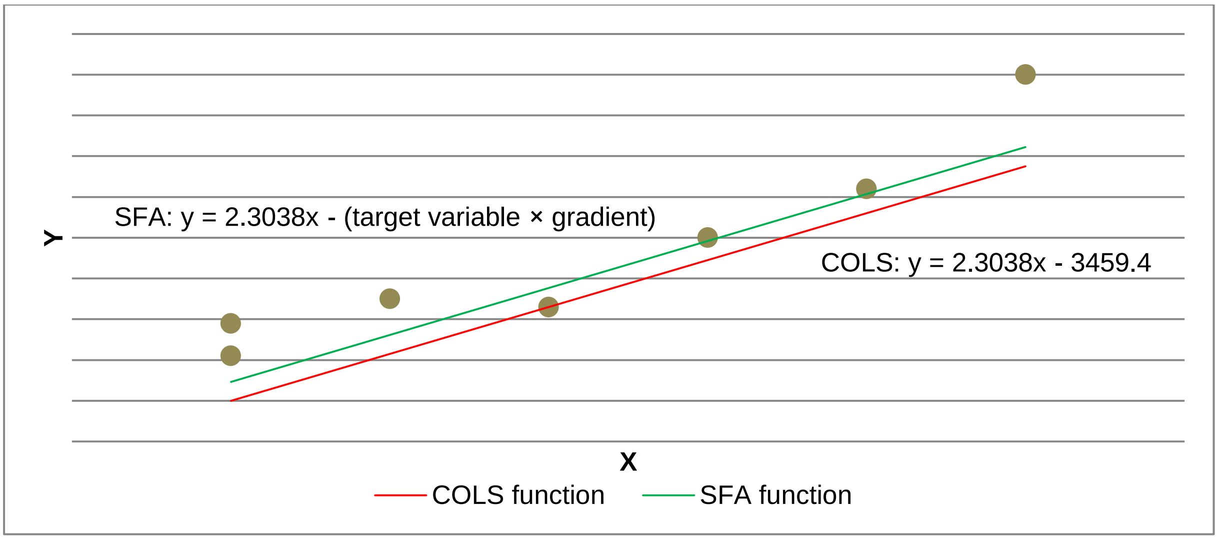


Figure 44: COLS-to-SFA function conversion

Not all COLS functions resulted in the ore mined and mine depth ranges being inaccurate. Table 40 shows each high demand system with the applicable best practice benchmark-development method that was used to obtain best practice benchmarking functions.

Table 40: Best practise benchmarking method per system

High demand system	Function	
	Summer	Winter
Compressed air	COLS	SFA
Cooling	SFA	SFA
Dewatering	SFA	
Ventilation	SFA	SFA
Hoisting	SFA	

Specifically for the dewatering system, it was found that due to the shape of the regression analysis originally used to determine the average benchmarking functions, a target of 0 tonnes for a best practice function was not feasible. It was determined that due to the dewatering function containing three independent variables, this would not be problematic and a target of 20 kilotonnes of ore mined for the SFA function was selected. The same procedure described in the three steps and in Figure 44 was used to determine the SFA function for dewatering systems.

After applying the COLS-to-SFA function conversion on all systems except for the compressed air system during summer months, new SFA functions were found (shown in Appendix D as Figure 111 to Figure 125). The method of combining per-system functions was again used and Equation 42 to Equation 48 were derived with the following variables:

- T representing kilotonnes of ore mined
- Z representing mine depth
- f representing amount of fissure water flow into the system

Equation 42: Compressed air system – SFA best practice energy (winter)

$$\boldsymbol{E_{bp_{comp}} = -1507.45 + 1.51(Z) + 33.36(T)}$$

With: $\boldsymbol{E_{bp_{comp}}}$ = Best practice benchmark for compressed air energy consumption (MWh)

Equation 43: Cooling system – SFA best practice energy (summer)

$$\boldsymbol{E_{bp_{comp}} = -2157.85 + 1.79(Z) + 44.50(T)}$$

With: $\boldsymbol{E_{bp_{cool}}}$ = Best practice benchmark for cooling energy consumption (MWh)

Equation 44: Cooling system – SFA best practice energy (winter)

$$\boldsymbol{E_{bp_{comp}} = -1704.1 + 1.42(Z) + 27.45(T)}$$

With: $\boldsymbol{E_{bp_{cool}}}$ = Best practice benchmark for cooling energy consumption (MWh)

Equation 45: Dewatering system – SFA best practice energy

$$\boldsymbol{E_{bp_{comp}} = -1533.83 + 0.91(Z) + 23.32(T) + 49.38(f)}$$

With: $\boldsymbol{E_{bp_{pump}}}$ = Best practice benchmark for dewatering energy consumption (MWh)

Equation 46: Ventilation system – SFA best practice energy (summer)

$$\boldsymbol{E_{bp_{vent}} = -1265.0 + 1.05(Z) + 26.12(T)}$$

With: $\boldsymbol{E_{bp_{vent}}}$ = Best practice benchmark for dewatering energy consumption (MWh)

Equation 47: Ventilation system – SFA best practice energy (winter)

$$E_{bp_{vent}} = -1382.65 + 1.15(Z) + 22.82(T)$$

With: $E_{bp_{vent}}$ = Best practice benchmark for dewatering energy consumption (MWh)

Equation 48: Hoisting system – SFA best practice energy

$$E_{bp_{hoist}} = -384.42 + 0.32(Z) + 7.33(T)$$

With: $E_{bp_{hoist}}$ = Best practice benchmark for dewatering energy consumption (MWh)

3.4.3 High demand system combined best practice benchmark

In Section 3.2.4, the individual high demand system average benchmark energy consumption functions were combined to obtain a single overall high demand system energy consumption requirement for both summer and winter months. The same principle is followed to acquire a best practice energy consumption benchmark for all high demand systems combined. Once again, all constants of the different system functions are summed as well as the gradients linked to each of the independent variables.

Table 41 and Table 42 display the development of the overall functions for summer and winter months respectively. Equation 49 and Equation 50 display the individual functions of obtaining the best practice energy consumption for all high demand systems combined for summer and winter months respectively.

Table 41: High demand system best practice function summary (summer)

			Gradient		
System	**Dependent variable**	**Constant**	**Mine depth**	**Ore mined**	**Fissure water**
Comp. air	$E_{bp_{comp}}$	-699.28	1.31	30.33	0
Cooling	$E_{bp_{cool}}$	-2 157.85	1.79	44.5	0
Dewatering	$E_{bp_{pump}}$	-1 533.83	0.91	23.32	49.38
Ventilation	$E_{bp_{vent}}$	-1265	1.05	26.12	0
Hoisting	$E_{bp_{hoist}}$	-384.42	0.32	7.33	0
Total		**-6 040.38**	**5.38**	**131.60**	**49.38**

Table 42: High demand system best practice function summary (winter)

System	Dependent variable	Constant	Gradient: Mine depth	Gradient: Ore mined	Gradient: Fissure water
Comp. air	$E_{bp_{comp}}$	-1507.45	1.51	33.36	0
Cooling	$E_{bp_{cool}}$	-1704.1	1.42	27.45	0
Dewatering	$E_{bp_{pump}}$	-1 533.83	0.91	23.32	49.38
Ventilation	$E_{bp_{vent}}$	-1 382.65	1.15	22.82	0
Hoisting	$E_{bp_{hoist}}$	-384.42	0.32	7.33	0
Total		**-6 512.45**	**5.31**	**114.28**	**49.38**

Equation 49: Total high demand system best practice energy (summer)

$$\boldsymbol{E_{bp_{tot}} = -6040.38 + 5.38(Z) + 131.60(T) + 49.38(f)}$$

With: $E_{bp_{tot}}$ = Total high demand system best practice energy (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

f = Fissure water flow rate (ℓ/s)

Equation 50: Total high demand system best practice energy (winter)

$$\boldsymbol{E_{bp_{tot}} = -6512.45 + 5.31(Z) + 131.60(T) + 49.38(f)}$$

With: $E_{bp_{tot}}$ = Total high demand system best practice energy (MWh)

Z = Depth of mine (m)

T = Tonnes of ore mined (kt)

f = Fissure water flow rate (ℓ/s)

Seeing as the functions obtained for best practice benchmarking are derived from the average benchmarks developed in Section 3.2.4 with the same gradients, the same normalisation functions can be used to score the mines. In the case of best practice benchmarks, the benchmark equals a score of 100%. The normalised scores of the different mines reflect their energy consumption against the best practice benchmark.

3.5 THE BENCHMARKING PROCEDURE

The system-specific functions for the benchmarking procedure were obtained together with scoring functions during the previous sections of this chapter. The final procedure for quantifying a mine's single high demand system required energy use per month can be described. The required energy use per month (obtained from the functions developed in Section 3.2.4) is the benchmark energy use as a function of the specific inputs used for that month. The steps to be taken by a mine energy manager to benchmark a high demand system are shown as a flowchart in Figure 45.

Step 1 is to identify a month for which the benchmark needs to be calculated. System-specific variables for this month must also be collected for use in the benchmarking functions. It was shown that for all systems, with dewatering being the only exception, mine depth and tonnes of ore mined were the only required variables.

Step 2 is to identify a high demand system to be benchmarked. The high demand systems include compressed air, cooling, dewatering, hoisting and ventilation systems for the purpose of this study. After the system is identified, the corresponding function developed for that system is selected.

Step 3 is to obtain the required energy use (benchmark) per month by inserting variables selected during Step 1 into the system-specific function identified in Step 2.

Step 4 is to calculate the value of $\%_{initial}$ by using Equation 32 (as described in Section 3.3.2).

Step 5 is to determine the value of $\%_{corrected}$ using the normalisation functions developed in Section 3.3.2. A $\%_{corrected}$ value of 100 will equate to score equal to the benchmark. A score of below 100 will show that the specific system on a specific mine is using more energy than the benchmark for that mine's variables. A score above 100 will show that less energy is used.

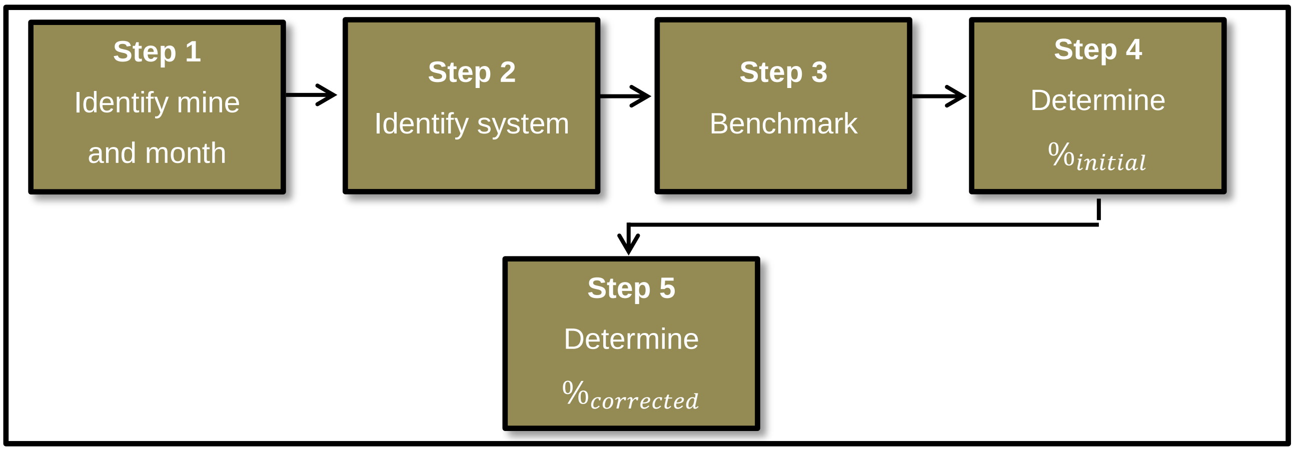


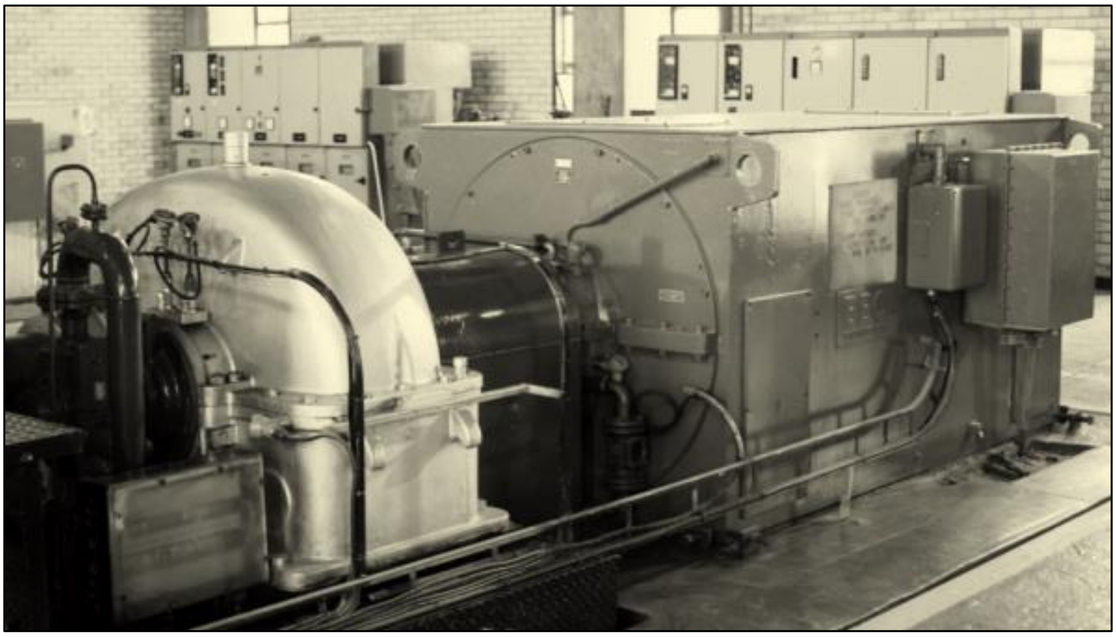
Figure 45: Benchmark and scoring procedure

3.6 SUMMARY

Developing benchmarking models (as was stated to be the objective of this study) was accomplished during the course of Chapter 3. At first, dual variable regression analysis was presented to verify the assumed correlations between energy consumption of different high demand systems and the independent variables identified in Chapter 2. After this verification was done, a method for using the average functions obtained from regression analyses was used to obtain high demand system-specific functions for average benchmarking.

To consider all high demand systems when determining relation to average benchmarks, an overall model was also developed. By using the different high demand benchmarking functions and the statistical accuracy thereof, a scoring technique was developed. The scores enable mines to determine the level of efficiency of each high demand system individually when compared with the industry average. Finally, the methods described in Chapter 2 concerning frontier benchmarking were used to obtain best practice benchmarking models for individual high demand systems and all the systems in combination.

CHAPTER 4 – Model verification



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[8]C. Cilliers, Personal photograph. "Compressor", Carletonville, 2014.

4.1 PREAMBLE

The need for new contributions to knowledge from this study was emphasised in Chapter 1. During the course of Chapter 3, the framework for these contributions were developed using actual data from actual deep-level mines situated in South Africa. Both average benchmarking models and best practice benchmarking models were derived from data representing multiple months per mine. The purpose of Chapter 4 is to verify the benchmarking models and their application as novel contributions.

The four contributions were defined as:

1. **New average benchmarking models for the energy use of deep-level mines' individual high demand systems based on actual data.**
2. **New best practice benchmarking models for the energy use of deep-level mines' individual high demand systems based on actual data.**
3. **A new method for prioritising energy efficiency interventions on deep-level mine high demand systems.**
4. **A new method for determining operational budgets of high demand systems on deep-level mines.**

4.2 VERIFICATION OF MODELS

The need to verify the benchmarking functions (as developed in Chapter 3) is paramount to the verification of the study as a whole. The fundamentals of each high demand system that this study focuses on were discussed within Chapter 2. From these equations, the variables were analysed. The independent variables that directly increase energy consumption for each system were identified. Relationships between the identified independent variables, tonnes of ore mined, as well as mine depth, were shown.

These observations were verified using system-specific fundamentals as groundwork for establishing that an increase in tonnes of ore mined and mine depth will increase energy consumption. This was also further proved by using actual data to create benchmarking models with coefficient of determination (R^2) values of more than 0.6 and an obvious positive correlation. However, it was deemed necessary to implement an independent third-party verification method.

By using simulations for each of the high demand systems and comparing the energy consumption provided by these simulations with the benchmark consumption (given by the benchmarking functions), final verification can be achieved. The demand of each system – whether it is compressed air volume, chilled water volume and so forth – need to be matched with the measured values of tonnes of ore mined and mine depth obtained. By implementing this strategy, the benchmark scores obtained for each system can be verified by comparing the scores with the system efficiencies found by the simulations.

4.3 AVERAGE MODEL VERIFICATION

Process Toolbox™ (PTB), a powerful simulation package for thermal hydraulic systems, was used to simulate the compressed air, cooling and dewatering systems. A software program to simulate ventilation system and hoisting system energy consumption was not available at the time of the study. This was, however, not problematic due to the fundamentals of ventilation and hoisting systems being available. For hoisting systems, the energy consumption fundamentals have direct implications on tonnes of ore mined (mass) and mine depth (vertical distance hoisted).

Compressed air system

For the compressed air system, it was decided that a system efficiency in terms of MWh/tonne be used to validate the benchmarking functions. Firstly, the amount of energy required to generate the amount of air/tonne was simulated. In Section 2.2.4 it was shown that the amount of air was between 12 kg/t and 24 kg/t. For the purpose of the simulation model, an average of 17.5 kg/t was selected. The total amount of air for each of the mines used during benchmarking model development was calculated for use in the simulation.

After the total amount of compressed air was calculated, the energy required to compress this air to the desired pressure, and to consistently provide this air was simulated. A delivery pressure set point of 620 kPa for the underground areas was selected, as this was the maximum pressure needed (as discussed in Section 2.2.4). The simulation inputs are summarised in Appendix E in Table 88 and Table 89. A simulation screenshot is shown as Figure 129 in Appendix F. By subtracting the energy required for tonnes of ore from the total energy, a surplus amount of energy is obtained. This energy is due to various other processes as well as leaks in the compressed air system.

Finally, using the surplus compressed air energy and dividing it with the amount of tonnes mined per mine, a surplus MWh/kt value is obtained. The benchmark ranks obtained from $\%_{corrected}$ values are compared with the ranks obtained from surplus MWh/kt. Lower MWh/tonne values mean higher efficiency. Table 90 and Table 91 in Appendix E display the simulated values for summer and winter months respectively. Table 43 and Table 44 compare the ranks obtained from this study's benchmarking models with the simulated values for summer and winter months respectively.

Table 43: Compressed air system – benchmark verification (summer)

Mine	Benchmark rank	Surplus MWh rank	Error
B	2	1	1
C	3	4	1
D	6	3	3
E	8	10	2
F	7	5	2
G	1	2	1
H	10	9	1
I	5	6	1
L	9	7	2
M	4	8	4
Average difference:		**1.8**	
Correct prediction:		**82%**	

Table 44: Compressed air system – benchmark verification (winter)

Mine	Benchmark rank	Surplus MWh rank	Error
B	7	3	4
C	2	4	2
D	5	2	3
E	6	10	4
F	10	7	3
G	1	1	0
H	9	8	1
I	4	5	1
L	8	6	2
M	3	9	6
Average difference:		**2.6**	
Correct prediction:		**74%**	

From Table 43 it is seen that the benchmarking model for compressed air systems had an average correct prediction of 82% for summer months. For winter months, the prediction was slightly lower at 74% (shown in Table 44). For a visual comparison between the benchmark models and the efficiency obtained from simulations, refer to Figure 46 and Figure 47. These figures show the $\%_{\text{corrected}}$ values against 1/(surplus MWh/kt). It is important to note that the $\%_{\text{corrected}}$ values should not necessarily be the same as those found for 1/(surplus MWh/kt). Higher $\%_{\text{corrected}}$ values should only correspond with higher 1/(surplus MWh/kt) values; lower $\%_{\text{corrected}}$ values should only correspond with lower 1/(surplus MWh/kt) values.

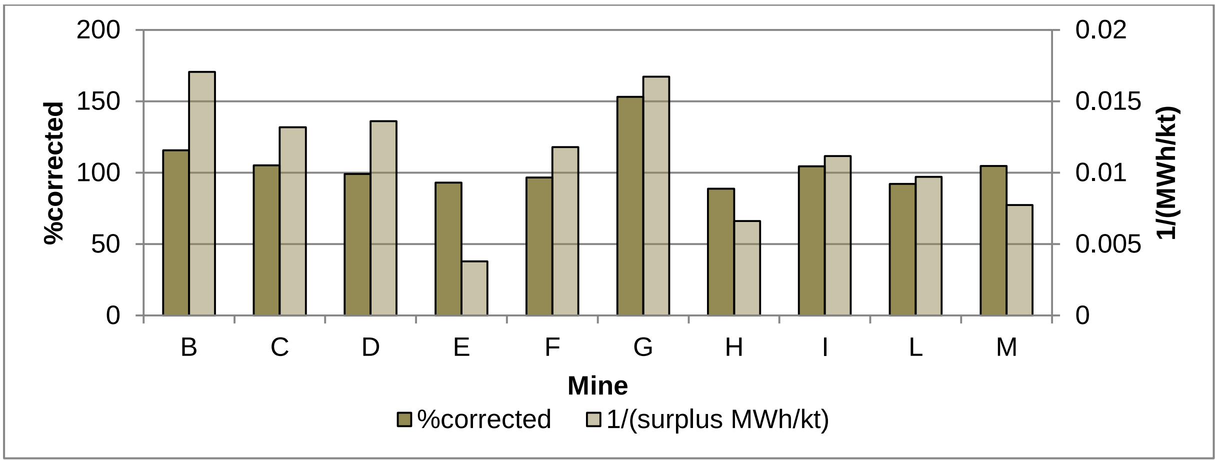


Figure 46: Compressed air system – percentage corrected versus 1/(surplus MWh/kt) (summer)

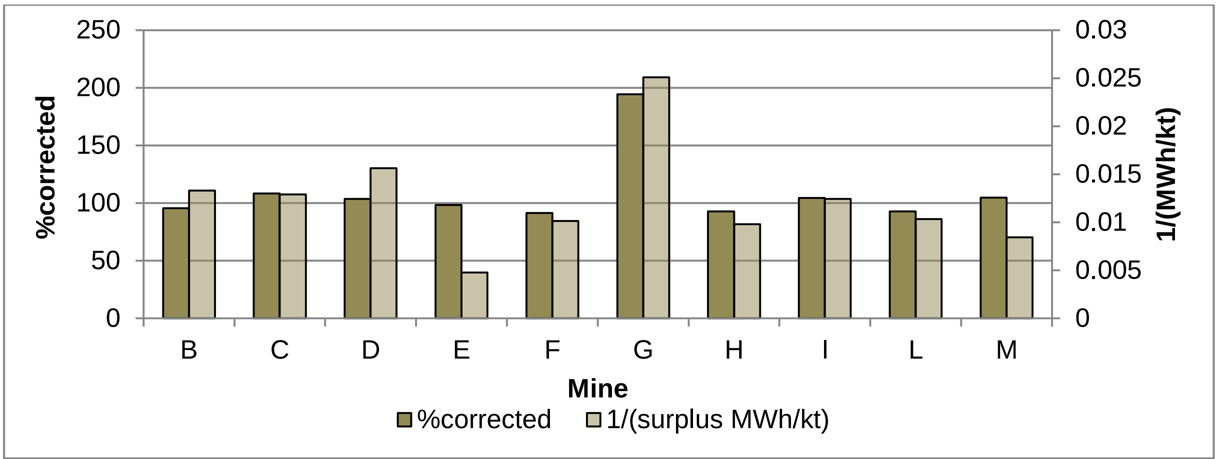


Figure 47: Compressed air system – percentage corrected versus 1/(surplus MWh/kt) (winter)

Cooling system

To verify the benchmarking models for the cooling system, a similar approach to the compressed air verification was used. In Section 2.3.4, it was mentioned that approximately 185 litre of water is used to mine one tonne of ore. Using this figure, the amount of water required per mine used in the benchmarking model was determined. This water is cooled on surface and sent down to the underground mining areas.

The simulation for cooling systems entailed a model that calculated the amount of energy required by cooling systems to chill the water needed for the drilling of blast holes. After this energy was calculated, it was subtracted from the total measured energy per mine cooling system. This was similar to the compressed air system, known as the surplus energy. The surplus energy per kilotonne (surplus MWh/kt) was calculated for each of the mines and compared with the $\%_{corrected}$ values obtained from cooling system benchmarks.

Simulation inputs are shown in Table 93 and Table 94 (Appendix E). Figure 130 (Appendix F) shows a screenshot taken in PTB. Simulation results are shown in Table 95 and Table 96 (Appendix E) for summer and winter months. Table 45 and Table 46 compare the cooling system rank according to this study's benchmarking models and the rank obtained from calculating the surplus MWh/kt for cooling systems.

Table 45: Cooling system – benchmark verification (summer)

Mine	Benchmark rank	Surplus MWh rank	Difference
C	5	4	1
D	3	3	0
E	7	7	0
H	4	5	1
J	6	6	0
L	2	2	0
M	1	1	0
Average difference:		**0.29**	
Correct prediction:		**96%**	

Table 46: Cooling system – benchmark verification (winter)

Mine	Benchmark rank	Surplus MWh rank	Difference
C	4	5	1
D	3	3	0
E	6	7	1
H	5	4	1
J	7	6	2
L	2	2	0
M	1	1	0
Average difference:		**0.57**	
Correct prediction:		**92%**	

Table 45 and Table 46 show that the benchmarking models for cooling systems, as developed for this study, predicted the efficiency rank of mines used in the models quite accurately. For the summer month model, a 96% correct prediction was achieved; for winter months, a 92% correct prediction was achieved. Figure 48 and Figure 49 further verify the benchmarking functions with $\%_{corrected}$ shown versus 1/(surplus MWh/kt).

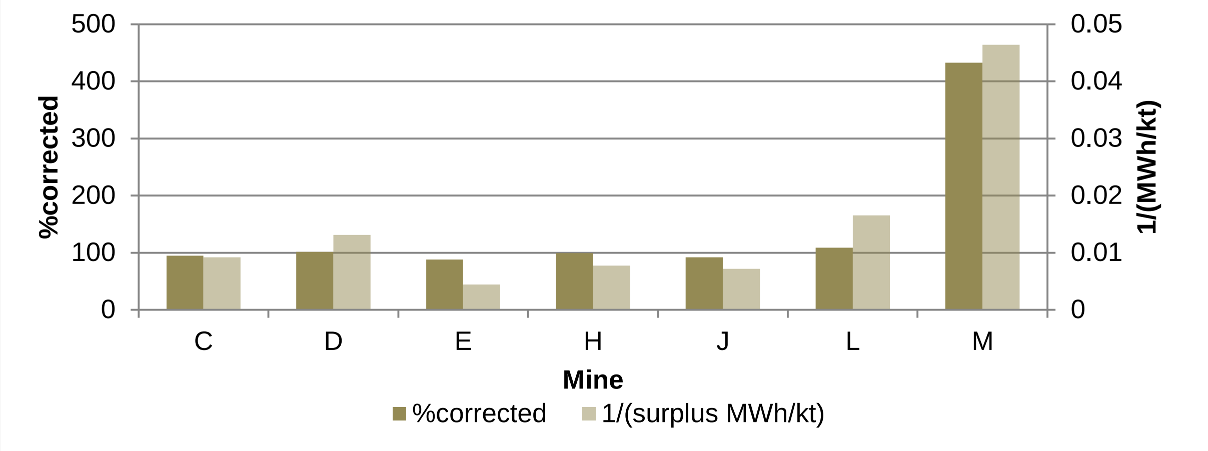


Figure 48: Cooling system – percentage corrected versus 1/(surplus MWh/kt) (summer)

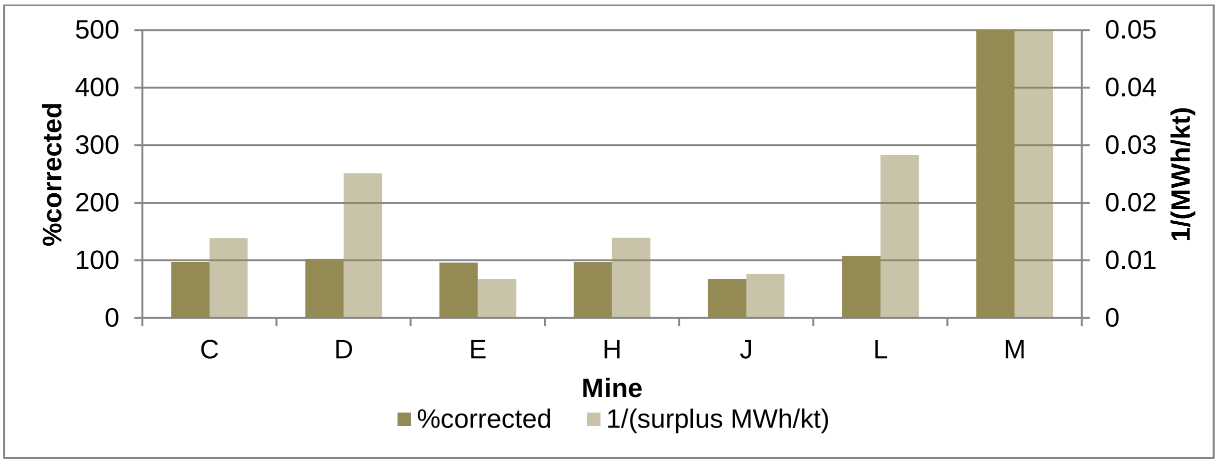


Figure 49: Cooling system – percentage corrected versus 1/(surplus MWh/kt) (winter)

Dewatering system

Where the dewatering system is concerned, the additional variable of fissure water has to be taken into account when attempting to verify the benchmarking models (as developed in Section 3.2.4). Once again, 185 litre of water/tonne of ore mined was used in the dewatering simulation. A simple dewatering system was simulated considering each of the model mines' depth, flow required for amount of tonnes and flow required to remove fissure water effectively.

The amount of energy obtained for both scenarios of flow for tonnes and flow for fissure water were used to calculate the surplus amount of energy used by the specific model mine. This was done by simply subtracting the energy for both tonnes and fissure water from the total actual measured energy used to create the benchmarking models. A value of surplus MWh/kt for dewatering systems was obtained for each mine and compared with the ranks obtained from the developed benchmarking models.

Table 98 in Appendix E shows the simulation input values. Figure 131 in Appendix F shows a simulation screenshot taken in PTB. The simulation results are shown in Table 99 (Appendix E). The benchmark ranks versus surplus MWh/kt ranks are shown in Table 47. It is seen that an accuracy of 91% was obtained when predicting the rank of a mine using the developed benchmarking models. Values of $\%_{corrected}$ compared with 1/(surplus MWh/kt) are shown in Figure 50 to further emphasise the verification of dewatering system benchmarking models.

Table 47: Dewatering system – benchmark verification

Mine	Benchmark rank	Surplus MWh rank	Difference
B	3	4	1
C	7	7	0
E	8	8	0
G	4	2	2
H	5	6	1
I	2	3	1
L	6	5	1
M	1	1	0
Average difference:		**0.75**	
Correct prediction:		**91%**	

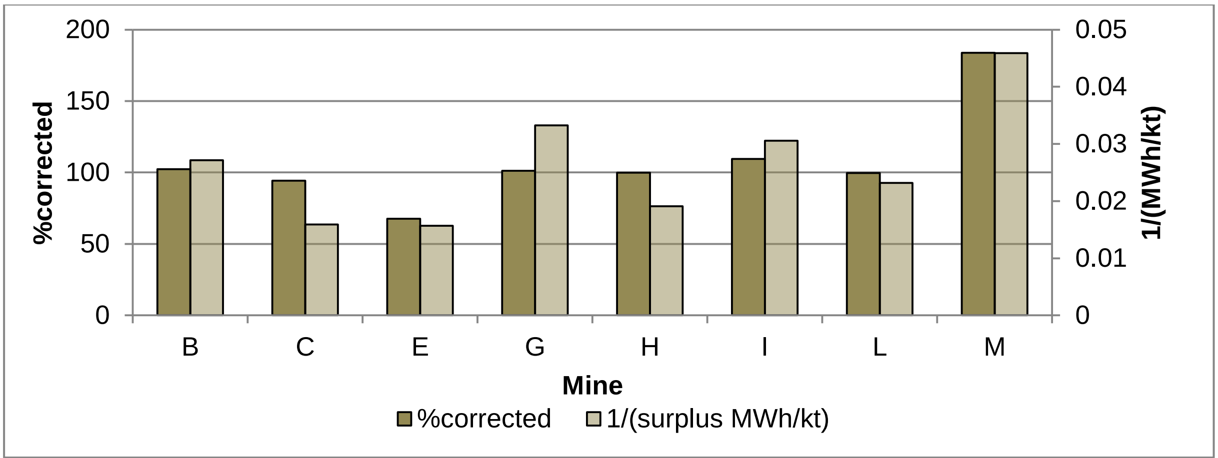


Figure 50: Dewatering system – percentage corrected versus 1/(surplus MWh/kt)

Ventilation system

As no software packages were available to simulate ventilation system energy consumption, it was decided to use fundamental fan equations (discussed in Section 2.5.4). By using Equation 14 to Equation 16, the volume air moved by ventilation fans in m^3 could be calculated for each mine that corresponded to the measured energy consumption of that mine.

With the volume of air known for each model mine, the ventilation intensity in terms of amount of ventilation air needed to be extracted from a mine per kilotonne of ore mined (m^3/kt) could be determined. This was done together with ventilation air per metre of mine depth (m^3/m) as none of these parameters could be converted directly to variables for use in Equation 14 to Equation 16.

The inputs for, and results of the equations used to determine the amount of ventilation air are seen in Table 101 and Table 102 in Appendix E. As was done for previous systems, the benchmarking model ranks obtained for model mines were again compared with an indication of efficiency, which in this case were the ventilation systems. Table 48 and Table 49 compare the benchmarking model ranks with m^3/kt and m^3/m efficiency ranks. For summer months, correct predictions of 90% and 83% were achieved. For winter months, the benchmarking models showed a prediction accuracy of 80% and 83%.

Table 48: Ventilation system – benchmark verification (summer)

Mine	Benchmark rank	m^3/kt rank	Difference	m^3/m rank	Difference
B	3	2	1	5	2
C	8	9	1	11	3
D	7	6	1	10	3
E	11	11	0	6	5
F	6	4	2	7	1
G	4	3	1	3	1
I	10	10	0	8	2
K	2	5	3	1	1
L	9	8	1	9	0
M	5	7	2	4	1
O	1	1	0	2	1
Average difference:		**1.09**		**1.82**	
Correct prediction:		**90%**		**83%**	

Table 49: Ventilation system – benchmark verification (winter)

Mine	Benchmark rank	m^3/kt rank	Difference	m^3/m rank	Difference
B	10	2	8	7	3
C	8	10	2	11	3
D	6	5	1	10	4
E	11	11	0	5	6
F	5	4	1	6	1
G	3	1	2	4	1
I	9	9	0	9	0
K	1	6	5	1	0
L	7	8	1	8	1
M	4	7	3	3	1
O	2	3	1	2	0
Average difference:		**2.18**		**1.82**	
Correct prediction:		**80%**		**83%**	

Further verification was achieved by directly comparing the values of $\%_{corrected}$ obtained from the ventilation system benchmarking models on model mines with $1/(m^3/kt)$ and $1/(m^3/m)$. In order to fit the comparison on one graph, averages of $1/(m^3/kt)$ and $1/(m^3/m)$ were used. As the values of $1/(m^3/m)$ were approximately 50 times that of $1/(m^3/kt)$, a factor was used to scale the values to the same order. This had to be done to ensure that the final average values obtained were representative of both $1/(m^3/kt)$ and $1/(m^3/m)$. Figure 51 and Figure 52 show the comparison for both summer and winter months.

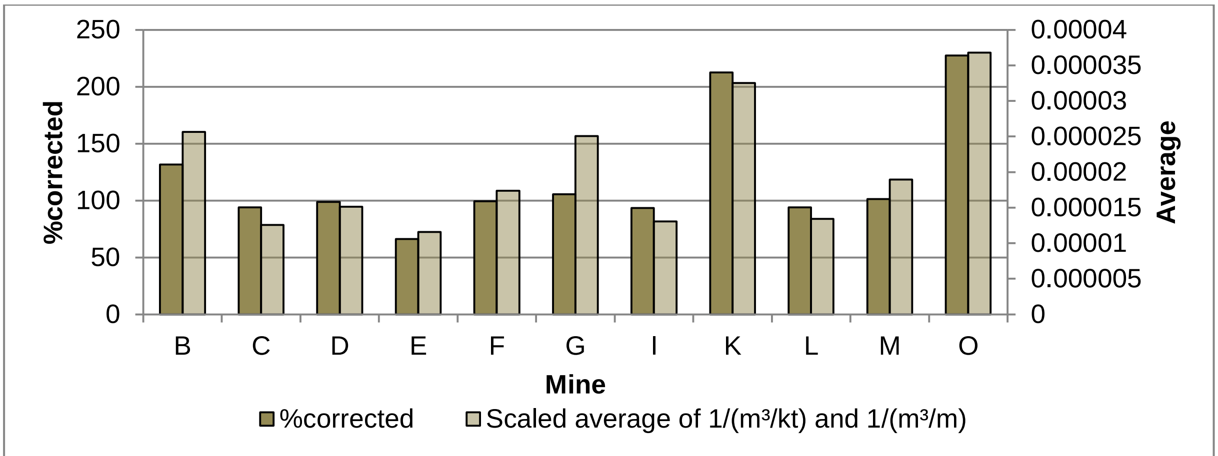


Figure 51: Ventilation system – percentage corrected versus scaled average of $1/(m^3/kt)$ and $1/(m^3/m)$ (summer)

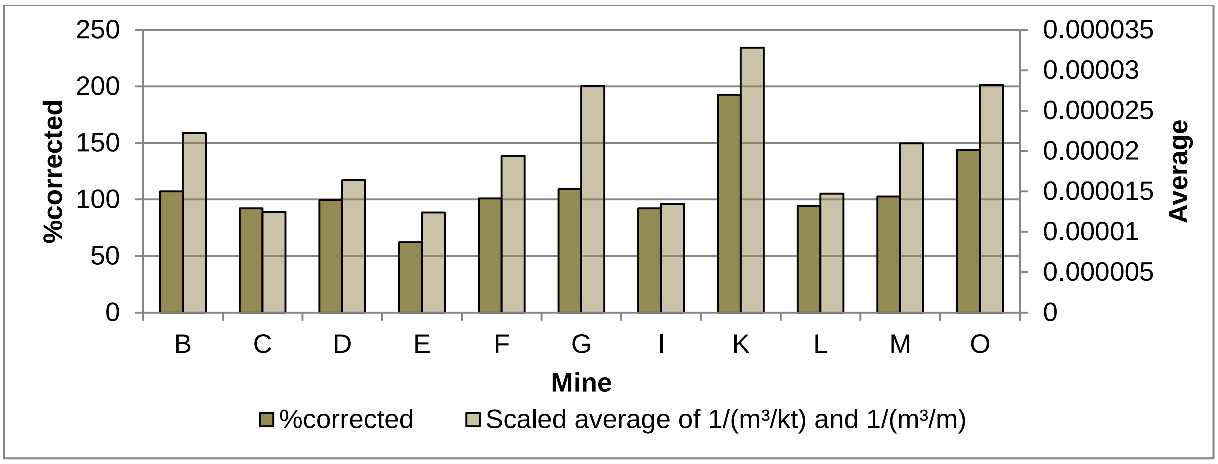


Figure 52: Ventilation system – percentage corrected versus scaled average of 1/(m^3/kt) and 1/(m^3/m) (winter)

Hoisting system

A similar approach as the ventilation system was taken to verify the hoisting system benchmarking models. Simulation software was not available for hoisting and fundamental equations of hoisting systems were used. By using Equation 17 and the data available for hoisting system model mines, the theoretical energy consumption for the model mines was calculated. The inputs and results for these calculations can be found in Table 104 in Appendix E.

The only inputs needed for Equation 17 were mass and vertical hoisting distance. Therefore, the theoretical energy calculated for hoisting systems was used to determine intensity in terms of tonnes of ore mined (MWh/kt) and mine depth (MWh/m). Using these intensities and the values of $\%_{corrected}$ obtained from the developed benchmarking models, efficiency ranks were again given to the different mines. Table 50 displays the ranks for benchmarking models, MWh/kt intensity and MWh/m intensity. The differences in ranks and the accuracy of the benchmarking model predictions are also shown.

Comparing the benchmarking model rank with the MWh/kt rank shows an accuracy of 75%. The comparison with MWh/m is slightly higher at 91%. Mine K is shown to be one of the largest contributors to the lower MWh/kt rank with a six-position difference in rank. To visually show the validation of the benchmarking models, the values of $\%_{corrected}$ were again compared with 1/(MWh/kt) and 1/(MWh/m). As was done for ventilation system verification, the scaled average values of 1/(MWh/kt) and 1/(MWh/m) were displayed on a single bar chart (Figure 53).

Table 50: Hoisting system – benchmark verification

Mine	Benchmark rank	MWh/kt rank	Difference	MWh/m rank	Difference
B	5	2	3	5	0
C	4	3	1	4	0
D	6	4	2	7	1
F	8	7	1	8	0
G	1	1	0	2	1
I	7	6	1	6	1
K	2	8	6	3	1
M	3	5	2	1	2
Average difference:		**2.00**		**0.75**	
Correct prediction:		**75%**		**91%**	

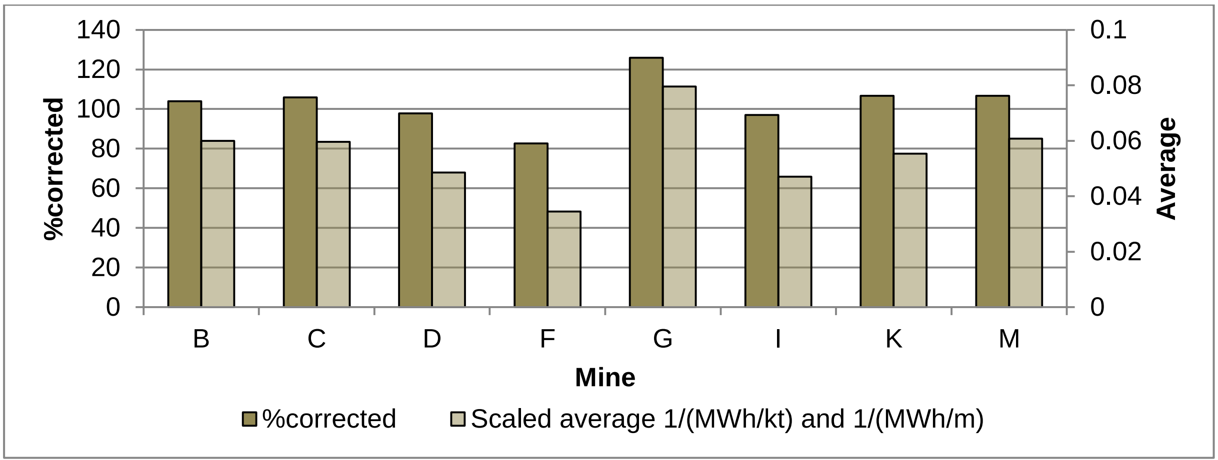


Figure 53: Hoisting system – percentage corrected versus scaled average of 1/(MWh/kt) and 1/(MWh/m)

Conclusion of average model verification

The objective of this section was to verify the developed average benchmarking models. Verification was attempted by using results obtained from simulated high demand systems and comparing them with calculated average benchmark scores. It was found that for all systems, a good efficiency prediction was obtained when compared with simulated values. It was thus verified that the developed average benchmarking models indicate efficiency correctly.

