



A framework to implement improved electricity cost budgeting systems on mines

A Cronjé

 **orcid.org/ 0000-0003-4975-6661**

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Promoter: Dr JC Vosloo

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ABSTRACT

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Author: A Cronjé

Supervisor: Dr JC Vosloo

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Electricity cost and consumption budgets are a key instrument for energy performance evaluation on mines. This allows mines to identify opportunities for improvements and to monitor ongoing energy management initiatives. Budgets are an important part of financial planning, providing insights into anticipated future expenses for strategic decision making and cost management.

There is no existing standard for quality evaluation of electricity consumption and cost budgets developed and used by mines. Additionally, there is no framework to guide budget development in the industry. This gap has become problematic, as electricity prices are increasing well beyond inflation rates, highlighting the need for energy performance evaluation and cost management. The quality and availability of electricity consumption data on mines have significantly improved in recent years. The combination of improved data availability and pressure to manage costs presents opportunities for improved energy management strategies which rely on budgets as instruments for performance evaluation.

This study develops a set of best practices and an evaluation survey to investigate existing budgeting methods in practice and identifies shortcomings of these methods and their results. Surveys of 41 mine business units led to the identification of four key barriers preventing the development of high-quality budgets in industry: Low resolution of input data and of budget results, lack of scalability of budgeting methods, inadequate costing of budgets and poor documentation of the budget process. In short, current practices do not produce budgets that can be of value for performance evaluation.

The goal of this study is to develop a framework to overcome the identified barriers preventing the development and implementation of high-quality budgets in the mining industry. This was done through a synthesis of the developed best practices with existing electricity consumption forecasting approaches used in other industries and the findings from the surveys. A framework

that can be used to develop and implement high-quality electricity cost budgets on mines is presented.

The developed framework was found to effectively address each of the identified barriers and was verified through application to a case study mine. The framework produced a high-resolution budget that could be used to evaluate energy consumption for performance assessment purposes in near real-time. The method was also found to be scalable to large datasets and high interval data, reducing time spent on budget development. Both the cost and consumption values forecasted using the framework were more accurate (5% and 4% respectively) than those produced by industry standard methods, enabling more detailed future planning. This demonstrates that the framework produces improved budgets that are both technically sound and implementable in practice. The framework hereby enhances stakeholder confidence by enabling accurate, scalable, detailed and transparent long-term forecasting.

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A Cronje, J.H. v Laar, J.F. v Rensburg, J.C. Vosloo

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DEFINITIONS AND ABBREVIATIONS

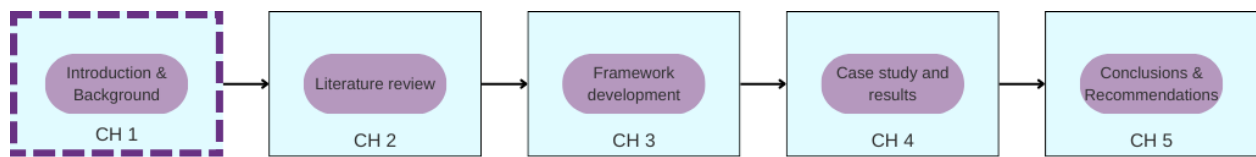
Definitions:

Best practices	- A set of conditions and requirements necessary to achieve high-quality outcomes in a given process, specifically for developing electricity consumption and cost budgets for the mining industry in this study.
Consumption budget dataset	- A time-based dataset representing the forecasted electricity consumption of a selected system.
Effective tariff	- A calculated average electricity cost for a selected system over a billing period.
Electricity consumption budget	- A forecast of expected electricity usage is used to evaluate actual electricity consumption and to monitor the effectiveness of energy management initiatives.
Electricity cost budget	- The forecast of the electricity consumption budget cost used for financial planning.
Electricity tariff structure	- A set of charges applied by a utility that determine total electricity cost.
High-frequency data	- Data recorded in short time intervals that enable detailed, near real-time analysis.
Point of delivery	- A single utility electricity supply and measurement point.
Representative cost	- A consolidated cost value that reflects the combined influence of all tariff components on electricity consumption.
Tariff budget dataset	- A time-based dataset with combined electricity tariff values that can be used, in conjunction with an electricity consumption budget dataset, to calculate the electricity cost budget.
Time-of-use periods	- Utility defined time periods with different electricity tariffs.

Abbreviations:

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
ARIMA	-	Autoregressive Integrated Moving Average
DBSCAN	-	Density-Based Spatial Clustering of Applications with Noise
EMD	-	Empirical Mode Decomposition
HVAC	-	Heating, Ventilation and Air Conditioning
ISO	-	International Organisation for Standardisation
MAPE	-	Mean Absolute Percentage Error
ML	-	Machine Learning
NMD	-	Notified Maximum Demand
POD	-	Point of Delivery
SCADA	-	Supervisory Control and Data Acquisition
SDG	-	Sustainable Development Goal
TOU	-	Time of Use

CHAPTER 1 INTRODUCTION AND LITERATURE



1.1 Background

1.1.1 Electricity in the South African mining industry

South African mines, especially deep-level mines, are facing significant energy challenges in the face of the country's ongoing energy crisis. All mines, but especially deep-level mines, are very energy intensive. This is a trend that can be seen globally, but that is also prevalent in South Africa [1], [2]. Deep mines are defined as from 1 500m and can reach over 4 000m in depth. These mines can have virgin rock temperatures of up to 70°C [3].

Due to the nature of their operation, deep mines rely heavily on services provided by large, energy intensive machinery. These machines provide services like compressed air, hoisting, refrigeration, ventilation and dewatering to the mines. These are required for mining activities, to maintain legal working temperatures, and to improve comfort levels for workers underground. These services are supplied by large fans, winders, refrigeration plants, compressors and pumping stations

The rising costs of electricity have become a significant challenge for most operations [4]. Electricity costs are escalating well beyond inflation, while year-on-year availability of electricity is decreasing. Over the last 20 years, the average price of electricity in South Africa has increased by 852%, which equates to an average annual increase of 13.5% [5]. Electricity costs are a significant portion of mine operating expenses. Electricity specifically has been found to be up to 24% of a mine's operating costs [6]. In addition to the rising costs, there is increasing social and legislative pressure on mines to reduce their electricity consumption for environmental reasons [7], [8].

Higher operating costs directly cause narrower profit margins, thus the reduction of cost and therefore the reduction of electricity cost is a focus area on South African mines. Reducing the cost of electricity used in mines has been a long-term effort [9]. Mines use energy management as a tool to regulate and optimise electricity consumption and associated costs by reducing the energy intensity of mines [2]. Energy efficiency projects are also used to address the

environmental concerns of high electricity usage and to comply with legal environmental requirements [10].

Three of the sustainable development goals (SDGs) instated by the United Nations promote the mindful use of energy [11]:

Affordable and Clean Energy (SDG 7): Focus on energy efficiency and energy management supports this goal by reducing emissions, lowering costs and promoting clean energy use.

Industry, Innovation, and Infrastructure (SDG 9): Automation and modernisation of energy management systems can lead to more energy-efficient operations that are less environmentally damaging, thus supporting sustainability.

Responsible Consumption and Production (SDG 12): Energy management and resulting energy efficiency promotes responsible energy consumption.

Most electricity consumed by mines in South Africa is generated by the national energy utility, Eskom. 15% of electricity generated by Eskom in 2024 was used by the mining industry [12]. Eskom tariffs are separated into groups depending on type of user and demand of the user. Most mines fall into the “Megaflex” tariff group, for urban users with a notified maximum demand (NMD) of greater than 1 MVA.

This tariff uses time-of-use (TOU) periods peak, standard and off-peak. Weekdays, Saturdays and Sundays each have a unique TOU subdivision, which also differs between the high demand season (winter) and the low demand season (summer). Public holidays are assigned either Saturday or Sunday in a yearly tariff booklet. Figure 1.1 duplicated from the Eskom tariff booklet shows the distribution of TOU periods for the two demand seasons.

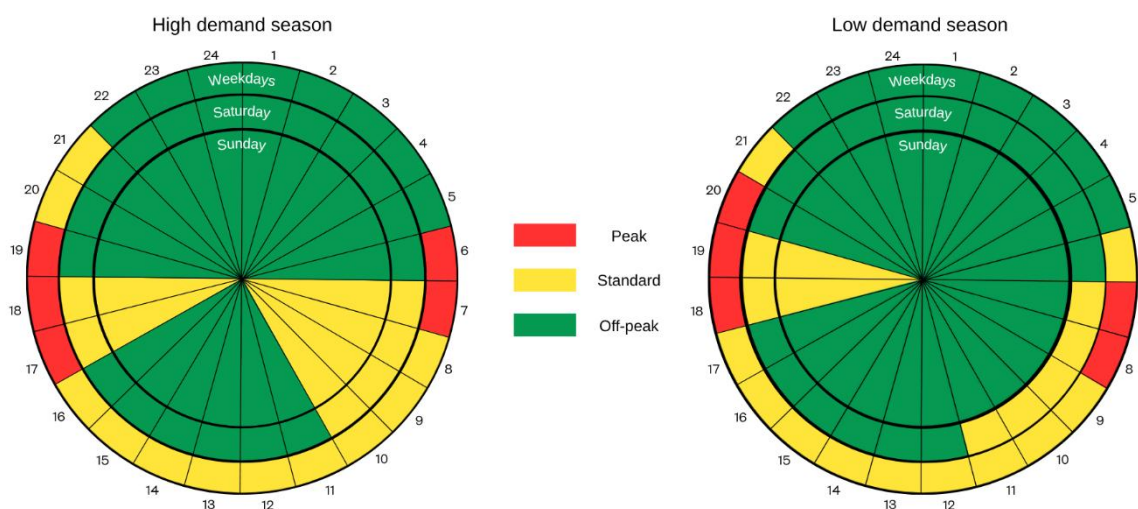


Figure 1.1: Eskom TOU time periods [13].

Megaflex tariffs are further grouped by the distance of the user in question from a central distribution point, and by the voltage of the user. Active energy is charged according to TOU utilised at the point of delivery (POD). Several additional charges are applied according to active energy use. These include the legacy charge, ancillary service charge, electrification and rural subsidy and the affordability subsidy charge. A charge is applied for network capacity according to the NMD, measured in kVA, and three charges are applied according to the utilised demand, network demand charge, generation capacity charge and transmission network charges. Administrative charges, the service charge and administration charge, are applied on a per POD per day basis. Reactive energy is billed in high demand season, for reactive energy supplied in excess of 30% when the power factor is 0.96 or less (determined per 30-minute interval), and only during peak and standard times. An example of these charges, as discussed, is shown in Table 1.1.