4.4 BEST PRACTICE MODEL VERIFICATION

Best practice models (as developed in Section 3.4) were verified in a similar manner to the procedure followed for average benchmarking. The same results obtained from simulations were used to quantify high demand system efficiency ranks. These ranks were compared with the best practice benchmark ranks for each system as were found by applying the best practice models (Equation 34 to Equation 41) to the different high demand systems.

Compressed air system

Best practice benchmark scores in terms of $\%_{corrected}$ (obtained for compressed air systems by applying the developed models on compressed air system model mines) are shown in Table 92 in Appendix E. The ranks from these scores and a comparison with simulation efficiency ranks are shown in Table 51 and Table 52. It was found that for summer months, the best practice benchmarking models predicted system efficiency correctly 94% of the time when compared with surplus energy consumption. For winter months, the prediction had an accuracy of 88%.

Table 51: Compressed air system – best practice benchmark verification (summer)

Mine	Benchmark rank	Surplus MWh rank	Difference
B	1	1	0
C	3	4	1
D	4	3	1
E	10	10	0
F	6	5	1
G	2	2	0
H	9	9	0
I	5	6	1
L	8	7	1
M	7	8	1
Average difference:		**0.6**	
Correct prediction:		**94%**	

Table 52: Compressed air system – best practice benchmark verification (winter)

Mine	Benchmark rank	Surplus MWh rank	Difference
B	5	3	2
C	3	4	1
D	2	2	0
E	10	10	0
F	9	7	2
G	1	1	0
H	6	8	2
I	4	5	1
L	8	6	2
M	7	9	2
Average difference:		**1.2**	
Correct prediction:		**88%**	

A visual representation is shown in Figure 54 and Figure 55 of the values of $\%_{\text{corrected}}$ versus the values of 1/(surplus MWh/kt). These are for summer and winter months respectively. It is important to note is that the higher values of $\%_{\text{corrected}}$ correspond with the higher values of 1/(surplus MWh/kt).

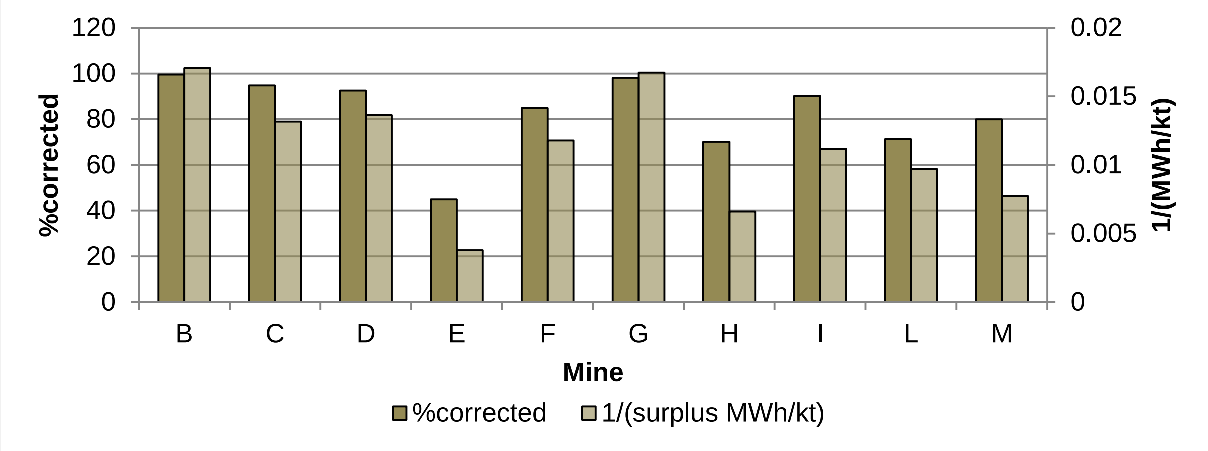


Figure 54: Compressed air – best practice percentage corrected versus 1/(surplus MWh/kt) (summer)

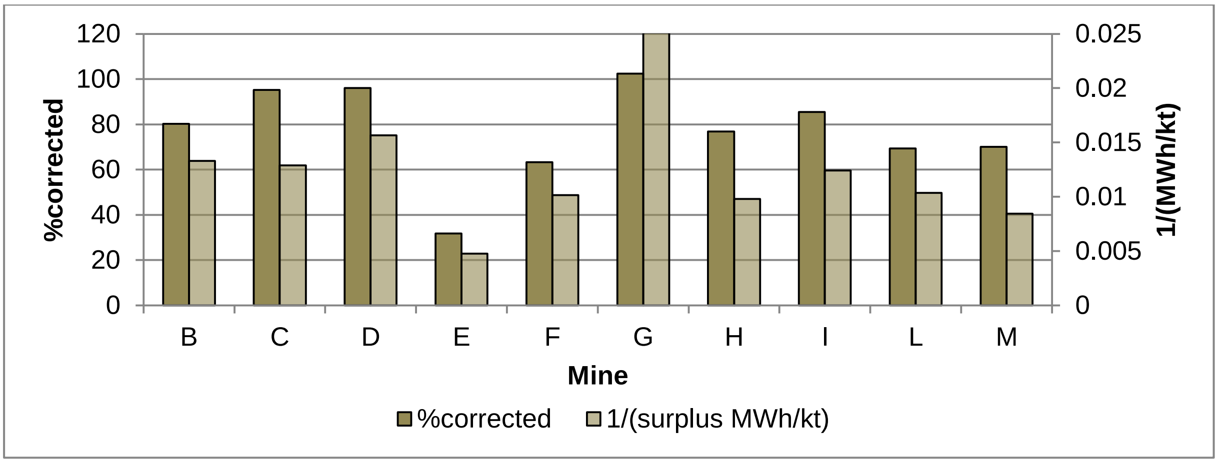


Figure 55: Compressed air – best practice percentage corrected versus 1/(surplus MWh/kt) (winter)

Cooling system

Cooling system best practice benchmark verification is shown in Table 53 for summer months and Table 54 for winter months. It was found that the summer month best practice model predicted cooling system efficiency correctly 96% of the time. The winter month model also had an accuracy of 96%. The best practice $\%_{\text{corrected}}$ values are shown in Appendix E in Table 97.

Table 53: Cooling system – best practice benchmark verification (summer)

Mine	Benchmark rank	Surplus MWh rank	Difference
C	5	4	1
D	3	3	0
E	7	7	0
H	4	5	1
J	6	6	0
L	2	2	0
M	1	1	0
Average difference:		**0.29**	
Correct prediction:		**96%**	

Table 54: Cooling system – best practice benchmark verification (winter)

Mine	Benchmark rank	Surplus MWh rank	Difference
C	4	5	1
D	3	3	0
E	7	7	0
H	5	4	1
J	6	6	0
L	2	2	0
M	1	1	0
Average difference:		**0.29**	
Correct prediction:		**96%**	

Figure 56 and Figure 57 compare the $\%_{\text{corrected}}$ values for each mine with the values of 1/(surplus MWh/kt) for summer and winter months.

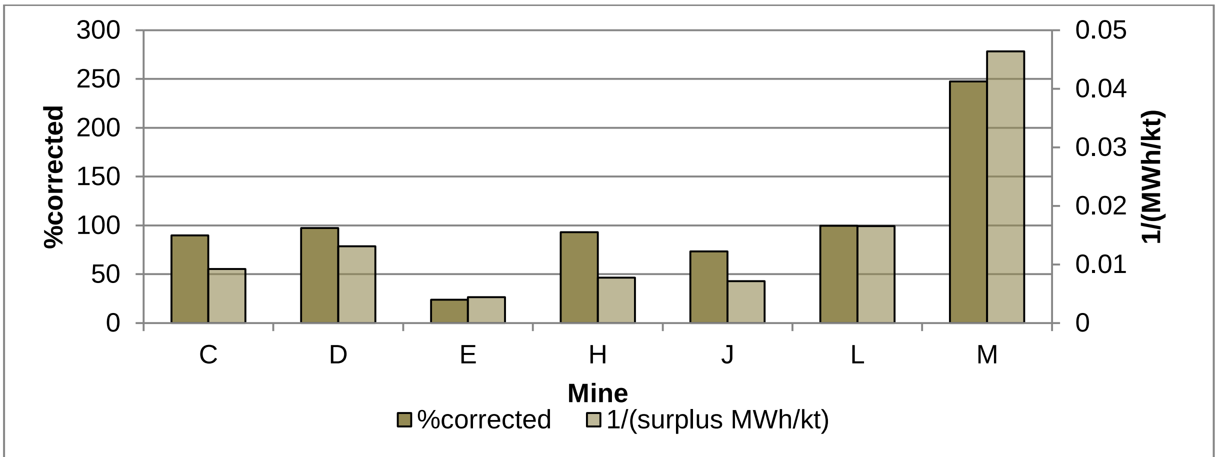


Figure 56: Cooling system – best practice percentage corrected versus 1/(surplus MWh/kt) (summer)

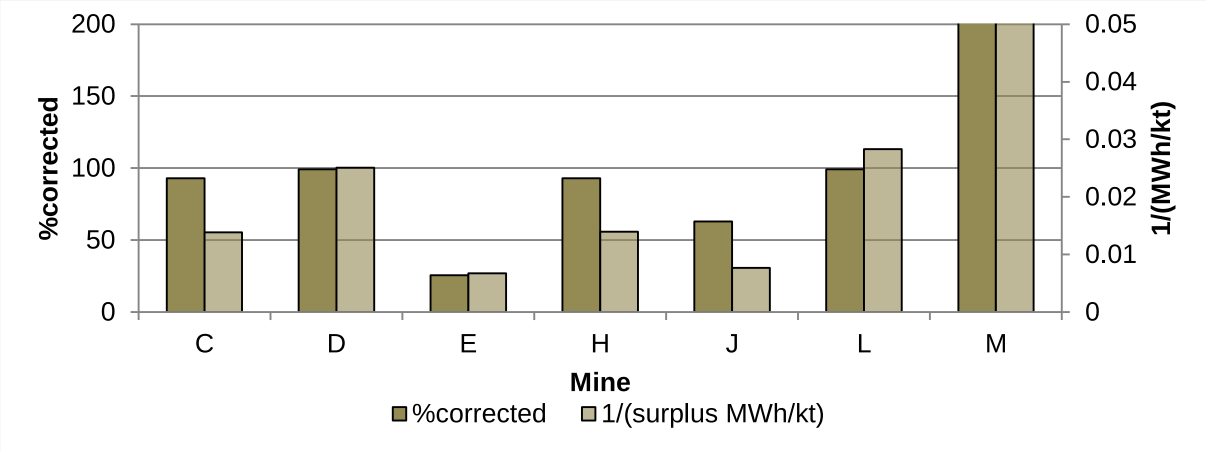


Figure 57: Cooling system – best practice percentage corrected versus 1/(surplus MWh/kt) (winter)

Dewatering system

Best practice benchmark verification for mine dewatering systems is shown in Table 55. In this case, the predicted accuracy was 84%. It is seen that Mine E obtained a $\%_{\text{corrected}}$ score of 0% (Table 100 in Appendix E). This was because the model mine produced less than the 20 kt of ore monthly average for dewatering systems (as described in Section 3.4.2). This indicated that the best practice model developed for dewatering systems was indeed sensitive to mines producing lower tonnes of ore. Keeping this in mind, the best practice model still predicted the rank of Mine E correctly.

Table 55: Dewatering system – best practice benchmark verification

Mine	Benchmark rank	Surplus MWh rank	Difference
B	3	4	1
C	6	7	1
E	8	8	0
G	7	2	5
H	4	6	2
I	2	3	1
L	5	5	0
M	1	1	0
Average difference:		**1.25**	
Correct prediction:		**84%**	

Figure 58 shows the values of $\%_{\text{corrected}}$ (found in Table 100 in Appendix E) obtained from the dewatering best practice model versus the values of 1/(surplus MWh/kt). The lower accuracy of the dewatering system best practice benchmarking model for Mine E can also be seen here.

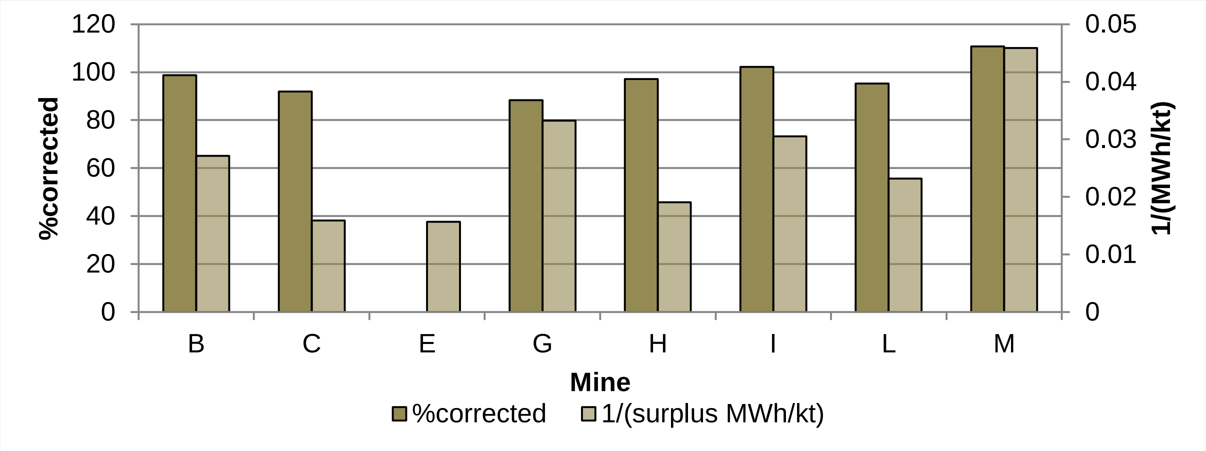


Figure 58: Dewatering system – best practice percentage corrected versus 1/(surplus MWh/kt)

Ventilation system

As was the case with the verification of average benchmarking models for mine ventilation systems, simulations to obtain volume of ventilation air were not used. Results from Equation 14 to Equation 16 (producing volume of air moved by ventilation fans) were again used to determine an efficiency rank to be compared with best practice benchmark ranks. Table 56 and Table 57 show these comparisons for summer and winter months respectively. It is seen that for summer months, accuracies of 90% and 79% were achieved. For the winter months, the prediction accuracies were 87% and 80%.

Table 56: Ventilation system – best practice benchmark verification (summer)

Mine	Benchmark rank	m^3/kt rank	Difference	m^3/m rank	Difference
B	3	2	1	5	2
C	8	9	1	11	3
D	4	6	2	10	6
E	11	11	0	6	5
F	6	4	2	7	1
G	5	3	2	3	2
I	10	10	0	8	2
K	2	5	3	1	1
L	9	8	1	9	0
M	7	7	0	4	3
O	1	1	0	2	1
Average difference:		**1.09**		**2.36**	
Correct prediction:		**90%**		**79%**	

Table 57: Ventilation system – best practice benchmark verification (winter)

Mine	Benchmark rank	m^3/kt rank	Difference	m^3/m rank	Difference
B	3	2	1	7	4
C	9	10	1	11	2
D	4	5	1	10	6
E	11	11	0	5	6
F	6	4	2	6	0
G	5	1	4	4	1
I	10	9	1	9	1
K	1	6	5	1	0
L	8	8	0	8	0
M	7	7	0	3	4
O	2	3	1	2	0
Average difference:		**1.45**		**2.18**	
Correct prediction:		**87%**		**80%**	

Further verification done by comparing the values of $\%_{\text{corrected}}$ with 1/(m^3/kt) and 1/(m^3/m) is shown in Figure 59 and Figure 60. Once again, averages of 1/(m^3/kt) and 1/(m^3/m) were used to fit the comparisons onto one graph. The values of $\%_{\text{corrected}}$ for the best practice benchmarks of ventilation system model mines can be found in Table 103 in Appendix E.

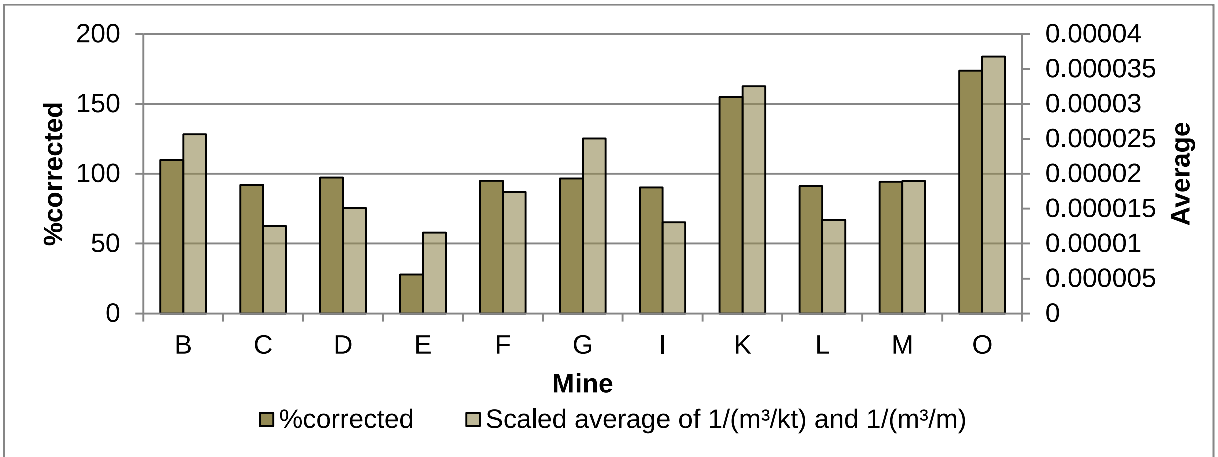


Figure 59: Ventilation system – best practice percentage corrected versus scaled average of 1/(m^3/kt) and 1/(m^3/m) (summer)

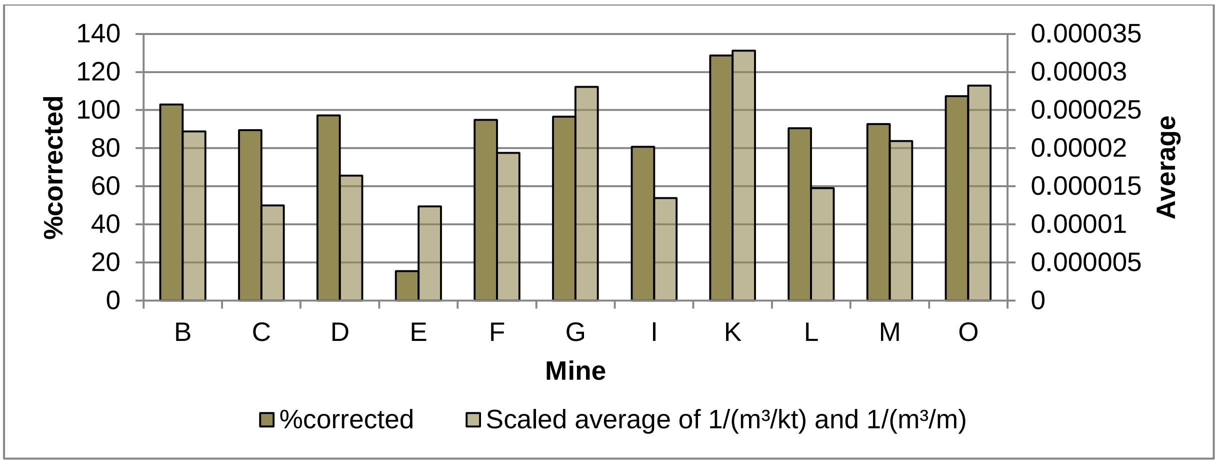


Figure 60: Ventilation system – best practice percentage corrected versus scaled average of $1/(m^3/kt)$ and $1/(m^3/m)$ (winter)

Hoisting system

The hoisting system best practice benchmarking models were verified in the exact same manner as average benchmarking models were done. Results obtained from applying Equation 17 to the available data for hoisting system model mines (as was done during average benchmark verification) were also used during the best practice model verification.

The ranks for best practice benchmarking models, MWh/kt intensity and MWh/m intensity are displayed in Table 58. The predictions of the models were found to be 78% correct when compared with ore intensity and 69% correct when compared with depth intensity.

Table 58: Hoisting system – best practice benchmark verification

Mine	Benchmark rank	MWh/kt rank	Difference	MWh/m rank	Difference
B	2	2	0	5	3
C	1	3	2	4	3
D	3	4	1	7	4
F	8	7	1	8	0
G	5	1	4	2	3
I	7	6	1	6	1
K	4	8	4	3	1
M	6	5	1	1	5
Average difference:		**1.75**		**2.50**	
Correct prediction:		**78%**		**69%**	

Figure 61 shows the values of $\%_{\mathrm{corrected}}$ (Table 105 in Appendix E) for each of the model mine best practice benchmark scores against 1/(MWh/kt) and 1/(MWh/m). As was the case with the average benchmarking model for ventilation system verification, the average values of 1/(MWh/kt) and 1/(MWh/m) were used.

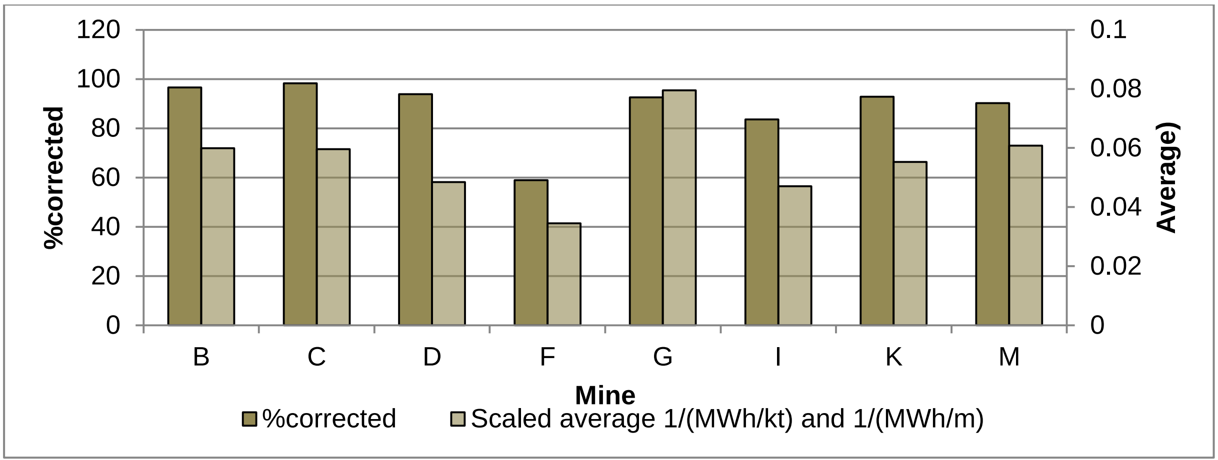


Figure 61: Hoisting system – best practice percentage corrected versus scaled average of 1/(MWh/kt) and 1/(MWh/m)

Conclusion of best practice model verification

Methods in Section 4.4 endeavoured to verify the use and accuracy of best practice benchmarks. This was achieved through good predicted efficiency scores obtained from developed best practice benchmarking models when compared with simulated values.

4.5 VERIFICATION OF ENERGY EFFICIENCY INITIATIVE PRIORITISATION

There is a need to verify the hypothesis that by using average or best practice energy consumption benchmarks, prioritisation of energy efficiency interventions can be made. Using average or best practice energy consumption benchmarks enables a mine to apply the benchmarking procedures on all high demand systems and, through the results, determine on which systems the focus for energy efficiency optimisation should be.

In order to test the hypothesis, it was decided that data before and after the implementation of energy efficiency initiatives would be used. By using previous studies on energy efficiency (mentioned for each high demand system in Chapter 2), mines were identified for verification purposes. However, since the energy efficiency initiatives had very specific performance start dates, data availability before and after these dates had to be considered.

Unfortunately, sufficient data was not readily available for each high demand system that coincided with the necessary before and after implementation dates of the specific energy efficiency initiatives. Thus, data could only be retrieved for compressed air systems on two mines, cooling systems on two mines and a dewatering system on one mine. As all of the benchmarking models were created using similar methods, it was assumed that verifying three out of the five high demand systems would be adequate for overall verification of the hypothesis.

Compressed air system

The objective of the projects, which entailed energy efficiency on compressed air systems, was to reduce energy consumption while still delivering enough compressed air volume and adequate pressure for normal operation. On both the mines where compressed air data was available (Mine X_comp and Mine Y_comp), the compressed air supply was matched with demand through intelligent control of compressors (supply) and compressed air network consumption (demand) [34].

Where necessary, compressors were automated and remapped to optimise compressed air delivery. Valves were installed either on surface compressed air networks or on individual underground mining levels. These valves were controlled remotely through a control system according to certain downstream pressure set points. The set points were adjusted during certain times of the day when more or less air was required on certain levels. A typical time when compressed air delivery was reduced was during blasting shifts when very little to no compressed air was required underground.

Due to an overall reduction in compressed air demand and an increase in valve upstream pressure, compressors were able to close their guide vanes and cut back substantially on power demand. Overall energy efficiency was thus achieved. The two mines that had adequate production data before and after implementation of the energy initiatives were benchmarked via the average benchmarking model developed in Chapter 3. The $\%_{\mathrm{initial}}$ values were calculated and placed in a bar chart to display the verification results.

The reason for using $\%_{\mathrm{initial}}$ and not $\%_{\mathrm{corrected}}$ in this case, was to visually enhance the difference between the pre- and post-implementation energy efficiency initiative results. The data used for both mines are shown in in Table 106, Appendix E. An average of three months of data before, and three months of data after energy efficiency initiative implementation was used. Table 106 displays both the actual energy consumption in

MWh/month before and after implementation together with the amount of ore mined in kilotonne.

Figure 62 presents the two mines (Mine X_comp and Mine Y_comp) with the values of $\%_{\text{initial}}$ for the compressed air system before and after project implementation. It can be seen that although not significant, Mine X_comp showed a $\%_{\text{initial}}$ increase of 6%. Mine Y_comp had a slightly larger increase of 22%.

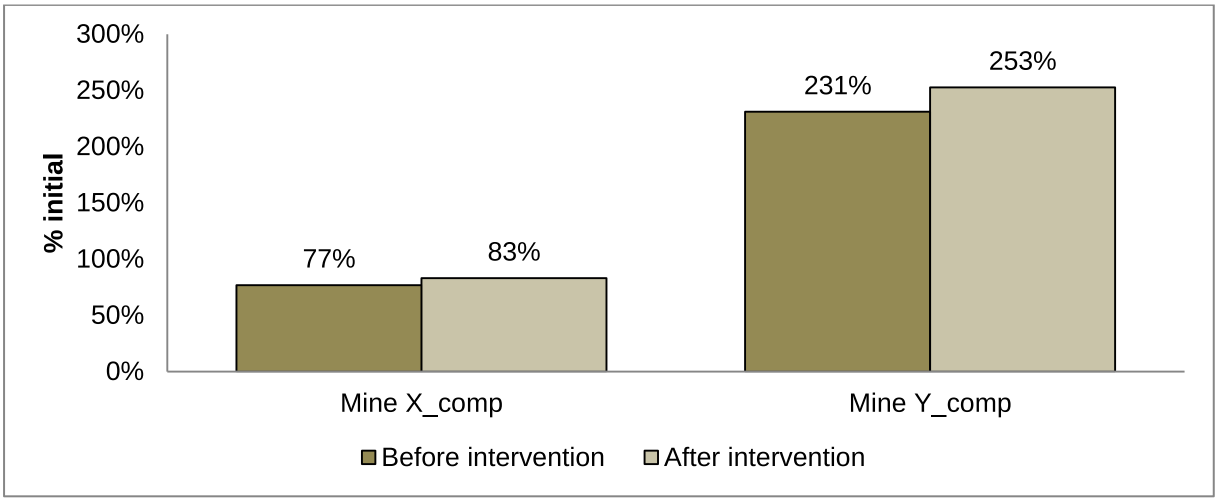


Figure 62: Mine X_comp and Mine Y_comp pre- and post-implementation

Cooling systems

Energy efficiency projects implemented on deep-level mine cooling systems focused on increasing the coefficient of performance of cooling systems as a whole. By increasing the coefficient of performance, cooling systems were able to induce more efficient cooling of water and air while reducing the electrical energy required. Both of the mines on which cooling system optimisation initiatives were implemented and that had available data for periods before and after implementation, used the same initiative approach.

The variable flow control of water moving through chiller machines was used to increase heat exchange efficiency. Variable flow was achieved by installing variable speed drives (VSDs) on evaporator pump motors. The ability of VSDs to reduce motor speed, and subsequently pump speed and water flow by a small margin while simultaneously reducing power use exponentially, made it the desired candidate for variable flow control.

Fridge plant compressors are usually controlled via an evaporator water outlet temperature set point of between 1 °C and 3 °C. Because water flow through the evaporator side of fridge plants was reduced (as was the objective of the two cooling system optimisation projects), an increase in heat exchange took place and a decrease in cooling was required. Subsequently, the fridge plant compressors were able to reduce compression to maintain temperature set points [6].

Another part of the cooling system optimisation initiatives was to use variable flow on BAC transfer pumps. These pumps were controlled by VSDs for a certain BAC outlet air temperature and resulted in a reduction in pump energy consumption during colder days.

As was the case with the compressed air system verification, two mines with available cooling system optimisation data were benchmarked. The mines were labelled Mine X_cool and Mine Y_cool. Pre- and post-implementation energy consumption together with tonnes of ore mined for these periods are shown in Table 107 in Appendix E. The values of $\%_{\text{initial}}$ are also shown and displayed in Figure 63. Mine X_cool showed a $\%_{\text{initial}}$ increase of 20% after cooling system optimisation and Mine Y_cool achieved an increase of 17%.

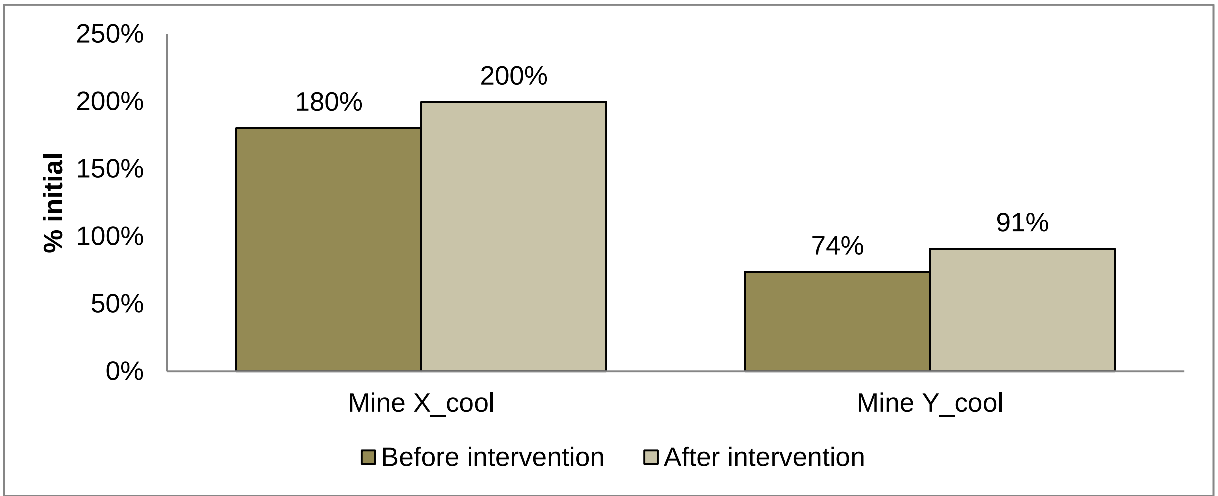


Figure 63: Mine X_cool and Mine Y_cool pre- and post-implementation

Dewatering system

As was mentioned earlier, only one project had the required energy efficiency data for dewatering systems. At Mine X_pump, water wastage in the form of leaks and unclosed hoses were identified as large contributors to the amount of water that had to be pumped to surface using dewatering pumps. Mitigation for this was investigated and individual mining level water control via control valves was identified as a solution.

By installing butterfly valves and bypass globe control valves on each of the water pipes on the mining levels, water use was controlled during times of the day when no water should have been used (blasting shifts). Downstream pressure was monitored by pressure transmitters that indicated whether water flow was experienced during blasting shifts. If pressure dropped, the butterfly valves were closed completely and bypass globe valves maintained the pressure set point. This set point typically allowed less water to be wasted and directly reduced the amount of water that had to be pumped to surface [63].

By applying the average benchmarking on Mine X_pump by using mine depth, tonnes of ore mined and amount of fissure water for three months before and three months after implementation of the energy efficiency initiative, a pre- and post-implementation value of $\%_{\text{initial}}$ was delivered. This data is shown in Table 108 in Appendix E. The comparison of $\%_{\text{initial}}$ values is shown in Figure 64. It is seen that although the specific dewatering system initially scored at almost twice the benchmark (199%), an additional increase of 86% was achieved.

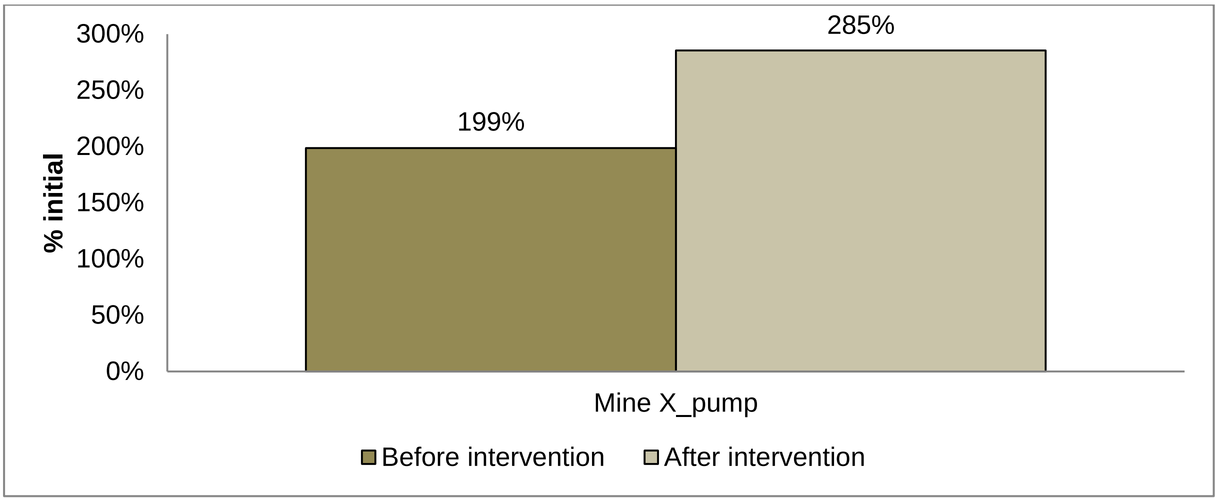


Figure 64: Mine X_pump pre- and post-implementation

Conclusion of energy efficiency initiative prioritisation verification

This section sought to verify the novel contribution of a new method for prioritising the implementation of energy efficiency initiatives on deep-level mines. It was proven that an increase in energy efficiency would increase the benchmark score for a particular high demand system. Thus, it can be stated that when comparing a single mine's benchmark scores for all high demand systems individually, energy efficiency initiative implementation should be prioritised from the lowest scoring systems to the highest scoring systems.

4.6 VERIFICATION OF ALTERNATIVE OPERATIONAL BUDGET FORECASTING

Different mines (or mine groups) use different methods when compiling operational budgets for energy consumption or costs. Numerous factors play a role when considering operational budgets. Electricity cost and a mine's (or mine group's) capacity to adhere to these costs, are some of the factors to be considered when budgeting for future energy consumption.

Mines are often either marginal (with costs amounting to a level very close to break-even point) or profitable (where costs are much lower) [110]. The two types of mines follow considerably different procedures when compiling operational budgets. Marginal mines strive to reduce costs where possible, which is reflected by lower operational budgets for energy consumption. The opposite is true for profitable mines where budgets might be higher.

Methods to compile operational energy consumption budgets for specific high demand systems vary significantly between mines or mine groups. Some mines might use the previous month's energy consumption as the following month's budget. Other mines might use the previous year's average energy consumption as a budget. Multiplying a factor is also used in some instances: when a mine shows increased profits, a factor higher than 1 is multiplied by a previous budget. When a mine shows decreased profits, a factor smaller than 1 is multiplied by a previous budget.

Because most mines do not know how well a specific high demand system performs in terms of energy consumption when compared with similar mines' systems, budgets are not compiled accordingly. Average benchmarking by using models created in Chapter 3 was applied to a mine to highlight this. The benchmark energy consumption per system was calculated and from that the values of $\%_{\mathrm{initial}}$. This was completed for a six-month period.

Figure 65 presents the results obtained from the compressed air system of a model mine. This figure shows the actual budgeted energy consumption the mine forecasted, the actual energy that was consumed that month, the new proposed budget obtained from average benchmarking and the value of $\%_{\mathrm{initial}}$ per month.

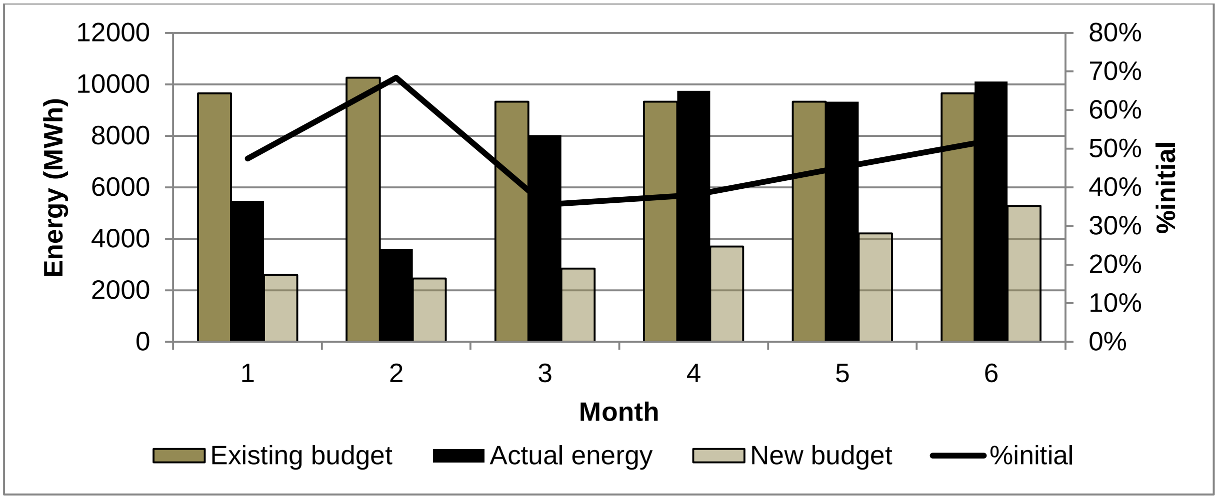


Figure 65: Verification of new budget forecast (compressed air system)

From Figure 65 it can be seen that an almost fixed energy consumption budget is used for compressed air systems. This shows that budgets are compiled before the start of a month and not altered according to other factors such as tonnes of ore mined. Applying average benchmarking resulted in a low score (between 36% and 68%) when this specific compressed air system was considered. This brought about very low proposed new budgets and indicated an inefficient system (when compared with peers).

Considering the cooling system (Figure 66) of the same mine, average benchmarks were calculated and compared with existing operational budgets. Because the cooling system was more efficient (scores between 75% and 167%) than the compressed air system, the proposed budget was very close to the actual energy consumption. This was contrary to the existing budgets that allowed the overconsumption of energy.

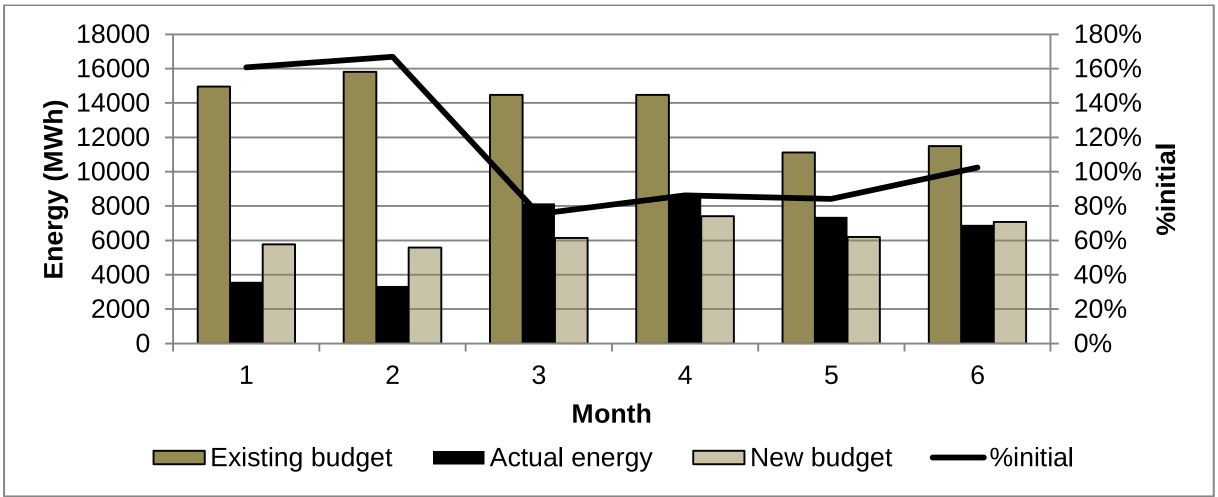


Figure 66: Verification of new budget forecast (cooling system)

The results of the remaining high demand systems (dewatering, ventilation and cooling) of the mine used for verification purposes are shown as Figure 126 to Figure 128 in Appendix E. For a mine to be able to use the average benchmarking models to forecast operational budgets, the budgets would have to be updated daily according to the tonnes of ore mined. If this was done for the compressed air and cooling system examples shown earlier, overbudgeting would not have occurred for Month 1 and Month 2.

When reviewing all the results for verification purposes, it is seen that budget forecasting for more efficient systems is greatly improved by using developed average benchmarking models. For less efficient systems, the new forecasted budgets show that mines are over budget. This, however, improves awareness of inefficient energy consumption on mines and produces budget targets for more efficient energy consumption.

4.7 SUMMARY

The objective of this chapter was to verify the accuracy and usability of the benchmarking models developed in Chapter 3 for deep-level mines. This was done in such a manner that all of the novel contributions stated to be accomplished from this study be verified individually. It was shown that by comparing benchmark scores with external methods for determining individual high demand system efficiency, acceptable accuracy was achieved. This was done for both average and best practice benchmarking models.

The two contributions for prioritising implementation of energy efficiency initiatives and alternative budget forecasting were also verified. Energy efficiency initiatives were prioritised by comparing benchmark scores on mines with data available for periods before and after known energy saving interventions were implemented. Budgets were verified by comparing actual energy budgets obtained from mines with new proposed budgets from average benchmarking.

Chapter 5 will be used to portray results when implementing average and best practice benchmarking on actual mines as well as prioritising energy efficiency initiatives and budget forecasting.

CHAPTER 5 – Validation through case studies

[9]

[9] C. Cilliers, Personal photograph. "Ventilation fans", Carletonville, 2014.

5.1 PREAMBLE

Both average and best practice benchmarking models (Contribution 1 and Contribution 2 in Section 4.1) were verified in Chapter 4. Contribution 3 and 4 were verified similarly. The purpose of Chapter 5 is to validate the use of these contributions. The models are applied as case studies on mines to confirm the usability and novelty thereof. Each of the novel contributions are validated separately using the framework benchmarking models that were developed and verified in Chapter 3 and Chapter 4.

5.2 CASE STUDIES

The mines selected as case studies had to comply with the requirement of having energy consumption data available for all of the high demand systems (compressed air, cooling, dewatering, ventilation and hoisting). To obtain adequate results in terms of quantity, the most recent data available for a six-month period was selected for these mines. It was found that nine mines complied with data availability. Some of these mines were also used in the model development phase (model mines) in Chapter 3.