Table 1.1: Megaflex tariff structure example [13].

Transmission Zone	Voltage	Active Energy Charges [c/kWh]									
		High demand season [Jun-Aug]			Low demand season [Sep - May]			Legacy Charge	Ancillary Service Charge	Rural Network Subsidy	Affordability Subsidy
		Peak	Standard	Off-Peak	Peak	Standard	Off-Peak				
≤ 300 km	≥ 500 V & < 66kV	669,92	166,73	111,15	276,78	155,62	111,15	22,2	0,39	4,94	4,69

Additional network charges [R/kVA/month]			
Generation Capacity Charge	Transmission Network Charge	Network Capacity Charge	Network Demand Charge
8,09	10,25	35,98	24,17

Admin charges [R/POD/day]	
Service Charge	Administration Charge
1 118,46	19,37

Aside from measurements by the utility company at the POD, mines have many electricity measurements available [14], [15]. Most mines measure power distribution to different feeder lines, to groups of large equipment, and power meters are even found on individual pieces of equipment, like pumps or compressors.

Data from power meters may be collected and stored in many different ways. Most mines have a supervisory control and data acquisition (SCADA) system running. This provides a live view of data collected from throughout the operation. The SCADA system can also be used for control, to implement energy management initiatives. Data can be historised from the SCADA, to be stored long term or for later analysis. Data is often also available on online platforms.

1.1.2 Energy management in the South African mining industry

To remain profitable, mines have to manage their electricity consumption carefully. Mines employ several forms of energy management strategies in an effort to reduce their electricity consumption and the cost thereof. Energy management can be used to reduce electricity consumption. It is

successfully used globally to lower electricity costs and the environmental impact of high energy consumption [1], [16], [17], [18], [19].

In a literature review of energy management in industry, Schulze [19] found that existing energy management strategies can be aggregated into five overarching categories: Strategy/planning, implementation/operational, control, organisational, and cultural. The first three categories are commonly seen on deep-level mines. Energy management initiatives can offer either energy savings, cost savings, or both. These projects are typically applied to groups of energy intensive machinery or to individual machines.

Load shifting is an example of a cost-saving energy management initiative. Load shifting entails moving electricity consumption from more expensive to less expensive TOU periods. This results in lower electricity costs but maintains consistent electricity consumption. Load shifting is an example of a strategy and planning type energy management initiative [20].

Another form of energy management is the implementation of energy efficiency initiatives. These involve the improvement of system and equipment efficiency, lowering electricity consumption and associated costs. This can be done through system use optimisation, or through the installation of more efficient machinery. This is an implementation/operational form of energy management [20], [21].

Demand management is a form of energy management that optimises service delivery through monitoring demand and only providing services when there is demand for them. This falls into the control group of energy management strategies [17], [18], [22].

The International Organisation for Standardisation (ISO) has an existing standard for energy management, ISO 50001. The standard suggests a structured approach towards energy management and is implemented throughout wider industry and the mining industry [15], [23], [24]. This standard is applied to meet existing energy and environmental goals and to achieve electricity cost savings [25].

The standard, referred to as the “Plan-Do-Check-Act” cycle, is based on a process of continuous improvement. This separates the implementation of energy management projects into four distinct steps:

- Plan:
 - Set an objective
 - Identify key performance indicators
 - Develop an electricity usage baseline

- Do:
 - Implement the planned energy-saving initiative
 - Ensure training and awareness surrounding the applied initiative
- Check:
 - Measure and monitor the performance of the applied initiative
 - Evaluate the performance of the implemented initiative
 - Report the results
- Act:
 - Review management inputs on the evaluated performance
 - Implement adjustments to conform to set objectives
 - Continuous improvement

From this standard, several things are clear. A clear plan of future electricity usage is a key element for energy management. Performance measurement is required to evaluate the effectiveness of cost and energy-saving measures implemented on mines. Without a plan and continuous monitoring against the plan, success and continuous improvement of energy management projects is unlikely.

Electricity budgets are frequently used by mines as a baseline to measure energy management efforts, and to monitor electricity-related costs. In the context of ISO 50001, budgets are used to Plan future electricity usage and cost [26] and developed budgets are used to Check performance of implemented efficiency projects. Baselines are commonly developed and compared to actual meter data to evaluate the performance of an energy efficiency project [27].

Improvements in metering infrastructure and connectivity have led to a new generation of energy management: smart energy management [15], [28], [29]. This revolution is being driven by big data [30]. Mines are increasingly investing in the gathering of high frequency data, as well as the storage, processing and analysis thereof. This data opens up new possibilities for more advanced and automated energy management initiatives [31], [32], [33], [34]. The rise of better real-time data availability will require better planning and finer, higher frequency evaluation than ever before.

1.1.3 The role of electricity cost budgeting on mines

Budgeting can be used for operational planning, performance evaluation, goal communication and strategy formation [35]. In the context of mining, an electricity budget is a forecasted plan of electricity usage and the cost thereof for a future period. Annual energy cost budgets are also used for the same purposes in industries outside of mining, such as education [36], healthcare

[37] and city planning [38]. Many industries are adopting new methods to forecast and manage electricity consumption as industries are trending towards more data-driven systems [39].

Electricity budgeting is a commonly used instrument for energy management for mines, and can be used to identify opportunities for improvement or to monitor the performance of implemented strategies [40], [41]. Budgets are used to plan for electricity consumption and related costs (part of the ISO energy management standard). Budgets can also be used as a baseline to evaluate electricity consumption (Check). Cost management is of vital importance in the mining industry. It is therefore important that budgets are not only an accurate representation of the planned electricity consumption of a mine, but also of the associated costs [26], [40]. Outside of their applications within energy management, budgets are also used to account for planned changes in operation on mines, such as downscaling or growth.

Cilliers [42] highlights the importance of evaluating performance against a reference performance in order to understand attained achievements or shortfalls. The study specifically focusses on the importance of effective benchmarks for performance in deep-level mines. Electricity consumption budgets can be used as benchmarks to contextualise operational data on an ongoing basis. They can also be used for long term financial planning and for financial performance evaluation. Electricity budgets are intended to represent ideal performance of a mine for performance management purposes. They are idealised and may not account for unplanned events.

Currently, electricity cost budgets on mines are available in monthly intervals and used for month-end performance evaluation. Electricity consumption and cost values from invoices are compared to monthly budgets, and a conclusion on performance is made depending on whether the invoice value is over or under the budgeted value, and by how much. The performance analysis is thus done reactively, and the current structure cannot be used for real time analysis which could improve real-time energy management. Budgets are also heavily relied upon for financial planning on the mine, as electricity represents a significant portion of mines' operating costs [6].

From the combination of Section 1.1.2 and Section 1.1.3, we can see that mines need energy management to manage challenges in cost and electricity availability. It is also clear that electricity cost and consumption budgets are of integral importance on mines. With improvements in data, there is an opportunity for improved energy management, or "smart" energy management. Mines need electricity consumption budgets as part of their energy management strategy, to evaluate the performance of implemented initiatives effectively in order to take action to correct or further improve operation. For this, mines will need improved electricity consumption and cost budgets.

1.1.4 Background on mine budget structure

For the purpose of this study, it is important that the structure of budgets is clearly defined. This will provide a foundation for understanding both the research problem and research methodology.

Mine electricity consumption and cost budgets form an integral part of the annual mine financial budgeting process [40]. This planning is typically conducted on an annual, year-ahead basis. Mines currently budget for costs and consumptions per POD invoice, with some mines breaking down budgets to consumptions and costs per energy-intensive system [43].

Mine budgets are seasonally dependent. This is due to different needs depending on weather patterns, such as lower refrigeration need during colder weather. Eskom also split their tariffs into a high and low demand season. Electricity costs are thus also seasonally dependent, even if the systems they represent have stationary operational patterns.

These conditions of mine budgets are fixed requirements within mines' planning frameworks. Any proposed improvements to mine budgeting practices must produce outcomes that remain compatible with these established parameters.

1.2 Identification of the research problem

1.2.1 Improvements in electricity monitoring equipment and systems

From the background section, it has been established that mines need budgets to monitor and manage implemented energy management initiatives effectively. It is also clear that there is growth in the field of electricity metering, enabling more advanced energy management strategies [44]. For these strategies to be feasible, high quality electricity consumption and cost budgets need to be available so that real-time evaluations can be done. A lack of real-time evaluations limits proactive action, making it difficult to identify and address issues.

The mining industry has seen a significant growth of data availability in recent years. Mines are investing in better metering to improve safety, productivity and environmental sustainability [45]. There has been a marked increase in “smart” meters in industry providing near real-time data [29].

This can be due to reduction in price of metering instrumentation, and is largely driven by the move towards digitisation in the face of the fourth industrial revolution [15]. Improvements in sensor technology allow for higher quality and higher frequency measurements [46]. Advancements in network technology are facilitating the collection and transfer of data collected in underground mines [14].

More data from more meters creates a wealth of opportunities for monitoring and data analysis. It removes uncertainty from operation, allows for more advanced measurement and verification practices to be used, and overall provides an opportunity for improved energy management [29], [27]. Improved metering also introduces an opportunity for improved electricity consumption forecasts [47].

There have been studies focussed on improving how project baselines are done, but they do not take in to account the overall electricity consumption budget of the mine, even though they cannot function independently from the larger financial plan.

1.2.2 Lack of improvements in energy management and budgeting practices

In the face of all the described opportunities afforded by improved metering and data availability, it is concerning that energy management practices on mines have not been advancing in line with the developments in industry [15]. From industry observations, there have also not been corresponding developments in budgeting as have been observed in measured operational data. For mines to capitalise on the opportunities offered by smart energy management, improvements in the quality of electricity consumption and cost budgets are needed.

Goosen [40] suggested a method to improve mine cost budgets in 2015. The study suggested using profile-based budgets for performance evaluation and applying Eskom TOU for cost calculations. This suggests that neither of these were common practice in industry. The study provides valuable methods, but no considerations for how the method should be applied in practice on scale. Little uptake of the methods described in this study have been noted in practice.

van Aarde [24] found that the budgets used on mines in South Africa may be inadequate due to their lack of accounting for operational changes. The study noted that there is no set criteria for the evaluation of the validity of the budgets used. The study incorporated existing M&V principles into the budgeting process in order to plan better for operational changes.