The selected mines ranged from 1 200 m to 4 000 m deep. Three of the mines are situated in the Vaal River area of South Africa in the North West province, two mines are situated close to Carletonville (also in the North West province) and four mines are in and around Welkom in the Free State. Table 59 shows the case study mines with their depth, average constant fissure water flow and amount of ore mined/month for a period of six months.

Table 59: Information for the case study mines

			Ore mined (kt)					
Mine	Depth (m)	Fissure flow (ℓ/s)	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
1	1 200	4	18	19	18	15	21	23
2	1 800	3	26	35	35	20	36	39
3	3 400	10	34	40	44	28	36	30
4	2 180	10	41	50	52	39	53	61
5	2 300	18	65	69	77	72	95	85
6	2 600	21	97	55	69	88	97	89
7	3 045	42	61	65	104	82	73	75
8	3 300	35	56	70	72	64	83	88
9	4 000	80	111	156	148	138	153	143

Before any of the four novel contributions to knowledge (Section 4.1) can be validated, the benchmarking models have to be applied to the case study mines (shown in Table 59). Equation 22 to Equation 31 were applied to each of the mines to calculate average benchmarks while considering summer and winter months. For best practice benchmarks, Equation 42 to Equation 48 were applied. The actual measured energy consumption per month for each of the nine case study mines, the average benchmark energy consumption and best practice benchmark energy consumption are shown in Table 109 to Table 135 in Appendix G.

5.3 VALIDATION OF BENCHMARKING MODELS

Contribution 1 (Section 1.7.1) and Contribution 2 (Section 1.7.2) stated that benchmarking models will be created for average and best practice benchmarking of individual high demand systems. This was verified through comparison with external methods in Chapter 4. By using the case studies mentioned in Section 5.2, the framework for contribution validation was built. This framework will now be used as a base for validating Contribution 1 and Contribution 2.

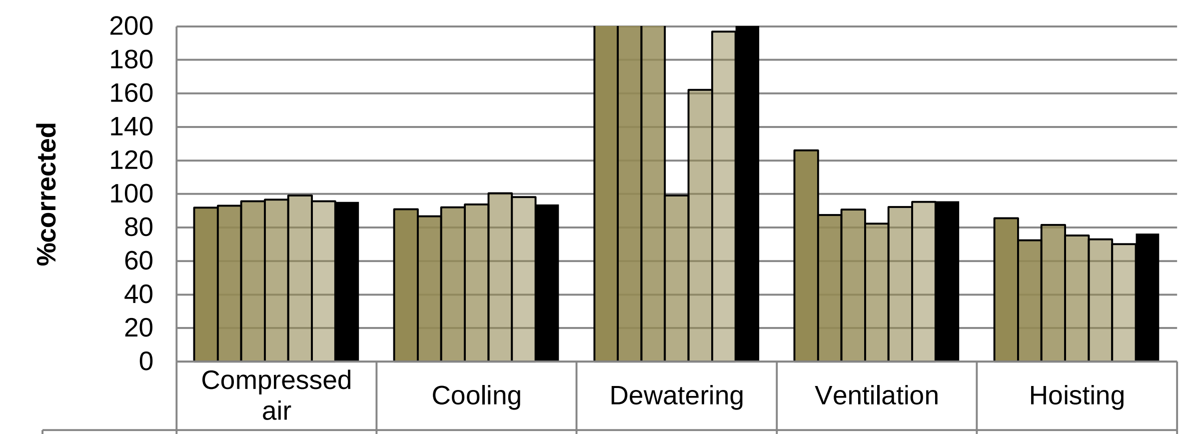
With the benchmarks available for each case study mine (after applying Equation 22–Equation 31 and Equation 42–Equation 48), the first step is to apply Equation 32 to obtain values of $\%_{\text{initial}}$ for each month of available data for the case study mines. As was stated in Chapter 3, this results in performance values of energy consumption as compared with benchmarks. It was mentioned that due to statistical degrees of error in the regression models when development occurred, the values of $\%_{\text{initial}}$ had to be converted to $\%_{\text{corrected}}$.

To obtain $\%_{\text{corrected}}$ values, the values of $\%_{\text{initial}}$ were analysed according to the criteria shown in Table 38 in Chapter 3. This determined whether the specific high demand system being analysed fell into one of three categories: underperformance, normal performance or overperformance. After performance per system per month was established, the required equations were applied from Table 38 to obtain the values of $\%_{\text{corrected}}$.

5.3.1 Case Study 1

Individual high demand systems

Mine 1, which is 1 200 m deep and situated in the Welkom area, was used as Case Study 1. The results of applying both the average and best practice benchmarking models for Mine 1 are shown in Table 110 and Table 111 in Appendix G. The values of $\%_{\text{initial}}$ for the average benchmark score results were converted to $\%_{\text{corrected}}$ and are displayed in Figure 67.



	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	92	91	4977	126	86
Month 2	93	87	742	87	72
Month 3	96	92	751	91	82
Month 4	97	94	99	82	75
Month 5	99	101	162	92	73
Month 6	96	98	197	95	70
Average	95	94	1155	96	76

Figure 67: Case Study 1 – percentage corrected values (average benchmarking)

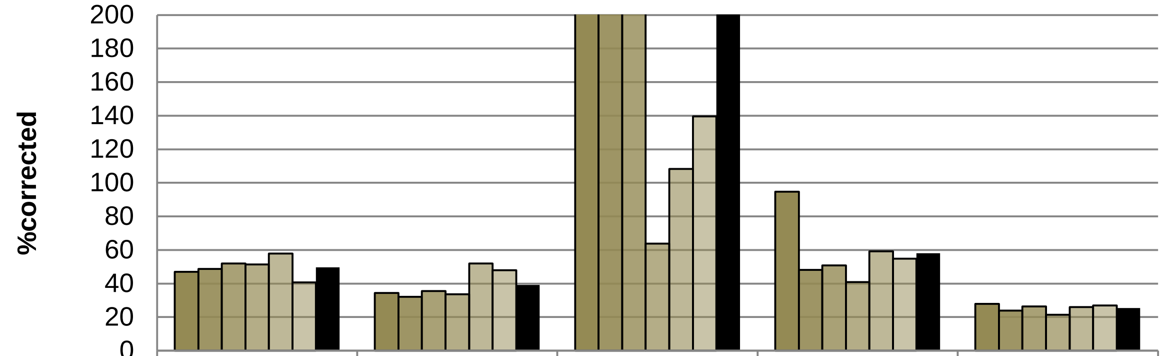
Interpreting the chart shows that when considering average benchmarks of the compressed air system, Month 5 (99%) had the highest score and Month 1 (92%) had the lowest score. Overall, the compressed air system on Mine 1 seemed to operate at a constant efficiency but slightly lower than the benchmark at an average of 95%.

For Mine 1's cooling system, it is seen that the highest scoring month was Month 5 (101%) again. The lowest scoring month was Month 2 (87%). Month 1 to Month 5 were classified as summer months; Month 6 as a winter month with the average ambient temperature lowering steadily from Month 1 to Month 6. This showed that during colder or winter months, Mine 1's cooling system operated more efficiently. The average score for cooling systems on Mine 1 was 94%.

When reviewing Mine 1's dewatering system, it is seen that a very low amount of energy consumption is apparent when compared with the average benchmark. Month 1 had an average benchmark score of 4 075% with the six-month average being 1 155%. The lowest month (Month 4) had a score of 99%.

The ventilation system of Mine 1 showed an inconsistent score of between 126% (Month 1) and 82% (Month 4). The six-month average score obtained for Mine 1's ventilation system amounted to 96%, which was 4% less than the benchmark for deep-level mine ventilation systems. The hoisting system of Mine 1 had the lowest average benchmark score (76%) of all of the high demand systems on Mine 1. The highest scoring month was Month 1 with 86%; the lowest scoring month was Month 6 with 70%.

The best practice benchmark scores obtained for each high demand system of Mine 1 are shown in Figure 68. It is seen that the compressed air system energy consumption had an average score of 50% over the six months when compared with best practice benchmarks. The cooling system of Mine 1 had a slightly lower average score of 39%. The best performing high demand system on Mine 1 when compared with best practice benchmarks was the dewatering system (average score of 757%).



	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	47	34	3273	95	28
Month 2	49	32	482	48	24
Month 3	52	36	474	51	26
Month 4	51	34	64	41	21
Month 5	58	52	108	59	26
Month 6	41	48	140	55	27
Average	50	39	757	58	25

Figure 68: Case Study 1 – percentage corrected values (best practice benchmarking)

The Mine 1 ventilation system scored an average of 58%. This is, however, misleading as the score for Month 1 (95%) was almost double that of the rest of the months. Finally, the lowest scoring high demand system on Mine 1 (when compared with best practice benchmarks) was the hoisting system again, as was the case with average benchmarks. The hoisting system scored an average of 25%.

All high demand systems combined

By using Equation 30 and Equation 31 on Mine 1's available data, the total high demand system average benchmarks were obtained (Appendix G, Table 136). Equation 32 was again applied to this data to determine the values of $\%_{\text{initial}}$ and thereafter $\%_{corrected}$ from the criteria and equations in Table 38. The values of $\%_{corrected}$ for Mine 1's total high demand system energy consumption are shown in Figure 69 for each of the six months. The black line represents the average $\%_{corrected}$ for Mine 1.

Analysing Figure 69 reveals that Mine 1's total high demand system performance was consistent – with the lowest month scoring 93% and the highest month scoring 99%. The average value of $\%_{corrected}$ for Mine 1 is 96%, which was very close to the average benchmark.

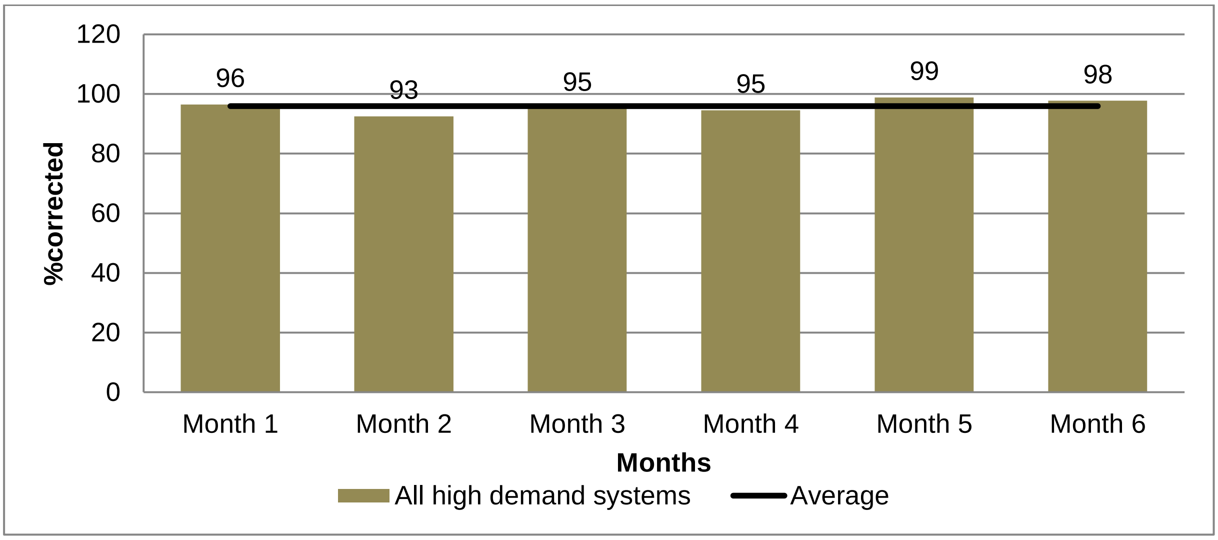


Figure 69: Case Study 1 – percentage corrected of systems combined (average benchmarking)

By applying Equation 49 and Equation 50 to Mine 1's data, the best practice energy consumption for all of the high demand systems combined was calculated. This is shown as Table 137 in Appendix G. Performing the same procedure as was mentioned in Section 5.3, the $\%_{\text{initial}}$ and $\%_{corrected}$ values were obtained. These values ($\%_{corrected}$) are shown in Figure 70. It is seen that the first five months of Mine 1 performed similarly at close to 50% of the best practice benchmark. The highest performing month was Month 5 with 56%; the lowest performing month was Month 4 with 42%. The average performance of Mine 1 when compared with the best practice benchmark was 47%.

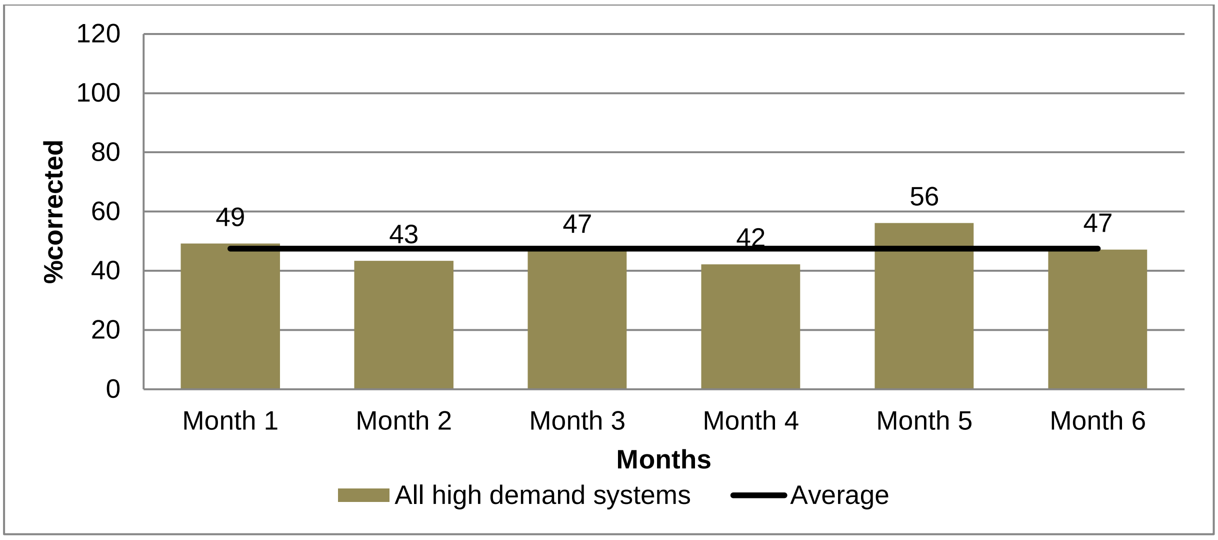


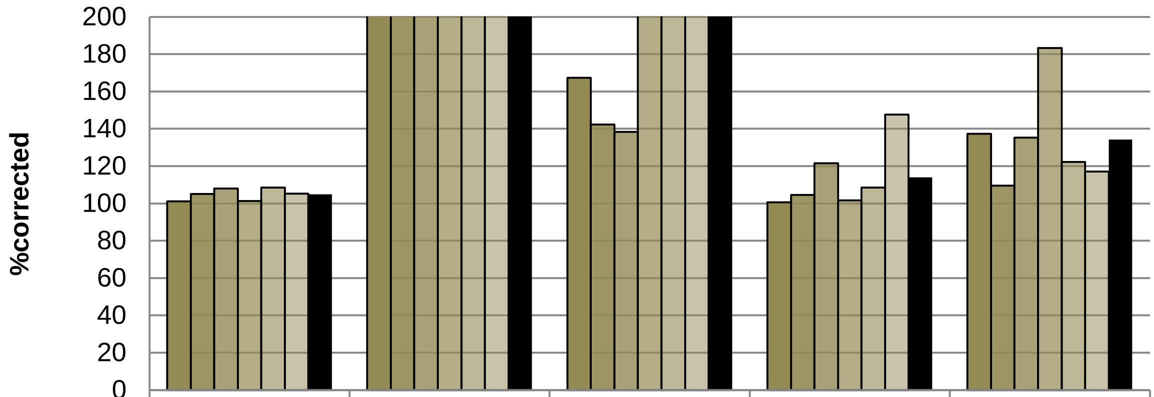
Figure 70: Case Study 1 – percentage corrected of systems combined (best practice benchmarking)

5.3.2 Case Study 2

Individual high demand systems

Mine 2, which is 1 800 m deep and situated in the Welkom area of the Free State, was used as Case Study 2. Table 113 and Table 114 in Appendix G display the average benchmark and best practice benchmark energy consumption for each of the six months used for Case Study 2. The $\%_{\text{initial}}$ and $\%_{corrected}$ values were calculated by the methods described in Chapter 3. The $\%_{corrected}$ values for the six-month data availability period are shown in Figure 71.

From Figure 71 it can be seen that Mine 2 operated at significant efficiency levels when considering the $\%_{corrected}$ score in terms of average benchmarks. The compressed air system performed consistently with a low score of 101% (Month 1 and Month 4) and a high score of 109% in Month 5. The average score obtained on the compressed air system of Mine 1 over the six-month period was 105%, which was above the average benchmark.



	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	101	316	167	101	137
Month 2	105	361	142	105	110
Month 3	108	438	138	121	135
Month 4	101	478	221	102	183
Month 5	109	1607	365	108	122
Month 6	105	9916	269	148	117
Average	105	2186	217	114	134

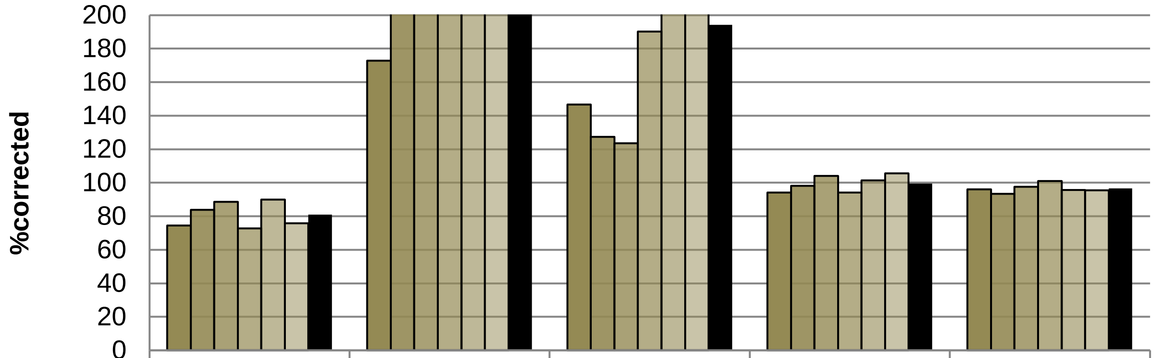
Figure 71: Case Study 2 – percentage corrected values (average benchmarking)

Mine 2's cooling system performed above the average benchmark. The lowest score (316%) obtained was during Month 1. Month 6, which was a winter month, showed a score of 9 916% as compared with the average benchmark. This very high score was due to the cooling system on Mine 1 consuming almost no energy during the winter months. The average six-month score of Mine 2's cooling system equated to 2 186%, which was significantly higher than the average benchmark.

Continuing the overperformance trend of high demand systems on Mine 2, the dewatering system also scored very high. The lowest month (Month 3) scored 138% and the highest month (Month 5) scored 365%. The average six-month score for dewatering systems on Mine 2 was 217%, which was more than double the average benchmark for dewatering systems on deep-level mines.

Analysing the ventilation system of Mine 2 showed that a higher than average benchmark score of 114% was obtained for the six months. The lowest scoring month was Month 1 with 101% and the highest scoring month was Month 6 with 148%. Finally, the hoisting system of Mine 2 also performed higher than the average benchmark for deep-level mines. Scores ranged between 110% and 183% and an average score of 134% was achieved over the six-month period.

Figure 72 displays the best practice benchmark scores in $\%_{corrected}$ for each of Mine 2's high demand systems. Once more, the scores were calculated for each of the systems over a six-month period. The trend of Mine 2's high demand systems scoring very high continued for the best practice benchmark results. The average score of the compressed air system was 81% for the six months – with a maximum score of 90% in Month 5 and a minimum score of 73% in Month 4.



	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	75	173	147	94	96
Month 2	84	217	127	98	93
Month 3	89	266	123	104	98
Month 4	73	256	190	94	101
Month 5	90	1038	333	101	96
Month 6	76	5999	246	106	95
Average	81	1325	194	100	97

Figure 72: Case Study 2 – percentage corrected values (best practice benchmarking)

As was the case with average benchmark scores, the cooling system scored significantly above the best practice benchmark for all months considered. With a range of between 173% in Month 2 and 5 999% in Month 6, an average of 1 325% was achieved. It was again apparent that Month 6 with the highest score occurred during a winter period when almost no energy was used for cooling purposes.

Dewatering system energy consumption of Mine 2 scored an average of 194%, which was almost twice the best practice benchmark. It is interesting to see that higher scores were obtained during colder months (Month 5 and Month 6) with 333% and 246% respectively. The lowest scoring month was Month 3 at 123%. The reason for the higher scores during colder months could have been that less water was being used at this specific mine when chilled water was not needed.

The Mine 2 ventilation system averaged on par with the best practice benchmark with an average score of 100% over the six months. The lowest scoring months for the ventilation system were Month 1 and Month 4, both with 94%; the highest scoring month was Month 6 with 106%. The hoisting system scored second-lowest. A best practice score of 97%, which was still close to the best practice benchmark, was achieved when considering the total six-month period. Scores ranged between 93% in Month 2 and 101% in Month 4.

All high demand systems combined

Equation 30 and Equation 31 were again used on Mine 2's data to obtain overall high demand system average and best practice benchmark scores. Figure 73 displays Mine 2's total high demand system average benchmark score for each of the six months when data was measured. The $\%_{\text{initial}}$ and $\%_{corrected}$ values were determined from the average benchmark energy consumption shown in Table 138 in Appendix G. The bars in Figure 73 show each of the months' scores and the line represents the average for the total period.

An inconsistent average benchmark score for all of Mine 2's high demand systems combined can be seen in Figure 73. Month 1 scored the lowest at 131% and was potentially the warmest month when considering months chronologically. It seems that the scores were higher for months closer to winter with 200% for Month 5 and 188% for Month 6. This indicated that Mine 2's high demand systems operated at a high efficiency during the colder or winter months. The average score of $\%_{corrected}$ for the six months when data for Mine 2 was available was 162%, which was 62% above the average benchmark.

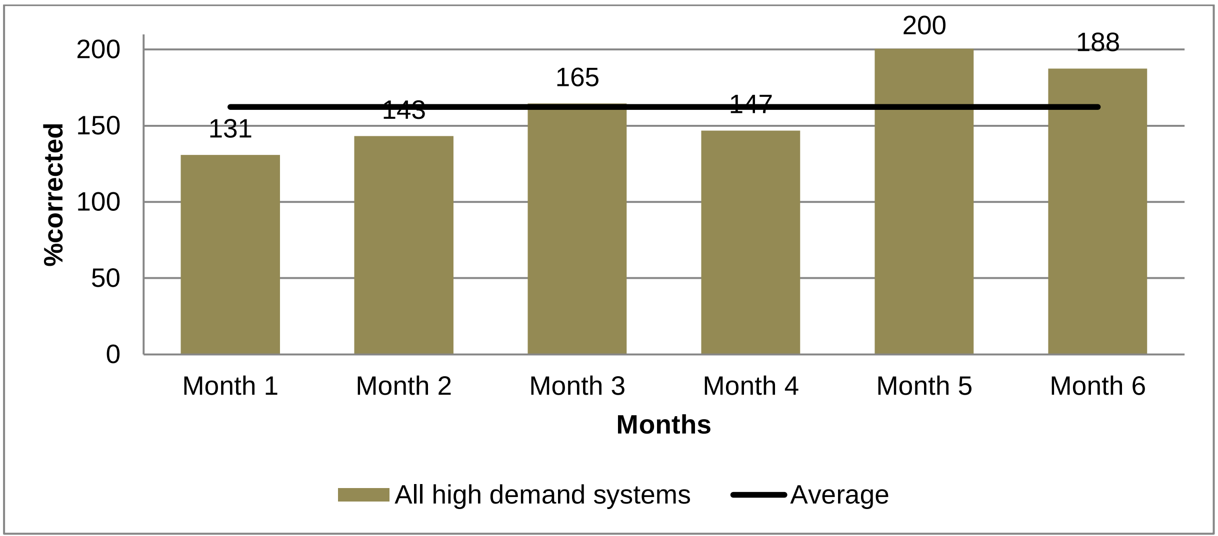


Figure 73: Case Study 2 – percentage corrected of systems combined (average benchmarking)

Figure 74 represents the best practice scores for the combined high demand systems at Mine 2. This was once again obtained by determining best practice energy consumption (Table 139 in Appendix G) using Equation 49 and Equation 50 and thereafter calculating $\%_{\text{initial}}$ and $\%_{corrected}$. A similar trend to the average benchmark scores is seen in Figure 74. Higher scores were again obtained during the colder months and lower scores during warmer months. The average score over the six months for best practice benchmarking was 108%.

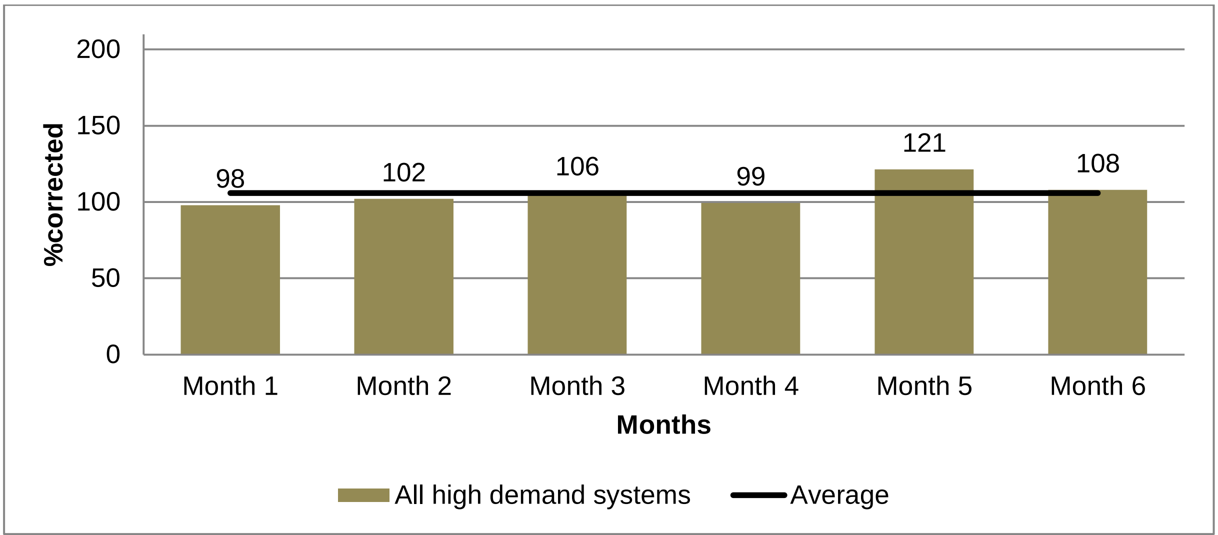


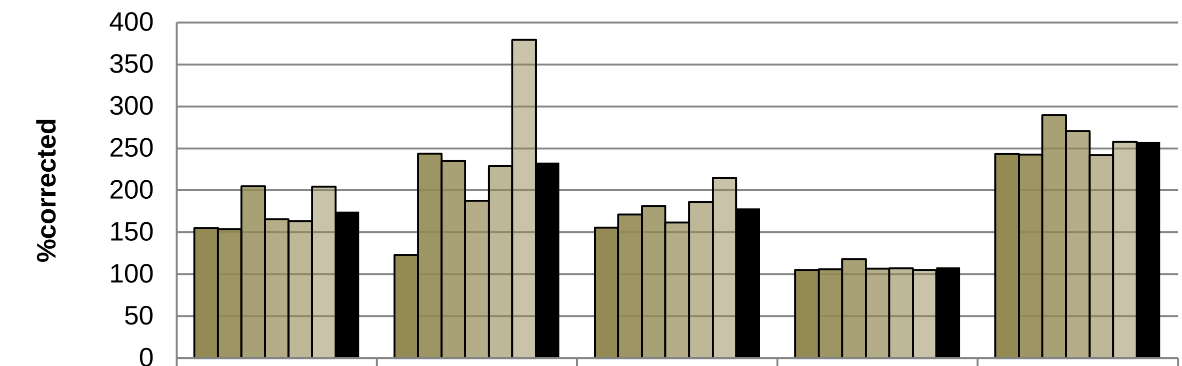
Figure 74: Case Study 2 – percentage corrected of systems combined (best practice benchmarking)

5.3.3 Case Study 3

Individual high demand systems

Mine 3, which is 3 400 m deep and situated in the Vaal River area of the North West province, was used as Case Study 3. The same exact procedure as for the previous case studies was used to determine the average benchmark energy consumption (Table 131 in Appendix G) for each of the high demand systems as well as the $\%_{\text{initial}}$ and $\%_{corrected}$ score values. Figure 75 presents the $\%_{corrected}$ scores for each high demand system over a six-month period at Mine 3.

Mine 3's compressed air system scored high against the average benchmark with an average $\%_{corrected}$ value of 175% for six months. The highest score obtained for the compressed air system at Mine 3 was 205% during Month 6 and the lowest score was 153% during Month 2. The cooling system of Mine 3 showed a significant range of scores between 123% in Month 1 and 379% in Month 6. Once again Month 6 was a winter month and it was indicated that very low cooling system energy consumption occurred during this time. The average cooling system score for Mine 3 was 233%.



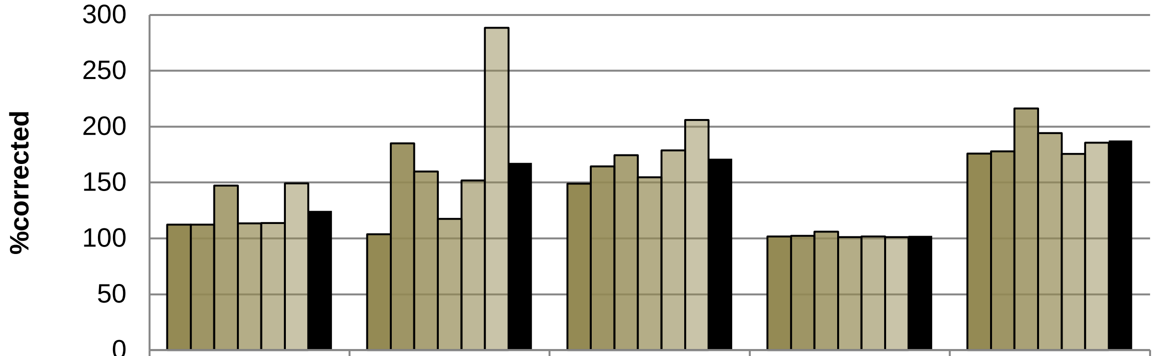
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	155	123	155	105	243
Month 2	153	244	171	106	242
Month 3	205	235	181	118	289
Month 4	166	188	162	107	270
Month 5	163	229	186	107	242
Month 6	205	379	215	105	258
Average	175	233	178	108	258

Figure 75: Case Study 3 – percentage corrected values (average benchmarking)

The dewatering system on Mine 3 scored similarly to the compressed air system with an average six-month score of 178%. The scores ranged from 155% in Month 1 to 215% in Month 6. The Mine 3 ventilation system scored the lowest of all of the high demand systems present at Mine 3. The highest scoring month was Month 3 with a $\%_{corrected}$ of 118% and the lowest scoring months both scored 105% (Month 1 and Month 6). The average score was respectable at 108%, which was still above the average benchmark.

Mine 3's hoisting system scored consistently higher than all the other high demand systems at Mine 3. An average score of 258% was obtained with scores ranging between 242% (Month 5) and 289% (Month 3). The average of 258% obtained indicated that the hoisting system operated approximately 2.5 times more efficiently than the average benchmark for hoisting systems on deep-level mines.

The values obtained for $\%_{corrected}$ – as was determined for best practice benchmark energy consumption (Table 117 in Appendix G) – are shown in Figure 76. It is apparent that the bar graph profiles are very similar to those found for the average benchmark scores in Figure 75. The compressed air system scored higher than the best practice benchmark at an average of 125% with high and low months of 147% (Month 3) and 112% (Month 1 and Month 2) respectively.



	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	112	104	149	102	176
Month 2	112	185	165	102	178
Month 3	147	160	174	106	216
Month 4	113	117	155	101	194
Month 5	114	152	179	102	176
Month 6	149	289	206	101	186
Average	125	168	171	102	188

Figure 76: Case Study 3 – percentage corrected values (best practice benchmarking)

The cooling system again showed a significant increase in $\%_{corrected}$ during the winter month (Month 6) with a score of 289%. However, due to the inconsistent scores for the other five months, the average cooling system score calculated to 168%. The lowest month for the cooling system was Month 1 with a score of 104%. Dewatering had a similar to average benchmarking relative consistent score ranging between 149% (Month 1) and 206% (Month 6). The average best practice benchmark score for dewatering systems on Mine 3 was 171%.

With a very consistent scoring range of between 101% (Month 4 and Month 6) and 106% (Month 3), the ventilation system on Mine 3 had an average score of 102% for six months. The hoisting system obtained the highest average score of all of the high demand systems on Mine 3 when compared with best practice benchmarks. An average score of 188% was obtained with a range of between 176% (Month 1) and 216% (Month 3).

All high demand systems combined

Table 140 and Table 141 (Appendix G) show the results after applying Equation 30 and Equation 31 for average benchmarking and Equation 49 and Equation 50 for best practice benchmarking of Mine 3's total high demand system energy consumption. The $\%_{corrected}$ values for both cases are displayed in Figure 77 and Figure 78 respectively. Each of the six months when data was available is presented in bars with a line representing the average values.

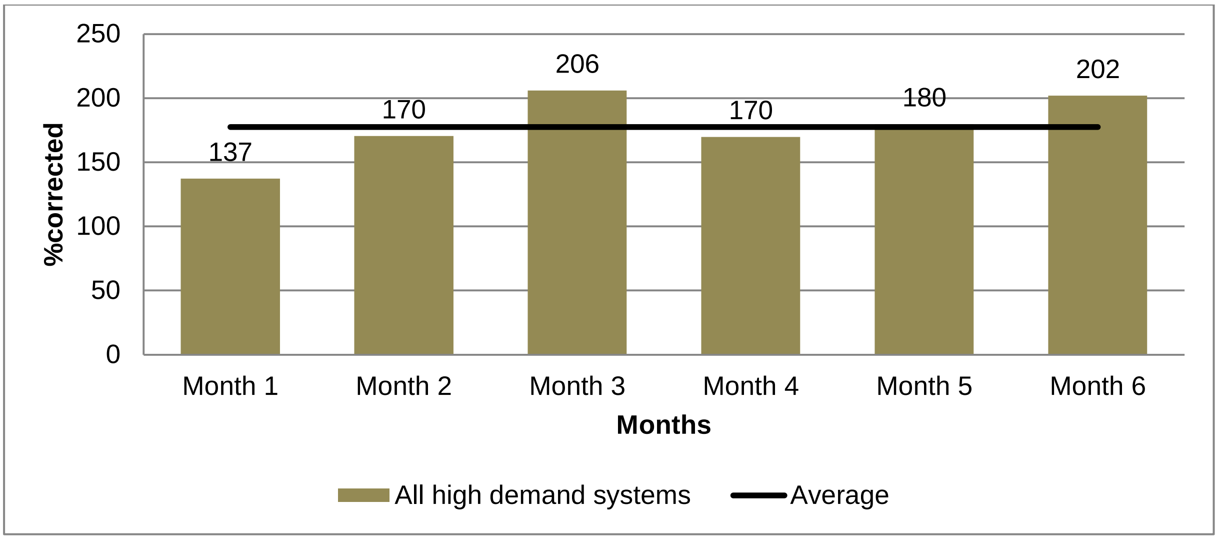


Figure 77: Case Study 3 – percentage corrected of systems combined (average benchmarking)

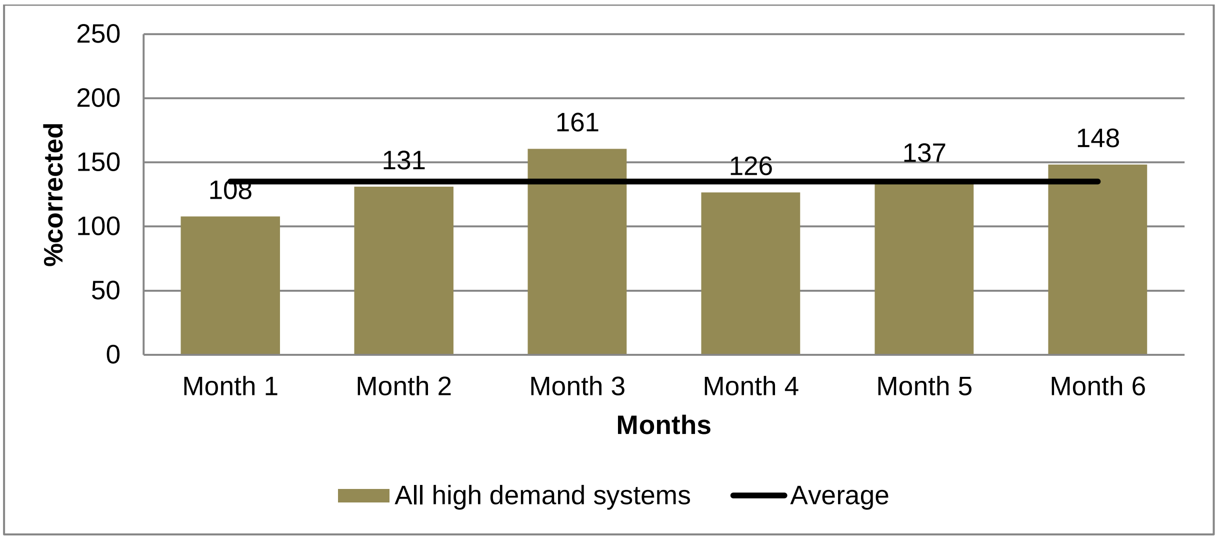


Figure 78: Case Study 3 – percentage corrected of systems combined (best practice benchmarking)

Both Figure 77 and Figure 78, which represent average and best practice benchmark scores for Mine 3 respectively, indicated a very inconsistent scoring range. The lowest scoring month in both cases was Month 1 with 137% and 108% respectively. Month 3 scored the highest at 206% and 161% respectively. Overall, the high demand systems at Mine 3 operated highly efficiently with an average score of 178% when compared with average benchmarks; and an average score of 135% when compared with best practice benchmarks.

5.3.4 Case Study 4 to Case Study 9

Six additional case studies were completed to validate average and best practice benchmarking models. The exact same procedure as discussed for Case Study 1 to Case Study 3 was followed to determine the results for the additional case studies. The figures describing the $\%_{corrected}$ values for each high demand system over a six-month period are shown as Figure 132 to Figure 143 in Appendix H. These figures include both average and best practice results.

The results of obtaining average and best practice benchmark scores for all high demand systems combined are also shown in Appendix H (Figure 144 to Figure 155). The energy consumption values determined via average and best practice models can be found in Appendix G (Table 142 to Table 153) with the values from the previous case studies.

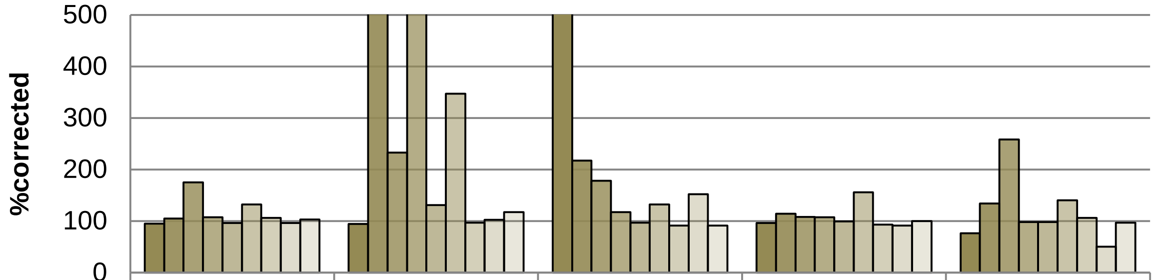
5.3.5 Results comparison

Individual high demand systems

The results of the nine case studies were discussed from Section 5.3.1 to Section 0. Different high demand systems from individual mines were compared to determine the highest and lowest system scores when compared with average and best practice benchmarks. The average score for each case study's (Mine 1 to Mine 9) total high demand system energy consumption was also calculated.

This section focuses on comparing the benchmark scores of high demand systems across mine boundaries. In doing so, the most and least efficient operating mines in terms of energy consumption for certain amounts of tonnes of ore mined can be determined. Once again, the energy consumption for individual, as well as high demand systems combined, was compared.

Figure 79 displays the average benchmarking scores retrieved from results shown in Section 5.3.1 to Section 0. This is shown for each high demand system for each case study mine individually.



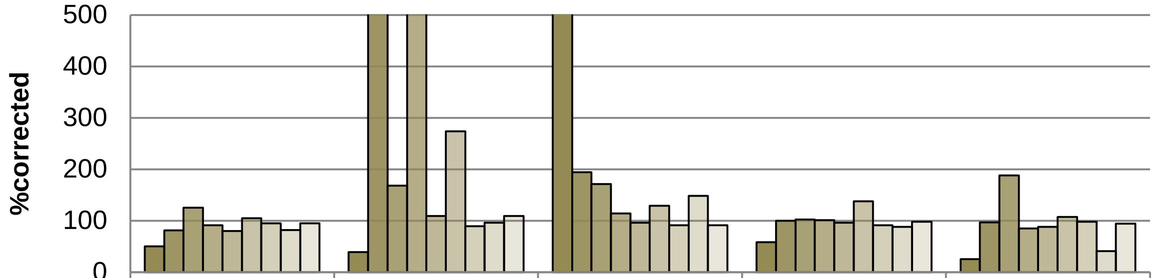
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Mine 1	95	94	1155	96	76
Mine 2	105	2186	217	114	134
Mine 3	175	233	178	108	258
Mine 4	107	1385	117	107	98
Mine 5	96	131	97	99	98
Mine 6	132	347	132	156	140
Mine 7	106	97	91	93	106
Mine 8	96	102	152	91	50
Mine 9	103	117	91	100	97

Figure 79: Case study mines percentage corrected for each system (average benchmarking)

The bar charts in Figure 79 identify the different case study mines that operate the high demand systems the least and most efficiently:

- The mine that scored the highest for compressed air systems was Mine 3 with an average $\%_{corrected}$ score of 175%. The lowest scoring mine was Mine 1 with a score of 95%. Overall, all of the case study mines scored close to the average benchmark of 100% for compressed air systems.
- For the cooling systems, the highest scoring mine was Mine 2 with a very high score of 2 186%. Mine 1 was the lowest scoring mine with 94%.
- Average benchmark scores for dewatering systems showed that Mine 1 operated the most efficiently with a score of 1 155%. The lowest scoring mines with 91% were Mine 7 and Mine 9.
- Ventilation system scores were relatively consistent for all case study mines with only one mine scoring convincingly higher. Mine 6 had a score of 156%, which was approximately 60% higher than the lowest scoring mine, which was Mine 8 with 91%.
- The hoisting system scores in terms of average benchmarks showed a significant range of 50% (Mine 8) to 258% (Mine 3).

The best practice benchmark scores for each of the case study mines and their high demand systems are shown in Figure 80. It is seen that similar results to average benchmark in terms of highest and lowest scoring mines are found, which is to be expected.



	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Mine 1	50	39	757	58	25
Mine 2	81	1325	194	100	97
Mine 3	125	168	171	102	188
Mine 4	91	981	114	101	85
Mine 5	80	109	96	96	88
Mine 6	105	274	129	138	107
Mine 7	95	89	91	91	98
Mine 8	82	96	148	88	41
Mine 9	95	109	91	98	94

Figure 80: Case study mines percentage corrected for each system (best practice benchmarking)

All high demand systems combined

Results in Figure 81 were obtained by taking the average of $\%_{corrected}$ values from applying average and best practice benchmarking models for total high demand systems combined over the six-month period. Using Figure 81, each of the case study mines can be compared in terms of total energy consumption for high demand systems when compared with the average and best practice benchmarks pertaining to specific depths and tonnes of ore mined.

According to Figure 81, the highest scoring case study mine (when considering average as well as best practice benchmarks) was Mine 3 with scores of 178% (average benchmark) and 135% (best practice benchmark) respectively. The lowest scoring case study mine was Mine 1. Average benchmarking scored 96% and best practice benchmarking scored 47%.

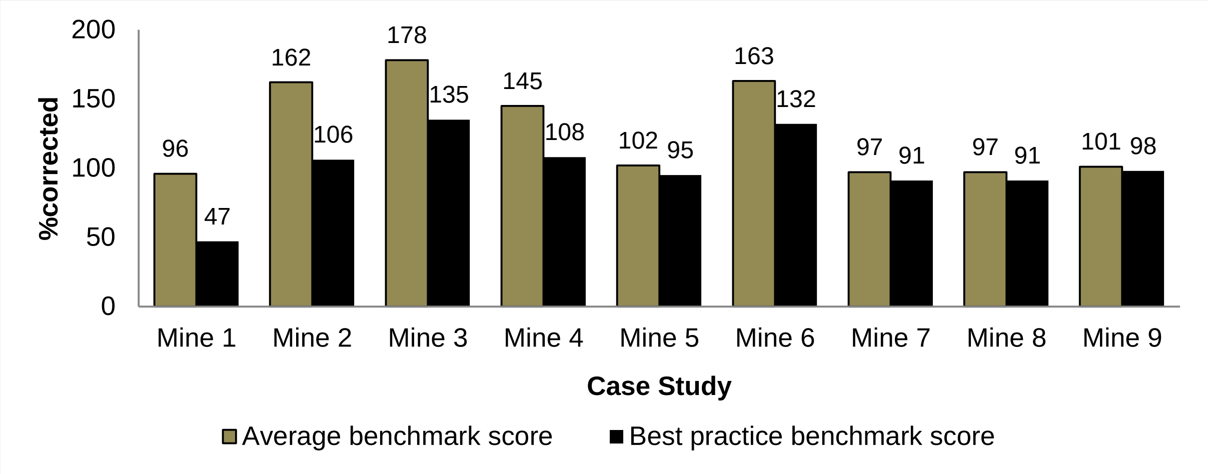


Figure 81: Case study mines – total high demand system benchmark scores

When considering the individual high demand system scores from Figure 79 and Figure 80, it is observed that Mine 3 did not score significantly higher when compared with other case study mines. This is especially apparent when looking at cooling and dewatering systems where very high $\%_{corrected}$ values were obtained by Mine 2 and Mine 4 (cooling) and Mine 1 (dewatering). The reason for Mine 3 emerging as the top scoring mine when viewing Figure 81 is due to the amount of energy consumed by each high demand system.

The cooling and dewatering systems of Mine 1, Mine 2 and Mine 4 contributed a very small percentage to the total high demand system energy consumption for the specific mines and, therefore, did not influence the overall score considerably.

5.4 VALIDATION OF ENERGY INITIATIVE PRIORITISATION

Contribution 3 (Section 1.7.3) stated that scores obtained from benchmarking models would assist in identifying the priority for implementing energy efficiency initiatives. This can be done by either using average benchmark scores or best practice benchmark scores. For the purpose of this study, the average benchmark score is used as it is accurate when considering the average energy consumption of the real mines from which the model was developed.

Analysing the results presented in the bar charts (Section 5.3), which display separate high demand system scores for each case study mine, aids in prioritising energy saving initiatives. During discussions in Chapter 2 regarding high demand systems, previous studies on energy efficiency initiatives for the different systems were summarised. These studies were implemented and displayed real-world results.

By prioritising the implementation of energy initiatives according to average benchmark scores, the results shown in Table 60 were obtained. A rank was given to each high demand system per mine to show the priority of the energy initiative implementation. The ranks range between values of 1 and 5 – with 1 indicating the highest priority and 5 the lowest priority. As was the case with Chapter 4, the $\%_{initial}$ values were used to emphasise the difference in scores.

Table 60: Energy efficiency priorities for case studies (initial percentage chronological rank)

High demand system	Case study system priority rank								
	Mine 1	Mine 2	Mine 3	Mine 4	Mine 5	Mine 6	Mine 7	Mine 8	Mine 9
Compressed air	4	1	2	2	1	1	4	3	4
Cooling	3	5	4	5	5	5	3	4	5
Dewatering	5	4	3	4	2	2	2	5	1
Ventilation	2	2	1	3	4	4	1	2	3
Hoisting	1	3	5	1	3	3	5	1	2

It might seem easy to prioritise the implementation of energy efficiency initiatives from Table 60 alone as a clear chronological range of priorities is shown for each case study mine. However, the values scored from average benchmarking should be taken into account as the actual difference in scores might not be as substantial as pure ranks from 1 to 5 indicate. Using the exact same table configuration and inserting the values of $\%_{initial}$ obtained from average benchmarking for each high demand system on every case study, Table 61 is found.

Table 61: Energy efficiency priorities for case studies (initial percentage)

High demand system	Case study system initial percentage								
	Mine 1	Mine 2	Mine 3	Mine 4	Mine 5	Mine 6	Mine 7	Mine 8	Mine 9
Compressed air	90	111	178	114	92	137	113	91	106
Cooling	82	1 554	224	1 017	143	314	92	105	129
Dewatering	971	214	182	130	94	138	80	161	77
Ventilation	82	127	124	122	96	164	77	73	100
Hoisting	59	149	245	95	94	148	118	39	92

By using the score of the lowest scoring high demand system for each case study mine as a baseline and determining a factor for each of the other systems' scores based on the baseline, different priorities can be obtained. This is necessary to consider that the score of any two systems might only be separated by a few percentage points. Table 62 shows the energy efficiency priorities with the following parameters:

- High: 1 ≤ factor < 1.5
- Medium: 1.5 ≤ factor < 2
- Low: factor ≥ 2

Table 62: Energy efficiency priorities for case studies (factor of lowest initial percentage)

High demand system	Case study system priority rank								
	Mine 1	Mine 2	Mine 3	Mine 4	Mine 5	Mine 6	Mine 7	Mine 8	Mine 9
Compressed air	Med	High	High	High	High	High	High	Low	High
Cooling	High	Low	Med	Low	Med	Low	High	Low	Med
Dewatering	Low	Med	High	High	High	High	High	Low	High
Ventilation	High	High	High	High	High	High	High	Med	High
Hoisting	High	High	Med	High	High	High	Med	High	High

The results shown in Table 62 only represent each mine individually – with interpretation only derived from comparing high demand system scores directly. In the case of Mine 6, it is seen that all high demand systems except for cooling systems were prioritised high for the implementation of energy efficiency initiatives. When viewing the actual scores for Mine 6 in Table 63, it is seen that all of the high demand systems from Mine 6 scored significantly higher than the average benchmark of 100%. Thus, implementing energy efficiency initiatives was not required and the results in Table 62 were imperfect.

Mitigation of the abovementioned flaw is to consider only the score values obtained from average benchmarking and to indicate the need for intervention via energy efficiency initiatives through this. Table 63 shows the new priorities per high demand system for each mine. For this specific validation, the ranges chosen for "High", "Medium" and "Low" priority systems were depicted by the following parameters:

- High: %initial < 90%
- Medium: 90% ≤ %initial < 110%
- Low: %initial ≥ 110%

Table 63: Energy efficiency priorities for case studies (ranges for initial percentage)

High demand system	Case study system priority rank								
	Mine 1	Mine 2	Mine 3	Mine 4	Mine 5	Mine 6	Mine 7	Mine 8	Mine 9
Compressed air	High	Low	Low	Low	Med	Low	Low	Med	Med
Cooling	High	Low	Low	Low	Low	Low	Med	Med	Low
Dewatering	Low	Low	Low	Low	Med	Low	High	Low	High
Ventilation	High	Low	Low	Low	Med	Low	High	High	Med
Hoisting	High	Low	Low	Med	Med	Low	Low	High	Med

Reviewing Mine 6 again, it can now be seen that the priority for interventions via energy efficiency initiatives was “Low” for all high demand systems. The results of Mine 2 and 3 also presented the same conclusion. Case study mines that had “High” priorities for implementing energy efficiency initiatives were Mine 1, Mine 7, Mine 8 and Mine 9. Mine 1 had “High” priorities on four of the five high demand systems.

The remaining case study mines (Mine 4 and Mine 5) had a combination of “Low” and “High” priority systems with Mine 5 approaching a “Medium” priority for almost all high demand systems. Depending on a mine energy manager’s preference, any of the tables (Table 60 to Table 63) could be used to prioritise implementation of energy efficiency initiatives. However, combining the results more accurately represents the prioritisation of high demand system energy efficiency initiatives.

5.5 VALIDATION OF BUDGET FORECASTING

Using average benchmarking models to predict operational budgets for high demand system energy consumption on deep-level mines was verified in Section 4.6. It was seen that due to the present use of static energy consumption budgets, the illusion of consumption under budget often prevailed during months of low production. The proposed mitigation was to calculate the budgets dynamically each day according to the previous month’s production figures and the forecasted figures for the rest of the month.

This section focuses on implementing the new energy consumption budget forecasting procedure on the nine case study mines. This is done in two ways. Firstly, the existing actual energy consumed by each high demand system on each of the case study mines (Mine 1 to Mine 9) is compared with the budgets that would have been selected for the months in question. Secondly, an example is given that illustrates the continuous dynamic recalculation of operational budgets as a month progresses.

To display the actual energy consumption compared with the budgeted energy as calculated by average benchmarking models, the available six months' data for each case study mine was averaged. This was done to ensure clarity in the graphs that follow. Figure 82 to Figure 84 present the actual versus budgeted energy consumption of all high demand systems on the first three case study mines. The results from Case Study 4 to Case Study 9 are shown as Figure 156 to Figure 161 (Appendix H).

The results from applying budget forecasting to Case Study 1 (Mine 1) showed that the operation of all high demand systems, except for the dewatering system, was over budget. Case Study 2 and Case Study 3 operated significantly under budget. The cooling system operation was especially efficient on both mines with actual energy consumption being more than 50% lower than budgeted.

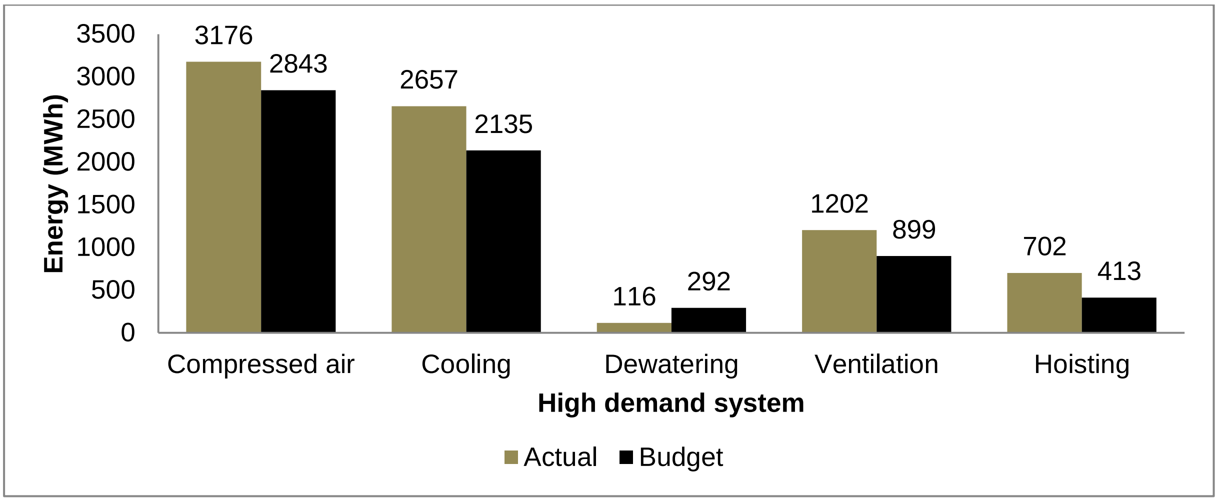


Figure 82: Case Study 1 – actual versus budgeted energy

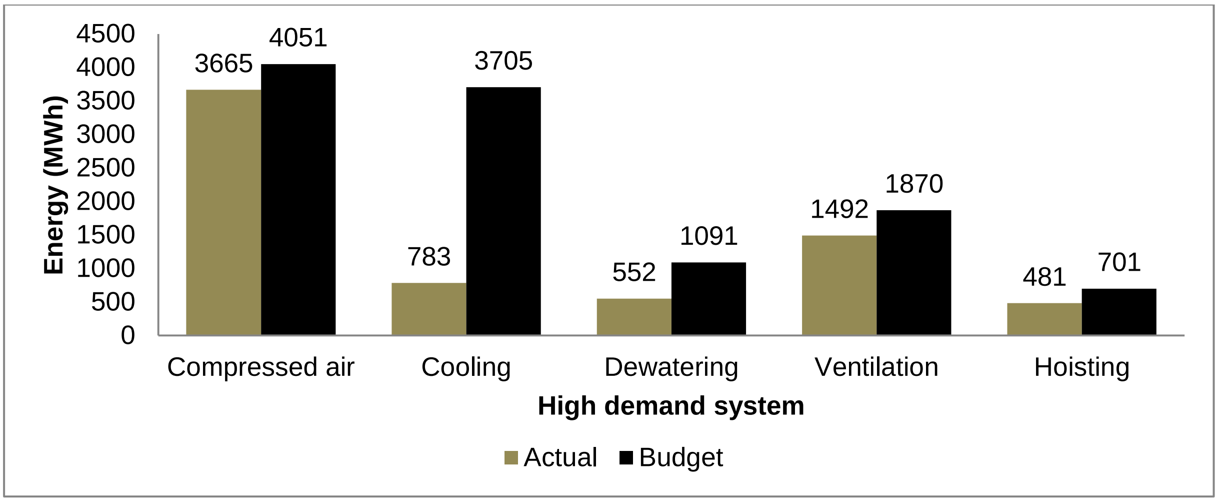


Figure 83: Case Study 2 – actual versus budgeted energy

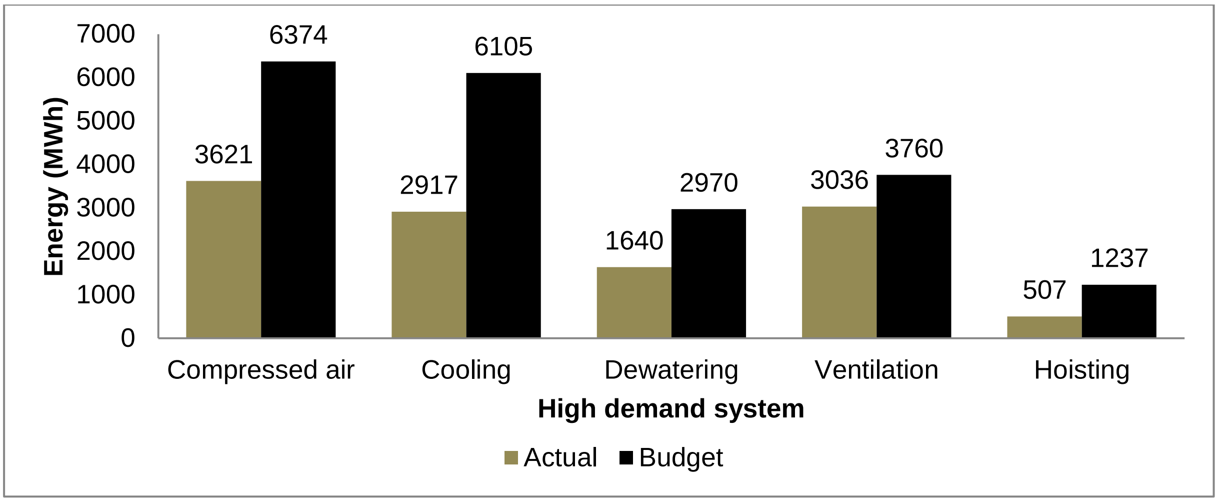


Figure 84: Case Study 3 – actual versus budgeted energy

Figure 85 shows the continuous adjustment of operational budgets for the compressed air system of Mine 9 as an example. The black bars in this figure show the cumulative tonnes of ore mined as the month progressed. The gold bars indicate the projected total production for the month according to cumulative production. The black line, which represents the energy consumption budget for the month, is observed to dynamically adjust according to the total projected production for the month.

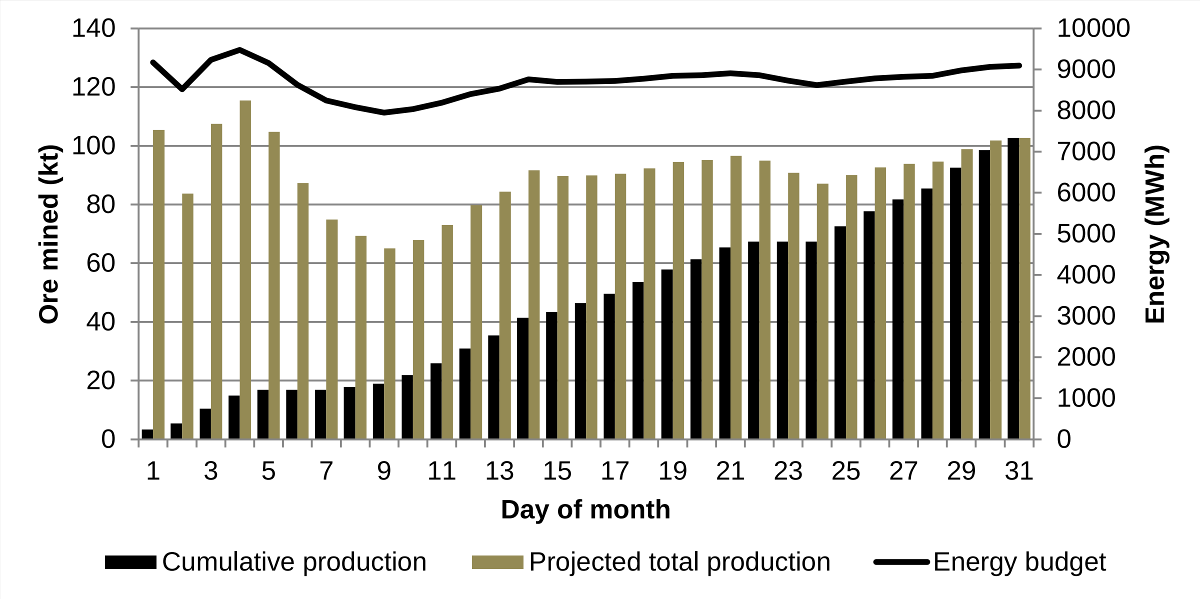


Figure 85: Mine 9 – dynamic budget example

An energy manager can use the budget adjustment method for each high demand system to be continuously aware of present energy consumed versus the budgeted energy for that month. As the budgets are calculated using benchmarking models, the mine will have peace of mind that budgets will not allow energy to be overused on any specific high demand system.

5.6 RESULT INTERPRETATION FOR USER

Various users in the energy management portfolio of a mine may find benefit from the results obtained after implementing the validated methods discussed from Section 5.3 to 5.5. The two positions most closely associated with energy management on South African mines are, Engineering Managers and Chief Electrical Engineers.

Engineering Managers are usually responsible for overall management of technical and operational procedures to ensure a safe and profitable mine. An Engineering Manager will benefit from energy consumption reporting and statistics involving the energy use of various sections of the deep-level mine the engineer is stationed at.

Chief Electrical Engineers are commonly found in a role where management of a whole mining group's energy consumption is done. Reporting on individual mine performance as compared to other mines under the management of the user will enable him/her to know which mines are underperforming in terms of energy consumption efficiency.

Examples of monthly reports that would typically be compiled for either Engineering Managers or Chief Electrical Engineers can be seen in Appendix I and Appendix J. The report in Appendix I is used by Engineering Managers. This report provides information regarding high demand system energy use and how it compares with average and best practice benchmarks for that month. The user can also see on which high demand systems priority must be given for energy efficiency implementations and whether systems performed above or below energy use budgets.

The report generated for Chief Electrical Engineers (Appendix J) contains information on every mine within the user's responsibility (three mines in example). On this report the user is made aware of individual high demand system performance as well as overall high demand system performance for each mine. The user is also informed about which mines are performing the most efficient and which mines are in need of energy efficiency interventions.

5.7 SUMMARY

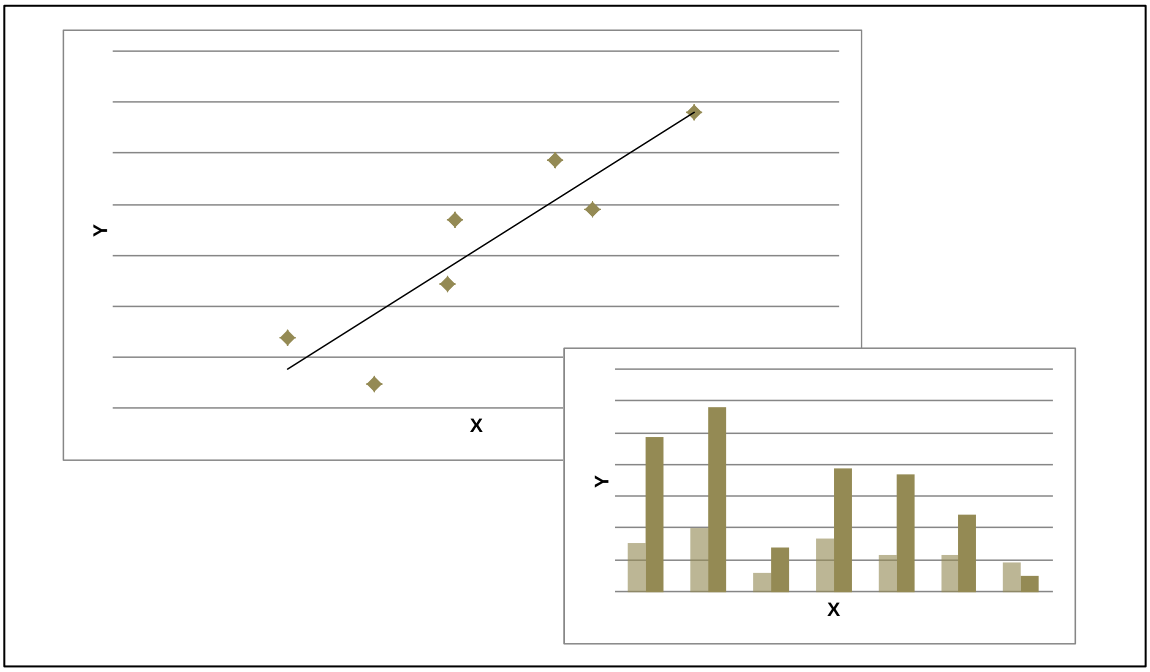
This chapter concluded the validation of the procedures developed during the course of this study. Nine actual mines in South Africa were used as case studies. Each of these mines' high demand systems was benchmarked according to average energy consumption and best practice energy consumption. Through this, the highest and lowest scoring systems in terms of energy consumption efficiency were identified on each mine.

By using models for benchmarking total high demand system energy consumption, individual case study mines were also scored as a whole. This gave an indication of the level of efficiency each of the mines operated at when compared with each other. Implementation of the prioritisation method for energy efficiency initiatives of high demand systems on deep-level mine was also shown. It was indicated that various interpretations could be used to finally decide which system should take priority.

Finally, budget forecasting on case study mines was implemented. It was seen that some of the mines' high demand systems were operating above allowed budgets (according to benchmarks) and others significantly below budget. The mines operating below budgets were also the mines that scored high during benchmarking when compared with other mines.

Examples of how results on case studies can be interpreted by users (Engineering Manager and Chief Electrical Engineers) were also discussed. It was shown that different information regarding either individual high demand system or total high demand system performance can be reported to users on a monthly basis. This information can be used for planning and audits on energy consumption.

CHAPTER 6 – Conclusion and recommendations for further study



6.1 SUMMARY

South Africa's geology allows for the deepest gold and platinum mines in the world. Various high power demand systems must operate continuously to ensure optimum production output at these deep-level mines. Systems – including the generation of compressed air, cooling of water and air, removal of water from underground, ventilation of breathable air and hoisting of mined ore – were shown to contribute approximately 60% of the total energy consumption on a deep-level mine.

Because of the high energy consumption from the high demand systems and the overall high operating costs contributed by electricity costs, it was decided that the focus of this study would be on the high demand systems in question. The selected approach was through benchmarking of the electrical energy consumption of these systems. It was shown that previous studies have been conducted to determine the effect of benchmarking, the awareness it creates towards energy consumption and the saving of energy.

After it was established that energy benchmarking aids in the awareness of electricity consumption, studies previously done on energy benchmarking were considered. The studies ranged from commercial to industrial energy benchmarking. The methods employed by these studies were discussed and critically reviewed to determine the potential for alternative approaches and a migration of previous methods to the deep-level mining industry. Through this, the objective of this study was formulated.

From the study objective, four novel contributions to knowledge were identified. It was stated that a new benchmarking method to determine the energy consumption of various high demand systems would be developed for both average and best practice situations. It was also shown that by using the first contributions, a new prioritisation method to implement energy efficiency initiatives would be realised. Finally, a novel forecasting method to determine operational energy consumption budgets was also shown to be possible.

With the objective of the study known, the different high demand systems on deep-level mines were studied. In-depth research was done on each of the systems to accumulate knowledge regarding the systems' operation, factors that influenced the systems' energy consumption and methods previously used to reduce energy consumption. Benchmarking procedures were also studied. It was shown that typical benchmarking compares system inputs, outputs and the efficiency thereof. With this in mind, the knowledge obtained from research on deep-level mine high demand systems together with previous studies on mine benchmarking, helped to identify variables that directly influence system energy consumption.

Through benchmarking methods learned during the literature study, models to benchmark energy consumption of deep-level mines were developed. Regression analysis was used with different dependent and independent variables that were identified to affect energy consumption. With this, the assumed relationship between the variables were proven. OLS, COLS and SFA techniques were used to create both average and best practice benchmarking models. A benchmark scoring technique that considered statistical errors was also developed.

The developed models were verified by using alternative methods for determining deep-level mine high demand system operation efficiency. This was done by comparing benchmark scores obtained from applying the developed models with efficiency results in terms of simulated energy consumption. Benchmark scores were used as efficiency rank predictions. It was found that the benchmarking models predicted the rank of efficiency accurately and in doing so, verified the development and usability thereof.

The first additional contribution of this study was derived from the benchmarking models and had to be verified. The method for prioritising energy efficiency initiatives on deep-level mine high demand systems was verified by identifying existing mines on which energy efficiency initiatives were implemented in the past. Available data (for benchmarking models) for periods before and after implementation of the initiatives was collected and inserted into the models. An increase in benchmark scores from pre- to post-implementation indicated that the systems in question operated more efficiently. This verified the usability of benchmarking models to prioritise energy efficiency initiatives.

The second additional novel contribution, which was a new method for calculating or predicting operational energy budgets, was also verified. By comparing actual monthly energy budgets from a well-known mining group in South Africa with new budgets calculated using the benchmarking models, it was seen that the new budgets were more accurate. However, mines with high demand systems that scored lower than the benchmarks, showed inaccurate new budgets. This was to be expected, as the budgets were equal to the benchmarks and would motivate a mine to increase individual or overall high demand system efficiency.

To validate the application of both average and best practice benchmarks, the models were applied to nine case study mines. The case studies were actual South African mines that had data available for six-month periods. The scores obtained from benchmarking the case studies gave an accurate indication of individual high demand system efficiency in terms of energy consumption and also of the high demand systems combined. With the results in hand, mines will be able to compare their performance with peers and make changes where necessary.

The developed method was used to prioritise energy efficiency initiatives on high demand systems on the nine case study mines. It was found that there were multiple ways of interpreting the results. Firstly, purely ranking high demand systems according to benchmark scores would yield a rank from 1 to 5, with 1 claiming the highest priority. The second interpretation showed that using factors of the lowest benchmark score could also be used to rank the priority of energy efficiency initiatives. This method resulted in “High”, “Medium” and “Low” priorities.

The final interpretation of benchmark results for prioritising energy efficiency initiatives was to consider the actual scores obtained from each high demand system on every case study mine across mine borders. In this case, it was found that some of the mines had very high scores throughout, which resulted in energy efficiency initiatives not necessarily being required. It was concluded that depending on a mine’s needs and its financial position, a combination of the interpretations could be used to prioritise energy efficiency initiatives.

Finally, the new method for budget forecasting was also validated by applying it to the nine case studies. It was found that some of the case studies performed over budget and others well under budget. The ability of the new budgeting method to adjust a monthly energy consumption budget dynamically throughout a month was also explained and shown in an example (Case Study 9).

6.2 RECOMMENDATIONS FOR FURTHER WORK

6.2.1 Study-specific recommendations

It was shown that models developed for this study were sensitive to available data. To ensure accuracy, it is thus recommended that models be reviewed periodically by using the latest available data. It was apparent that accuracy was already reduced when the benchmarking models were applied on mines that had recent data available. The reason for this might be due to an increase in electricity costs, which motivated mines to save energy. As a result, many of the case study mines and systems scored very close to the benchmark.

To further increase accuracy, more data in terms of different mines could also be used. For this study, data that included a period of a few years for nearly all of the deep-level mines in South Africa was used. It would thus be difficult to find additional data. However, including shallower mines in the scope of the study might yield different models to accommodate a broader range of the South African mining industry. International mines, both deep-level and shallow, can also be used to further strengthen the model.

6.2.2 Recommendations for expansion of study methods

The deep-level mining industry in South Africa is but one of many large contributors to high electricity consumption in the country. Industries such as steel manufacturing, cement production and chemical companies also play an important role in the ever-increasing power demand. This study showed that awareness of electricity consumption could be attained by breaking industries down to core systems that have high individual power demands and by analysing these systems separately.

This study's procedure to analyse high demand systems could also be applied to other industries. Knowledge on the fundamentals of subsystems for any industry can thus be used to determine inputs and outputs for energy benchmarking. Variables would not necessarily be as apparent as those for deep-level mine high demand systems but similar procedures can still be used.

An example from the cement production industry can be described as follows. One of the highest energy consumers on a cement plant is the raw meal-grinding mill. The input to this mill is electrical energy. The mill produces ground raw meal in tonnes as an output. A correlation between the amount of energy consumed and the amount of raw meal produced (in tonnes) can be found. This correlation in conjunction with other factors that should become known during research can produce a model for energy benchmarking.

The example explained above is of a simple system with a low number of inputs and outputs that will produce a benchmarking model with little effort. There are, however, numerous systems in various industries with a large number of factors that could affect the development and accuracy of energy benchmarking models. This specific study, which focused only on high demand systems on deep-level mines, is an example.

Due to the procedure developed for this study making use of inputs and outputs to systems, it should be noted that inputs do not have to be limited to energy consumption. Similar to an increased demand for energy, water requirements might also be constrained in the near future. Using water consumption as an input to a water intensive system, benchmarking of water use implemented similarly to this study's energy benchmarking might yield favourable results.

6.3 CLOSE

Throughout this study, it was proven that individual high demand systems could be benchmarked according to energy consumption. This was shown to be viable for both average and best practice circumstances and indicated the first two novel contributions. Further, it was shown that benchmarking models could be used to prioritise both energy efficiency initiatives on high demand systems and to forecast accurate energy consumption budgets. This was offered as the third and fourth novel contributions. The objective of this study was thus achieved and the contributions were verified and validated.

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Appendix A – Model mine data and regression arrays

Table 64: Model mines available system data

Mine	Depth (m)	Comp. air	Cooling	Dewatering	Ventilation	Hoisting
A	3 400	×	×	×	✓	×
B	2 600	✓	×	✓	✓	✓
C	3 045	✓	✓	✓	✓	✓
D	4 000	✓	✓	✓	✓	✓
E	1 200	✓	✓	✓	✓	×
F	2 000	✓	×	×	✓	✓
G	1 400	✓	×	✓	✓	✓
H	3 300	✓	✓	✓	✓	×
I	2 180	✓	×	✓	✓	✓
J	2 350	×	✓	×	×	×
K	2 350	✓	×	×	✓	✓
L	2 300	✓	✓	✓	✓	✓
M	1 800	✓	✓	✓	✓	✓
N	2 250	×	×	✓	×	×
O	2 200	×	×	×	✓	×

Table 65: Compressed air system LINEST function array (summer)

28.5542144	1.69311303	-269.823787
21.6 155702	0.8596274	1 324.77005
0.79180307	1 282.56771	
15.2125792	8	
50 048 775.3	13 159 839.5	

Table 66: Compressed air system LINEST function array (winter)

54.1642862	0.77694506	406.758977
19.2995386	0.93075308	1 362.94629
0.86073927	1 229.83831	
24.723101	8	
74 787 493.2	12 100 018.2	

Table 67: Compressed air system combined regression array (summer)

30.3308144	1.306064089	737.2132802
8.116284301	970.5165746	
0.758912387	1 232.641411	
34.51930988	8	
40 631 641.2	12 907 663.04	

Table 68: Compressed air system combined regression array (winter)

33.36076529	1.508059504	172.7850801
5.631813269	1 025.174306	
0.828765897	1 266.602695	
38.72355646	8	
62 118 570.4	12 834 526.32	

Table 69: Cooling system LINEST function array (summer)

44.503297	1.7982188	-768.44269
11.653092	1 820.8912	
0.7834075	1928.9678	
18.421584	5	
67 535 775	18 671 944	

Table 70: Cooling system LINEST function array (winter)

27.44549	1.420009	-464.441
10.46968	1 878.551	
0.656698	2035.498	
10.00744	5	
39 924 759	20 871 432	

Table 71: Dewatering system LINEST function array

23.32337	0.90994	49.3806	-1140.91
8.59616	739.442		
0.862566	805.398		
113.0953	6		
29 065 708	4 631 073		

Table 72: Ventilation system LINEST function array (summer)

26.12035	1.054142	-847.939
4.8408	853.4 852	
0.732733	1 064.218	
25.84109	9	
28 182 973	10 279 845	

Table 73: Ventilation system LINEST function array (winter)

22.81977	1.15221	-811.198
4.232272	807.209	
0.767514	1 037.95	
29.87018	9	
32 042 385	9 705 904	

Table 74: Hoisting system LINEST function array

7.32906	0.32036	-109.865
1.4 0642	304.713	
0.7749	311.53	
22.8013	6	
2 043 343	593 587	

Appendix B – Benchmark score variable ranges

Compressed air system

Table 75: Compressed air system error percentage

	Summer	Winter
$\%_{error}$	21.93%	21.01%

Table 76: Compressed air system – variables for regression for categories (summer)

Underperformance (f1)		Normal performance (f2)		Overperformance (f3)	
$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$
0.00	0.00	78.07	90.00	121.93	110.00
78.07	90.00	121.93	110.00	200.00	200.00

Table 77: Compressed air system – variables for regression for categories (winter)

Underperformance (f1)		Normal performance (f2)		Overperformance (f3)	
$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$
0.00	0.00	78.99	90.00	121.01	110.00
78.99	90.00	121.01	110.00	200.00	200.00

Cooling system

Table 78: Cooling system error percentage

	Summer	Winter
$\%_{error}$	29.94%	40.57%

Table 79: Cooling system – variables for regression for categories (summer)

Underperformance (f1)		Normal performance (f2)		Overperformance (f3)	
$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$
0.00	0.00	70.06	90.00	129.94	110.00
70.06	90.00	129.94	110.00	200.00	200.00

Table 80: Cooling system – variables for regression for categories (winter)

Underperformance (f1)		Normal performance (f2)		Overperformance (f3)	
$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$
0.00	0.00	59.43	90.00	140.57	110.00
59.43	90.00	140.57	110.00	200.00	200.00

Dewatering system

Table 81: Dewatering system error percentage

	Summer and Winter
$\%_{error}$	27.00%

Table 82: Dewatering system – variables for regression for categories

Underperformance (f1)		Normal performance (f2)		Overperformance (f3)	
$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$
0.00	0.00	73.00	90.00	127.00	110.00
73.00	90.00	127.00	110.00	200.00	200.00

Ventilation system

Table 83: Ventilation system error percentage

	Summer	Winter
$\%_{error}$	36.43%	32.9%

Table 84: Ventilation system – variables for regression for categories (summer)

Underperformance (f1)		Normal performance (f2)		Overperformance (f3)	
$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$
0.00	0.00	63.57	90.00	136.43	110.00
63.57	90.00	136.43	110.00	200.00	200.00

Table 85: Ventilation system – variables for regression for categories (winter)

Underperformance (f1)		Normal performance (f2)		Overperformance (f3)	
$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$
0.00	0.00	67.10	90.00	132.90	110.00
67.10	90.00	132.90	110.00	200.00	200.00

Hoisting system

Table 86: Hoisting system error percentage

	Summer and Winter
$\%_{error}$	30.14%

Table 87: Hoisting system – variables for regression for categories

Underperformance (f1)		Normal performance (f2)		Overperformance (f3)	
$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$	$\%_{initial}$	$\%_{corrected}$
0.00	0.00	69.86	90.00	130.14	110.00
69.86	90.00	130.14	110.00	200.00	200.00

Appendix C – Benchmark score variable functions

Compressed air system

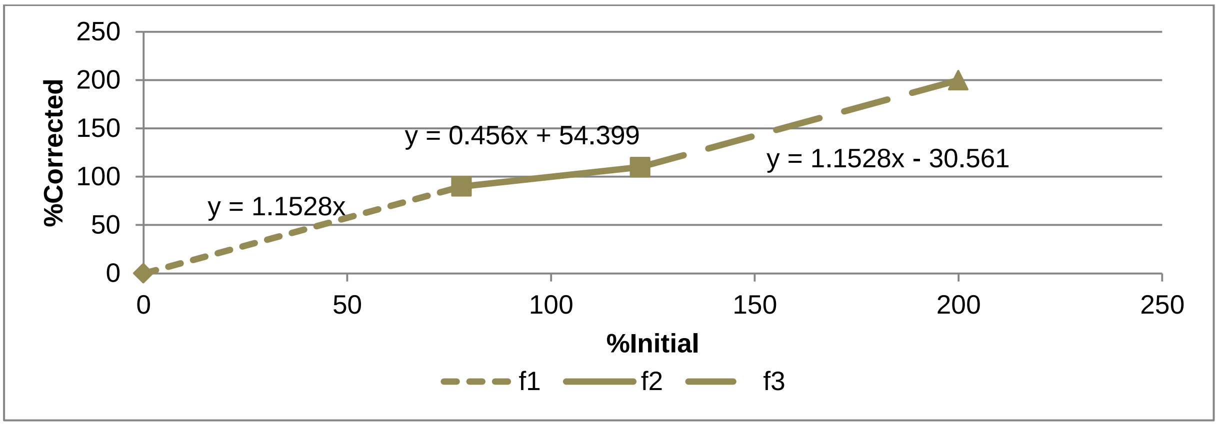


Figure 86: Compressed air system – corrected versus initial percentage (summer)

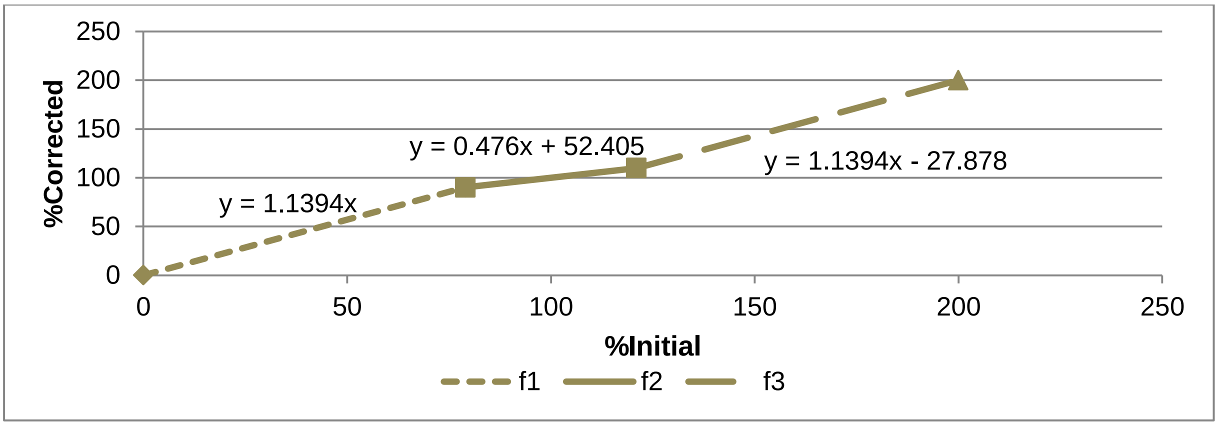


Figure 87: Compressed air system – corrected versus initial percentage (winter)

Cooling system

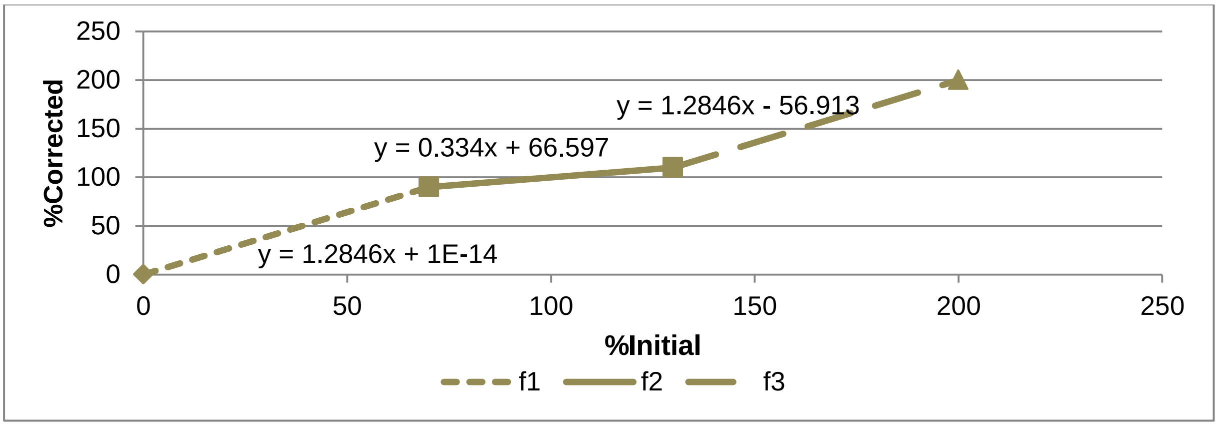


Figure 88: Cooling system – corrected versus initial percentage (summer)

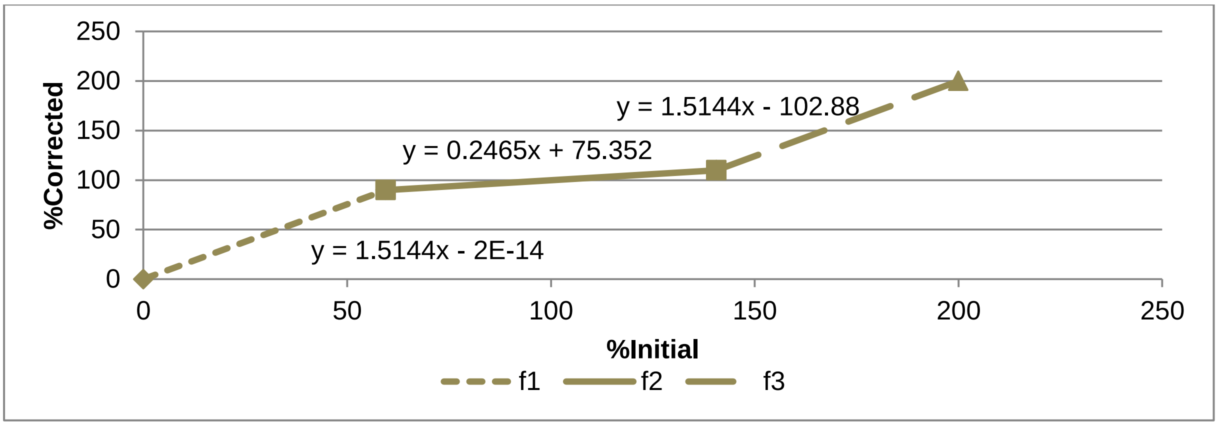


Figure 89: Cooling system – corrected versus initial percentage (winter)