The study did not evaluate existing budgets in practice. While the budget developed in the study was high frequency and costed according to TOU, no indication was given that this was due to the frequency of the actual data. The study also did not put forth a framework for how to develop budgets. As a result, despite the publication having been available for four years, no uptake of the literature has been noted in practice.

Several studies centre around benchmarking for project evaluation on mines [42], [49], [50]. These often touch on energy management as part of the goal of the benchmarking. While several of these studies produced repeatable methods to compile benchmarks and baselines, they only focus on the energy impact. When they do include cost, it is not in detail. These studies also all

focus on single systems or commodities, and do not provide long term forecasts for the entire mine.

The need for high-quality electricity consumption and cost budgets is discussed in detail in Section 1.1.2 and Section 1.1.3. In short, energy management is reliant on a circular process of planning, implementation, checking and adjustment. Budgets are used to plan for both electricity consumption and cost, and later in the process to evaluate the performance of implemented initiatives. This allows for the identification of non-conformance to plans in real time, so that operational adjustments can be made and targets can be achieved.

Budgets are less useful tools for energy management if they do not align with available actual data quality and frequency. The following section will investigate why budgets in the mining industry are not keeping up with developments in data availability and energy management technologies and will identify barriers to be overcome to address this. Available methods and data are not utilised towards the creation of high-quality budgets.

Budgets need to keep up with actuals to be effective, but as actual values keep evolving, this is a moving target. The objective the budgets need to meet is thus nonstationary. There is no established method for the evaluation of the objective to understand the needs for the budget to be developed. There is also no framework for the development of the budget that will overcome the barriers faced by industry that prevent high-quality budget development.

1.2.3 Development of budgeting best practices

The content of this section was published by the author as an article in the journal *Mining* [51]. A copy of the article is attached in Appendix A.

To show that budgets developed in industry are not high quality, a baseline of what a high-quality budget looks like is required. This section will determine the characteristics of a high-quality electricity budget from literature and expand upon it based on industry knowledge. The analysis will identify best practices for a high-quality budget that can be used as an effective instrument for energy management. The developed best practices will be used to conduct surveys in Section 1.2.4. The results will demonstrate that current budgeting practices on mines often fall short of these best practices, limiting their usefulness for both financial planning and operational decision-making.

Particular attention is given to the barriers that prevent the consistent application of best practices, highlighting the shortcomings that undermine budget quality. By identifying these barriers, the section will establish a clear basis for assessing how the proposed framework can address existing deficiencies and improve the role of electricity budgets in energy management.

The goal of this section is to establish what a high-quality electricity and cost budget for a mine should be according to literature. This will allow for the establishment of a set of best practices for the development of high-quality electricity cost budgets.

This section will present a narrative literature review with an overview of existing literature in electricity cost budgeting in South Africa to identify the steps used to construct existing budgets. Additional literature per step will be gathered to establish what the actual data may look like, and then to establish what a budget would need to match up best with this actual data.

Known studies from industry were used as a basis for this literature review. The foundation set with these known studies was expanded upon by searching for additional literature. The following databases were searched, and papers with relevant titles from the first 20 results were selected for further investigation:

- Science Direct
- IEEE Xplore
- Google Scholar

Keywords used for the search are given in Table 1.2. The core keywords used were forecasting and variations on the term, with * used as a wildcard in the search to allow for variations at the ends of the words. Two pre-modifiers were used, ensuring that every version of electricity consumption forecast description was covered. Method was used as a post modifier, as this section is focussed on methods for forecasting. Note that a more comprehensive literature study on electricity forecasting is presented in Chapter 2.

Table 1.2: Literature review keywords for existing budgeting methods.

Pre-modifier 1	Pre-modifier 2	Core keywords	Post modifier
Energy	Consumption	Forecast*	Method*
Electricity	Usage	Budget*	Practice*
Electrical		Benchmark*	

The practice of electricity forecasting is widely used throughout industry. The role of it in energy management is also well established [52]. The study identified increasing complexity in the techniques used in forecasting, reinforcing the need for current methods to be reevaluated.

One study was found that is focussed on energy forecasting for South Africa:

Krishnamurthy et. al. (2024) - Artificial intelligence-based forecasting models for integrated energy system management planning: An exploration of the prospects for South Africa [53]

The study primarily investigates the role of artificial intelligence (AI) based forecasting models in advancing energy production planning. It highlights the need for smarter energy resource management to address challenges such as balancing supply and demand and ensuring efficient use of energy sources. The research aims to support grid stability and recognises that reliable forecasting is key to managing energy supply. The study discussion remains at the level of technical modelling and systems level planning.

While the study offers valuable insights into forecasting, its emphasis is on energy production forecasting, rather than energy consumption. As a result, the study stops short of outlining how forecasts should be structured, standardised, or applied to practical budget development processes, leaving a gap between advanced forecasting capabilities and their integration into consumption budgeting and energy management practice. The study does not give any guidelines for the development of budgets in the mining industry.

Two studies relating directly to energy budgeting on mines in South Africa were identified:

Pelser (2021) - Improved energy budgeting process for mines using measurement and verification principles [48]

The study presents a structured analysis of the energy budgeting process in mining operations, with emphasis on identifying and formalising the steps involved. The study uses a methodology that parallels the budgeting process with principles of measurement and verification (M&V), suggesting that the methods can improve the accuracy and transparency of budget development. It suggests targeted improvements to existing processes that should lead to more accurate and accountable energy budgeting in the mining sector.

While the study makes a valuable contribution, it does not evaluate the effectiveness of the resulting budgets as they relate to energy management efforts. The study also does not set any best practices for budget development. This absence limits the relevance of the study. It does, however, provide a foundation upon which future research in the field can be built.

Goosen (2015) - A method for accurate electricity budget cost calculations for a deep mine [40]

Goosen (2015) found that the budgets used by mines have vastly oversimplified electricity costing. Despite the age of this study, this still rings true in industry. The study suggests new methods and improvements for calculating electricity cost budgets, factoring in key metrics such

as TOU and seasonal differences in electricity costs. The study further emphasises the importance of accurate costing for budgeting purposes.

While the methodology touches on cost forecasting for mining operations, it does not cover the development of electricity consumption budgets. The study improves budgeting accuracy in a narrow context, but does not provide best practices or evaluation metrics for budget development.

From these studies, six key steps to the development of a budget for a mine could be distilled. They are described below in Table 1.3.

Table 1.3: Underlying best practice budget development steps from literature.

Step	Description
1. Inform	Choose the boundaries and data resolution for the budget.
2. Data	Gather data to construct.
3. Evaluate	Establish expected changes to the baseline.
4. Develop	Create the budget using the gathered information.
5. Convert	Assign costs to the developed usage budget.
6. Report and approve	Formally report the final budget and obtain required approvals.

Using these identified steps as a basis for best practice of budget development, further investigation and scrutiny was applied to each step. Literature was used to investigate actual data availability for each section and to determine what the actual data on a mine may look like. This was then used to adapt the steps from literature in the best way to be applicable in industry.

Step 1: Inform

Before starting with budget creation, it is important to define the scope and the intended purpose of the budget. This involves determining the areas the budget will cover, a process called boundary selection by the reference studies. Pelser [48] proposes a decision tree to guide this step, offering a choice between a single budget for a full facility or a component isolation approach. Notably, Pelser does not include energy management or performance evaluation as factors in the selection process.

In contrast, studies focussed on advanced energy management on mines recommend the isolation of energy-intensive systems during evaluation [24], [23]. This is possible due to widespread installation of meters on electrical feeders on mines, enabling system level monitoring. Monitoring of systems is more effective than monitoring individual machines, as maintenance and outages of individual components do not affect the availability of data. Individual components may be instrumented and can provide more detail data. Ultimately, the best budget

will be one that best aligns with the actual electricity consumption data availability and implemented energy management initiatives.

To determine the appropriate budget resolution, Pelser [48] employs another decision tree. It considers whether the budget will be used for performance evaluation and whether component operation varies throughout a given day. This study specifically aims to improve budgets for use for performance evaluation purposes. Budget resolution should thus match the interval of the available operational data. Due to the dual role of budgets in both cost management and performance evaluation, the budget should be at least half-hourly, aligning with Eskom's highest billing interval [13]. For cases involving other utilities or billing structures, the budget resolution should reflect the frequency of those billing systems. Ideally, input data resolution should be either equal to the actual data availability, or at least half-hourly, whichever is higher.

Step 2: Data

The second literature step in the budget development process involves acquiring and evaluating the relevant data. This data must be traceable to calibrated meters so that its origin is verifiable and should undergo thorough checks for consistency and quality. The integrity of the budgeting process is heavily dependent on the reliability of this data. As noted in literature, poor quality inputs directly lead to poor budget outputs [54].

Electricity consumption data should be used as the main form of input data. Studies show a weak correlation between overall mining production, such as tonnes mined or tonnes hoisted, and electricity consumption across most mining systems [48]. This is due to most energy-intensive systems operating independently from the production of material.

Production forecasts may still be valuable for estimating the consumption of systems that are directly tied to material production, such as rock hoisting or ore processing [16]. Outside of these exceptions, electricity consumption data is the most reliable and consistent foundation for budget development.

Step 3: Evaluate

The third step in the budget development process focusses on creating and refining the electricity consumption baseline. This involves incorporating anticipated energy efficiency initiatives and operational changes so that the budget is reflective of planned developments and not only historical data. The adjustments must be made from relevant information gathered from credible sources.

Accurate forecasting depends on detailed knowledge of planned equipment additions or removals, the opening of new mining areas, and any planned up- or downscaling of operations. Deviations of electricity consumptions to past budgets may be studied and used to evaluate whether changes are needed. For systems directly tied to production levels, scaled increases can be made based on production forecasts [16].

As specialised knowledge of the future plans of the mine is required for this step, the budget developer must be actively involved in future planning, and the mine must plan interventions at least a year ahead.

Step 4: Develop

The development step integrates insights from the preceding three phases of the budget creation process. This step, like the previous ones, must also be done by an individual with sufficient knowledge of the mining operation. This knowledge is critical for the ultimate accuracy of the produced budget. Mines typically have real-time data available [55], allowing for detailed consideration of the TOU electricity tariffs. Changes between the baseline and budget period in TOU, such as number of weekends versus weekdays in a month, the presence of public holidays and leap day must be considered and adjusted for.

For the budgeting process to be effective across different operations, the method must be scalable and capable of handling high-resolution inputs and outputs regardless of the size and complexity of the mine. Adaptability is very important for achieving reliable electricity forecasting, especially when working with large datasets [56], [57]. A flexible approach enables consistent accuracy and relevance of the method.

Step 5: Convert

Step 5 involves assigning costs to the components of the electricity budget developed in the previous steps. Costing must be done according to the relevant utility, in this case Eskom Megaflex [13]. To ensure accurate cost allocation, budgets must be compiled according to utility grouping such as Eskom POD, consistent with official utility bills. All electricity consumption from downstream systems should add up to the respective POD. This allows for budgets to be created per energy intensive system as required by the Input step.

Active energy costs can be assigned directly to budgeted electricity consumption. Additional fixed costs should be allocated proportionally to the energy-intensive systems. Details of the cost breakdown are available in Section 1.1.3. Generating separate effective tariffs per energy intensive system accounts for differences in usage patterns across systems which often leads to

different costs due to TOU. Cost breakdown should be itemised according to the utility structure for maximum transparency of the process.

Step 6: Report and Approve

The final step of the budget development process from literature sources involves reporting and obtaining approval for the completed budget. This phase includes thorough documentation of both the development procedure and the validation of results, which is essential for ensuring accuracy and transparency.

Validation should be conducted by comparing the newly developed budget against historical budgets and actual consumption data to check for consistency and identify deviations. Any discrepancies from the baseline input data must be clearly documented, including changes arising due to TOU. To promote understanding of the developed budget and support informed decision making, the budget results must be presented in a clear and concise format and supported by visual aids [58].

Findings summary

In short, the finding from literature is this: for accurate and high-quality budgets, the input data used needs to also be accurate and of high quality. Care should be taken with the identification, collection and cleaning of the data to be used. Data should be in high enough intervals to be comparable to actual electricity consumption data and should be separated into groups representing energy-intensive equipment.

To ensure accurate and scalable electricity cost budgets, adjustments to the baseline need to be informed by planned changes in consumption to energy intensive systems. It is also important to account for differences in the TOU between the baseline and future budgeting period. These adjustments should be overseen by an individual or team with expertise in the mines' electricity consumption patterns, ensuring that the process is reflective of reality and grounded in technical knowledge.

Once adjustments are complete, costs should be assigned to the created electricity consumption budget using the appropriate utility costing structure. The resulting budget should then undergo a validation process, using historical data and planned changes to confirm its accuracy and reliability.

Any modifications made to the input data during the budget development process should be thoroughly documented to maintain transparency and enable future auditing or review processes. Following validation, both the budget and its supporting documentation should receive formal

approval from a responsible authority. The finalised budget should then be reported in an accessible and easily understood format, ideally through visual tools or dashboards that encourage interpretation and engagement.

The budgeting process, as identified in the literature, can be sectioned into three core components, as seen in Figure 1.2:

- Input: Involves gathering and evaluating all the needed data and information relevant to the budgeting process.
- Method: Refers to the transformation of the input data into electricity consumption profiles and cost estimations.
- Output: Entails communicating the results derived from the method to the appropriate individuals.

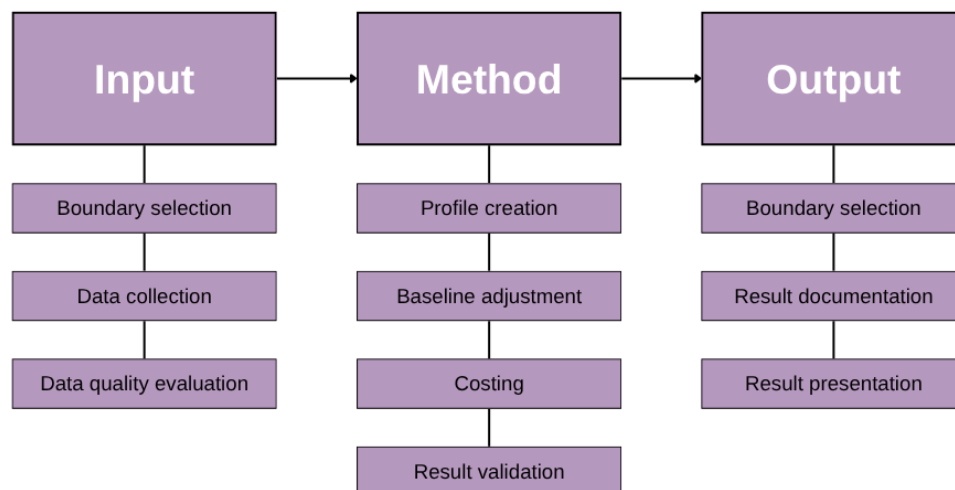


Figure 1.2: Budget process flow chart.

From these three main steps and the literature section preceding it, best practices for the creation of high-quality electricity consumption budgets were synthesised from literature.

Electricity cost and consumption budget development best practices:

Input

The budget input component serves as a foundation for the budget development process, where relevant data is collected and system boundaries are defined. To ensure the success of the resulting budget, the following best practices should be applied:

- a Budgets should be developed per energy-intensive system.
- b Input data should be in at least a half-hourly resolution.
- c Input data should be of verifiable quality.
- d Electricity usage data should be used for most systems. Production data can be used for systems directly related to processing or hoisting.
- e Relevant data should be used to adjust the historic electricity usage baseline.

Method

The method section of the budget involves the transformation of input data into an electricity usage and cost budget. This includes incorporating planned operational changes to the baseline values. To ensure the success of the resulting budget, the following best practices should be applied:

- a Budgets should be developed by a person with established knowledge of the energy management systems of the mining operation.
- b Time-of-use should be accounted for in the development of the electricity budget.
- c Tariff structures from the relevant utility company should be used to assign costs to electricity forecasts. In the case of most South African mines this is the Eskom Megaflex tariff structure.
- d The budgeting method should be scalable and adaptable.
- e Developed budgets (electricity and cost) should be validated before being presented for use.

Output

The output section of budget development includes reviewing, approving and presenting the developed electricity and cost budget. To ensure the success of the resulting budget, the following best practices should be applied:

- a The developed budget should be available per energy-intensive system.
- b The developed budget should be available in at least an hourly resolution.
- c Costs and effective tariffs should be available per energy-intensive system and should have different tariffs according to their operation.
- d Planned deviations from historic electricity usage patterns should be well documented for traceability.
- e Developed budgets should be presented in a concise manner and visualised in an appropriate way for the intended audience.

In summary, the outlined best practices present a structured metric that can be used to evaluate whether a budget is transparent, consistent and traceable. The next step is to examine whether these best practices are actively applied within industry. This will be done in the form of a survey.

1.2.4 Industry standard budgeting practices: Survey development

The surveys used in this section were developed and conducted as part of an article by the author for the journal *Mining* [51]. The article details the survey development and research approach. This section is a summary thereof; the article can be seen in Appendix A.

This section will take the developed best practices from the previous section and use them to construct a survey that can be used to evaluate existing budgeting practices on mines. The survey will be used to identify barriers preventing mines from implementing best practices and achieving high-quality budget outputs in industry. Participants were selected based on two criteria: a minimum of two years' experience with mine budget creation, and a working knowledge of the complete mine development process. To prevent bias, the survey presented clear, neutral questions derived from the literature review. All responses were collected anonymously.

Representatives who conform to the abovementioned criteria were identified from several deep-level gold and platinum mines and invited to participate in this survey. Prior to survey administration, the research problem was briefly introduced to each participant. Following completion of the questionnaire, a discussion was held to explore any deviations from literature best practices and the underlying reasons for the discrepancies. A summary of the questions asked and the components of budget best practices addressed by each question is given in Table 1.4.

Table 1.4: Survey questions and budget components evaluated.

Question		Budget component/s evaluated
1.	To what level of the operation is the budget separated?	Input (a), Output (a)
2.	What is the resolution of the budget?	Input (b), Output (b)
3.	How is the quality of the input data ensured?	Input (c)
4.	What input data is used in the budget creation process?	Input (d), Input (e)
5.	How are planned changes budgeted for?	Input (f)
6.	Who is responsible for budget development?	Method (a)
7.	Are adjustments made to account for changes in TOU in the future budget period?	Method (b)
8.	Is costing done using the official Eskom tariff structure?	Method (c)
9.	How time consuming and labour-intensive is the current budgeting process?	Method (d)
10.	How is the budget output validated before use?	Method (e)
11.	Is costing split into beyond POD level, and if so, how?	Output (c)
12.	Are changes to the budget baseline documented?	Output (d)
13.	How is the budget presented?	Output (e)

The developed survey was used to assess whether the budgeting practices of 41 mine business units are yielding high-quality budgets that align with available real-time electricity consumption data and that can be used effectively to evaluate electricity consumption. The evaluated operations belong to prominent mining companies in South Africa.

1.2.5 Barriers to the development of high-quality budgets in industry

The following section presents the results from the survey conducted across 41 mine business units. These findings offer insights into the extent to which industry standards align with literature best practices. Examining the patterns of behaviour and deviations from best practice will allow for identification of barriers to high-quality budget development, as well as areas where improvements will have the most impact. Figure 1.3 gives a breakdown of the feedback for the Input section of the survey. Full questions and response options can be seen in the article by the author in the journal *Mining* [51] and in Appendix A.