Dewatering system

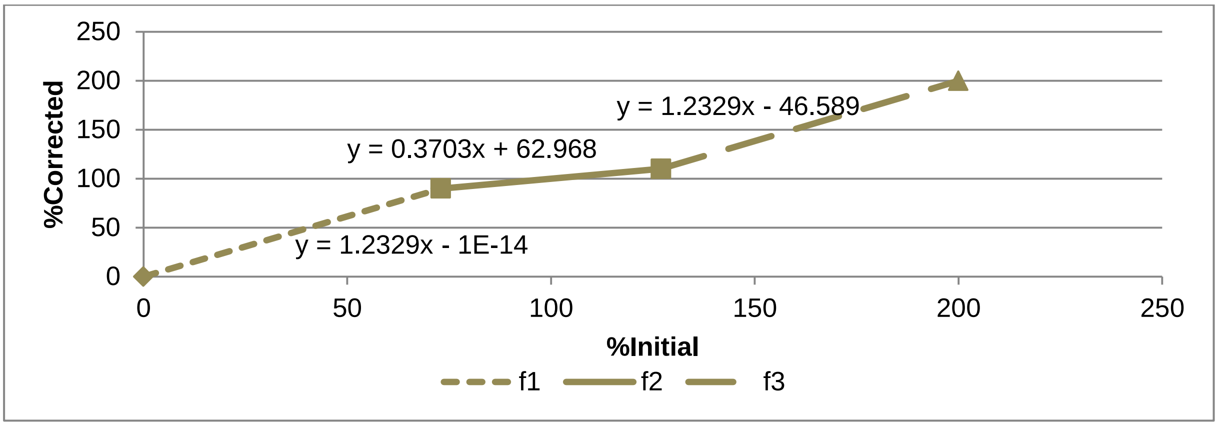


Figure 90: Dewatering system – corrected versus initial percentage

Ventilation system

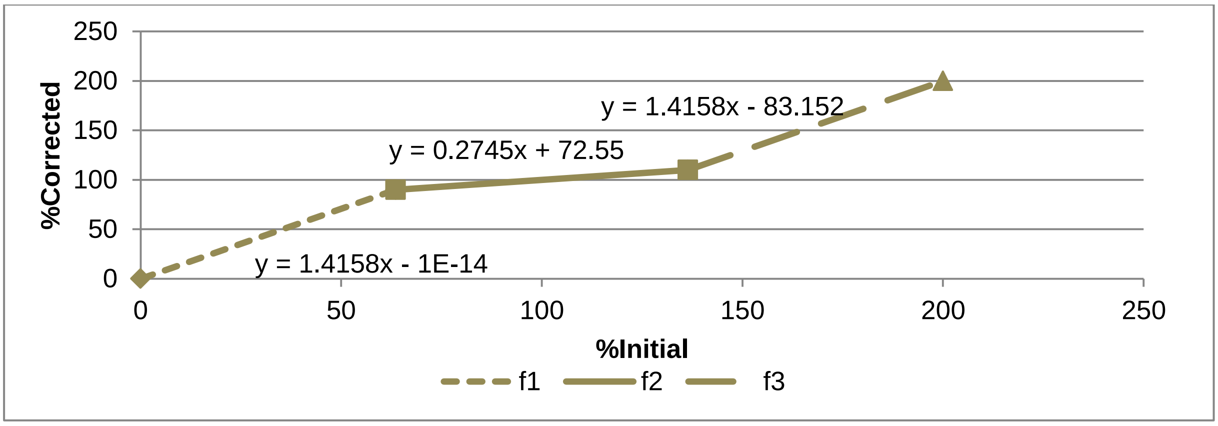


Figure 91: Ventilation system – corrected versus initial percentage (summer)

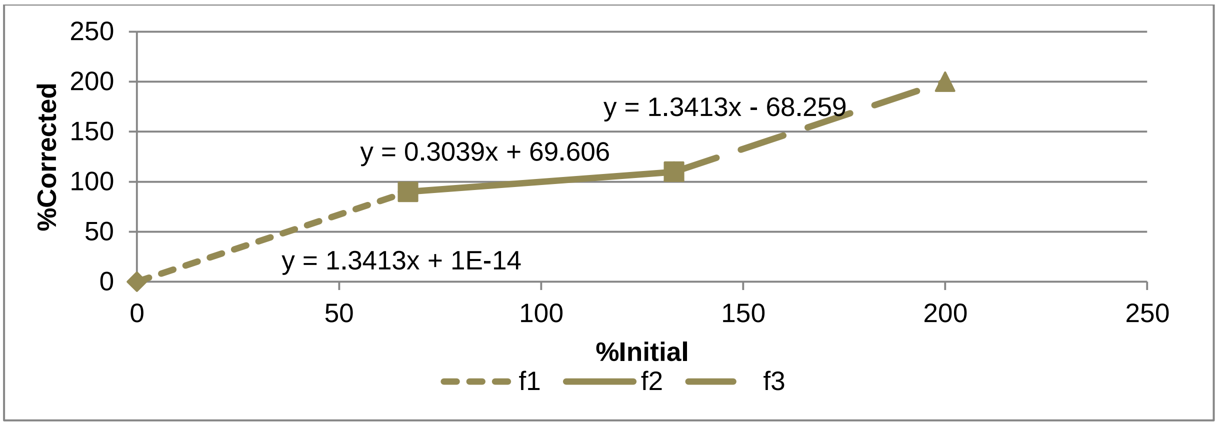


Figure 92: Ventilation system – corrected versus initial percentage (winter)

Hoisting system

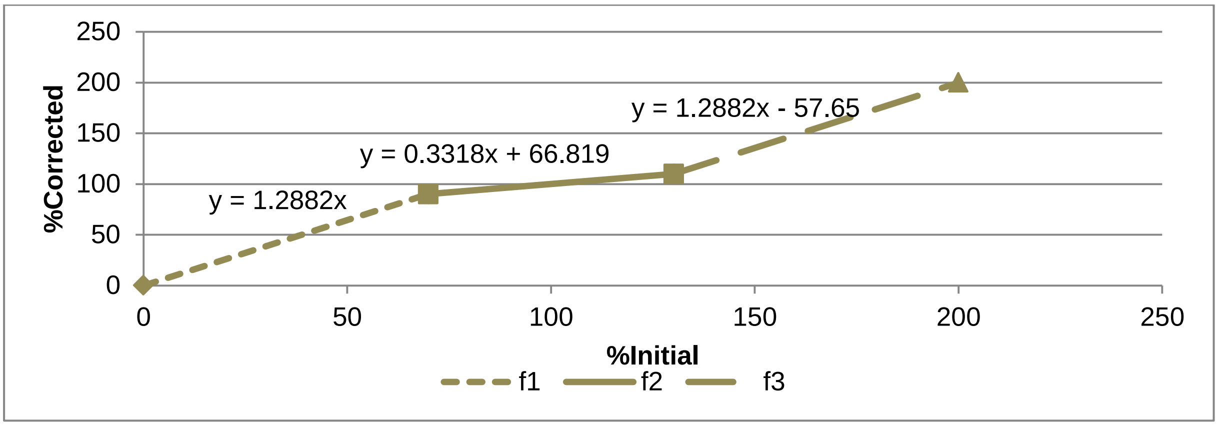


Figure 93: Hoisting system – corrected versus initial percentage

Appendix D – Best practice benchmark functions

Compressed air system – COLS

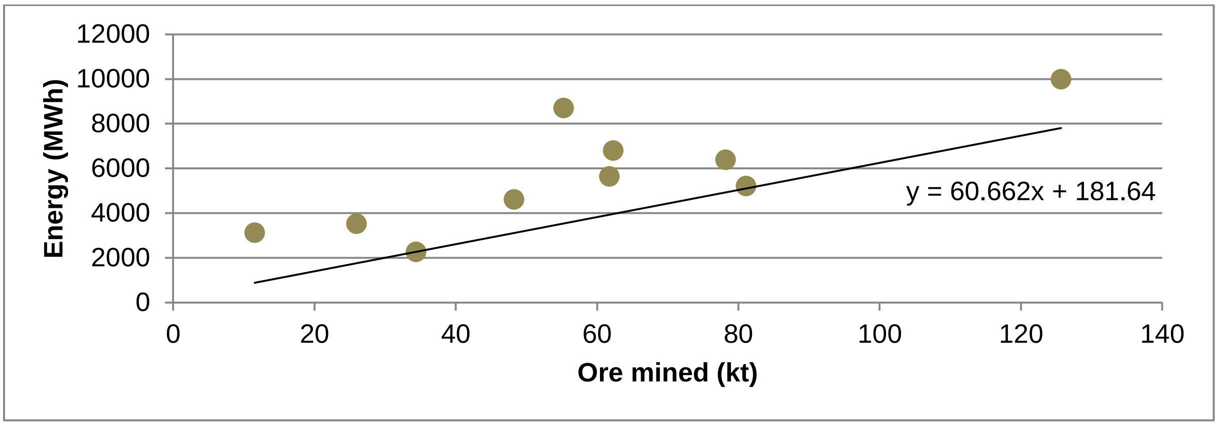


Figure 94: Compressed air system – MWh versus kt – COLS best practice (summer)

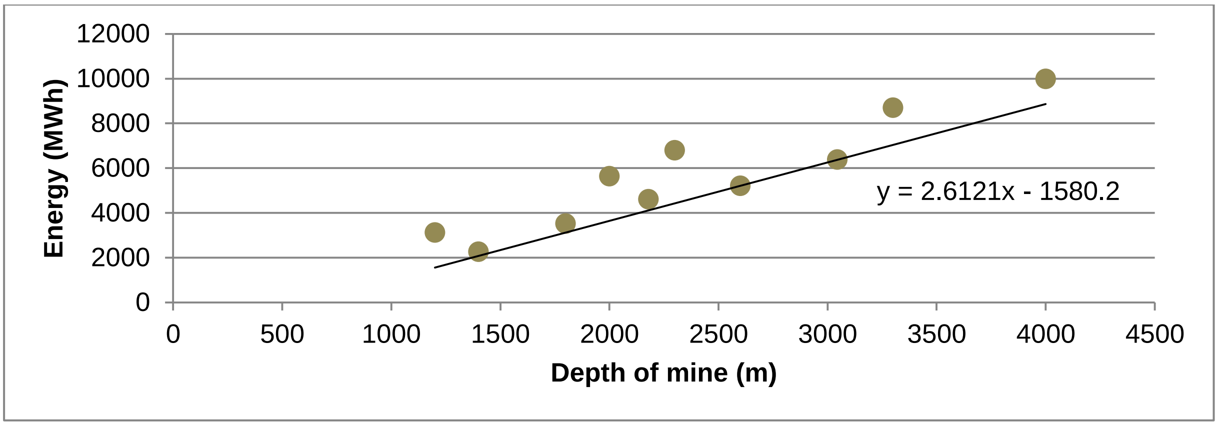


Figure 95: Compressed air system – MWh versus mine depth – COLS best practice (summer)

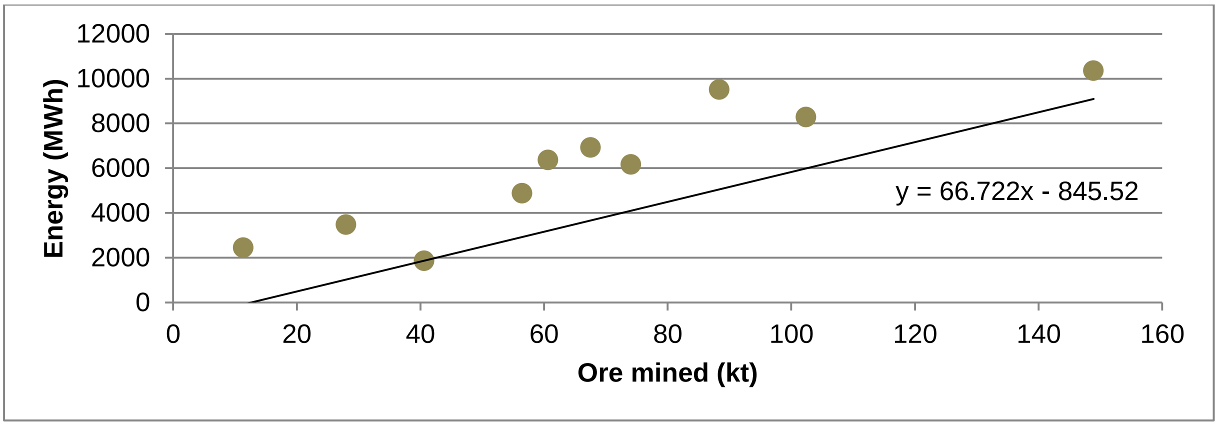


Figure 96: Compressed air system – MWh versus kt – COLS best practice (winter)

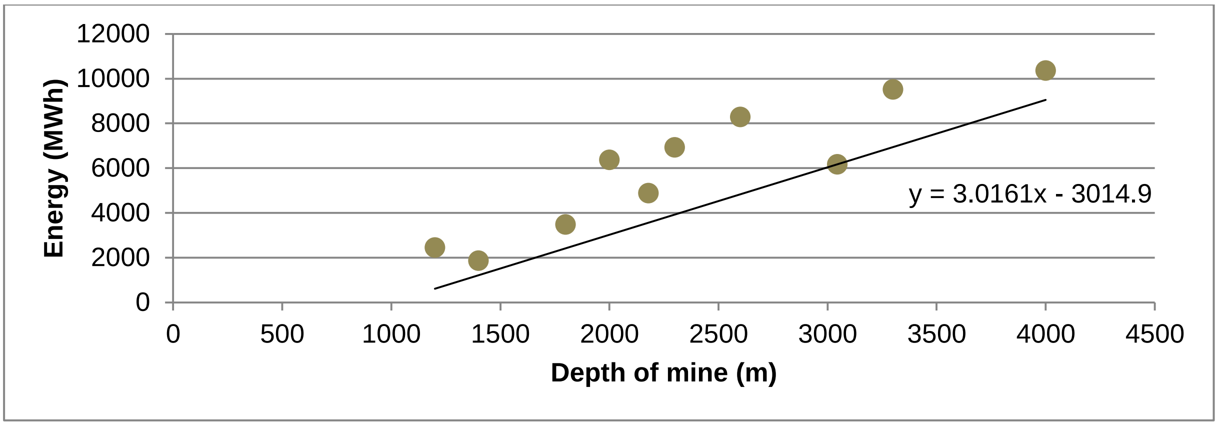


Figure 97: Compressed air system – MWh versus mine depth – COLS best practice (winter)

Cooling system – COLS

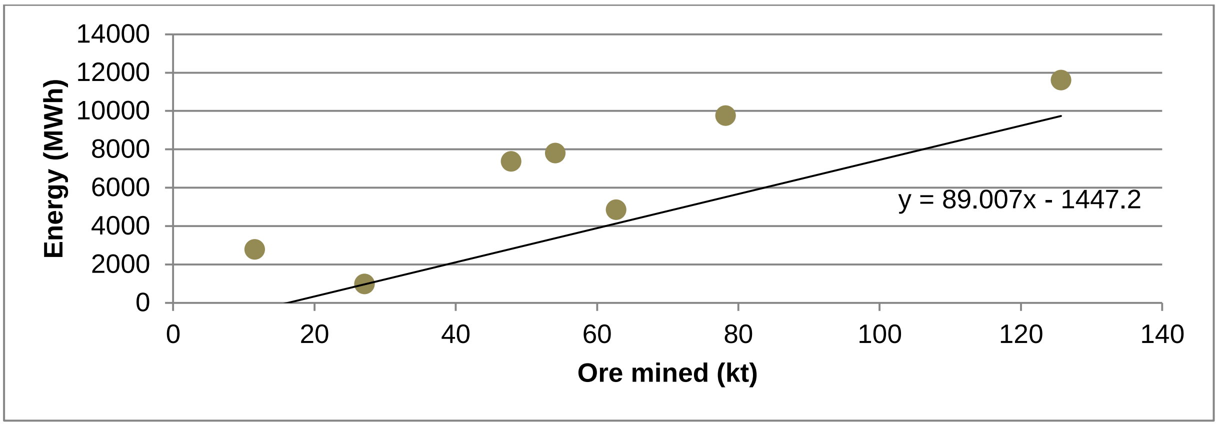


Figure 98: Cooling system – MWh versus kt – COLS best practice (summer)

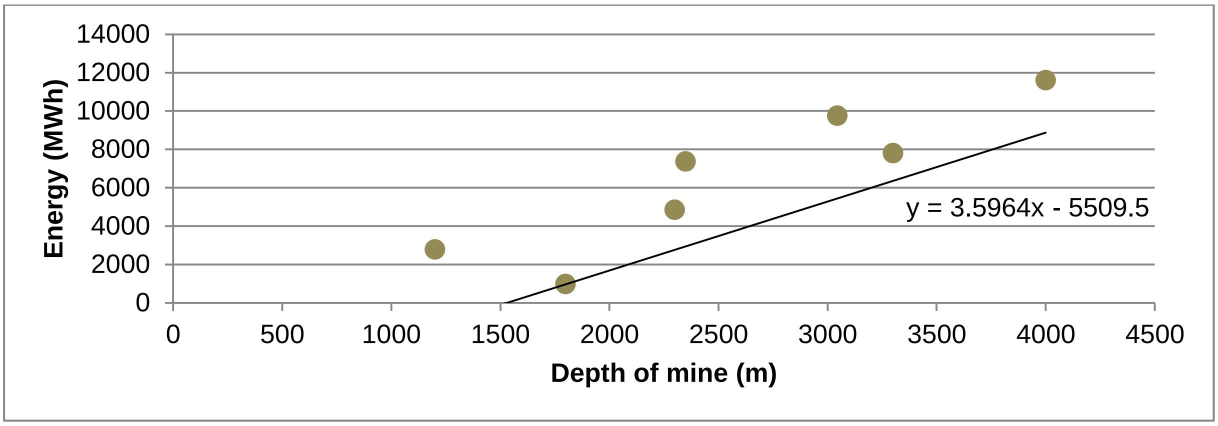


Figure 99: Cooling system – MWh versus mine depth – COLS best practice (summer)

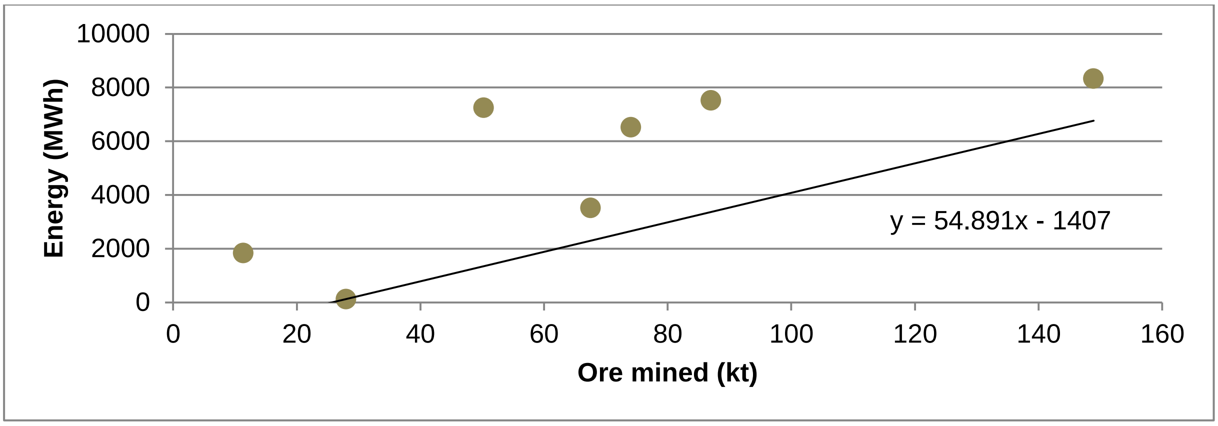


Figure 100: Cooling system – MWh versus kt – COLS best practice (winter)

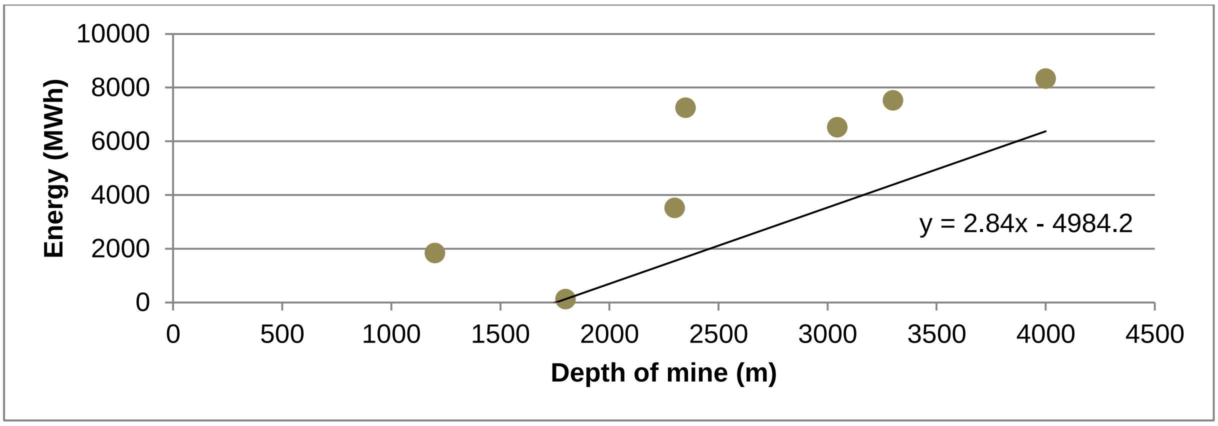


Figure 101: Cooling system – MWh versus mine depth – COLS best practice (winter)

Dewatering system – COLS

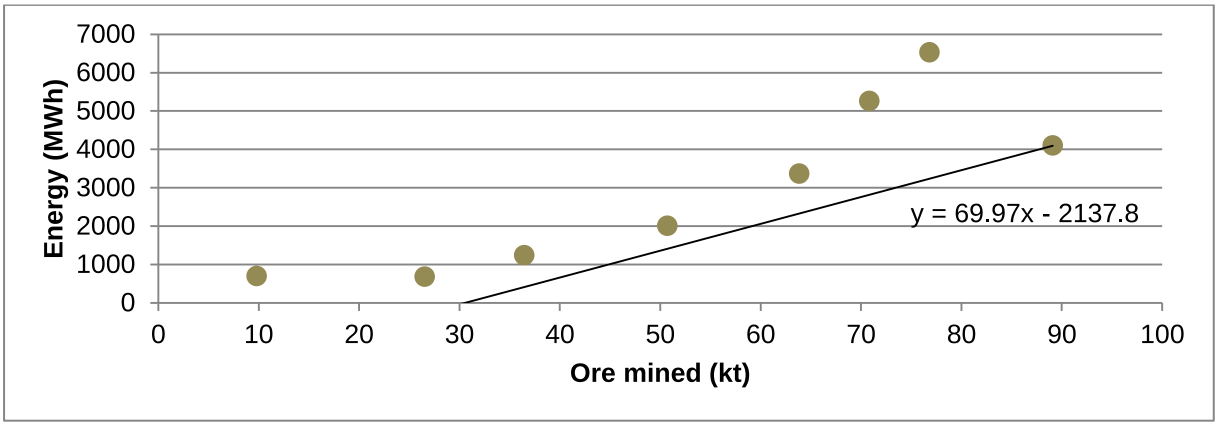


Figure 102: Dewatering system – MWh versus kt – COLS best practice

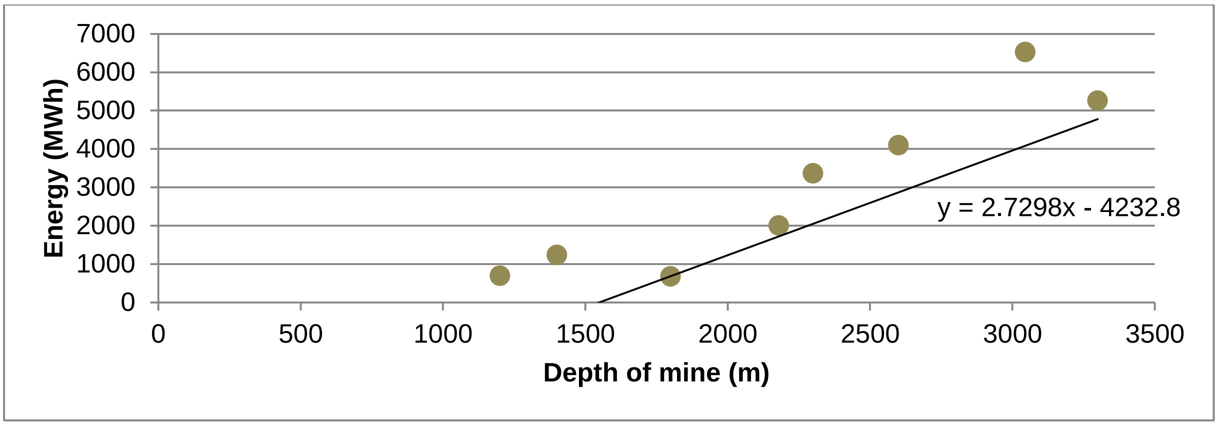


Figure 103: Dewatering system – MWh versus mine depth – COLS best practice

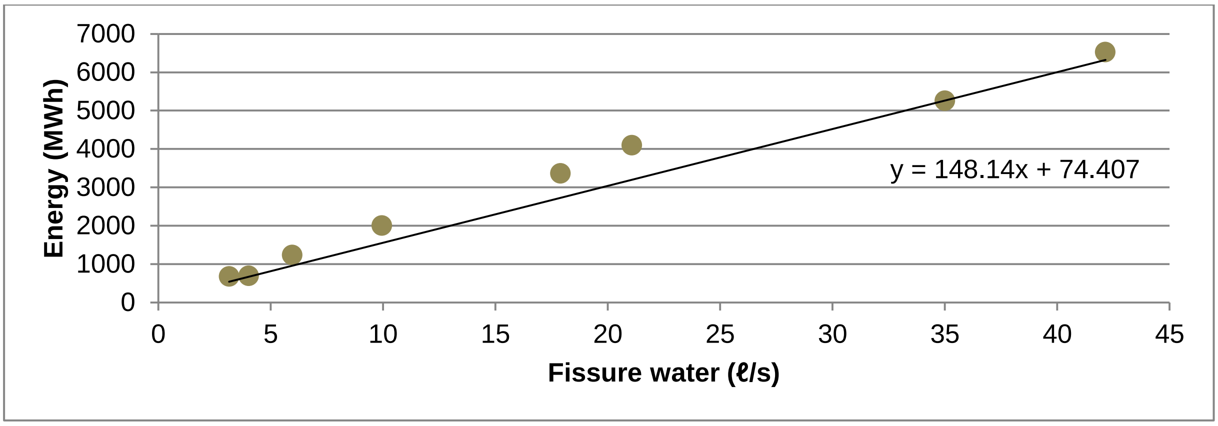


Figure 104: Dewatering system – MWh versus fissure water – COLS best practice

Ventilation system – COLS

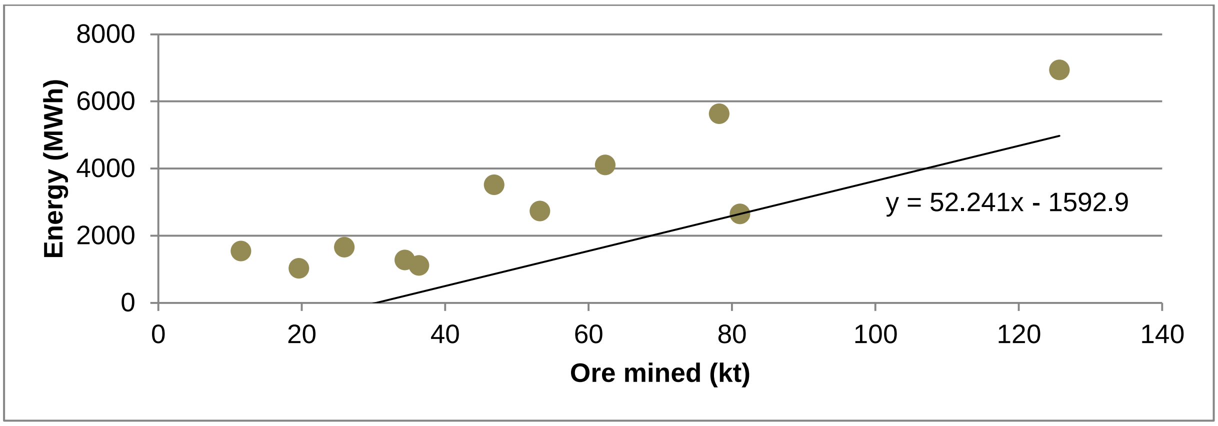


Figure 105: Ventilation system – MWh versus kt – COLS best practice (summer)

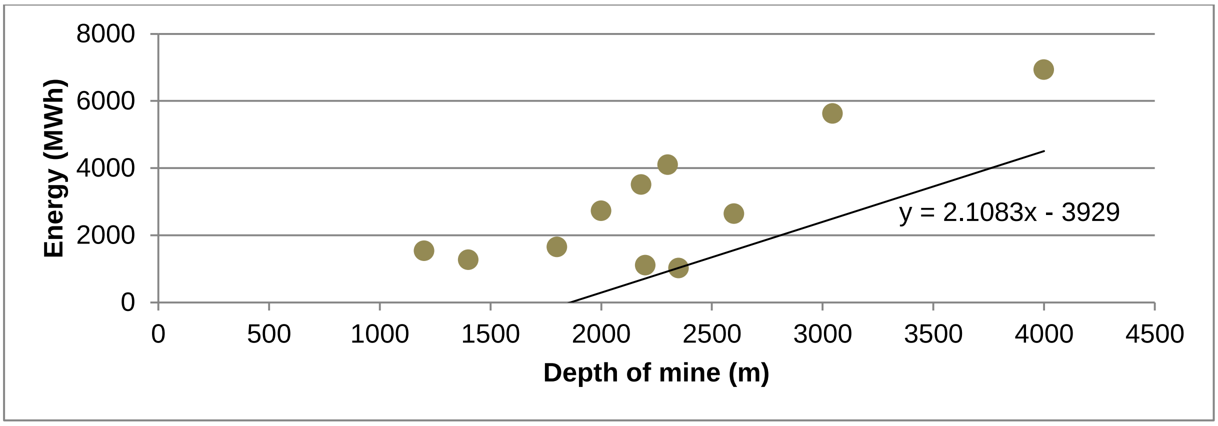


Figure 106: Ventilation system – MWh versus mine depth – COLS best practice (summer)

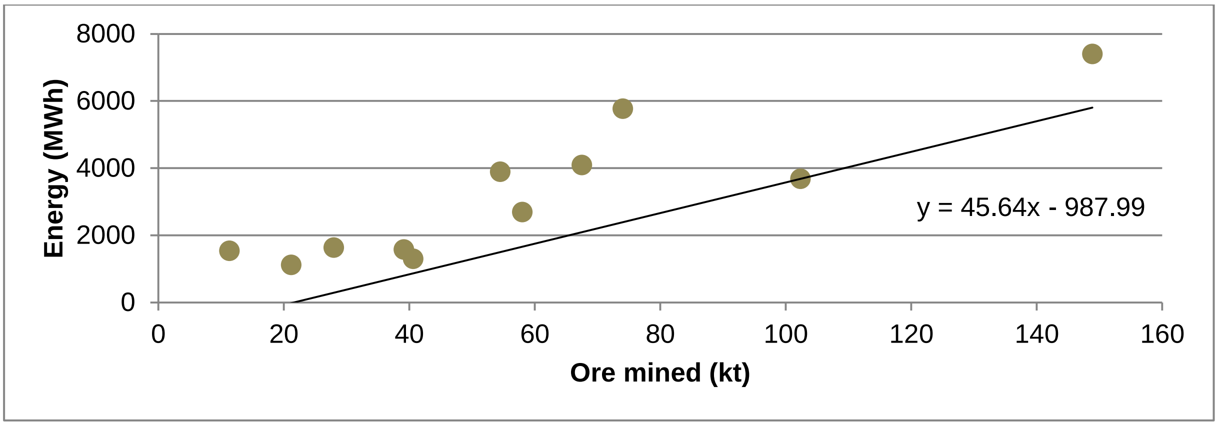


Figure 107: Ventilation system – MWh versus kt – COLS best practice (winter)

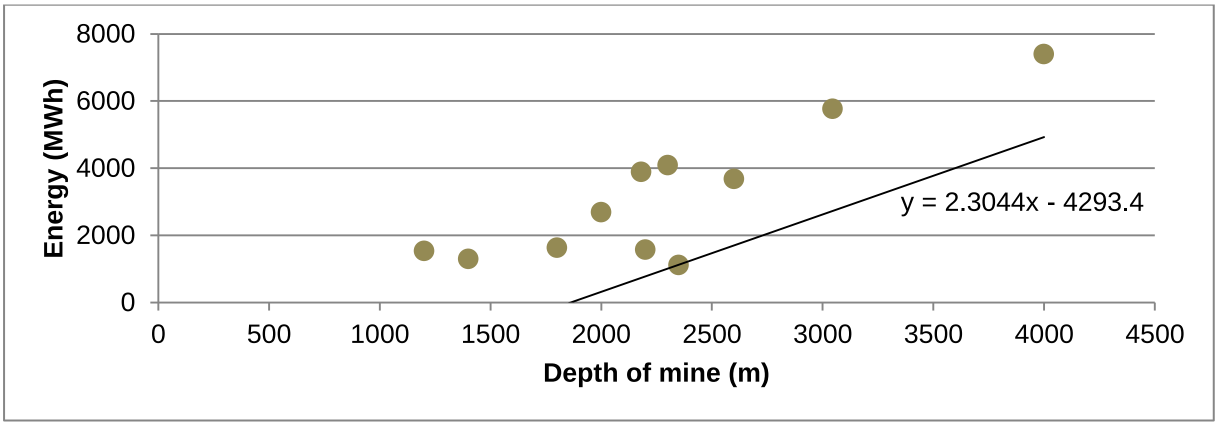


Figure 108: Ventilation system – MWh versus mine depth – COLS best practice (winter)

Hoisting system – COLS

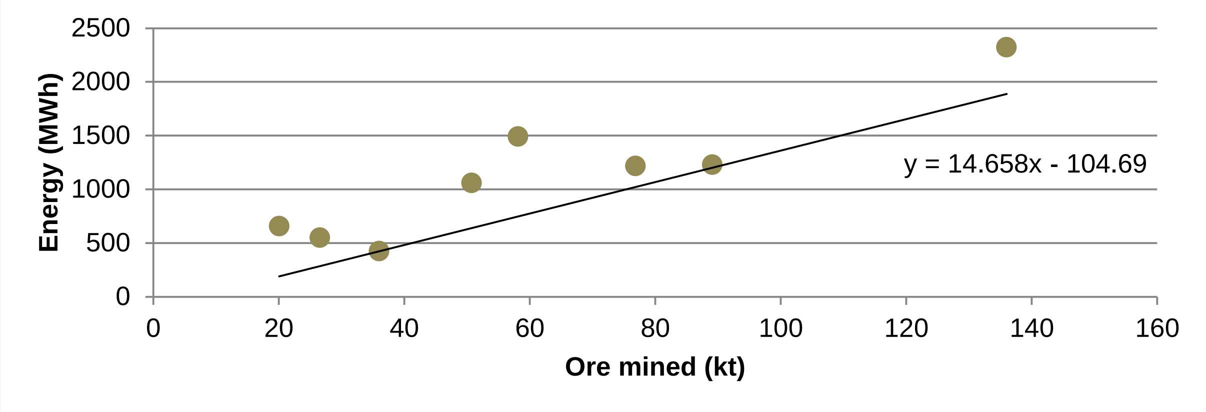


Figure 109: Hoisting system – MWh versus kt – COLS best practice

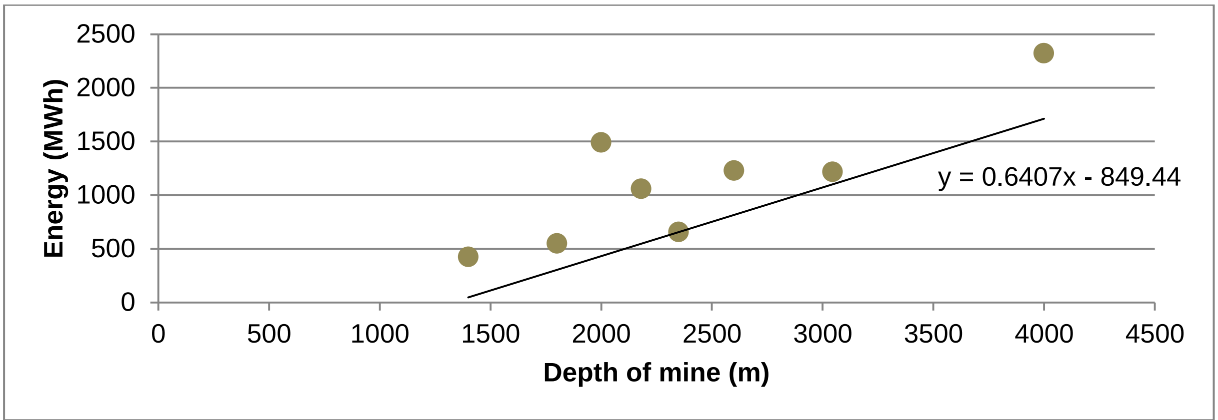


Figure 110: Hoisting system – MWh versus mine depth – COLS best practice

Compressed air system – SFA

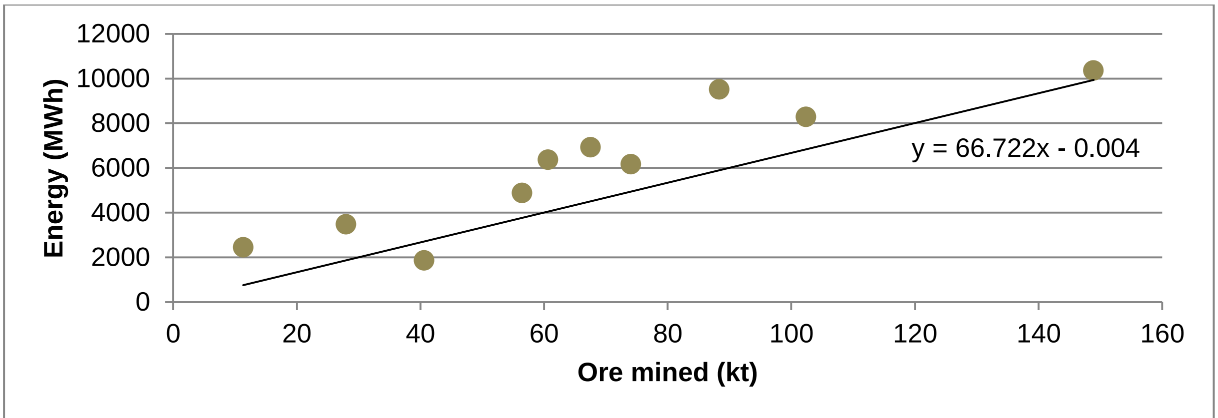


Figure 111: Compressed air system – MWh versus kt – SFA best practice (winter)

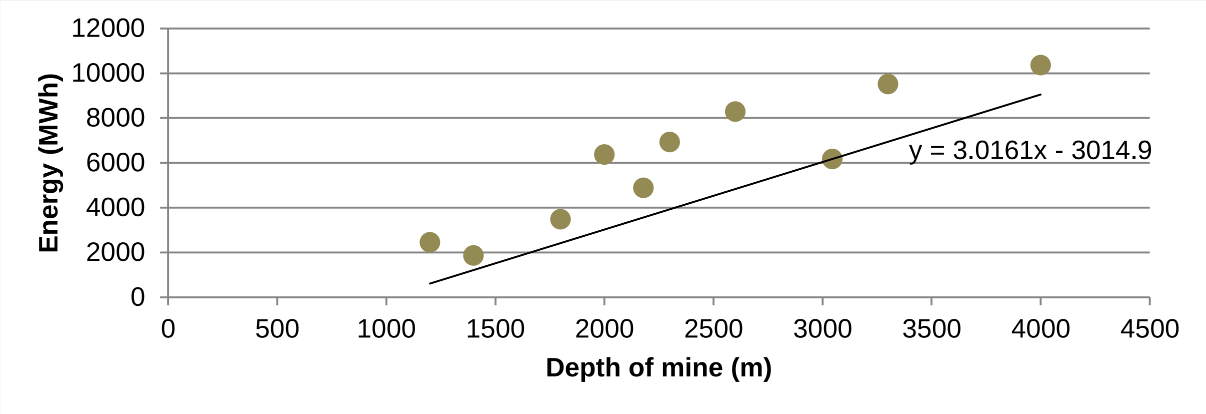


Figure 112: Compressed air system – MWh versus mine depth – SFA best practice (winter)

Cooling system – SFA

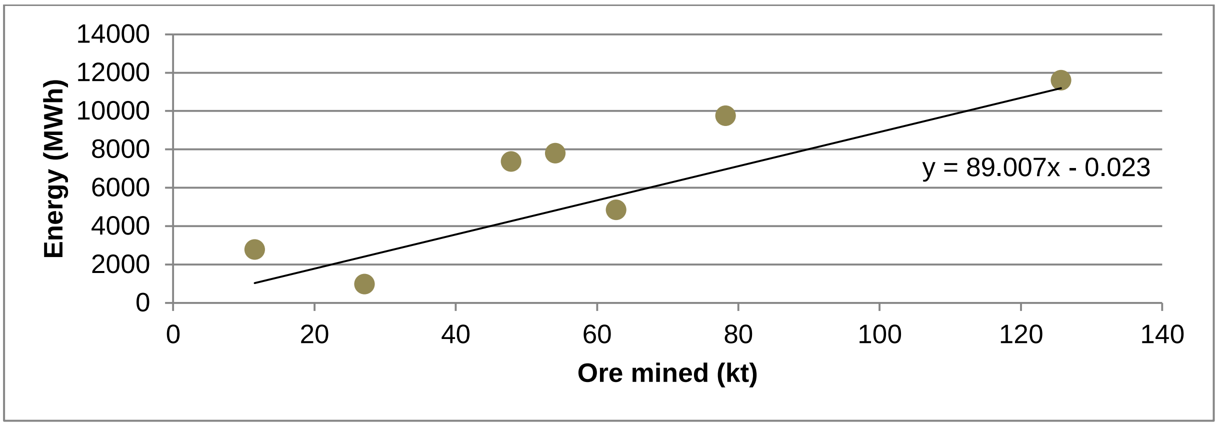


Figure 113: Cooling system – MWh versus kt – SFA best practice (summer)

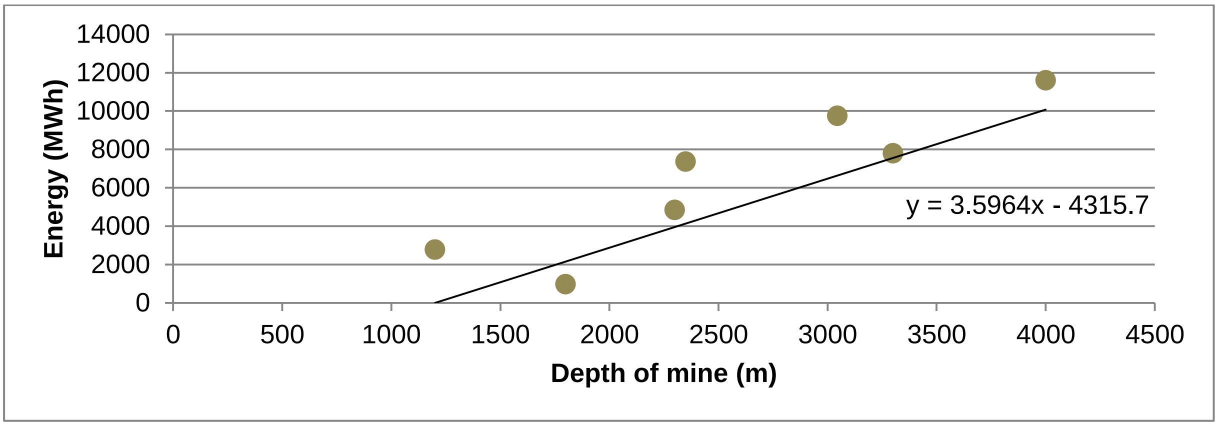


Figure 114: Cooling system – MWh versus mine depth – SFA best practice (summer)

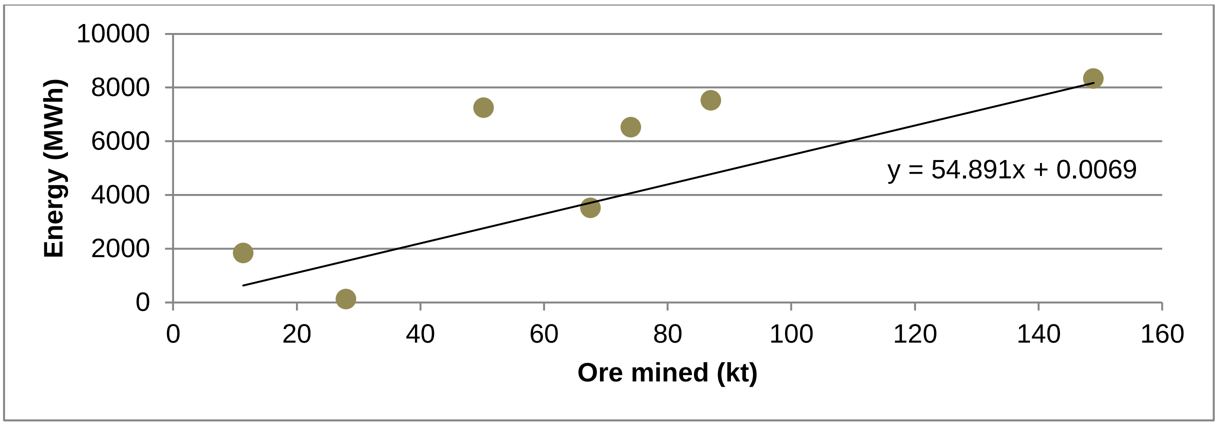


Figure 115: Cooling system – MWh versus kt – SFA best practice (winter)

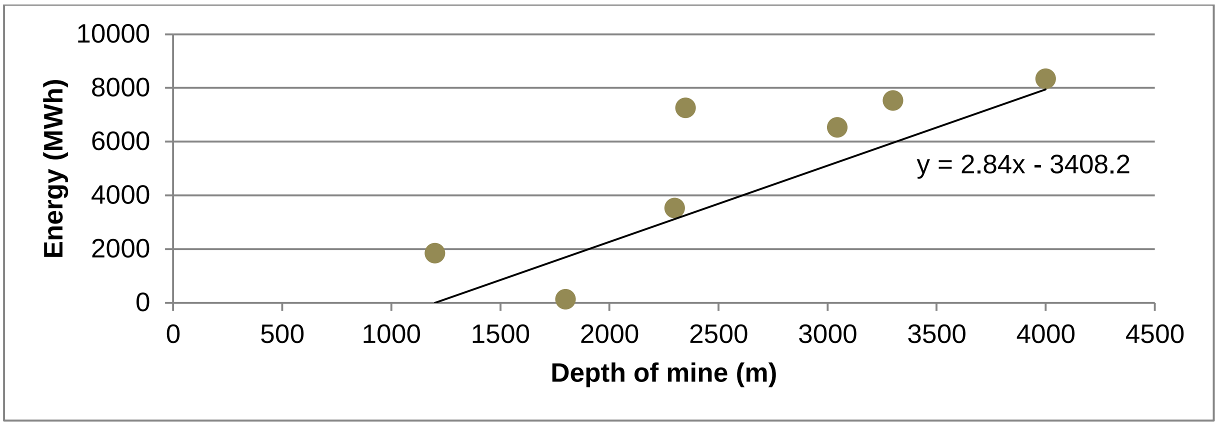


Figure 116: Cooling system – MWh versus mine depth – SFA best practice (winter)

Dewatering system – SFA

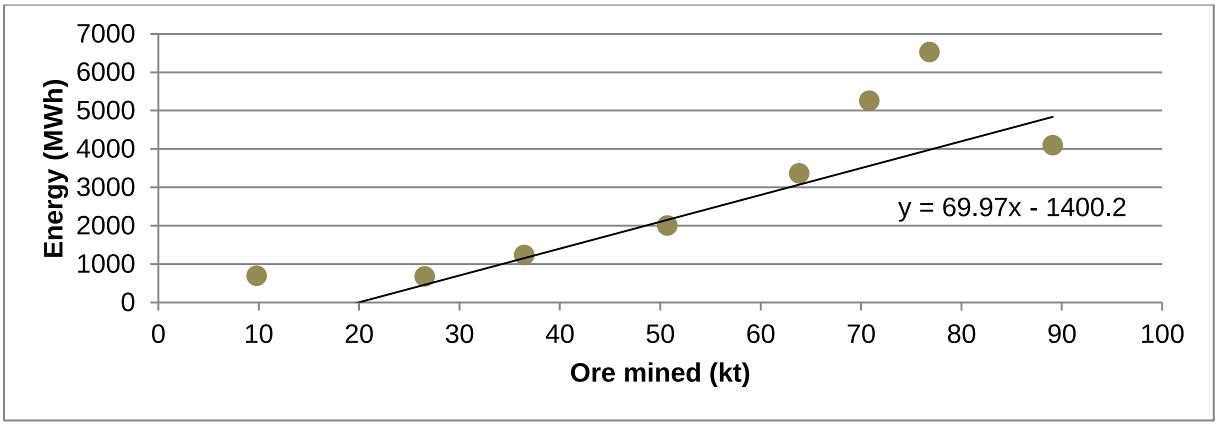


Figure 117: Dewatering system – MWh versus kt – SFA best practice

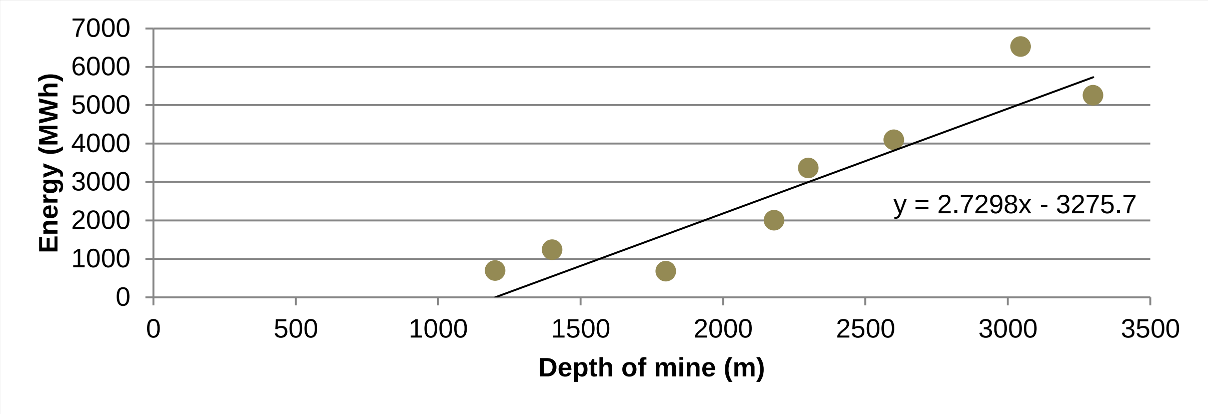


Figure 118: Dewatering system – MWh versus mine depth – SFA best practice

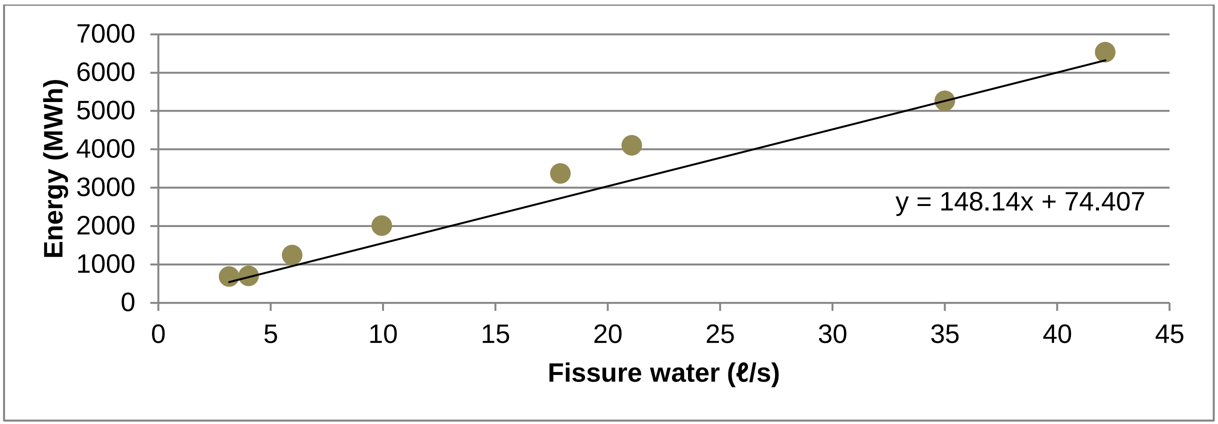


Figure 119: Dewatering system – MWh versus fissure water – SFA best practice

Ventilation system – SFA

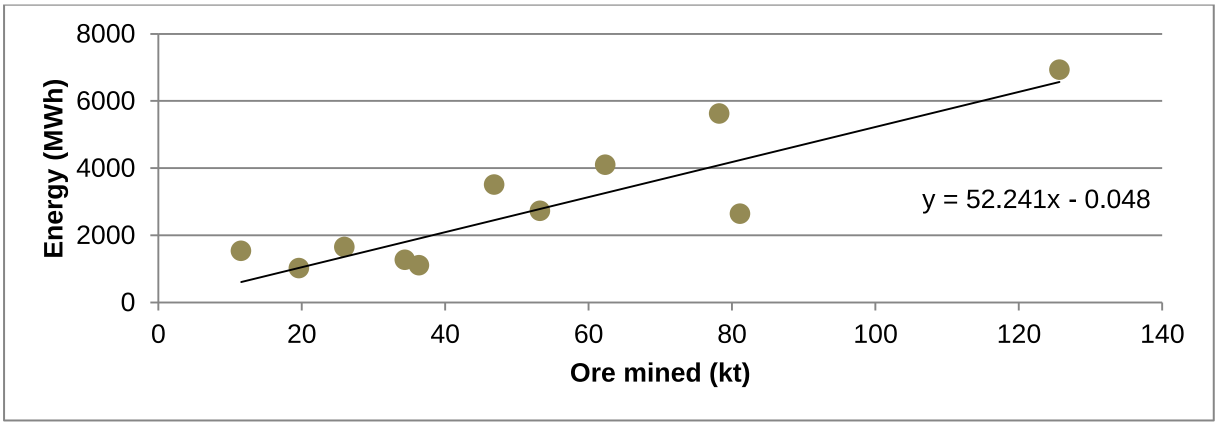


Figure 120: Ventilation system – MWh versus kt – SFA best practice (summer)

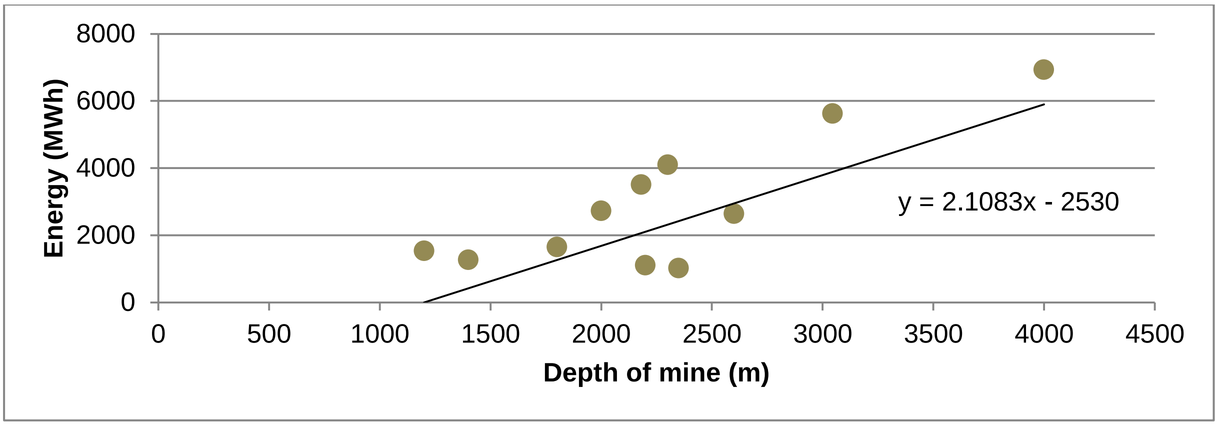


Figure 121: Ventilation system – MWh versus mine depth – SFA best practice (summer)

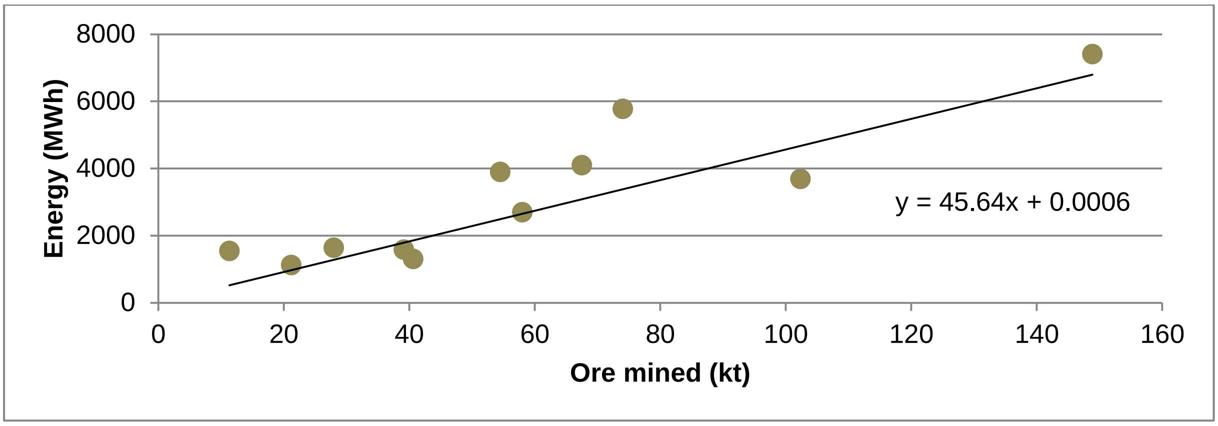


Figure 122: Ventilation system – MWh versus kt – SFA best practice (winter)

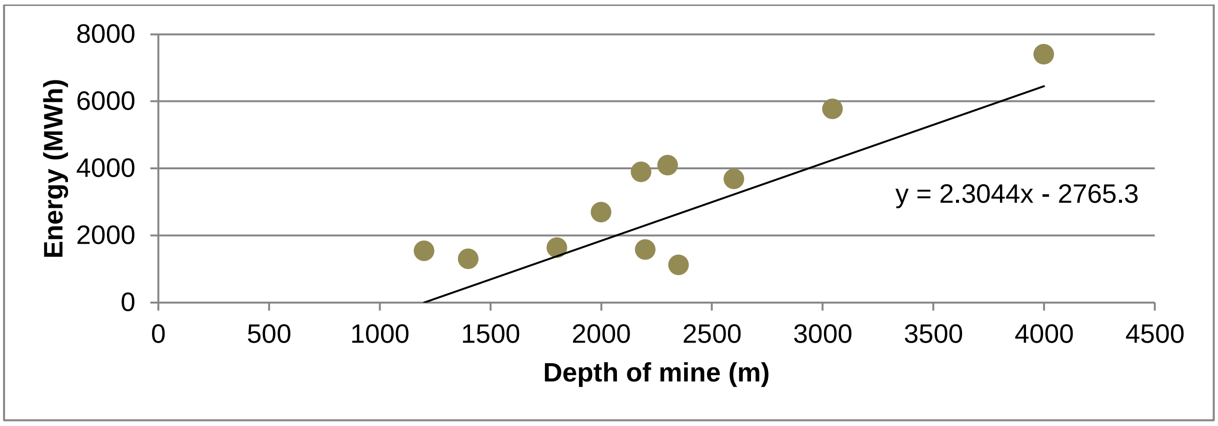


Figure 123: Ventilation system – MWh versus mine depth – SFA best practice (winter)

Hoisting system – SFA

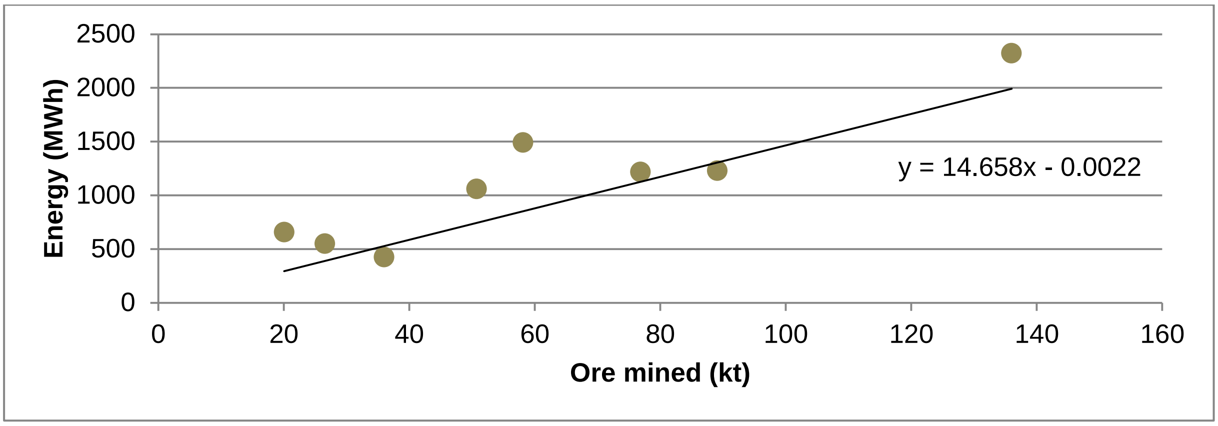


Figure 124: Hoisting system – MWh versus kt – SFA best practice

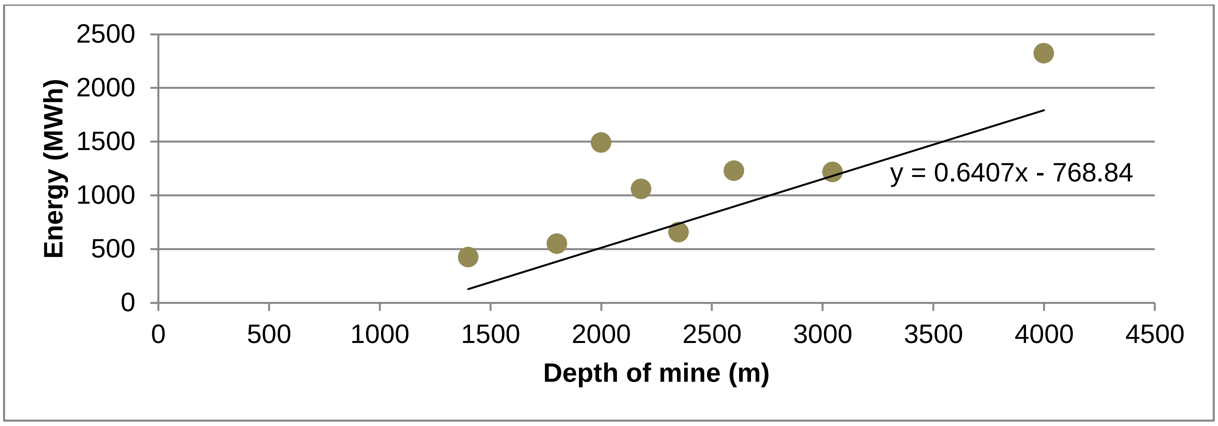


Figure 125: Hoisting system – MWh versus mine depth – SFA best practice

Appendix E – Simulation data and verification results

Compressed air system – Simulation

Table 88: Compressed air system – simulation inputs (summer)

Mine	Depth	kt	T_in K	p1	P2_surface	p2_UG	Airflow (kg/s)
B	2 600	81	292.55	86.67	584	620	0.539
C	3 045	78	292.55	86.67	579	620	0.520
D	4 000	126	291.75	84.45	567	620	0.835
E	1 200	12	292.05	86.04	603	620	0.077
F	2 000	62	291.75	84.45	592	620	0.410
G	1 400	34	292.05	86.04	600	620	0.228
H	3 300	55	291.75	84.45	575	620	0.367
I	2 180	48	292.05	86.04	590	620	0.321
L	2 300	62	292.05	86.04	588	620	0.414
M	1 800	26	292.05	86.04	595	620	0.172

Table 89: Compressed air system – simulation inputs (winter)

Mine	Depth	kt	T_in K	p1	P2_surface	p2_UG	Airflow (kg/s)
B	2 600	102	284.65	86.29	583	620	0.680
C	3 045	74	284.65	86.29	578	620	0.492
D	4 000	149	284.15	84.03	566	620	0.989
E	1 200	11	283.15	85.59	602	620	0.075
F	2 000	61	284.15	84.03	591	620	0.403
G	1 400	41	283.15	85.59	599	620	0.270
H	3 300	88	284.15	84.03	574	620	0.587
I	2 180	56	283.15	85.59	589	620	0.375
L	2 300	68	283.15	85.59	587	620	0.449
M	1 800	28	283.15	85.59	594	620	0.186

Table 90: Compressed air system – simulation results (summer)

Mine	kt	$\%_{corrected}$	MWh for tonnes	Surplus MWh	Surplus MWh/kt
B	81	116	451	4 760	59
C	78	105	446	5 941	76
D	126	99	750	9 231	73
E	12	93	70	3 052	264
F	62	97	391	5 242	85
G	34	153	211	2 058	60
H	55	89	334	8 366	151
I	48	104	283	4 321	90
L	62	92	379	6 416	103
M	26	105	166	3 354	129

Table 91: Compressed air system – simulation results (winter)

Mine	kt	$\%_{corrected}$	MWh for tonnes	Surplus MWh	Surplus MWh/kt
B	102	96	589	7 696	75
C	74	108	426	5 743	78
D	149	104	843	9 514	64
E	11	98	70	2 375	209
F	61	91	385	5 979	99
G	41	195	246	1 618	40
H	88	93	508	9 012	102
I	56	105	337	4 543	80
L	68	93	393	6 527	97
M	28	105	170	3 309	118

Table 92: Compressed air system – best practice results

Mine	$\%_{corrected}$ (summer)	$\%_{corrected}$ (winter)
B	100	80.2
C	95	95.3
D	92	96.0
E	45	31.7
F	85	63.2
G	98	102.4
H	70	76.8
I	90	85.5
L	71	69.4
M	80	70.1

Cooling system – Simulation

Table 93: Cooling system – simulation inputs (summer)

Mine	Depth	kt	ℓ/s for tonnes	Water temp in	Water temp out
C	3 045	78	5.49	15	2
D	4 000	126	8.82	15	2
E	1 200	12	0.81	15	2
H	3 300	54	3.80	15	2
J	2 350	48	3.36	15	2
L	2 300	63	4.40	15	2
M	1 800	27	1.90	15	2

Table 94: Cooling system – simulation inputs (winter)

Mine	Depth	kt	ℓ/s for tonnes	Water temp in	Water temp out
C	3 045	74	5.20	10	2
D	4 000	149	10.45	10	2
E	1 200	11	0.80	10	2
H	3 300	87	6.11	10	2
J	2 350	50	3.53	10	2
L	2 300	68	4.74	10	2
M	1 800	28	1.96	10	2

Table 95: Cooling system – simulation results (summer)

Mine	kt	$\%_{corrected}$	Litre water	MWh for tonnes	Surplus MWh	Surplus MWh/kt
C	78	95	14 473 151	1 245	8 503	109
D	126	101	23 251 133	2025	9 579	76
E	12	88	2 138 000	162	2 618	227
H	54	99	10 013 673	797	6 996	129
J	48	92	8 853 385	671	6 692	140
L	63	109	11 598 895	1 055	3 794	61
M	27	433	5 011 809	380	584	22

Table 96: Cooling system – simulation results (winter)

Mine	kt	$\%_{corrected}$	Litre water	MWh for tonnes	Surplus MWh	Surplus MWh/kt
C	74	98	13 698 603	1 178	5 339	72
D	149	103	27 545 853	2 400	5 935	40
E	11	96	2 099 129	159	1 679	148
H	87	97	16 100 779	1 282	6 245	72
J	50	67	9 290 237	705	6 548	130
L	68	108	12 495 017	1 137	2 386	35
M	28	2 472	5 172 902	392	0	0

Table 97: Cooling system – best practice results

Mine	$\%_{corrected}$ (summer)	$\%_{corrected}$ (winter)
C	89.6	92.9
D	97.2	99.2
E	23.8	25.7
H	93.1	92.9
J	73.2	62.9
L	99.4	99.2
M	247.5	1 815.3

Dewatering system – Simulation

Table 98: Dewatering system – simulation inputs

Mine	ℓ/s for tonnes	ℓ/s for fissure	Depth
B	6.26	21.1	2 600.0
C	5.39	42.1	3 045.0
E	0.69	4.0	1 200.0
G	2.56	6.0	1 400.0
H	4.97	35.0	3 300.0
I	3.56	10.0	2 180.0
L	4.48	17.9	2 300.0
M	1.86	3.2	1 800.0

Table 99: Dewatering system – simulation results

Mine	kt	Fissure	$\%_{corrected}$	Litre water	MWh for tonnes	MWh for fissure	Surplus MWh	Surplus MWh/kt
B	89	21	102	16 484 888	170	645	3 282	37
C	77	42	94	14 214 968	167	1 530	4 831	63
E	10	4	68	1 813 709	8	56	626	64
G	36	6	101	6 745 763	42	98	1 096	30
H	71	35	100	13 104 217	191	1 360	3 708	52
I	51	10	109	9 382 410	91	255	1 660	33
L	64	18	100	11 814 810	122	486	2 755	43
M	27	3	184	4 913 102	39	63	579	22

Table 100: Dewatering system – best practice results

Mine	$\%_{corrected}$
B	98.7
C	92.0
E	0.0
G	88.3
H	97.1
I	102.2
L	95.3
M	110.8

Ventilation system – Calculations

Table 101: Ventilation system – equation inputs and results (summer)

Mine	kt	MWh	P_motor (kW)	P_shaft (kW)	P_fan (kW)	Q (m^3/s)	Total air (m^3)	m^3/kt	m^3/m
B	81	2 646	3 614	2 892	1 735	0.96	2 539 928	31 304	977
C	78	5 632	7 694	6 155	3 693	2.05	5 406 758	69 111	1 776
D	126	6 930	9 468	7 574	4 545	2.52	6 653 197	52 937	1 663
E	12	1 538	2 101	1 680	1 008	0.56	1 476 120	127 728	1 230
F	53	2 726	3 724	2 979	1 788	0.99	2 616 955	49 167	1 308
G	34	1 266	1 729	1 383	830	0.46	1 215 254	35 320	868
I	47	3 515	4 802	3 842	2 305	1.28	3 374 666	72 019	1 548
K	20	1 025	1 401	1 121	672	0.37	984 405	50 182	419
L	62	4 104	5 607	4 486	2 691	1.50	3 940 172	63 213	1 713
M	26	1 648	2 251	1 801	1 080	0.60	1 581 638	60 897	879
O	36	1 104	1 508	1 206	724	0.40	1 059 600	29 154	482

η_imp:	0.6
η_mot:	0.8

Table 102: Ventilation system – equation inputs and results (winter)

Mine	kt	MWh	P_motor (kW)	P_shaft (kW)	P_fan (kW)	Q (m^3/s)	Total air (m^3)	m^3/kt	m^3/m
B	102	3 685	5 034	4 027	2 416	1.34	3 537 640	34 551	1 361
C	74	5 767	7 878	6 302	3 781	2.10	5 535 878	74 762	1 818
D	149	7 402	10 111	8 089	4 853	2.70	7 105 444	47 721	1 776
E	11	1 539	2 103	1 682	1 009	0.56	1 477 682	130 231	1 231
F	58	2 689	3 674	2 939	1 763	0.98	2 581 501	44 488	1 291
G	41	1 301	1 778	1 422	853	0.47	1 249 434	30 762	892
I	55	3 890	5 314	4 251	2 551	1.42	3 734 074	68 490	1 713
K	21	1 122	1 533	1 226	736	0.41	1 077 092	50 867	458
L	68	4 094	5 594	4 475	2 685	1.49	3 930 686	58 197	1 709
M	28	1 637	2 236	1 789	1 073	0.60	1 571 259	56 193	873
O	39	1 577	2 154	1 723	1 034	0.57	1 513 790	38 665	688

η_imp:	0.6
η_mot:	0.8

Table 103: Ventilation system – best practice results

Mine	$\%_{corrected}$ (summer)	$\%_{corrected}$ (winter)
B	109.9	102.9
C	92.0	89.4
D	97.2	97.2
E	27.8	15.6
F	95.0	94.9
G	96.6	96.6
I	90.2	80.7
K	155.0	128.7
L	91.2	90.4
M	94.4	92.7
O	173.8	107.4

Hoisting system – Calculations

Table 104: Hoisting system – equation inputs and results

Mine	kt	Depth	MWh	Model MWh	$\%_{corrected}$	Theory MWh	MWh/t	MWh/m
B	89	2 600	1 229	1 376	104	903	13.79	0.47
C	77	3 045	1 215	1 429	106	912	15.82	0.40
D	136	4 000	2 323	2 168	98	2 119	17.08	0.58
F	58	2 000	1 492	957	83	453	25.66	0.75
G	36	1 400	423	602	126	196	11.75	0.30
I	51	2 180	1 057	960	97	431	20.84	0.48
K	20	2 350	656	790	107	184	32.71	0.28
M	27	1 800	550	661	107	186	20.69	0.31
η:	0.7							

Table 105: Hoisting system – best practice results

Mine	$\%_{corrected}$
B	96.6
C	98.3
D	93.9
F	58.9
G	92.5
I	83.6
K	92.9
M	90.2

Verification of energy efficiency initiative prioritisation

Table 106: Mine X_comp and Mine Y_comp pre- and post-implementation results

	Pre-implementation				Post-implementation			
Mine	MWh	kt	Average benchmark	$\%_{initial}$	MWh	kt	Average benchmark	$\%_{initial}$
Mine X_comp	8 213	42	6 314.4	77	8 671	71	7 205.58	83
Mine Y_comp	1 652	8	3 816.72	231	1 509	8	3 814.1	253

Table 107: Mine X_cool and Mine Y_cool pre- and post-implementation results

	Pre-implementation				Post-implementation			
Mine	MWh	kt	Average benchmark	$\%_{initial}$	MWh	kt	Average benchmark	$\%_{initial}$
Mine X_cool	7 097	143	12 788	180	5 428	99	10 830	200
Mine Y_cool	11 530	75	8 485	74	9 882	86	8 974	91

Table 108: Mine X_pump pre- and post-implementation results

	Pre-implementation				Post-implementation			
Mine	MWh	kt	Average benchmark	$\%_{initial}$	MWh	kt	Average benchmark	$\%_{initial}$
Mine X_pump	1 526	25	3 029	199	1 123	32	3 204	285

Verification of energy budget forecasting

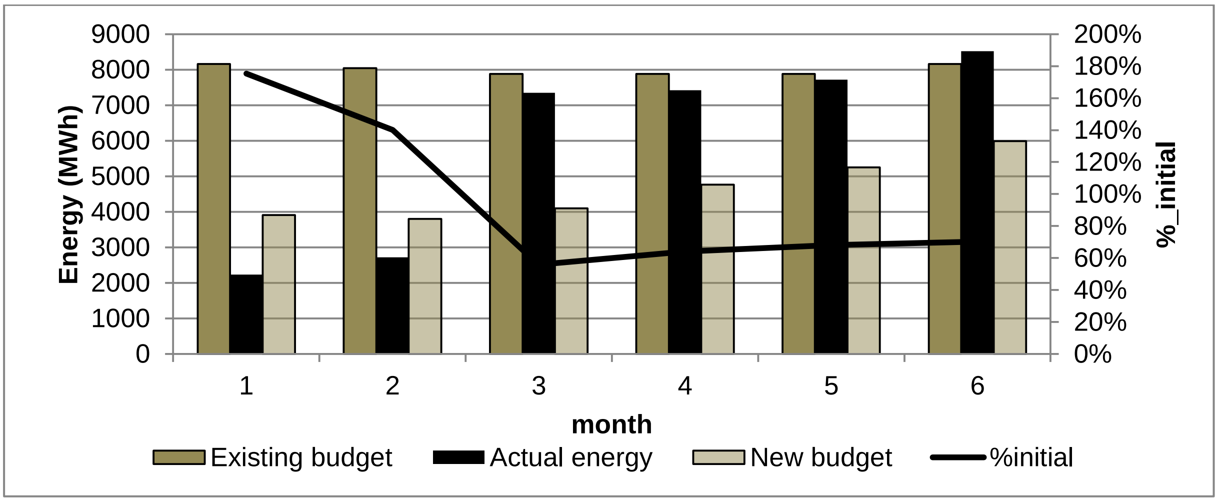


Figure 126: Verification of new budget forecast (dewatering system)

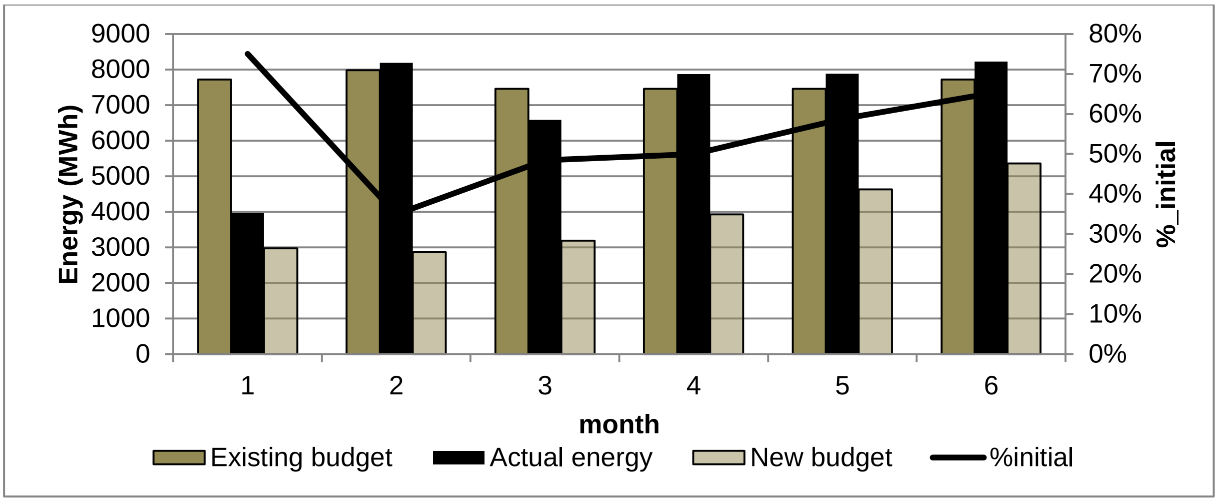


Figure 127: Verification of new budget forecast (ventilation system)

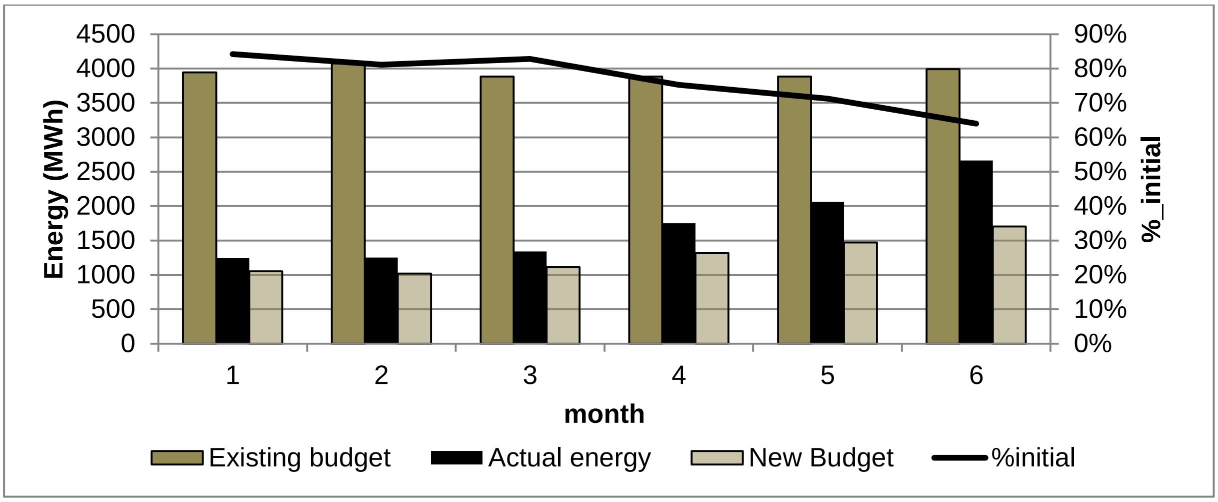


Figure 128: Verification of new budget forecast (hoisting system)

Appendix F – Simulation screenshots

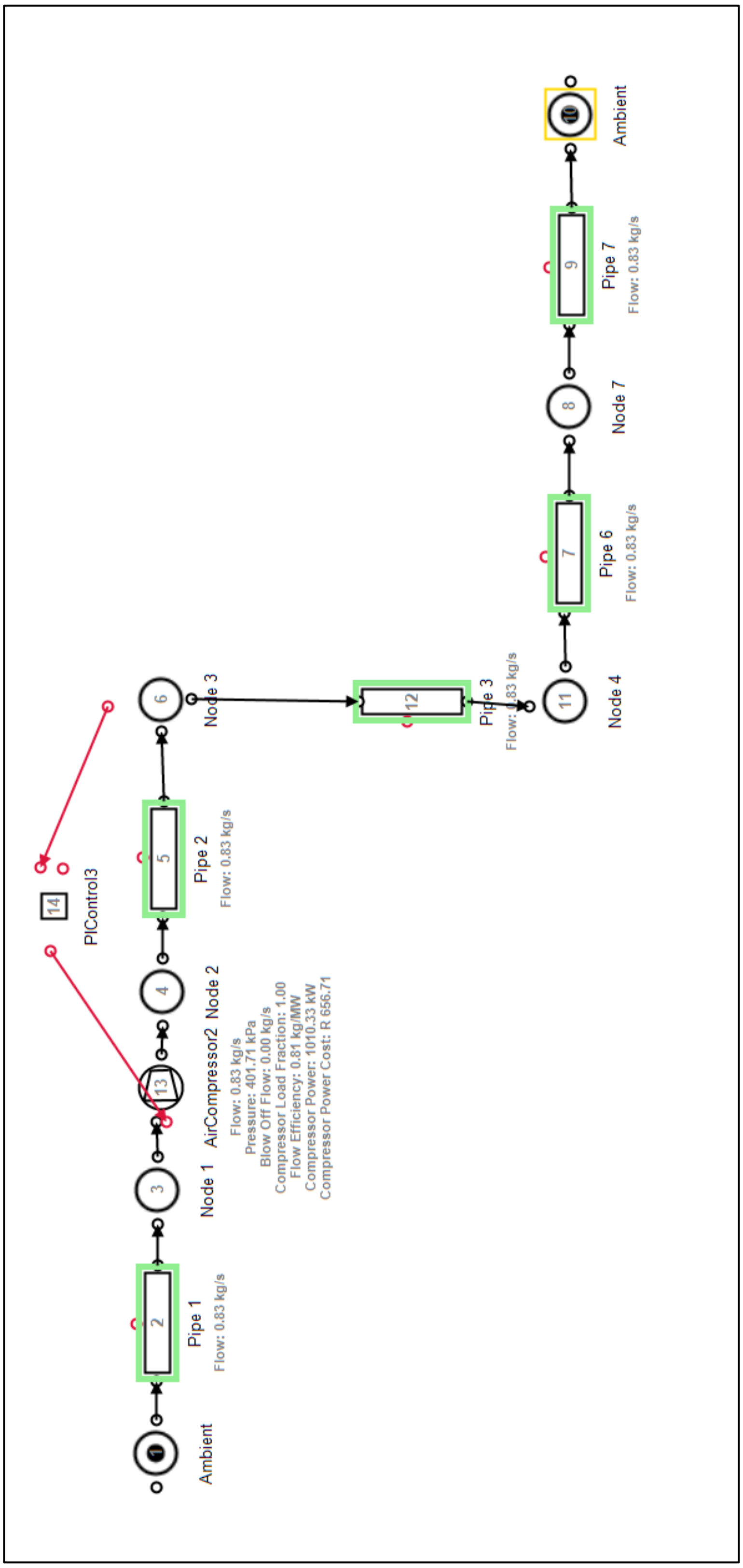


Figure 129: Compressed air system – simulation layout

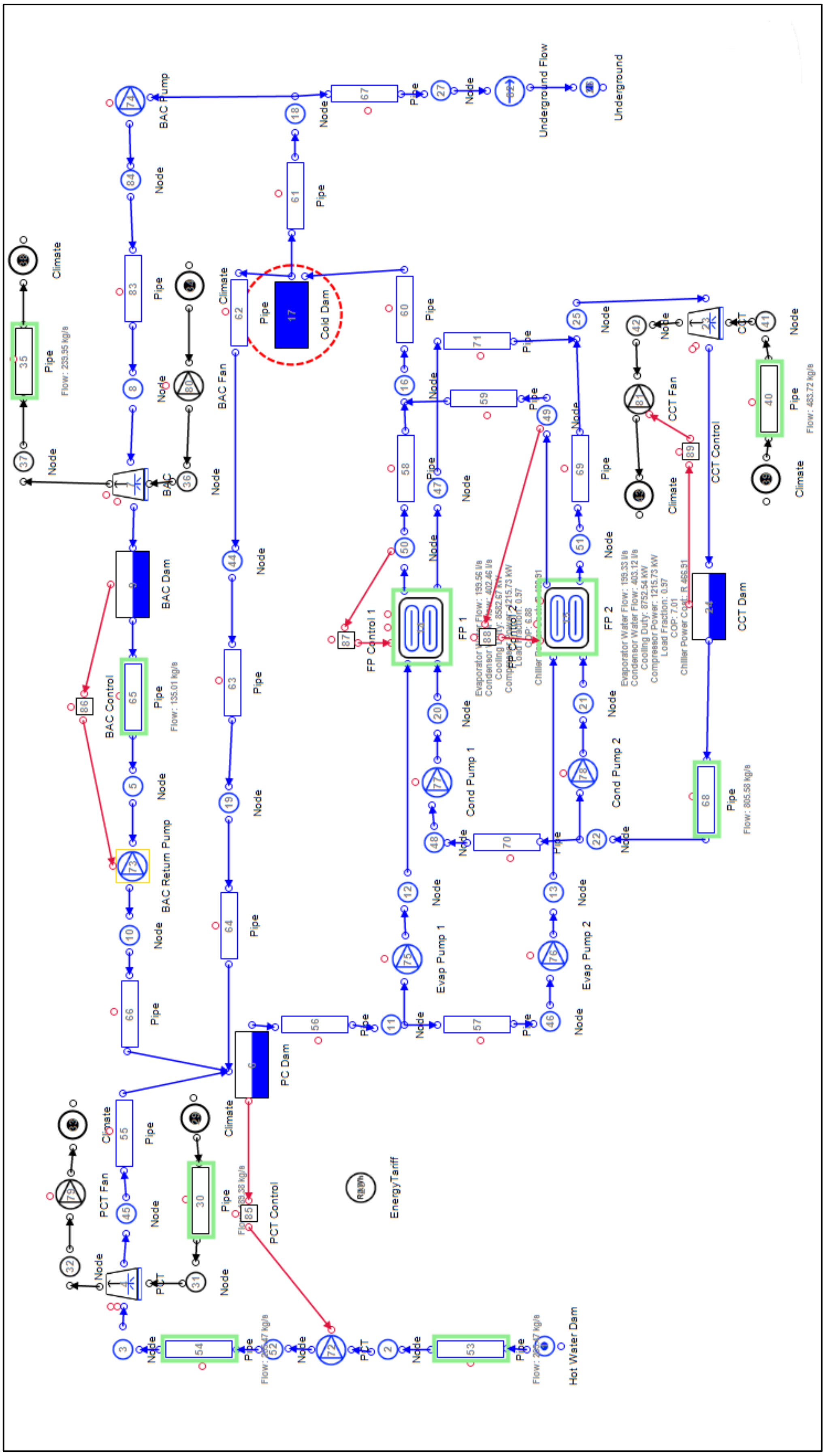


Figure 130: Cooling system – simulation layout

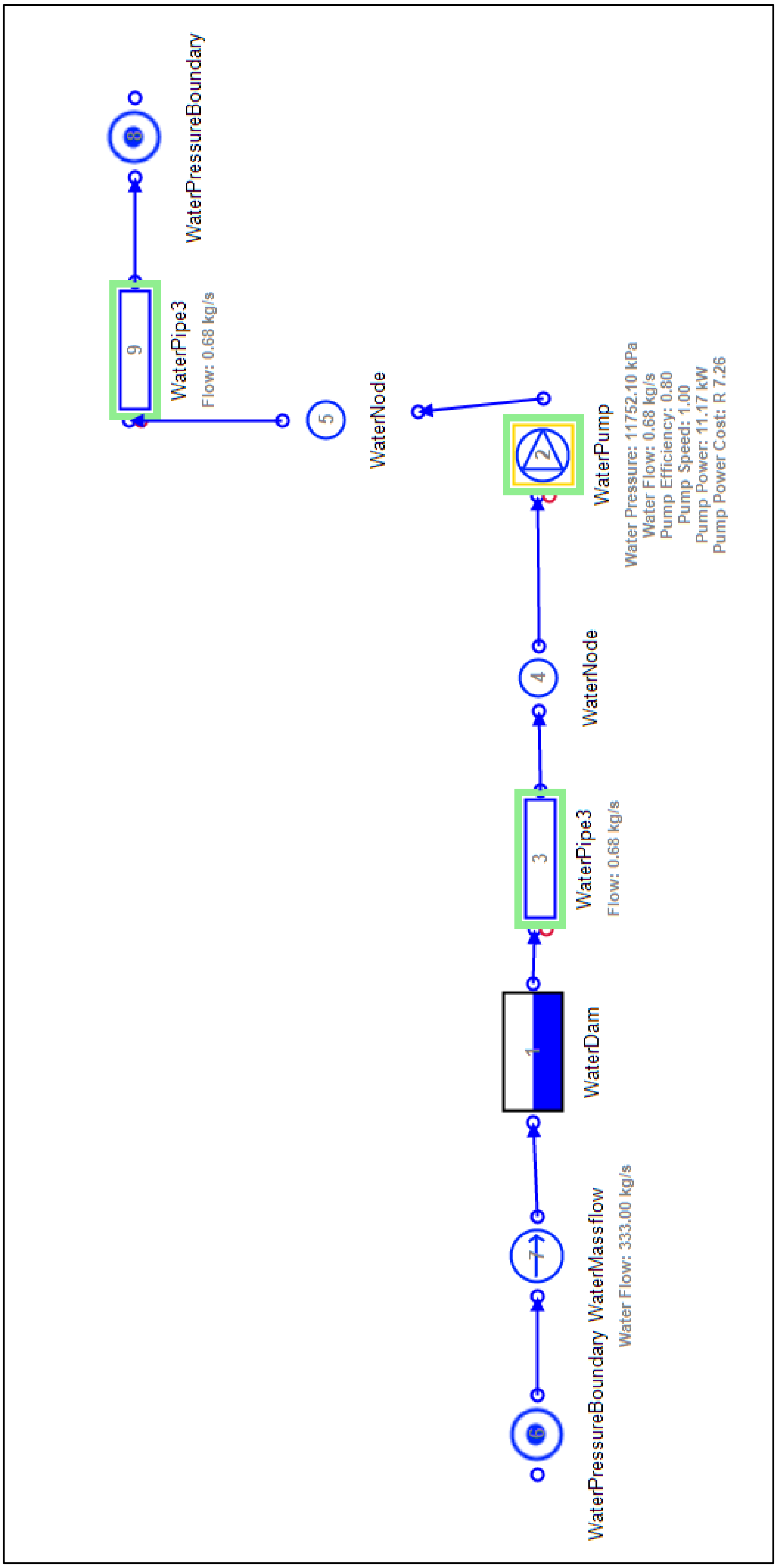


Figure 131: Dewatering system – simulation layout

Appendix G – Case study results (data)