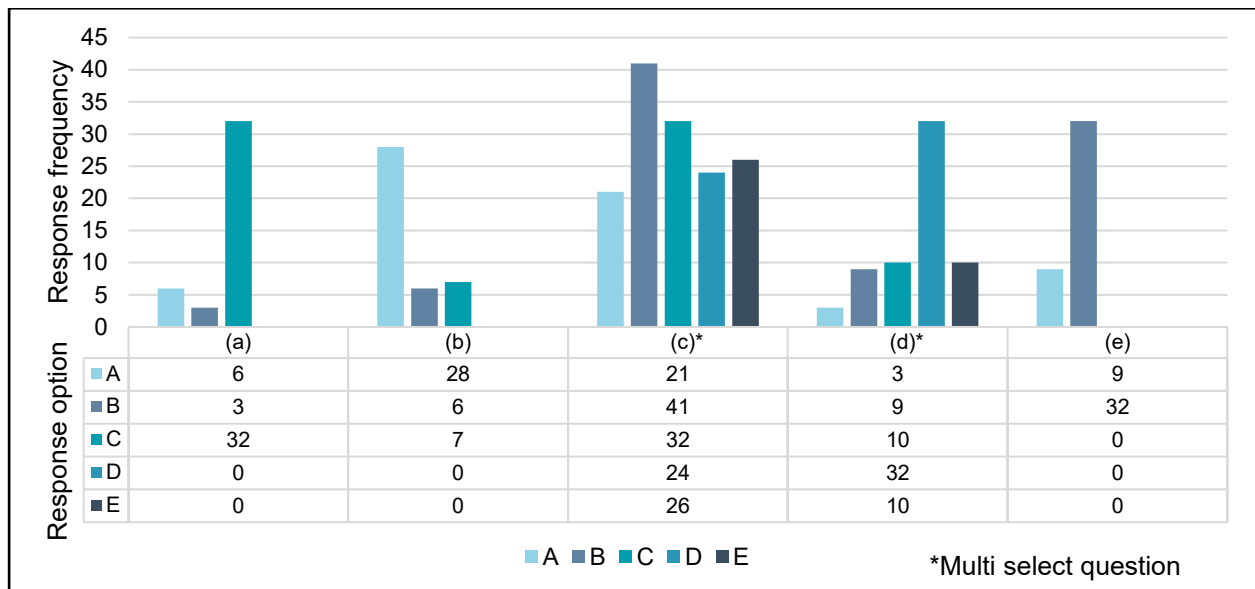


Figure 1.3: Input section survey results.

- a Most of the surveyed mines (78%) develop electricity budgets per energy-intensive system, in alignment with best practice recommendations. The remaining sites construct budgets either per feeder, or for the entire POD. 85% of mines separate input data to at least a feeder level, which meets the minimum requirement for effective budget development.
- b Monthly data input is the predominant resolution used in the budgeting process across the surveyed business units. Only seven mines reported using half-hourly data, which is the recommended resolution according to the literature best practices.
- c The quality of input data used in electricity cost budgeting was determined to be high across the surveyed mines. All the participating mines use third-party metering companies (response option B in Figure 1.3), where data quality is contractually enforced. Additionally, half of the business units also report using calibrated meters. To meet best practice standards fully, the budgeting process should incorporate at least two independent data checks, which all participating mines did.
- d Electricity consumption data is used by 78% of the sites as their primary input data, as recommended by best practices. Nine of the sites based their projections solely on production scaling, which deviates from literature best practice, particularly when applied to systems not directly linked to hoisting and ore processing.
- e Similarly, 78% of the sites planned for future changes using projected electricity increases per system, while nine only scaled up or down according to their production projections. Production scaling for systems not directly related to ore transportation and processing is not aligned with best practices.

While the surveyed mines generally utilise appropriate types of data for their input, on correctly identified boundaries and with high-quality data, the resolution of input data remains a critical shortfall. Monthly budgets are insufficient for effective energy management in an age where real-time electricity consumption data has become the norm. Further, the Eskom Megaflex tariff structure is built around hourly and half-hourly data intervals. Budget data can thus not be accurately costed in monthly intervals.

All surveyed sites reported access to at least hourly data intervals for systems requiring energy management, and approximately 61% have real-time data available. This indicates that the capacity for developing high-resolution budgets exists. The underutilisation of this data is reported to be mostly due to time constraints. Addressing these constraints would enable the use of high frequency input data (at least hourly), allowing for the development of high-quality, high-resolution electricity budgets that can be used for advanced energy management.

The developed survey questions proved effective in capturing the necessary data regarding the input data used in budget development on mines. Figure 1.4 gives a breakdown of the feedback for the Method section of the survey. Full questions and response options can be seen in the article by the author in the journal *Mining* [51] and in Appendix A.

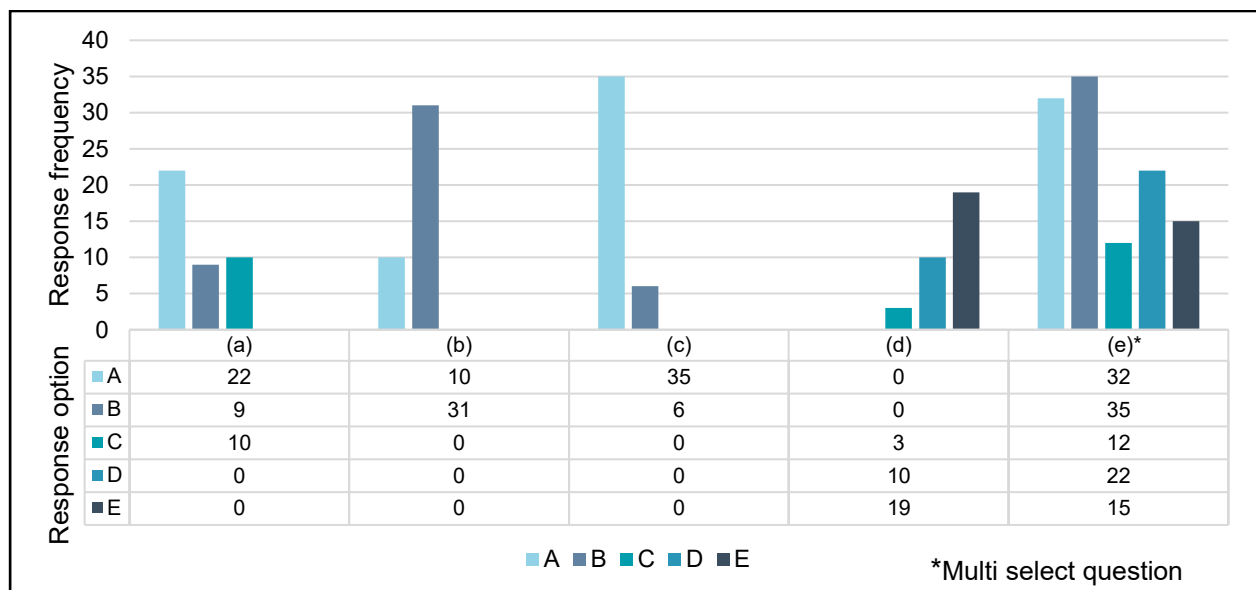


Figure 1.4: Method section survey results.

- a In most surveyed mines, the engineering department is responsible for developing the electricity cost budget. In the remaining cases budgets are prepared either by financial departments or by third-party companies contracted for energy management services to the mines. According to best practice, the engineering department of a mine must play a central role in budget development, as the process requires both technical expertise and operational insight.

- b With a majority of mines using monthly input data, TOU costing in detail is lacking. 68% of mines did costing on a monthly basis, which is not in accordance with best practices.
- c Budget costing methods were found to be largely uniform across surveyed mines. Typically, historical percentage splits of TOU periods are applied to budgeted active energy values, and then combined with fixed charges and adjusted for anticipated tariff increases. Only six of the 41 sites incorporated detailed TOU costing according to the Eskom tariff structure, made possible by the fact that they used high frequency input data to create the budget.
- d Respondents rated their budgeting process as highly time consuming, with an average score of 9 out of 10. This suggests that current methods lack scalability and may not be easily adapted to broader applications, higher frequencies or additional systems.
- e Budget validation is widely implemented, with 85% of sites employing at least two validation methods. The most common approach involves comparing the developed budget to past actual consumption and budget values. Both internal and third-party validation is used throughout industry. Despite these measures, errors persist, primarily due to human error which is compounded by the volume of budgets developed in a short period of time and the reliance on excel-based workflows with a lack of embedded error checking.

Findings reveal that in some cases, electricity consumption budgets are developed by financial departments lacking the technical expertise to account for operational changes. While most mines utilise Eskom tariff structures for their costing, few incorporate TOU in high detail in their costing. The methods used are generally not scalable, contributing to the limited availability of high-resolution budgets seen in practice.

A key shortcoming identified in the method section is the insufficient level of detail in electricity cost forecasting. This limitation stems directly from the low-resolution input data that is used to create the budgets. Given that tariff structures and cost components are well defined, detailed costing can be automated easily. Using high-resolution input data would also enable more accurate budget forecasts, especially where planned changes in electricity usage are expected. Figure 1.5 gives a breakdown of the feedback for the Output section of the survey. Full questions and response options can be seen in the article by the author in the journal *Mining* [51] and in Appendix A.

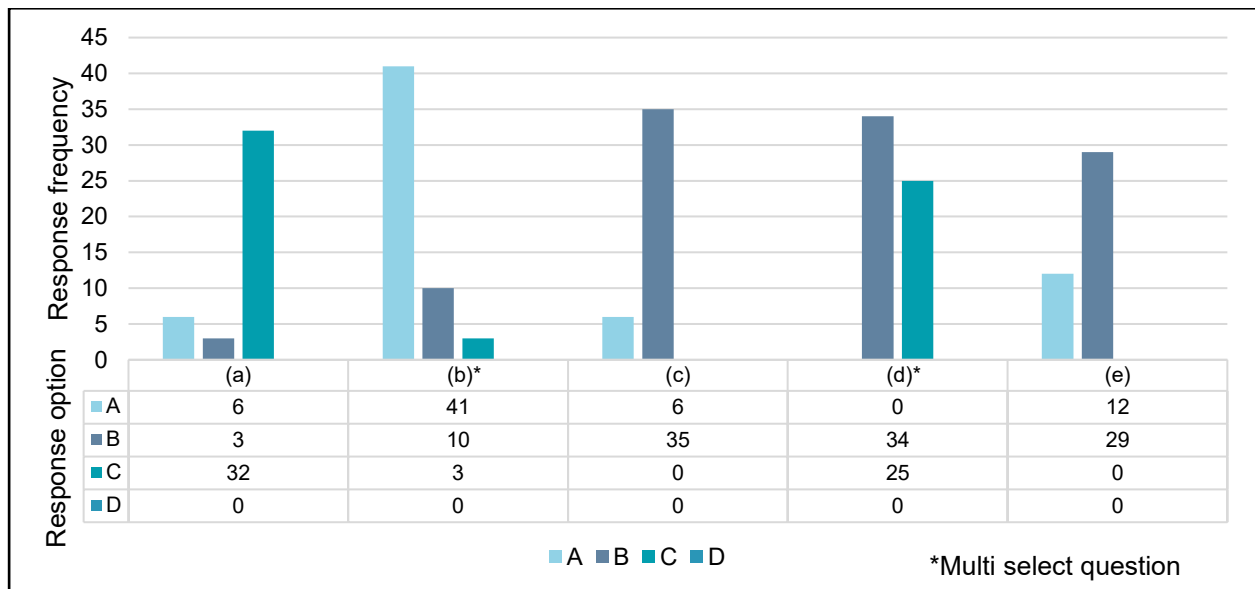


Figure 1.5: Output section survey results.