Mine 1 – Individual high demand systems

Table 109: Case Study Mine 1 – actual energy

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	3 490	3 395	3 149	2 976	3 004	3 045
Cooling (MWh)	3 002	3 270	2 850	2 512	2 273	2 034
Dewatering (MWh)	7	44	41	202	198	200
Ventilation (MWh)	583	1 408	1 296	1 335	1 292	1 300
Hoisting (MWh)	614	729	640	657	755	819

Table 110: Case Study Mine 1 – average benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	2 862	2 872	2 854	2 763	2 943	2 766
Cooling (MWh)	2 191	2 205	2 179	2 046	2 309	2 812
Dewatering (MWh)	274	281	268	198	336	395
Ventilation (MWh)	861	870	854	776	931	1 103
Hoisting (MWh)	408	410	406	384	427	446

Table 111: Case Study Mine 1 – best practice benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	1 426	1 436	1 418	1 327	1 506	1 086
Cooling (MWh)	802	816	790	656	920	643
Dewatering (MWh)	181	189	175	105	243	302
Ventilation (MWh)	471	480	464	386	541	532
Hoisting (MWh)	133	136	131	109	153	171

Mine 2 – Individual high demand systems

Table 112: Case Study Mine 2 – actual energy

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	3 793	3 760	3 522	3 598	3 531	3 789
Cooling (MWh)	1 250	1 243	1 038	806	314	48
Dewatering (MWh)	551	766	768	376	357	493
Ventilation (MWh)	1 663	1 665	1 328	1 457	1 498	1 340
Hoisting (MWh)	435	563	481	328	524	556

Table 113: Case Study Mine 2 – average benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	3 890	4 172	4 146	3 706	4 193	4 202
Cooling (MWh)	3 619	4 033	3 995	3 350	4 064	4 100
Dewatering (MWh)	956	1 173	1 153	815	1 189	1 262
Ventilation (MWh)	1 699	1 942	1 920	1 541	1 960	2 156
Hoisting (MWh)	658	726	720	614	731	754

Table 114: Case Study Mine 2 – best practice benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	2 453	2 735	2 709	2 270	2 756	2 522
Cooling (MWh)	2 230	2 644	2 606	1 961	2 675	1 931
Dewatering (MWh)	863	1 080	1 060	722	1 096	1 169
Ventilation (MWh)	1 309	1 552	1 530	1 151	1 570	1 584
Hoisting (MWh)	384	452	445	339	457	480

Mine 3 – Individual high demand systems

Table 115: Case Study Mine 3 – actual energy

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	3 852	4 020	3 321	3 672	3 870	2 993
Cooling (MWh)	4 881	3 050	2 502	2 672	2 437	1 963
Dewatering (MWh)	1 789	1 750	1 722	1 656	1 578	1 345
Ventilation (MWh)	2 998	3 088	2 956	3 055	3 165	2 954
Hoisting (MWh)	524	547	484	464	533	489

Table 116: Case Study Mine 3 – average benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	6 209	6 417	6 785	6 234	6 493	6 104
Cooling (MWh)	6 811	7 117	5 580	5 127	5 339	6 657
Dewatering (MWh)	2 930	3 090	3 180	2 795	2 976	2 849
Ventilation (MWh)	3 572	3 751	4 110	3 733	3 910	3 481
Hoisting (MWh)	1 224	1 274	1 303	1 182	1 239	1 199

Table 117: Case Study Mine 3 – best practice benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	4 773	4 981	5 105	4 554	4 813	4 668
Cooling (MWh)	5 422	5 727	4 340	3 887	4 100	5 268
Dewatering (MWh)	2 837	2 997	3 087	2 702	2 883	2 756
Ventilation (MWh)	3 182	3 361	3 539	3 162	3 339	3 091
Hoisting (MWh)	950	1 000	1 028	907	964	924

Mine 4 – Individual high demand systems

Table 118: Case Study Mine 4 – actual energy

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	7 069	7 376	6 736	6676	6 657	5 862
Cooling (MWh)	5 675	5 661	5 210	4 999	3 756	3 052
Dewatering (MWh)	3 745	4 575	4 029	3 565	3 328	2 795
Ventilation (MWh)	4 269	4 104	3 691	3 599	3 733	3 139
Hoisting (MWh)	1 006	1 504	1 190	1 329	1 388	1 285

Table 119: Case Study Mine 4 – average benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	5 722	5 843	6 095	5 942	6 630	6 493
Cooling (MWh)	6 241	6 419	6 789	6 564	7 574	6 074
Dewatering (MWh)	3 057	3 150	3 344	3 226	3 755	3 532
Ventilation (MWh)	3 238	3 342	3 559	3 427	4 020	3 782
Hoisting (MWh)	1 103	1 132	1 193	1 156	1 322	1 252

Table 120: Case Study Mine 4 – best practice benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	4 285	4 406	4 658	4 505	5 194	4 813
Cooling (MWh)	4 852	5 030	5 399	5 174	6 185	3 905
Dewatering (MWh)	2 964	3 057	3 251	3 133	3 662	3 439
Ventilation (MWh)	2 848	2 952	3 169	3 037	3 630	3 210
Hoisting (MWh)	828	857	918	881	1 048	977

Mine 5 – Individual high demand systems

Table 121: Case Study Mine 5 – actual energy

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	8 471	4 627	4 701	4 386	3 872	4 778
Cooling (MWh)	2 641	3 772	3 982	3 654	1 883	1 348
Dewatering (MWh)	5 524	2 701	2 632	2 429	2 380	2 618
Ventilation (MWh)	4 385	2 362	2 072	2 328	2 082	2 321
Hoisting (MWh)	1 656	668	789	888	829	913

Table 122: Case Study Mine 5 – average benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	7 077	5 800	6 231	6 825	7 088	6 840
Cooling (MWh)	8 190	6 316	6 949	7 820	8 205	7 842
Dewatering (MWh)	4 218	3 236	3 568	4 024	4 226	4 035
Ventilation (MWh)	4 382	3 282	3 653	4 165	4 391	4 177
Hoisting (MWh)	1 431	1 122	1 227	1 370	1 434	1 374

Table 123: Case Study Mine 5 – best practice benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	5 641	4 363	4 795	5 389	5 651	5 403
Cooling (MWh)	6 801	4 927	5 560	6 431	6 816	6 453
Dewatering (MWh)	4 125	3 143	3 475	3 931	4 133	3 943
Ventilation (MWh)	3 992	2 891	3 263	3 775	4 001	3 787
Hoisting (MWh)	1 157	848	952	1 096	1 159	1 099

Mine 6 – Individual high demand systems

Table 124: Case Study Mine 6 – actual energy

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	6 890	6 261	6 377	6 019	6 267	6 071
Cooling (MWh)	10 825	9 637	10 366	8 162	7 497	5 536
Dewatering (MWh)	7 422	6 263	6 541	6 064	6 594	6 287
Ventilation (MWh)	5 803	5 303	5 792	5 630	5 822	5 711
Hoisting (MWh)	1 168	1 034	1 443	1 327	1 197	1 121

Table 125: Case Study Mine 6 – average benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	6 585	6 712	7 876	7 223	6 949	7 266
Cooling (MWh)	7 409	7 596	9 304	8 346	7 944	6 842
Dewatering (MWh)	4 833	4 931	5 826	5 324	5 113	5 148
Ventilation (MWh)	3 923	4 032	5 035	4 473	4 237	4 397
Hoisting (MWh)	1 314	1 344	1 626	1 468	1 402	1 413

Table 126: Case Study Mine 6 – best practice benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	5 148	5 275	6 440	5 787	5 513	5 586
Cooling (MWh)	6 020	6 206	7 914	6 957	6 554	4 673
Dewatering (MWh)	4 740	4 838	5 733	5 231	5 020	5 055
Ventilation (MWh)	3 533	3 642	4 645	4 083	3 847	3 826
Hoisting (MWh)	1 039	1 070	1 351	1 193	1 127	1 138

Mine 7 – Individual high demand systems

Table 127: Case Study Mine 7 – actual energy

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	8 338	8 638	7 779	6 768	7 313	9 924
Cooling (MWh)	8 167	9 503	7 815	6 468	7 013	7 271
Dewatering (MWh)	2 513	3 243	3 023	2 998	3 055	3 896
Ventilation (MWh)	6 942	6 514	5 697	5 286	6 088	6 718
Hoisting (MWh)	4 431	5 003	3 778	3 831	4 087	2 724

Table 128: Case Study Mine 7 – average benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	6 755	7 171	7 242	7 015	7 572	8 081
Cooling (MWh)	7 625	8 236	8 340	8 006	8 823	7 557
Dewatering (MWh)	4 594	4 913	4 968	4 793	5 221	5 335
Ventilation (MWh)	4 050	4 408	4 469	4 273	4 753	4 985
Hoisting (MWh)	1 356	1 456	1 473	1 419	1 553	1 589

Table 129: Case Study Mine 7 – best practice benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	5 319	5 735	5 805	5 578	6 135	6 401
Cooling (MWh)	6 236	6 847	6 950	6 617	7 434	5 389
Dewatering (MWh)	4 501	4 821	4 875	4 700	5 128	5 242
Ventilation (MWh)	3 660	4 018	4 079	3 883	4 363	4 413
Hoisting (MWh)	1 081	1 182	1 199	1 144	1 279	1 314

Mine 8 – Individual high demand systems

Table 130: Case Study Mine 8 – actual energy

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	3 843	4 966	4 586	4 423	4 371	4 709
Cooling (MWh)	1 345	1 727	1 566	1 291	568	116
Dewatering (MWh)	1 801	1 847	1 766	1 603	1 509	1 672
Ventilation (MWh)	2 276	2 343	2 209	2033	2 279	2 214
Hoisting (MWh)	937	1 079	1 093	1 004	833	1 093

Table 131: Case Study Mine 8 – average benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	4 850	5 115	5 174	4 772	5 210	5 506
Cooling (MWh)	4 978	5 366	5 454	4 864	5 506	5 240
Dewatering (MWh)	2003	2 207	2 252	1943	2 280	2 464
Ventilation (MWh)	2 497	2 725	2 776	2 429	2 807	3 092
Hoisting (MWh)	892	955	970	873	978	1 036

Table 132: Case Study Mine 8 – best practice benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	3 414	3 678	3 738	3 335	3 773	3 825
Cooling (MWh)	3 589	3 977	4 064	3 474	4 117	3 071
Dewatering (MWh)	1910	2 114	2 160	1 850	2 187	2 371
Ventilation (MWh)	2 107	2 334	2 386	2039	2 417	2 521
Hoisting (MWh)	617	681	695	598	704	762

Mine 9 – Individual high demand systems

Table 133: Case Study Mine 9 – actual energy

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	10 576	11 714	10 019	10 543	9 155	8 684
Cooling (MWh)	11 289	10 024	8 457	7 676	7 181	7 097
Dewatering (MWh)	12 724	13 361	12 241	12 261	11 822	11 176
Ventilation (MWh)	7 507	7 586	7 523	7 513	6 984	5 494
Hoisting (MWh)	2033	2 662	2 371	2 585	2 539	2 282

Table 134: Case Study Mine 9 – average benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	9 340	10 707	11 163	10 810	11 331	10 324
Cooling (MWh)	11 325	13 331	9 289	8 999	9 427	12 768
Dewatering (MWh)	8 735	9 786	9 610	9 363	9 727	9 491
Ventilation (MWh)	6 221	7 398	7 175	6 934	7 290	7 068
Hoisting (MWh)	1983	2 313	2 258	2 180	2 295	2 221

Table 135: Case Study Mine 9 – best practice benchmarks

System	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Compressed air (MWh)	7 903	9 271	9 483	9 130	9 651	8 887
Cooling (MWh)	9 935	11 942	8 049	7 759	8 187	11 379
Dewatering (MWh)	8 642	9 693	9 517	9 271	9 634	9 398
Ventilation (MWh)	5 831	7 008	6 604	6 362	6 718	6 678
Hoisting (MWh)	1 708	2039	1983	1906	2020	1946

Mine 1 – Total of high demand systems

Table 136: Case Study 1 – average benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	7 695	8 846	7 977	7 682	7 521	7 397
Average benchmark (MWh)	6 923	6 966	6 888	6 493	7 272	6 893

Table 137: Case Study 1 – best practice benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	7 695	8 846	7 977	7 682	7 521	7 397
Best practice benchmark (MWh)	3 013	3 056	2 978	2 583	3 362	2 735

Mine 2 – Total of high demand systems

Table 138: Case Study 2 – average benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	7 691	7 997	7 137	6 565	6 222	6 226
Average benchmark (MWh)	11 149	12 374	12 260	10 353	12 465	11 845

Table 139: Case Study 2 – best practice benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	7 691	7 997	7 137	6 565	6 222	6 226
Best practice benchmark (MWh)	7 239	8 463	8 350	6 443	8 554	7 686

Mine 3 – Total of high demand systems

Table 140: Case Study 3 – average benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	14 043	12 455	10 985	11 519	11 582	9 745
Average benchmark (MWh)	21 073	21 976	22 487	20 314	21 334	19 634

Table 141: Case Study 3 – best practice benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	14 043	12 455	10 985	11 519	11 582	9 745
Best practice benchmark (MWh)	17 163	18 065	18 577	16 404	17 424	15 475

Mine 4 – Total of high demand systems

Table 142: Case Study 4 – average benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	10 202	11 962	11 220	10 353	9 561	9 804
Average benchmark (MWh)	15 547	16 695	16 953	15 208	17 108	16 708

Table 143: Case Study 4 – best practice benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	10 202	11 962	11 220	10 353	9 561	9 804
Best practice benchmark (MWh)	11 637	12 784	13 043	11 297	13 198	12 549

Mine 5 – Total of high demand systems

Table 144: Case Study 5 – average benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	21 764	23 220	20 856	20 167	18 863	16 133
Average benchmark (MWh)	19 687	20 213	21 306	20 641	23 629	20 503

Table 145: Case Study 5 – best practice benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	21 764	23 220	20 856	20 167	18 863	16 133
Best practice benchmark (MWh)	15 776	16 303	17 396	16 731	19 718	16 344

Mine 6 – Total of high demand systems

Table 146: Case Study 6 – average benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	22 677	14 130	14 176	13 685	11 047	11 979
Average benchmark (MWh)	25 625	20 082	21 956	24 531	25 670	22 650

Table 147: Case Study 6 – best practice benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	22 677	14 130	14 176	13 685	11 047	11 979
Best practice benchmark (MWh)	21 714	16 172	18 045	20 621	21 760	18 491

Mine 7 – Total of high demand systems

Table 148: Case Study 7 – average benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	32 108	28 498	30 519	27 202	27 377	24 727
Average benchmark (MWh)	24 390	24 942	29 993	27 161	25 972	24 437

Table 149: Case Study 7 – best practice benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	32 108	28 498	30 519	27 202	27 377	24 727
Best practice benchmark (MWh)	20 479	21 032	26 083	23 251	22 061	20 278

Mine 8 – Total of high demand systems

Table 150: Case Study 8 – average benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	30 391	32 901	28 091	25 351	27 556	30 535
Average benchmark (MWh)	24 707	26 512	26 819	25 834	28 249	26 919

Table 151: Case Study 8 – best practice benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	30 391	32 901	28 091	25 351	27 556	30 535
Best practice benchmark (MWh)	20 797	22 601	22 908	21 923	24 338	22 760

Mine 9 – Total of high demand systems

Table 152: Case Study 9 – average benchmarks (systems total)

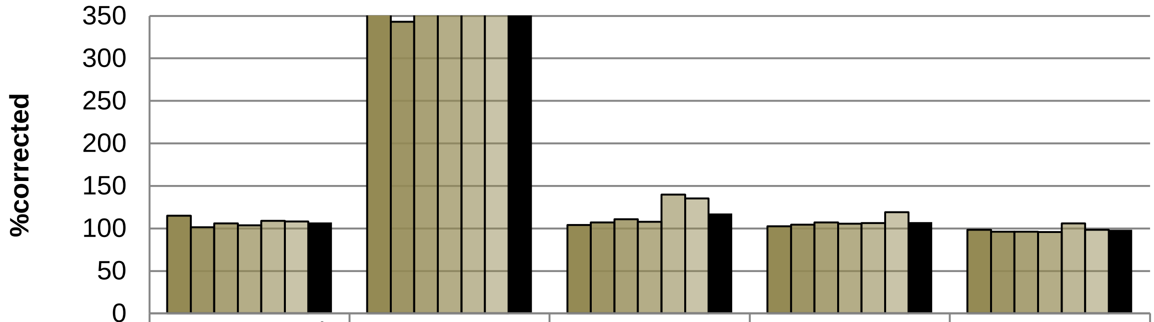
All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	44 129	45 346	40 612	40 579	37 681	34 733
Average benchmark (MWh)	37 929	43 863	42 869	41 477	43 531	39 213

Table 153: Case Study 9 – best practice benchmarks (systems total)

All systems	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Actual total (MWh)	44 129	45 346	40 612	40 579	37 681	34 733
Best practice benchmark (MWh)	34 019	39 953	38 959	37 567	39 621	35 055

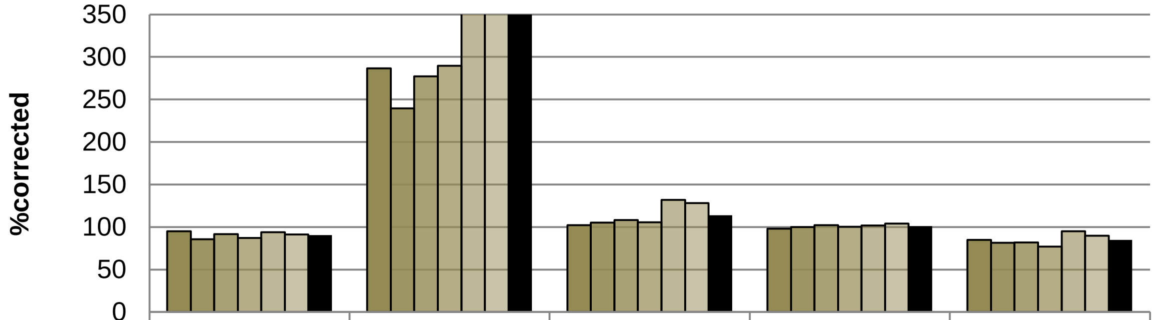
Appendix H – Case study results (graphs)

Case Study 4 to Case Study 9 results – Individual high demand systems



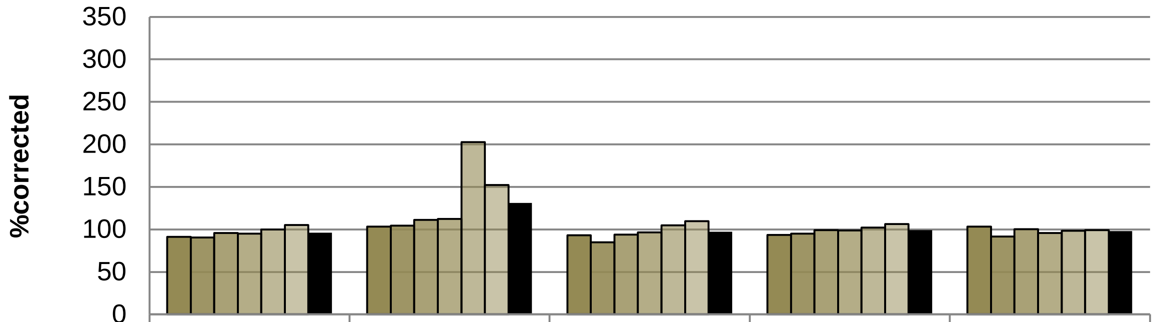
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	115	419	104	103	98
Month 2	101	343	107	104	96
Month 3	106	391	111	107	96
Month 4	104	428	108	105	96
Month 5	109	1188	140	106	106
Month 6	108	5538	135	119	98
Average	107	1385	117	107	98

Figure 132: Case Study 4 – percentage corrected values (average benchmarking)



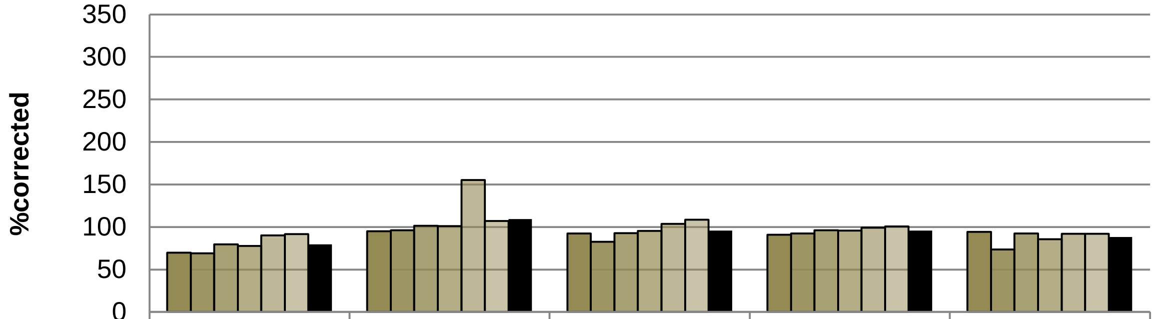
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	95	287	102	98	85
Month 2	85	240	105	100	81
Month 3	92	277	108	102	82
Month 4	87	290	106	100	77
Month 5	94	874	132	102	95
Month 6	91	3916	128	104	90
Average	91	981	114	101	85

Figure 133: Case Study 4 – percentage corrected values (best practice benchmarking)



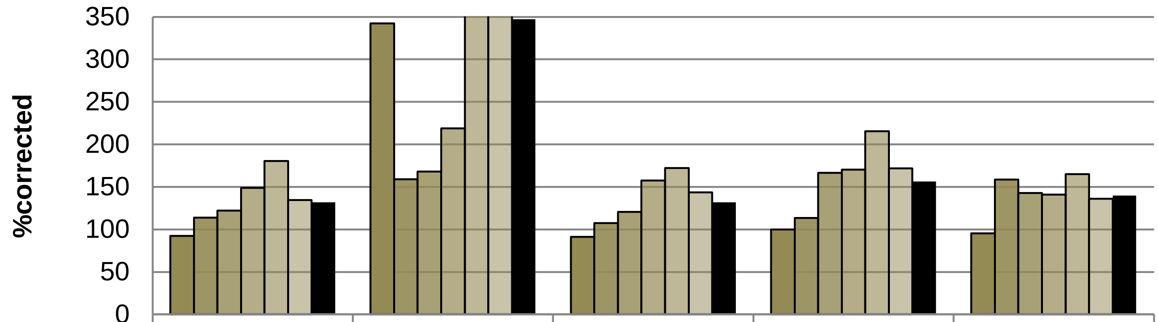
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	91	103	93	93	103
Month 2	91	104	85	95	92
Month 3	96	111	94	99	100
Month 4	95	112	96	99	96
Month 5	100	203	105	102	98
Month 6	105	152	110	106	99
Average	96	131	97	99	98

Figure 134: Case Study 5 – percentage corrected values (average benchmarking)



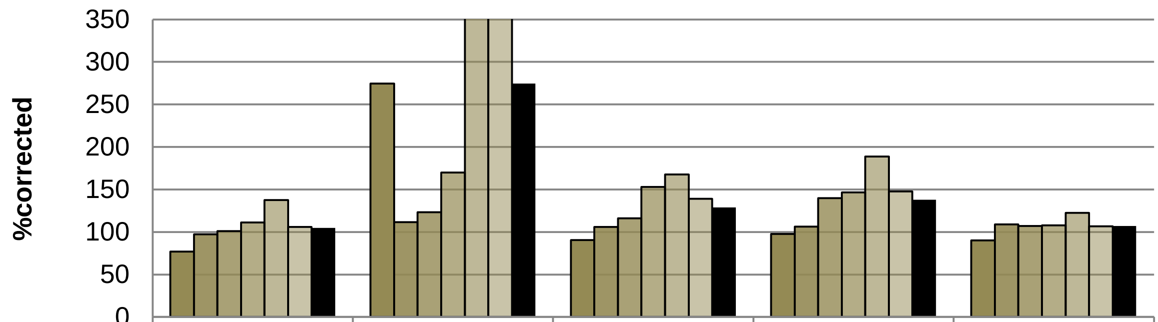
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	70	95	92	91	94
Month 2	69	96	82	92	73
Month 3	80	101	93	96	92
Month 4	78	101	96	96	85
Month 5	90	155	104	99	92
Month 6	91	107	109	101	92
Average	80	109	96	96	88

Figure 135: Case Study 5 – percentage corrected values (best practice benchmarking)



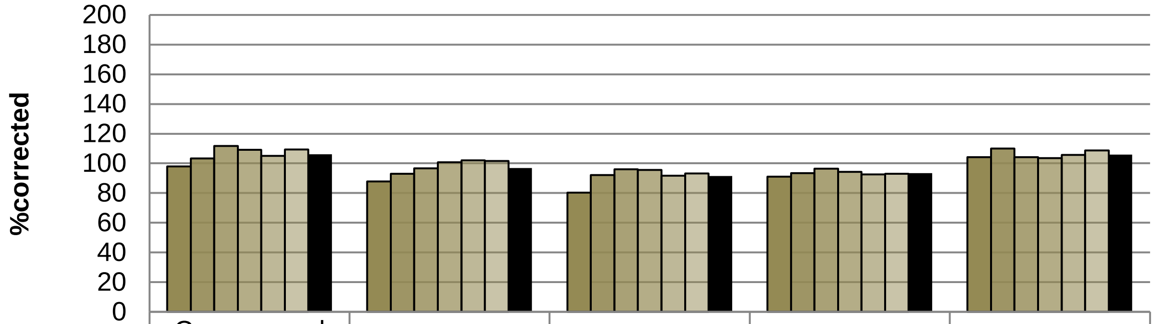
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	92	342	91	100	95
Month 2	114	159	107	114	159
Month 3	122	168	121	167	143
Month 4	149	219	158	170	141
Month 5	180	504	172	215	165
Month 6	134	691	143	172	136
Average	132	347	132	156	140

Figure 136: Case Study 6 – percentage corrected values (average benchmarking)



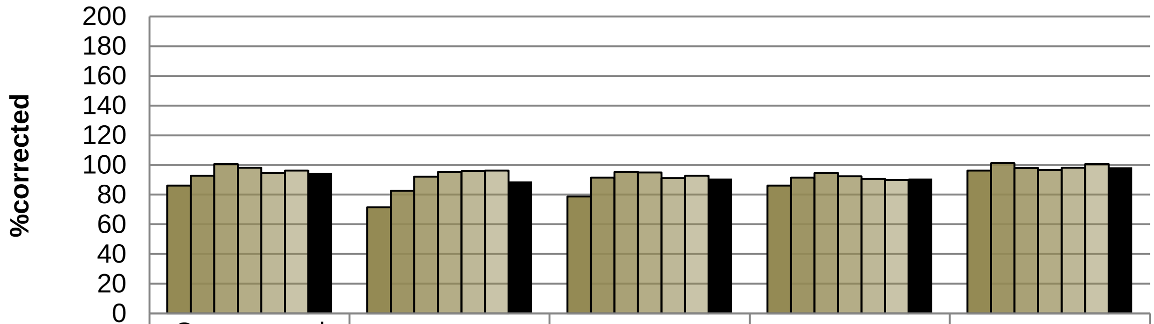
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	77	275	91	98	90
Month 2	97	112	106	106	109
Month 3	101	123	116	140	107
Month 4	111	170	153	146	108
Month 5	138	409	167	189	122
Month 6	106	559	139	148	107
Average	105	274	129	138	107

Figure 137: Case Study 6 – percentage corrected values (best practice benchmarking)



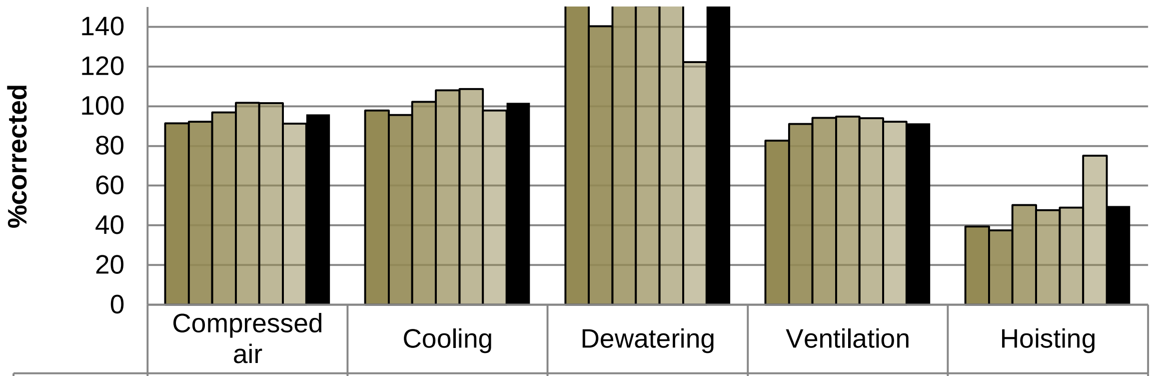
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	98	88	80	91	104
Month 2	103	93	92	93	110
Month 3	112	97	96	96	104
Month 4	109	101	95	94	104
Month 5	105	102	92	93	106
Month 6	109	102	93	93	109
Average	106	97	91	93	106

Figure 138: Case Study 7 – percentage corrected values (average benchmarking)



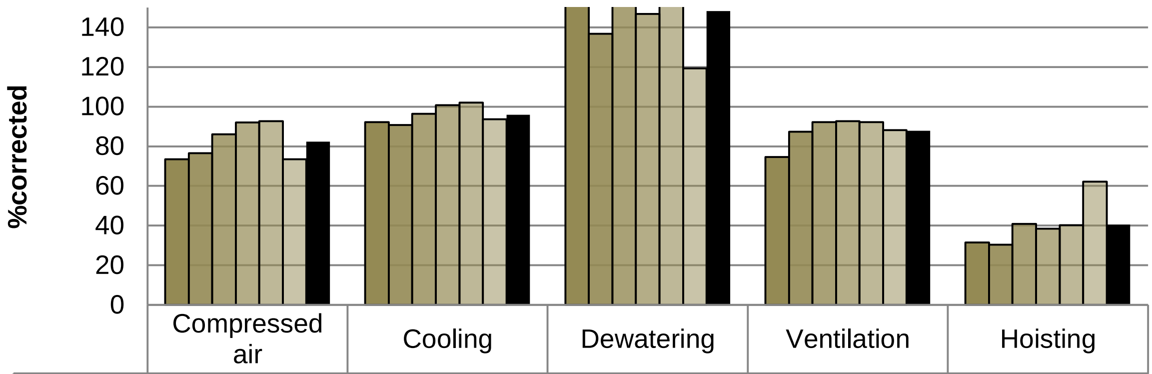
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	86	71	79	86	96
Month 2	93	83	92	91	101
Month 3	100	92	95	95	98
Month 4	98	95	95	92	97
Month 5	95	96	91	91	98
Month 6	96	96	93	90	101
Average	95	89	91	91	98

Figure 139: Case Study 7 – percentage corrected values (best practice benchmarking)



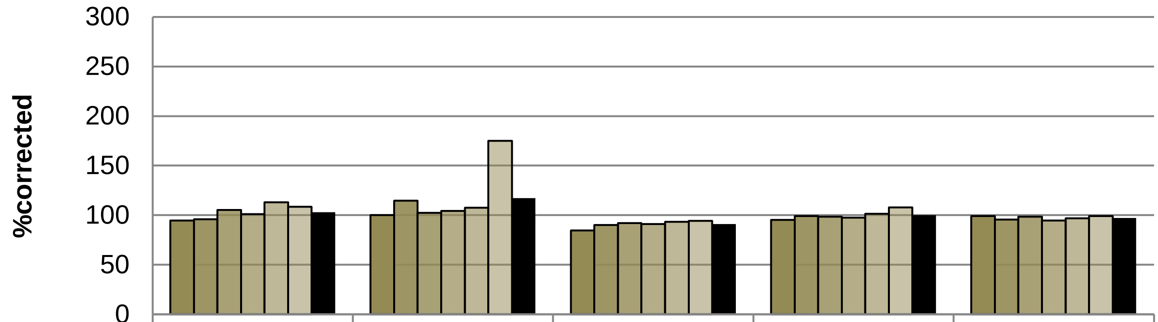
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	91	98	179	83	39
Month 2	92	96	140	91	37
Month 3	97	102	156	94	50
Month 4	102	108	151	95	48
Month 5	102	109	164	94	49
Month 6	91	98	122	92	75
Average	96	102	152	91	50

Figure 140: Case Study 8 – percentage corrected values (average benchmarking)



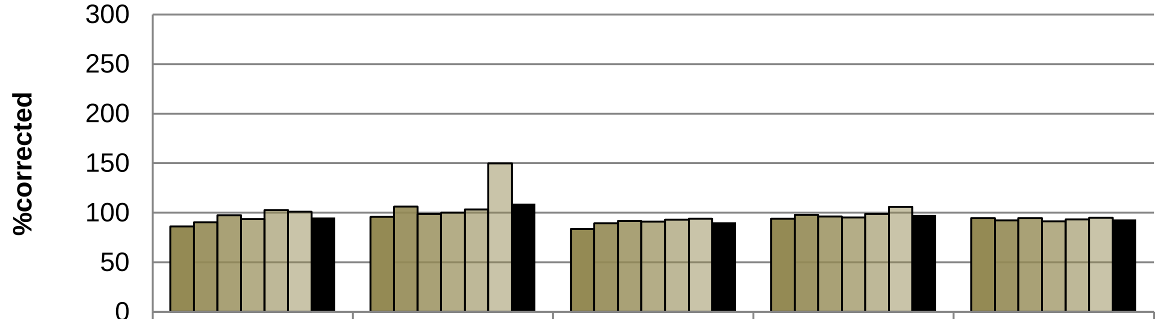
	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	74	92	174	75	31
Month 2	77	91	137	87	30
Month 3	86	96	152	92	41
Month 4	92	101	147	93	38
Month 5	93	102	160	92	40
Month 6	73	94	119	88	62
Average	82	96	148	88	41

Figure 141: Case Study 8 – percentage corrected values (best practice benchmarking)



	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	95	100	85	95	99
Month 2	96	115	90	99	96
Month 3	105	102	92	99	98
Month 4	101	104	91	98	95
Month 5	113	108	93	101	97
Month 6	109	175	94	108	99
Average	103	117	91	100	97

Figure 142: Case Study 9 – percentage corrected values (average benchmarking)



	Compressed air	Cooling	Dewatering	Ventilation	Hoisting
Month 1	86	96	84	94	95
Month 2	90	106	89	98	92
Month 3	97	99	92	96	95
Month 4	94	100	91	95	91
Month 5	103	103	93	99	93
Month 6	101	150	94	106	95
Average	95	109	91	98	94

Figure 143: Case Study 9 – percentage corrected values (best practice benchmarking)

Case Study 4 to Case Study 9 results – High demand systems combined

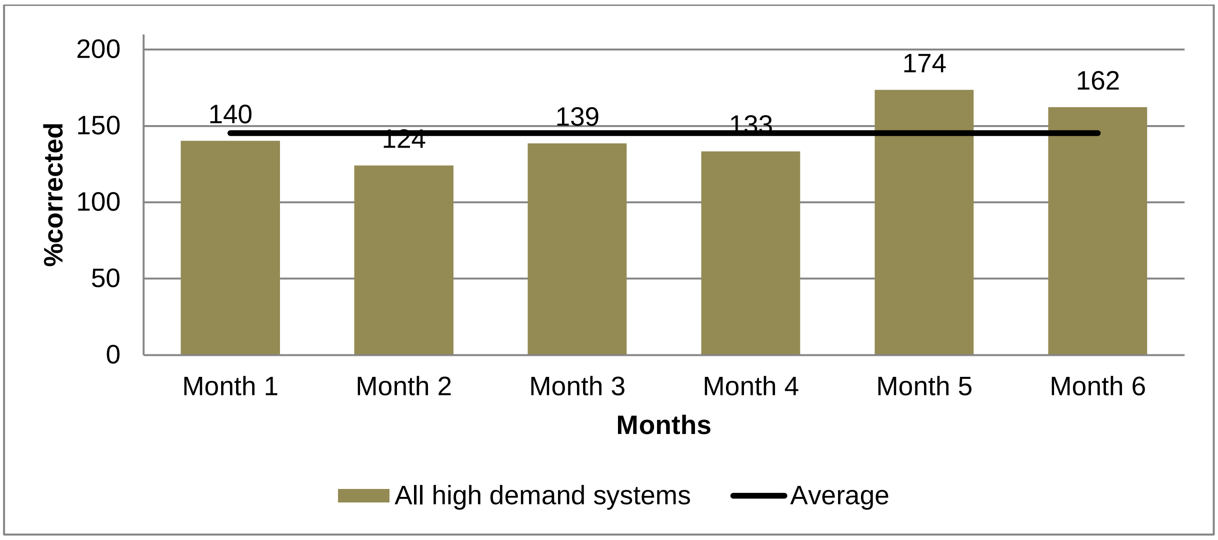


Figure 144: Case Study 4 – percentage corrected of systems combined (average benchmarking)

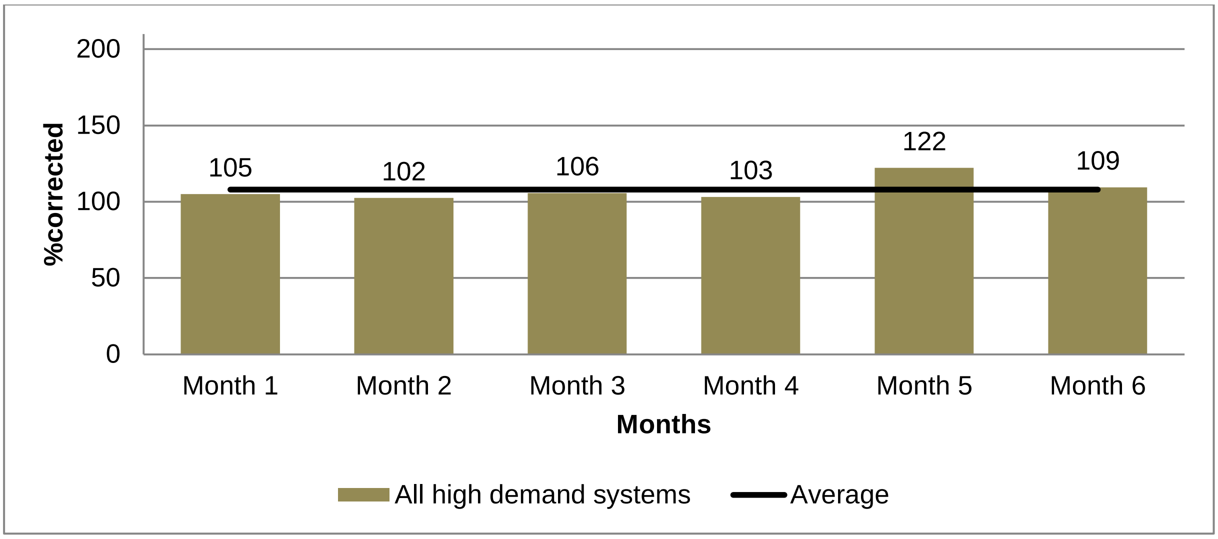


Figure 145: Case Study 4 – percentage corrected of systems combined (best practice benchmarking)