- a Consistent with results from the Input section and the input data used, 85% of surveyed mines develop their electricity budgets per energy-intensive system or feeder. This aligns with best practices to ensure that evaluation is possible on a systems level.
- b Budgets were predominantly developed in a monthly resolution, in line with the frequency of the input data. All participating business units presented their budgets in monthly formats, even when there was higher resolution data available. While some sites utilised daily input data for pre-processing checks like data quality and cleaning, they ultimately developed monthly budgets. Out of the 41 sites, ten developed daily budgets, and three developed half-hourly budgets.
- c Most mines divided electricity costs into systems. This was typically done by proportionately splitting the costs according to the electricity consumption of a system, not according to TOU. Only six out of the 41 sites applied detailed TOU-based costing with individual tariffs per system.
- d Formal documentation of changes made to baseline data during the budget development process was limited, with only 29% of mines producing such documents.
- e All participating mines visualised the results of their budgeting processes in some way. Most sites adapted the format of their presentation based on the target audience, as recommended by best practices. 82% of mines presented a combination of visuals and values, which was found to be the most effective for communicating complex information.

The survey questions effectively assessed the extent to which mines' budget outputs align with developed literature best practices. Budgets are generally separated into energy-intensive

systems mirroring the data input used and adhering to best practices. Limitations in input data resolution prohibited the development of high-resolution budget outputs. While cost allocation to systems were found to be common, the method of cost allocation does not align with best practices, as it does not account for differences in TOU. Documentation of the budget process for accountability and repeatability were found to be lacking across most sites. Reporting of the budgets, however, is effectively done and in line with literature best practices for most sites.

Survey result summary

Survey findings indicate that the monthly budgets currently produced by South African mines are not suitable instruments for real-time energy management and performance evaluation. Budgets developed by the participating mines had significant shortcomings both in future consumption and cost estimates.

The survey results found that the best practices as established in Section 1.2.3 are not consistently implemented in practice on South African mines. This results in the mines developing budgets that cannot be used as effective instruments for proactive real-time energy and cost management.

Table 1.5 summarises the findings of the survey done in the aforementioned article [51]. Each best practice per section of budget development is rated for its performance in industry, as per the surveys performed. Green equates to more than 80% of business units surveyed conforming to the best practice, thus passing. Orange equates to 50% - 80% of business units conforming to the best practice, and red equates to less than 50% of business units conforming to the best practice, thus failing.

Table 1.5: Survey result summary.

Section	Focus area		Pass/fail
Input	(a)	Budgets should be developed per energy intensive system.	Pass
	(b)	Input data should be in at least an hourly resolution.	Fail
	(c)	Input data should be of verifiable quality.	Pass
	(d)	Electricity usage data should be used for most systems.	Fail
	(e)	Production data can be used for certain systems.	Fail
	(f)	Relevant data should be used for adjustments to the baseline.	Fail
Method	(a)	Budget should be developed by an informed person.	Fail
	(b)	TOU should be accounted for.	Fail
	(c)	Relevant tariff structure should be applied.	Pass
	(d)	Method should be scalable and adaptable.	Fail
	(e)	Results should be validated.	Pass
Output	(a)	Result should be per energy intensive system.	Pass
	(b)	Result should be in at least hourly resolution.	Fail
	(c)	Cost and tariff should be separate per system.	Fail
	(d)	Deviations from historic patterns should be documented.	Fail
	(e)	A report of deviations should be compiled.	Fail
	(f)	Results should be well presented and visualised.	Pass

The evaluation of budgeting practices against key quality criteria revealed mixed results.

Input:

Budgets are generally developed per energy-intensive system, which aligns with best practice and supports accountability in energy management. Similarly, the quality and verification of input data were found to meet acceptable standards, indicating that mines have established adequate procedures for ensuring data reliability. Significant shortcomings were identified in the resolution of input data. Most budgets were based on monthly or daily data rather than the recommended minimum of hourly intervals, limiting their usefulness for detailed analysis and proactive management. Over half of mines used electricity consumption data as input, but it was not a universal practice, and production scaling was still found to be prevalent. Production data and other relevant operational metrics were incorporated inconsistently, particularly in relation to baseline adjustments.

To improve overall budget quality, mines should prioritise the use of high-resolution data and ensure that electricity consumption data used as input for the budget development process represents all major systems.

Method:

Budgets are mostly developed by personnel with some knowledge of mine operations, though not always by individuals deeply informed about energy systems and their dynamics. The application of the relevant tariff structures was consistently executed, with most mines correctly implementing the utility's cost framework. Two major areas of concern were identified. First, TOU considerations were largely absent from current practices, despite their importance in accurately representing cost variations throughout the day and improving energy management decisions. Second, the methods used were found to lack scalability and adaptability, indicating that existing processes cannot be easily applied to more detailed datasets or across operations of varying complexity.

To improve budget quality, mines must incorporate TOU in detail in their costing processes. This can only be done if the budget is developed using high-frequency data from the start. Mines must also reduce reliance on manual methods so that their budgeting processes can be made more scalable, especially to accommodate higher frequency data.

Output:

The evaluation of the outputs produced by current budgeting practices revealed several critical weaknesses, despite some positive elements. Budgets were successfully produced per energy-intensive system, allowing for system-level visibility and accountability. Similarly, results were generally presented and visualised effectively, supporting clear communication of findings to management. The majority of other criteria in this category were not met. Most notably, results were not generated at hourly or higher resolutions, limiting their usefulness for operational decision-making and short-term performance evaluation. Costs and tariffs were not separated per system, which prevents accurate attribution of expenses and obscures the contribution of individual systems to overall electricity costs. It is notable that budget accuracy was not reported as a problem. Deviations from historical patterns or input data baselines were infrequently documented, and formal reports of such deviations were not compiled.

To improve the quality and practical relevance of outputs, future budgeting practices should prioritise higher-resolution results, implement system-specific cost breakdowns, and introduce structured procedures for documenting and reporting deviations from historical baseline consumption patterns.

The collective assessment of current budgeting practices revealed several recurring shortcomings that limit the quality and usefulness of electricity budgets in the mining industry. Across the evaluation criteria, a consistent pattern emerged. Four main barriers to best practice budget development and implementation were identified:

1. Budget resolution, both in input data and output result.
2. Lack of scalability and adaptability of the budgeting method.
3. Detailed costing, both in the method and the output result presentation.
4. Documentation and traceability of the budgeting process.

Addressing these four barriers requires the establishment of a structured, scalable, and adaptable framework that enables consistent application of best practices across operations. Such a framework should integrate the barriers identified in this survey, aligning industry practice with literature-based standards to produce actionable and cost-accurate budgets. By streamlining data handling, incorporating automation where feasible, and embedding processes for validation and verification, the framework would bridge the gap between technical capability and practical implementation. Improving the quality and traceability of electricity budgets will strengthen their role as instruments for real-time energy management in the mining sector. Improving budgets in this way addressed the identified problem by making use of all available data and methods and producing high-quality budgets.

Problem statement:

Mines are developing and implementing electricity cost budgets that are low resolution, have limited scalability, with costing in insufficient detail and with poor documentation for traceability. A framework is required to drive the implementation of improved budgets.

1.3 Aim and objectives

The previous section highlighted the nature of the problem this study will focus on. We know and can prove from existing literature that actual data quality and availability on mines is improving. It was shown that budgets are not showing corresponding improvements and are not high quality. Four barriers to the development of high-quality budgets in practice were identified. Identifying existing solutions to address the identified obstacles will enable the development of a framework that can be followed to create high-quality electricity consumption and cost budgets.

The study aim is to develop and test a framework to construct electricity cost budgets for mines. Three objectives have been identified to achieve this aim. Table 1.6 gives a summary of the objectives identified for this study, the methodologies that will be followed to achieve them, and the deliverables expected from each objective.

Table 1.6: Research objectives.

	Objective	Research methodology	Deliverable
1	Evaluate available literature on electricity consumption forecasts inside and outside the mining industry.	Narrative literature review	1. Show that there are no existing solutions addressing the identified barriers. 2. Identify methods from literature that can be adapted to overcome the identified barriers.
2	Develop a framework based on research findings to overcome the identified barriers.	Mixed methods research methodology	1. Produce a framework that addresses the identified barriers using a combination of research findings from industry and literature.
3	Evaluate the developed framework based on its ability to overcome the identified barriers.	Case study methodology	1. Construct a budget using both the industry standard method and the new framework method. 2. Evaluate the framework results according to the best practices and their ability to overcome the identified barriers.

The investigation began by confirming the need for improved budgets and identifying the barriers to development of high-quality budgets faced by industry. This was done through the establishment of best practices and an industry survey. In the following chapters, the objectives of the study will be addressed through a literature review in Chapter 2 (Objective 1), the development of a methodology in Chapter 3 (Objective 2), and a case study implementation of the developed framework in Chapter 4 (Objective 3). This progression is illustrated in the flow diagram given in Figure 1.6. A validation of these objectives is presented in Section 5.2.

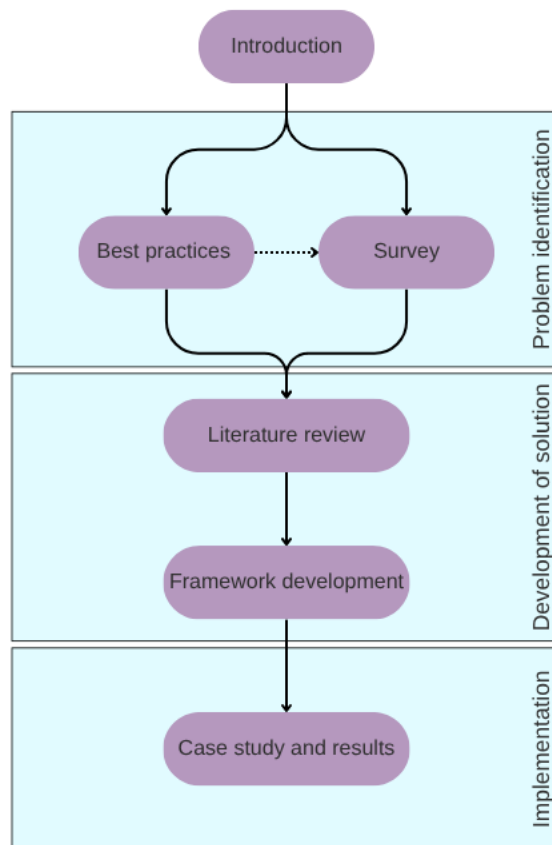


Figure 1.6: Research approach breakdown.