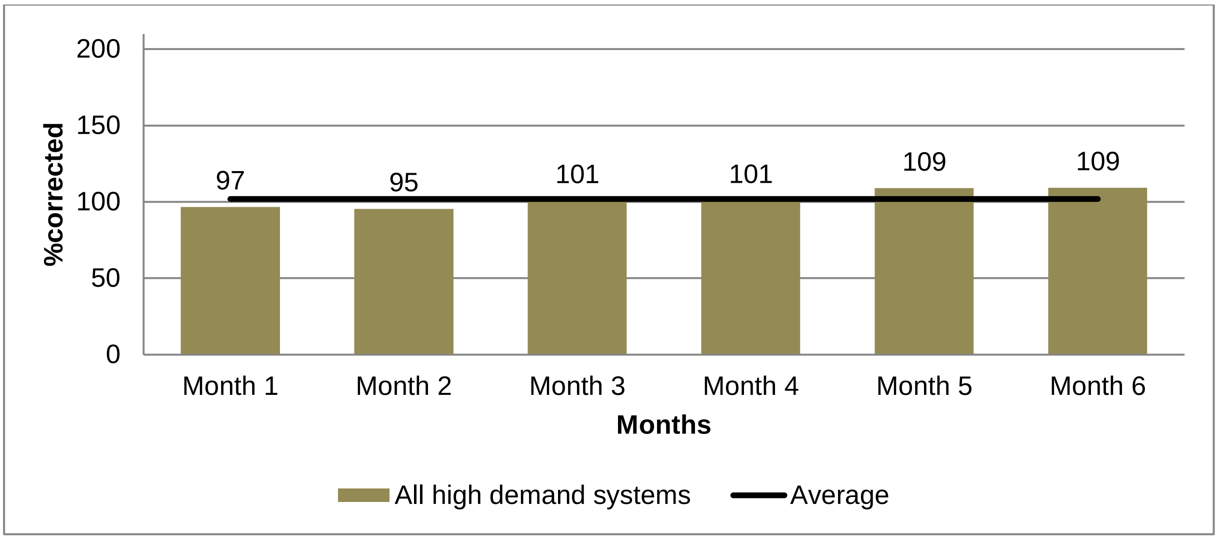


Figure 146: Case Study 5 – percentage corrected of systems combined (average benchmarking)

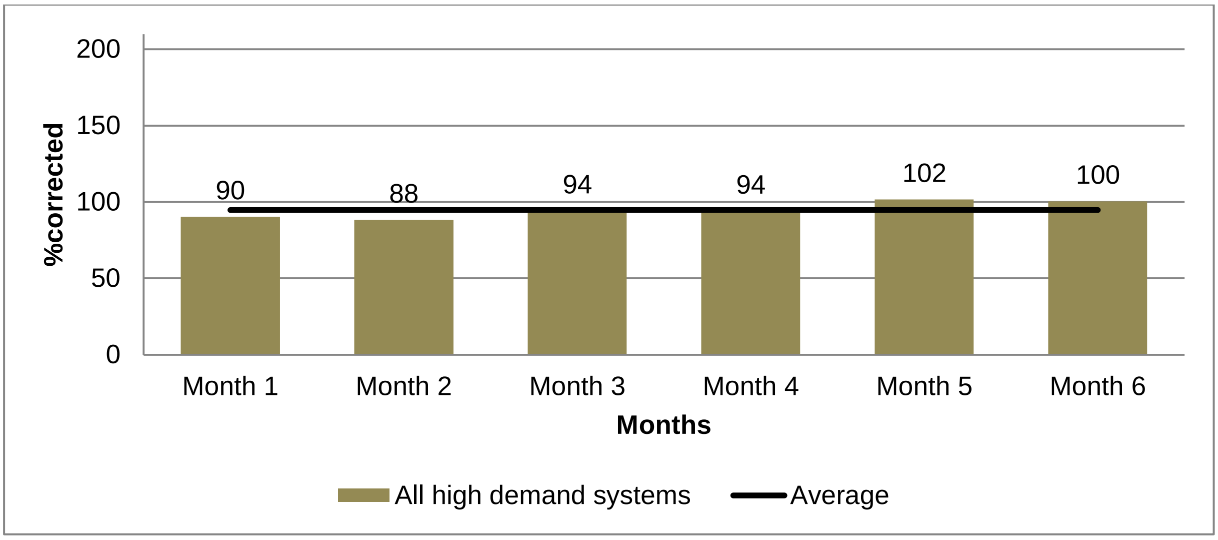


Figure 147: Case Study 5 – percentage corrected of systems combined (best practice benchmarking)

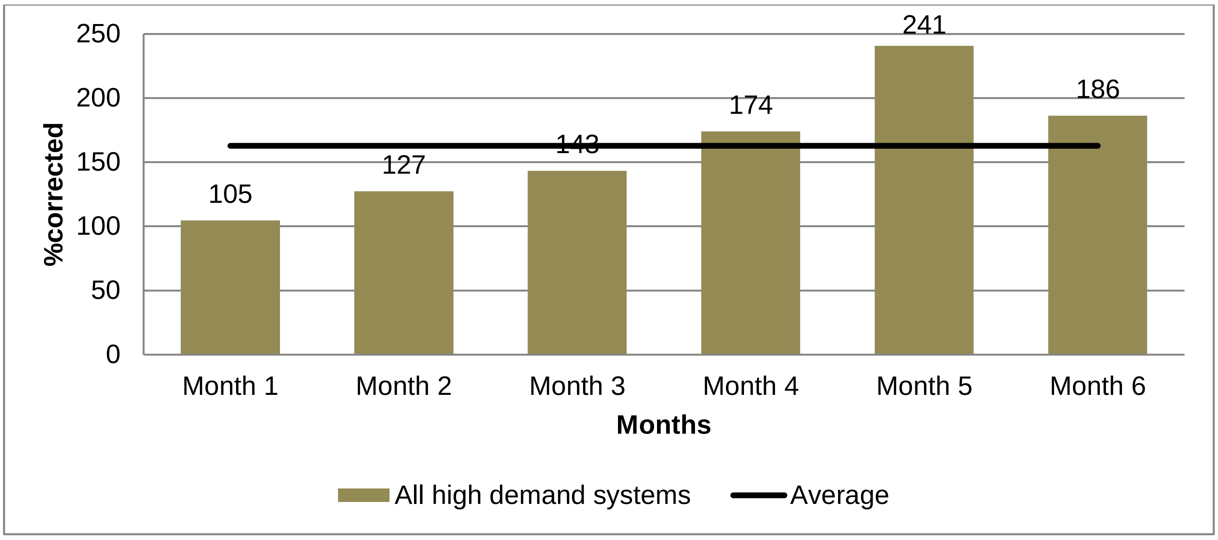


Figure 148: Case Study 6 – percentage corrected of systems combined (average benchmarking)

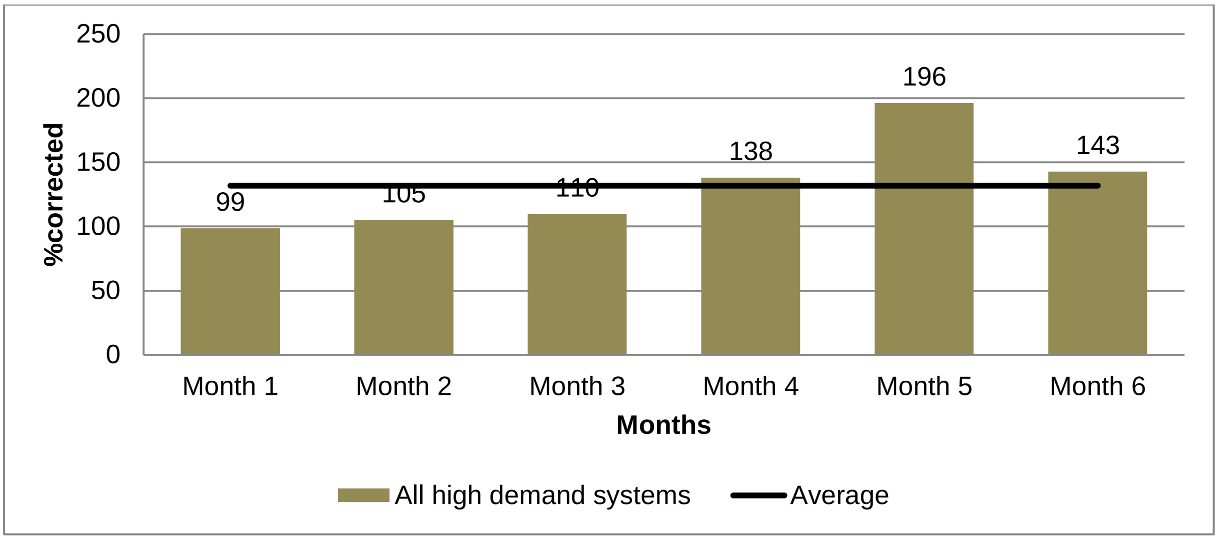


Figure 149: Case Study 6 – percentage corrected of systems combined (best practice benchmarking)

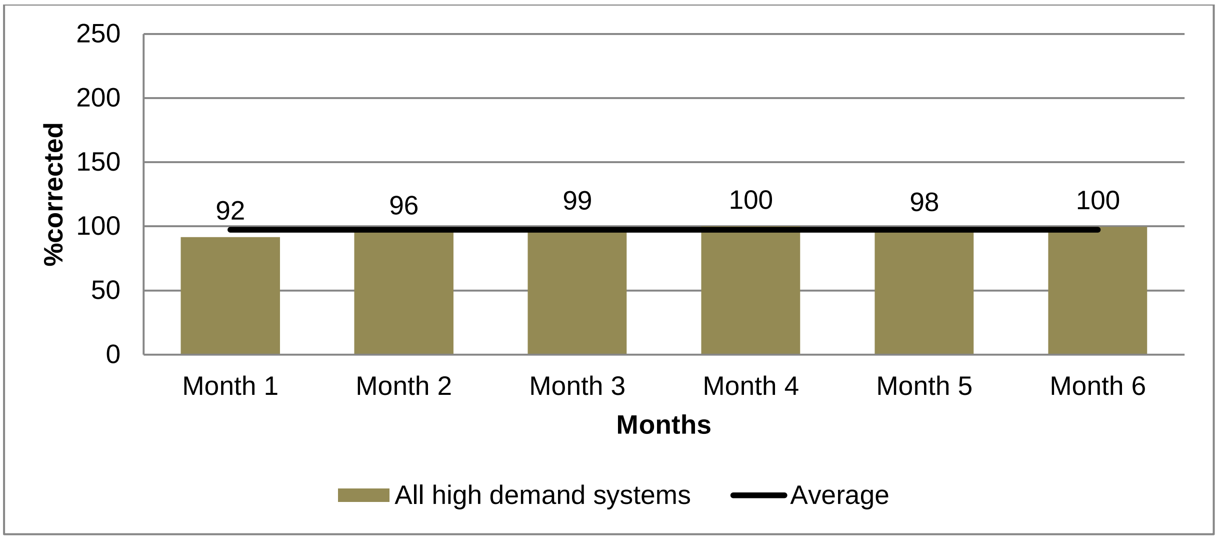


Figure 150: Case Study 7 – percentage corrected of systems combined (average benchmarking)

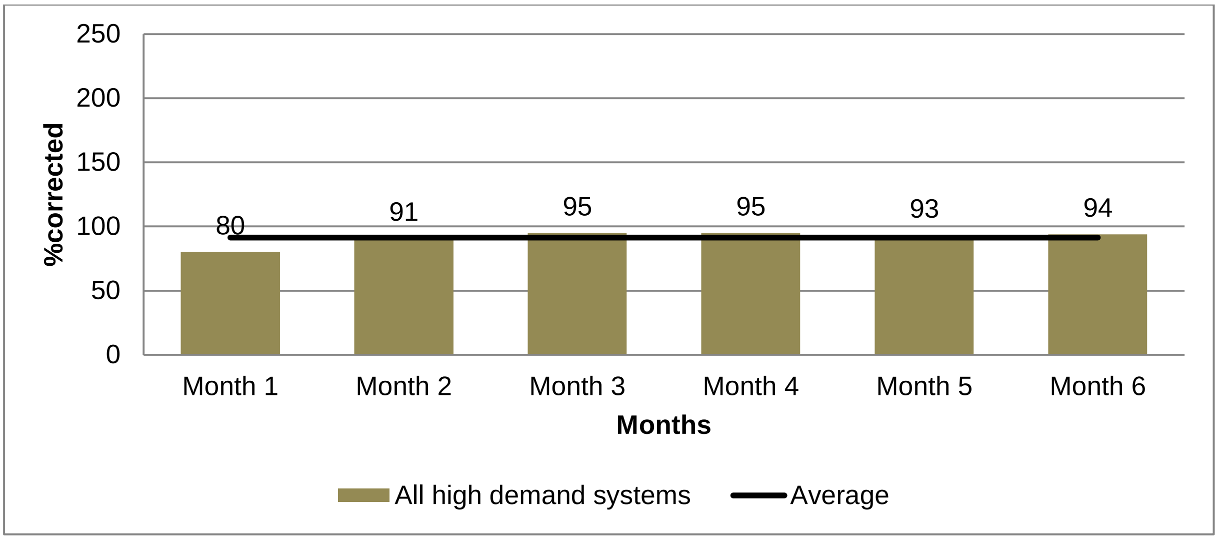


Figure 151: Case Study 7 – percentage corrected of systems combined (best practice benchmarking)

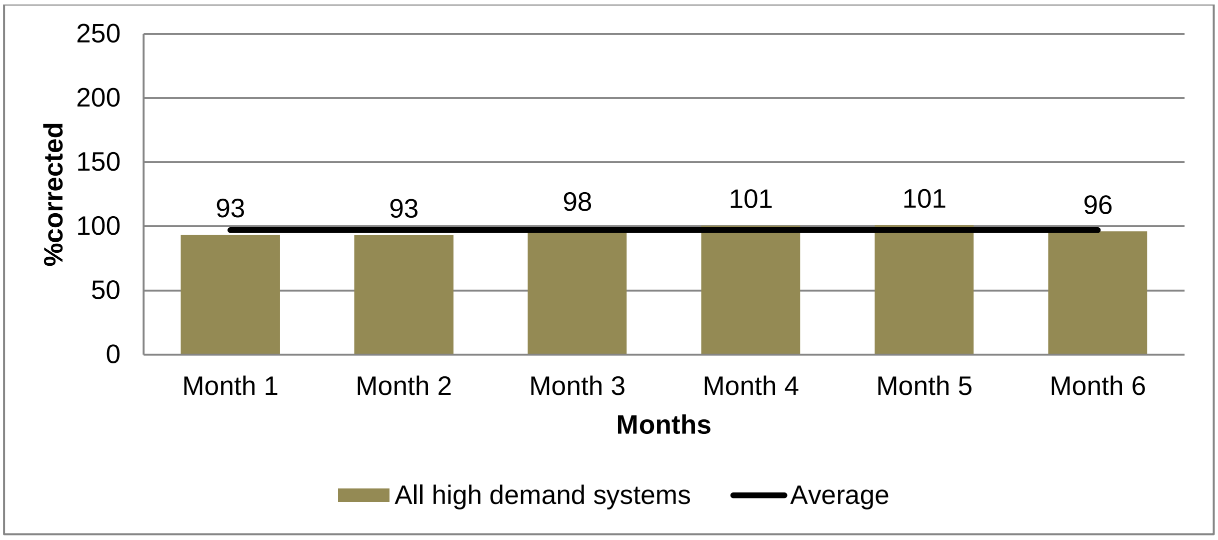


Figure 152: Case Study 8 – percentage corrected of systems combined (average benchmarking)

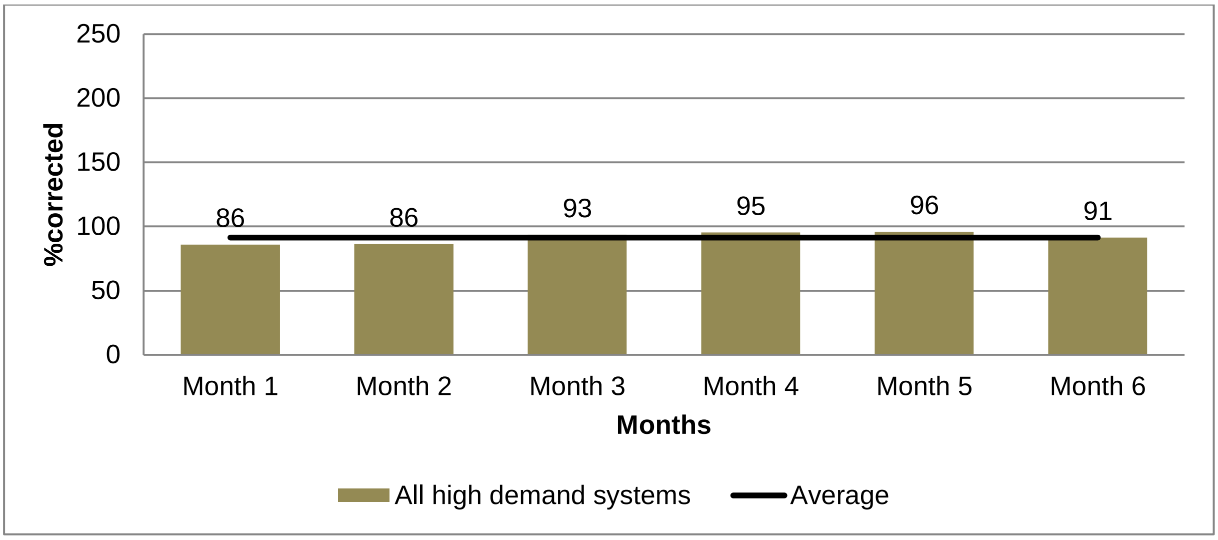


Figure 153: Case Study 8 – percentage corrected of systems combined (best practice benchmarking)

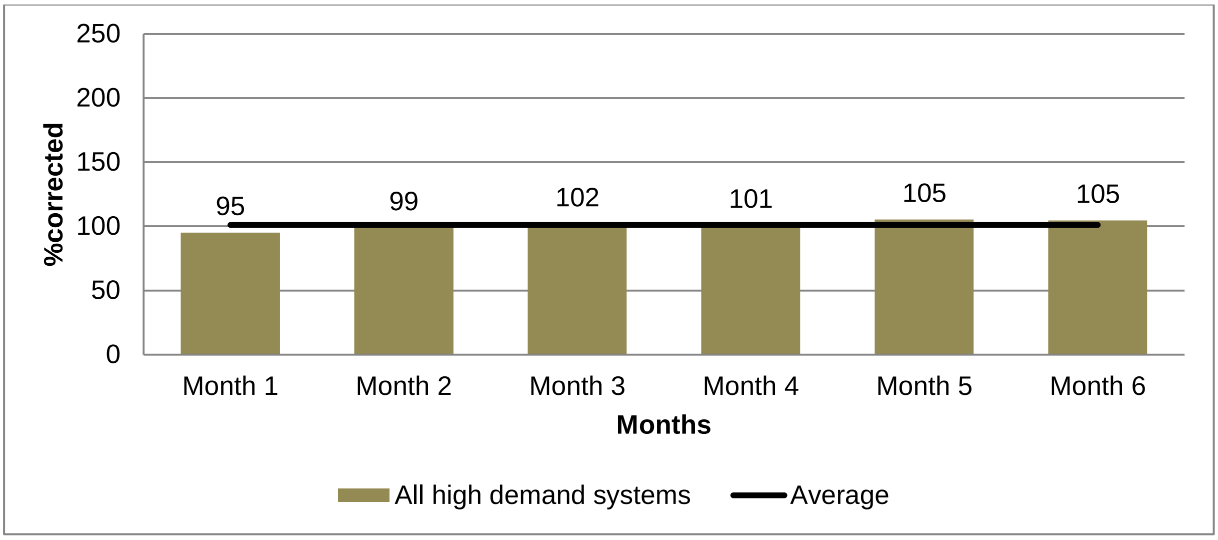


Figure 154: Case Study 9 – percentage corrected of systems combined (average benchmarking)

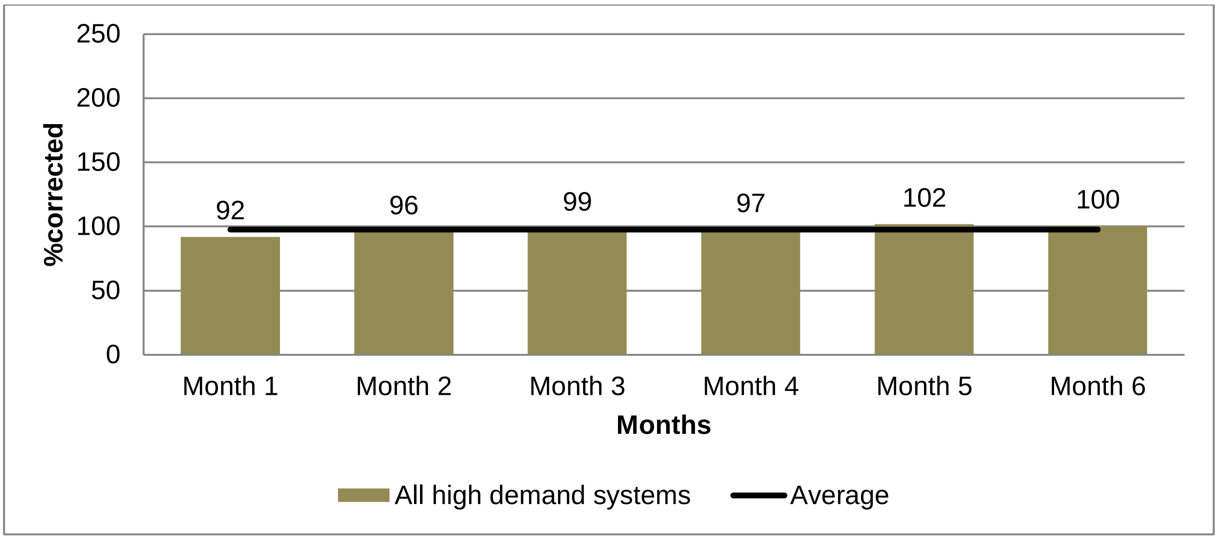


Figure 155: Case Study 9 – percentage corrected of systems combined (best practice benchmarking)

Case Study 4 to 9 results – Energy budget forecasting

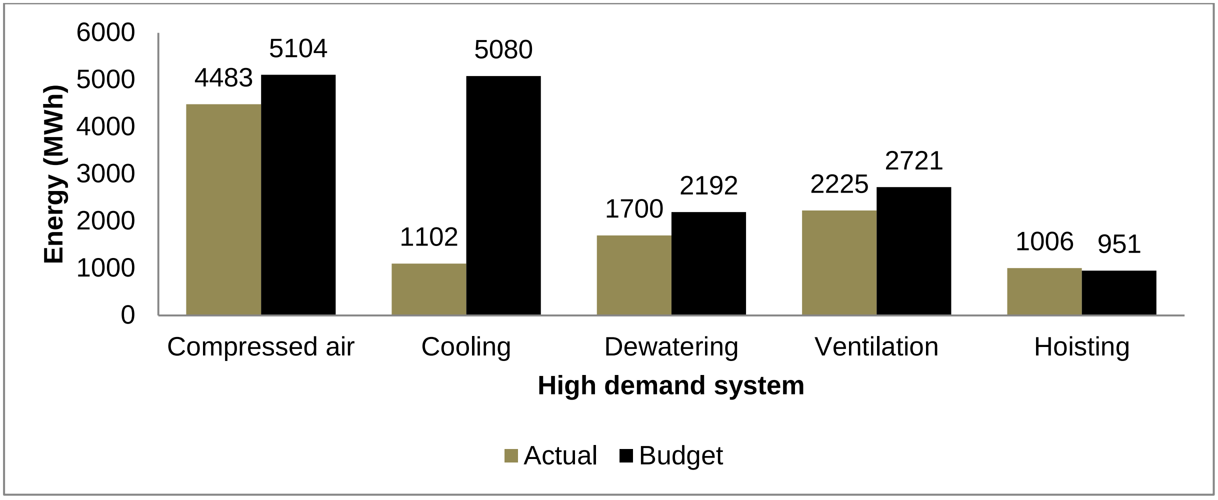


Figure 156: Case Study 4 – actual versus budgeted energy

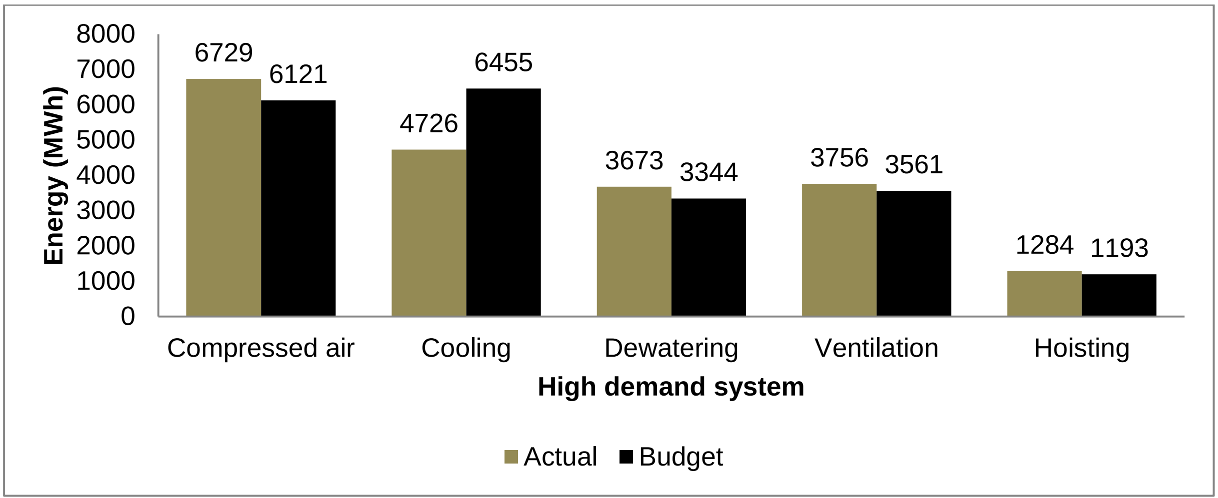


Figure 157: Case Study 5 – actual versus budgeted energy

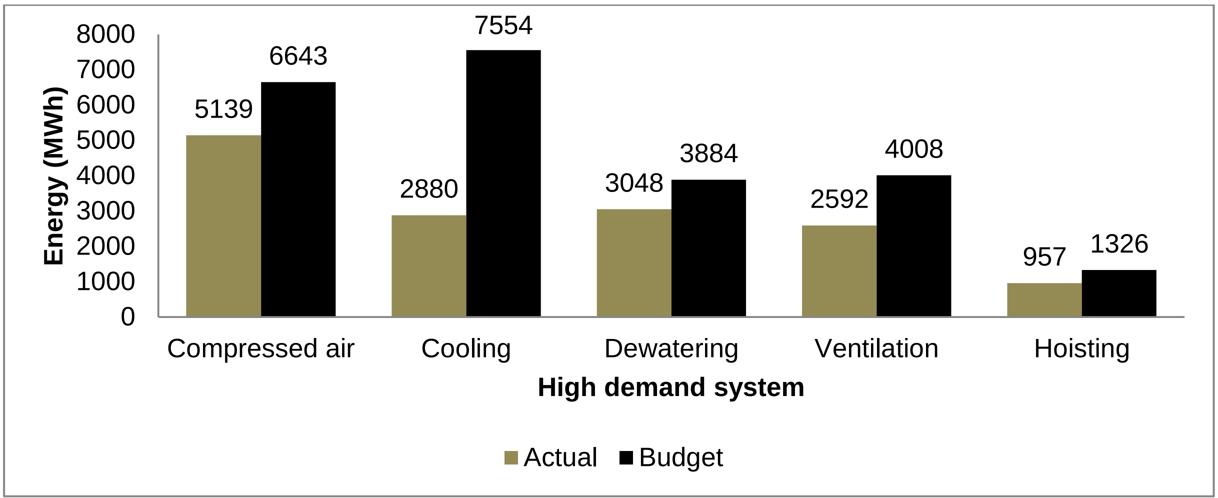


Figure 158: Case Study 6 – actual versus budgeted energy

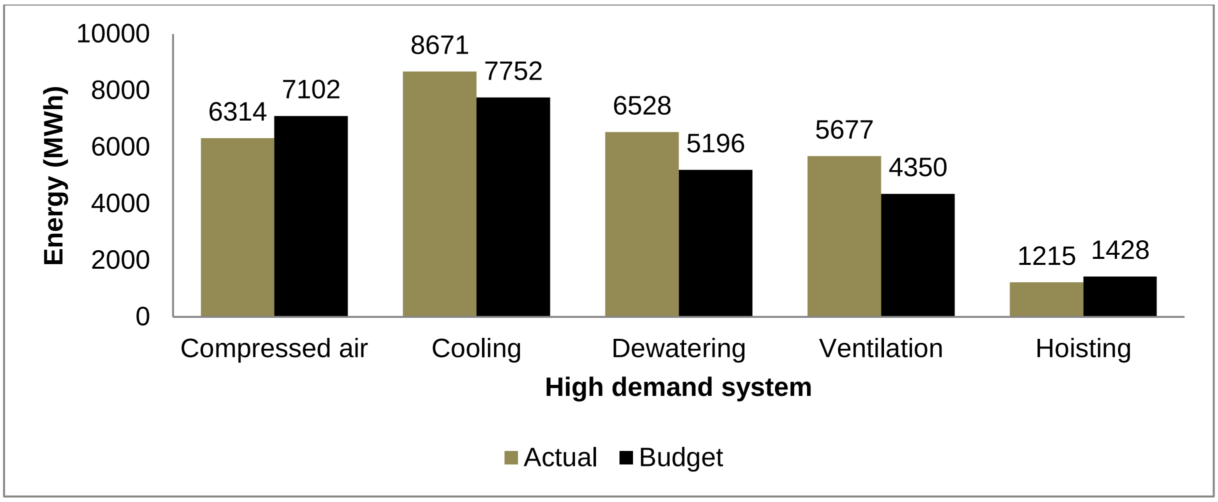


Figure 159: Case Study 7 – actual versus budgeted energy

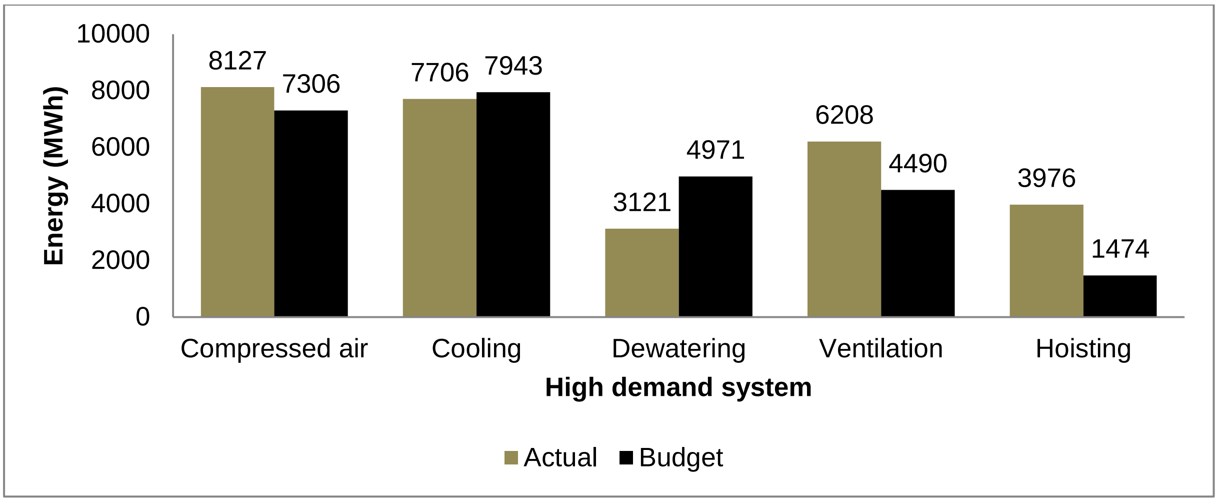


Figure 160: Case Study 8 – actual versus budgeted energy

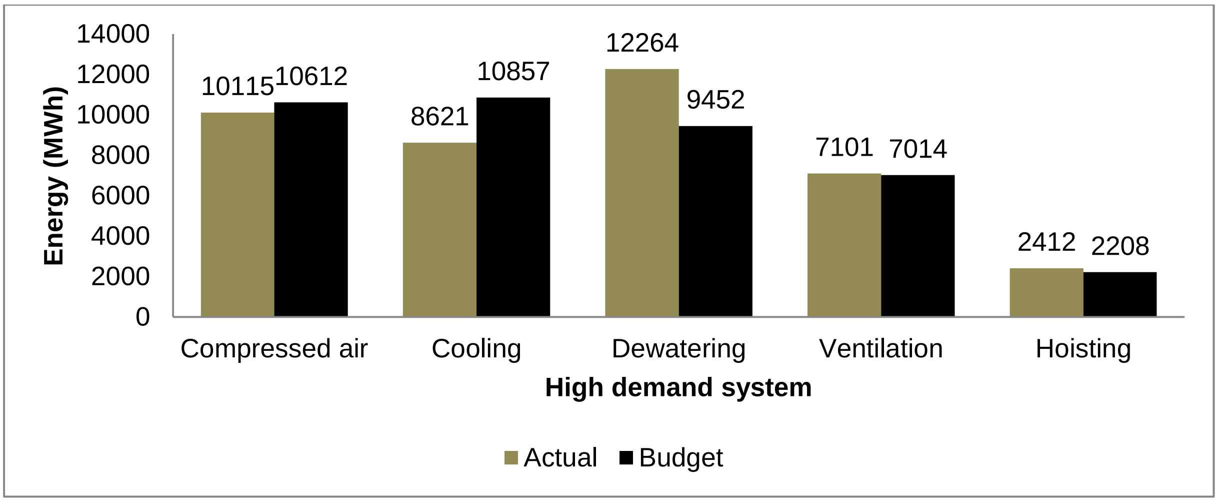


Figure 161: Case Study 9 – actual versus budgeted energy

Appendix I – Engineering Manager report

Mine 1

Monthly Energy Report

Month: ________________

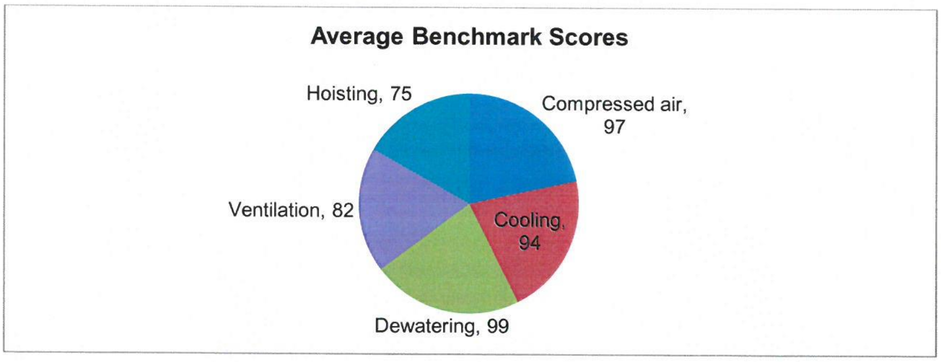
Year: ________________

1. Benchmarks

System	Energy use (MWh)	Average (MWh)	Best practice (MWh)
Compressed air	2976	2763	1327
Cooling	2512	2046	656
Dewatering	202	198	105
Ventilation	1335	776	386
Hoisting	657	384	109

System	Average Benchmark score	Best practice benchmark score
Compressed air	97	51
Cooling	94	34
Dewatering	99	64
Ventilation	82	41
Hoisting	75	21

Rank	System
1	Dewatering
2	Compressed air
3	Cooling
4	Ventilation
5	Hoisting



Mine 1 – Monthly energy report Page 1

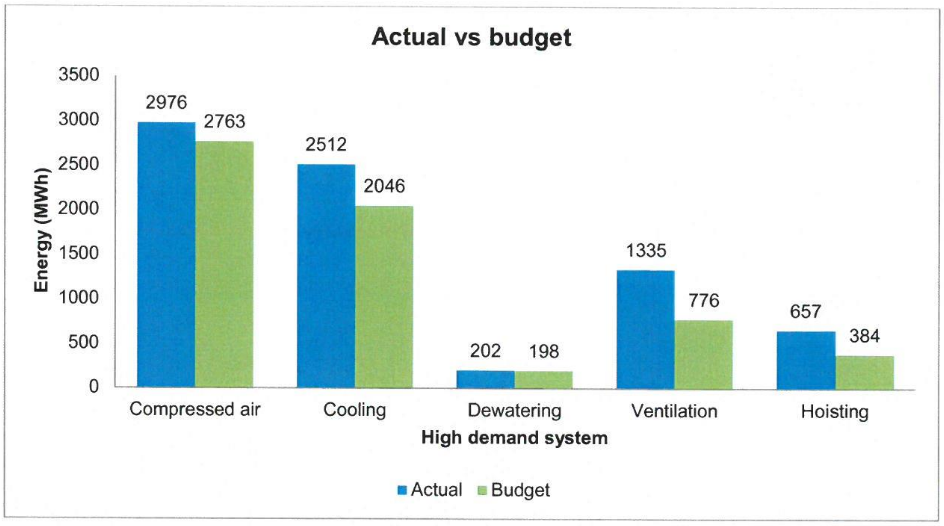
Figure 162: Engineering Manager - Monthly report page 1

2. Energy use reduction priorities

System	Priority
Compressed air	Med
Cooling	Med
Dewatering	Med
Ventilation	High
Hoisting	High

3. Budget statistics

System	Actual use (MWh)	Budget (MWh)	Over/Under (MWh)	% over/under
Compressed air	2976	2763	213	8%
Cooling	2512	2046	466	23%
Dewatering	202	198	5	2%
Ventilation	1335	776	559	72%
Hoisting	657	384	273	71%



Mine 1 – Monthly energy report Page 2

Figure 163: Engineering Manager - Monthly report page 2

Appendix J – Chief Electrical Engineer

Group X

Monthly Energy Report

Month: ____________________

Year: ____________________

1. Energy use benchmarks

Mine 1

System	Energy use (MWh)	Average Benchmark (MWh)	Best practice benchmark (MWh)
Compressed air	2976	2763	1327
Cooling	2512	2046	656
Dewatering	202	198	105
Ventilation	1335	776	386
Hoisting	657	384	109

Mine 2

System	Energy use (MWh)	Average Benchmark (MWh)	Best practice benchmark (MWh)
Compressed air	3598	3706	2270
Cooling	806	3350	1961
Dewatering	376	815	722
Ventilation	1457	1541	1151
Hoisting	328	614	339

Mine 3

System	Energy use (MWh)	Average Benchmark (MWh)	Best practice benchmark (MWh)
Compressed air	4423	4772	3335
Cooling	1291	4864	3474
Dewatering	1603	1943	1850
Ventilation	2033	2429	2039
Hoisting	1004	873	598

Group X – Monthly energy report Page 1

Figure 164: Chief Electrical Engineer - Monthly report page 1

2. Benchmark scores

Mine 1

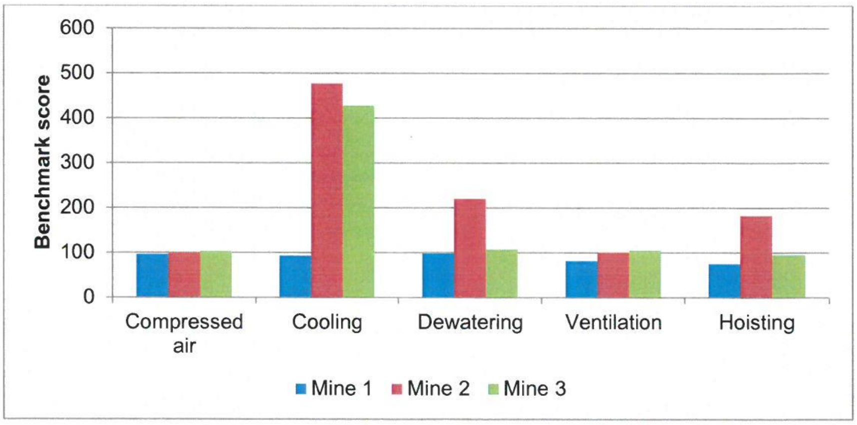
System	Average Benchmark score	Best practice benchmark score
Compressed air	97	51
Cooling	94	34
Dewatering	99	64
Ventilation	82	41
Hoisting	75	21

Mine 2

System	Average Benchmark score	Best practice benchmark score
Compressed air	101	73
Cooling	478	256
Dewatering	221	190
Ventilation	102	94
Hoisting	183	101

Mine 3

System	Average Benchmark score	Best practice benchmark score
Compressed air	104	87
Cooling	428	290
Dewatering	108	106
Ventilation	105	100
Hoisting	96	77



Group X – Monthly energy report Page 2

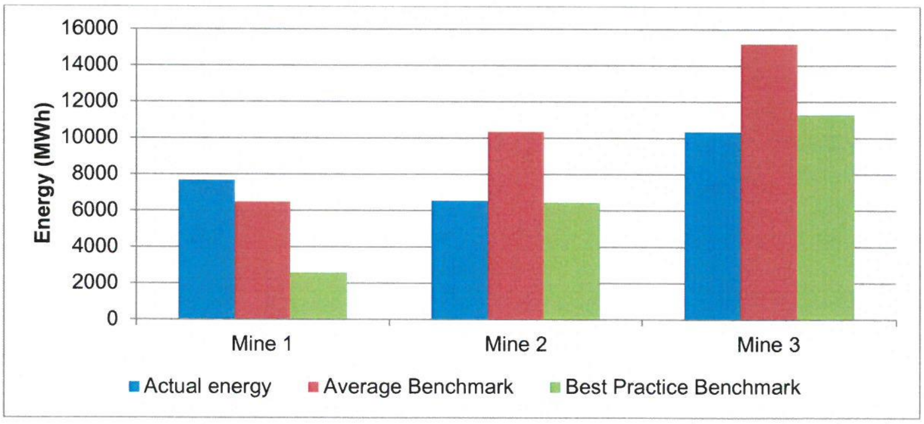
Figure 165: Chief Electrical Engineer - Monthly report page 2

3. High demand systems combined

Mine	Energy use (MWh)	Average Benchmark (MWh)	Best practice benchmark (MWh)
Mine 1	7682	6493	2583
Mine 2	6565	10353	6443
Mine 3	10353	15208	11297

Mine	Average Benchmark score	Best practice benchmark score
Mine 1	95	42
Mine 2	147	99
Mine 3	133	103

Rank	Mine
1	Mine 2
2	Mine 3
3	Mine 1



Group X – Monthly energy report

Page 3

Figure 166: Chief Electrical Engineer - Monthly report page 3