By following the approach as laid out above, the study will produce a validated framework that is grounded in both literature findings and actual industry experiences. The case study application will prove the applicability and effectivity of the developed solution in practice. This will satisfy all the objectives stated for the study, producing and validating a method to overcome the identified barriers to high-quality budget development.

1.4 Novelty

1. Compilation of best practices for mine electricity consumption and cost budgeting process, evaluation of the industry process and identification of barriers preventing implementation of best practices.

- This contribution was published in the journal *Mining*, see article attached in Appendix A.
- **What:** The state and quality of current budgeting practices and resulting budgets is unknown. There is no standard and there has not been a thorough evaluation of the state of electricity consumption and cost budgets used in industry.

- **What is currently done:** Mine budgets are not held to a specific standard; no existing best practice compilation was found through literature. No literature could be found describing hinderances preventing the development of high-quality budgets on mines.
- **Why are current practices insufficient:** Budgets are not of high enough quality to be used for energy management, thus an evaluation tool is needed to check if the budget is “good enough”. There are no known barriers hindering the creation of high-quality budgets in practice. All that is known is that the budgets being developed are no longer effective energy management instruments. Barriers to the development of high-quality budgets need to be identified so that they can be improved upon.
- **How does the study solve the problem:** A list of best practices and an evaluation survey were produced that can be used to evaluate a budget for its potential effectiveness as an energy management instrument. Using the developed best practices, a survey was developed. 41 mines were evaluated to understand current mine budgeting practices better. Comparing survey results to developed best practices, significant deviations from best practices were identified to be addressed.

2. Development and application of framework for the creation of electricity consumption and cost budgets that comply with the identified best practices.

- **What:** Budgets must function as effective energy management instruments by aligning with the available, evolving actual electricity consumption data. An overarching method is required combining the findings of this study into a repeatable method that can be implemented despite a changing data landscape to develop high-quality electricity consumption and cost budgets.
- **What is currently done:** Budgets are often developed without adequate consideration of the existing actual electricity consumption values against which they will be compared. There is no established framework along which budgets, particularly for deep-level mine electricity consumption and cost, can be systematically developed.
- **Why are current practices insufficient:** Comparing budgets with incompatible actual consumption values undermines effective energy management and yields weak performance insights. The absence of a detailed, step-by-step, repeatable budgeting framework tailored to deep-level mining and mindful of the nonstationary nature of real consumption data prevents consistent, high-quality budget development.

- **How does the study solve the problem:** The study introduces a method that begins by evaluating the objective, the available actual electricity consumption values, so that each budget is aligned for meaningful performance evaluation. It then provides a comprehensive, repeatable workflow in the form of a framework that incorporates budgeting best practices and explicitly accounts for the nonstationary characteristics of actual electricity consumption, enabling robust, high-quality electricity consumption and cost budgets.

1.5 Research methodology

This study uses a hybrid research approach to isolate and address the observed problems with electricity cost and consumption budgets in industry. Multiple methods were selected to combine their strengths and mitigate limitations. The research process was structured in four phases: the administration of an industry survey, the review of existing literature, the combination of findings into a framework, and the validation of the created framework through a case study.

A survey methodology was employed in Chapter 1 to gather qualitative data on the state of electricity cost and consumption budgets in the mining industry. A survey methodology was selected for this phase of the research as it allows for the collection of qualitative data from a broad sample [59]. The approach is well suited and effectively identified common barriers to the development of high-quality budgets in practice.

A literature review done in Chapter 2, guided by the results of the survey was used as a foundation for the development of a framework intended to address and overcome the identified barriers. The synthesis of literature and qualitative survey findings led to the construction of a robust framework in Chapter 3 that can be applied in practice to develop electricity consumption and cost budgets for mines. A mixed methods research methodology approach was followed to combine theory and practice consistently [60].

A case study methodology was used in Chapter 4 to validate the developed framework and test its applicability in practice. The case study approach was selected for its ability to provide an in-depth examination of context-specific processes [61], [62]. This methodology enabled evaluation of the framework performance on each of the identified barriers compared to the industry standard method for budget development.

1.6 Thesis layout

Chapter 1 presents background on the importance of electricity budgeting for energy management in deep-level mines, providing a foundational understanding for the study to follow. A problem with the process of budget creation in mines is identified. Best practices for the

development of mine electricity cost and consumption budgets are derived from literature and used as the basis for a survey to investigate the state of electricity consumption budgets on mines in practice. This is used to identify a set of shortcomings with the current methods used and the outcomes they achieve. Objectives for the developed solution to address the identified barriers is given, along with a research methodology of how this will be achieved. Finally, the novel contributions of this study are presented.

Chapter 2 presents a narrative literature review to evaluate approaches within the mining industry and identify existing theoretical solutions to the identified shortcomings. First the field of energy forecasting is explored, and thereafter energy consumption forecasting. Based on these findings, studies on electricity consumption budgets in the mining industry are evaluated for their potential applicability to the identified barriers. Finally, studies on energy consumption forecasting in other industries are evaluated for theoretical solutions to the identified barriers preventing the development of high-quality electricity consumption and cost budgets.

Chapter 3 lays out the methodology proposed to overcome the barriers identified in Chapter 1 using theoretical strategies adapted from literature in Chapter 2. The framework is developed in four sections, based on the existing methodologies identified in Chapter 1. Each section discusses the disconnect between the industry standard and the best practice and provides a step-by-step workflow to overcome the identified barriers and produce high-quality electricity budgets for mines that will function as useful instruments for energy management.

Chapter 4 presents the study results and discussion. In this chapter, a case study mine is identified and the developed framework is followed to configure a full electricity consumption and cost budget for the case study mine. A companion budget based on the industry standard practices is developed in Appendix C using the same dataset. The developed methodology is validated in this chapter, both for its applicability *in situ*, and for its performance in overcoming the identified barriers to high-quality budget development.

Chapter 5 concludes the study and makes recommendations for further work based on the study findings. The objectives of the study, as given in Section 1.3, are considered and the performance of the study to achieve them is validated. The presented novelty of the study is also evaluated and concluding remarks on the study are given.

Figure 1.7 provides a visual representation of the layout of the study and the contents of each chapter. Together, these sections combine theory, best practices and survey results to develop a step-by-step framework to address and overcome each identified barrier and to produce best practice budgets.

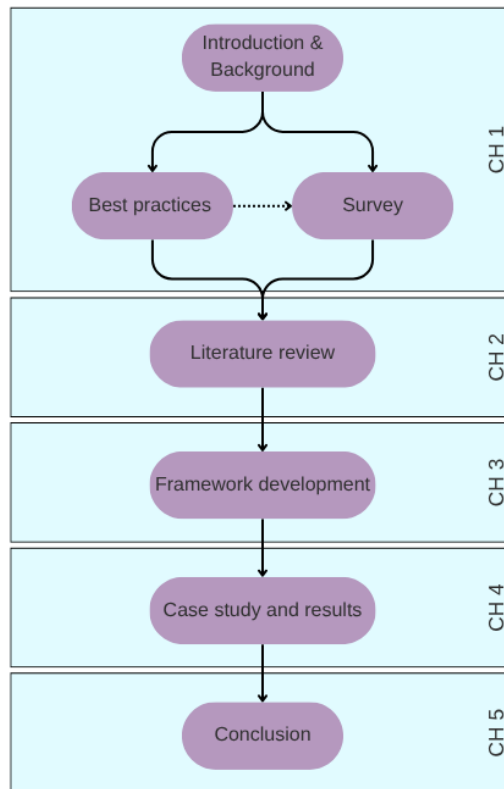
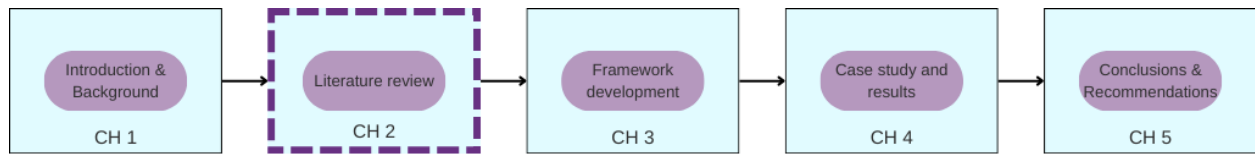


Figure 1.7: Thesis layout visualisation.

References and appendices are included after the study conclusion.

CHAPTER 2 LITERATURE REVIEW



2.1 Introduction

Chapter 1 set out to evaluate whether the electricity budget development practices currently employed within the South African mining sector yield high-quality outputs suitable for real-time energy and cost management. In doing so, it addressed a notable gap in the literature: the absence of formal evaluation criteria for assessing the effectiveness of electricity cost budgets. In the process, it became clear that there is another gap to be addressed. Several barriers hindering the development of budgets according to best practice were identified.

The goal of this section is to investigate whether there are solutions available in literature for the barriers identified for budget development in mines in Section 1.2.5 of this study. This section will present a narrative literature review on the field of forecasting, electricity consumption forecasting and budget development methods on mines.

The literature survey will be led by the barriers to development of high-quality electricity consumption and cost budgets as identified in Section 1.2.5. These barriers are:

1. Budget resolution, both in input data and output result.
2. Lack of scalability and adaptability of the budgeting method.
3. Detailed costing, both in the method and the output result presentation.
4. Documentation and traceability of the budgeting process.

In addition to the identified barriers, the best practices along with the known budget structure will be used to evaluate methods from literature critically for application in mine budgeting.

All the identified barriers come back to the reliance on manual methods for creating future budgets. Lower interval data is routinely used, as large data sets are impractical for manual human-centred methods. The methods are not scalable or easily adaptable, because they are rooted in manual data processing performed by people. Costing is over-simplified due to the low frequency of data used as input, and due to perceived time constraints of applying detailed costing. Documentation is tedious and time consuming when done by hand, and adds additional labour on top of the development of the budgets.

All of these problems could be solved by implementing automated methods for forecasting the future values. This literature review will therefore focus on existing electricity forecasting methods with the aim of identifying applicable models and methods to be used in the mining sector.

2.2 Literature search approach

This section will use a narrative literature review to evaluate available solutions to the identified barriers in Chapter 1 within the mining sector and in broader industry. A broad review on the prevalence of energy forecasting and then energy consumption forecasting will be the starting point. Thereafter literature on electricity and energy consumption forecasting specific to the mining industry will be evaluated, along with energy consumption forecasting in other industries that may be applicable in the mining industry, to address the identified barriers faced during budget development.

For the initial broad search for energy consumption forecasting practices, the following method was used to search for studies and filter them for relevance:

Several combinations of keywords and modifiers, as given in Table 2.1, were used to search for relevant studies. Using forecast(ing) and variations thereof as the core keywords, two pre-modifiers and one post-modifier were used to ensure the most relevant studies were found. An asterisk (*) is used to indicate a wildcard search, allowing flexible text matching.

Table 2.1: Literature search keywords for narrative literature review.

Pre-modifier 1	Pre-modifier 2	Core keywords	Post-modifier
Electric*	Consumption	Benchmark*	Mine*
Energy	Usage	Budget*	Mining
Power		Forecast*	
		Projection*	

The following databases were searched, and papers with relevant titles from the first 50 results were selected for further investigation:

- Science Direct
- IEEE Xplore
- Google Scholar
- Springer Link

The following were immediately excluded:

- All articles from life sciences journals (energy budget as expenditure of energy by a living being),
- Studies focussed only on energy demand/load and not energy usage,
- Studies on forecasting energy generation,
- Studies forecasting price in environments where electricity has dynamic pricing structures,
- Studies focussed only on renewable energy or on forecasting carbon budgets,
- Studies focussed only on the overall financial budgets of mines,
- Financial studies focussing on budget balance.

Undermind AI research tool was used as an additional search layer. The tool asks questions to refine a search prompt and performs a deep search accordingly. An additional benefit is that the tool continues to notify the researcher about newly published studies inside the research scope, ensuring that literature is up to date. The following “deep search” prompts were used:

- Electricity cost forecasting methodologies for dynamic, mining-specific energy demands
- Long-term electricity forecasting and ISO 50001 benchmarking for SA mining
- Automated year-ahead half-hourly electricity usage forecasting for deep-level mines

All papers collected through either search method were manually screened by abstract by the author to ensure relevance to the research topic. Key identified studies were uploaded to *Research Rabbit* research tool. This was used to ensure that all studies linked significantly to the key identified studies had been screened for inclusion. Additional studies found through this method were also screened by abstract. Figure 2.1 details the search approach used in every section of this review.

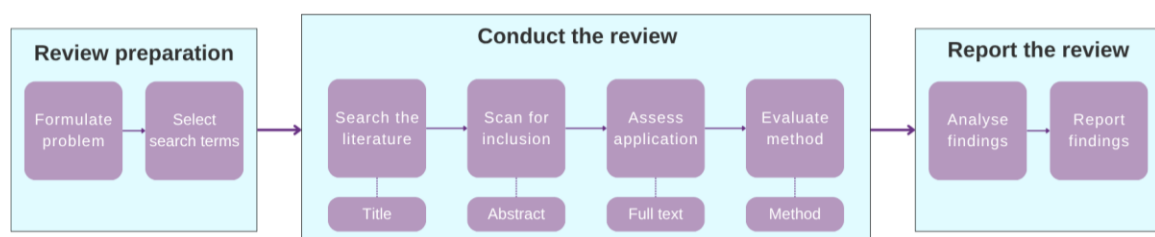


Figure 2.1: Literature search approach.

The full literature search returned a multitude of relevant studies.

It is clear that a wide range of well-established methods exist for forecasting electricity usage. This abundance of approaches highlights both the importance and complexity of energy

forecasting as a field of study. A narrative approach to the discussion of the literature on electricity cost forecasting was selected to guide the reader through the field and the place of mining within it. First the field of forecasting and energy forecasting will be explored. Thereafter the field of electricity consumption forecasting will be reviewed. As per Figure 2.1, the problem and search terms were reconfigured for every section. Details of which search terms from Table 2.1 were used for which section is provided in each section. 156 studies were deemed relevant by title, as per Figure 2.1 and were screened by abstract for inclusion. From this three studies were selected for discussion of energy forecasting as a whole, and a further three for energy consumption forecasting. Eight studies focussed on energy consumption forecasting in the mining industry were selected and discussed. Five studies with applicable methods to address and overcome the identified barriers were selected and discussed.

On this foundation, the full review will be presented, where studies on forecasting of energy and electricity in the mining sector will be examined. The shortcomings with the existing literature will be explored and thereafter an exploratory review of studies presenting solutions to the presented barriers identified earlier is undertaken to be used in the development of a framework to address the problem as given in Chapter 1.

2.3 Background literature on energy forecasting

To situate the present research within this field, this section provides the theoretical foundation by drawing on existing literature. For this search only pre-modifier 1 and the core keywords of Table 2.1 were used as search terms, and the process as in Figure 2.1 was followed. Three of the returns from the search are discussed here. They discuss the wider field of forecasting as well as focussing on the field of energy forecasting.

1. Petropoulos et.al (2022) - Forecasting: theory and practice [63]

The article provides a comprehensive introduction to the concept of forecasting, outlining both theoretical foundations and practical applications. It highlights essential aspects such as data pre-processing, variable selection and model selection processes that are all critical for accurate forecasting. The article explores the concept of forecast combination for enhanced performance. The importance of evaluating and validating results is emphasised.

In the practice section the article presents several common forecasting applications. A dedicated sub-section focusses on energy forecasting and its applications, and underscores the importance of forecasting for energy planning and management. Building energy consumption forecasting is examined in detail and presents methodologies that could be adapted for applications within the mining industry. The paper stresses the importance of accurate forecasts of energy, considering

various factors such as end-user demand, user behaviour, equipment efficiency and weather conditions.

The article identifies three principle approaches to energy consumption forecasting: engineering methods, statistical methods and machine learning methods. It also notes that long-term energy consumption forecasting is most commonly performed using past energy consumption data alone, and notes that there tend to be too many non-linear dependencies that can influence energy consumption to be representatively included in forecasting models. A key takeaway from the energy consumption section is the conclusion that there is no conclusive single method for energy forecasting in literature. The field is too wide, and the most appropriate method will depend heavily on the specific application. All of this will be considered in the development of a method to address the identified problems.

2. Debnath and Mourshed (2018) - Forecasting methods in energy planning models [56]

The study provides a broad, method-structured map of electricity demand forecasting within energy planning models, showing that computational intelligence and hybrid designs generally outperform classical statistics and that forecasting has matured in both short-term, high-frequency load and longer-horizon consumption studies. There is focus on the importance of energy planning for energy management in an environmental sense. The review covers 483 energy planning models and 50 different forecasting methods and found that artificial neural networks are the most frequently used approach (about 40% of models). Most consumption-focussed cases are national in scope (Türkiye, China, Greece), so direct model transfer will require adaptation, but the method-level trends remain broadly applicable for electricity consumption applications.

For high-frequency electricity consumption and load, the review's method overview points toward neural and hybrid approaches that combine inputs such as weather with flexible nonlinear components, using statistical models as baselines or ensemble components rather than standalones. Such approaches are advantageous for capturing seasonality and weather-related nonlinearities. Preprocessing steps like load-profile clustering and careful feature engineering are implied as useful precursors to improve fit and interpretability.

There is an emphasis on method selection by data availability and planning objectives, which frames relevance to both high-frequency and long-term electricity forecasting tasks which are required for mines. For long-term consumption forecasting, the review indicates that computational intelligence and hybrids are suitable across horizons and can be augmented and that fuzzy and grey methods can help when inputs are sparse or uncertain, as they often are in

multi-year planning. Collectively, the paper provides several candidate methods and considerations for the study.

3. Mystakidis et.al. (2024) - Energy Forecasting: A Comprehensive Review of Techniques and Technologies [52]

The paper presents a comprehensive review of techniques and technologies used in energy forecasting, emphasising the role of accurate prediction in maintaining the balance between energy suppliers and consumers. The study provides a structured overview of forecasting approaches, encompassing statistical, machine learning, and deep learning models, and highlights how each class of methods aligns with specific forecasting needs and contexts. A key contribution of the review lies in its discussion of input data requirements, where it categorises the types and sources of data used across studies and analyses their influence on forecasting accuracy and applicability. This focus on data type and quality underscores the dependence of model performance on the availability and suitability of input information.

The study further identifies that the choice of forecasting algorithm is influenced by the forecasting horizon, with short-, medium-, and long-term forecasts each requiring different methodological considerations. The authors also outline several challenges inherent to energy forecasting, including issues of data quality, model complexity, and adaptability. These issues directly affect the reliability of forecasting models in practice. While additional challenges such as ethics, privacy, and security are discussed, these are less relevant in the context of electricity consumption forecasting for mines.

Overall, the review finds broad consensus in the literature regarding which forecasting methods are most appropriate for different applications and demonstrates that hybrid approaches, which combine methods, can enhance accuracy and robustness. However, the authors caution against unnecessary model complexity, particularly when models are intended for practical, ongoing use. This balance between complexity and usability reinforces the need for forecasting frameworks that are both methodologically sound and operationally feasible, a consideration that aligns closely with the objectives of the broader study on electricity consumption forecasting.

Findings summary

From these three studies it is clear that energy forecasting is a well-established but growing field. There is also notably no single model recommended outright for energy forecasting. Instead, it is apparent that the type of model is dependent on the scenario in which it will be utilised and the type of data that is available for the forecast. There is consensus throughout the studies that computer-aided forecasting offers improved quality and accuracy, and that hybrid models

combining statistical and computer-aided models are a popular choice in the field of energy forecasting. The finding from Petropoulos et.al [63] that recommends single variable forecasting using only energy data will be carried forward. They note that there are too many non-linear dependencies to accurately measure and model. Section 1.2.5 provides evidence that electricity consumption data is readily available and of high quality, and therefore methods that can capitalise on this will be favoured.

2.4 Electricity consumption forecasting

The studies discussed in the previous section addressed the broader field of forecasting and energy forecasting. As there is no consensus of methods to be used in energy forecasting as a whole, the search was broadened to include pre-modifier 2 from Table 2.1, and used in the search process as in Figure 2.1. The following three studies specifically centre around electricity or energy consumption forecasting and review numerous methods and approaches used in the field. From this, methods can be identified to be included in the search for solutions to the identified barriers in Chapter 1.

4. Misiurek et.al. (2025) - Review of Methods and Models for Forecasting Electricity Consumption [64]

The study underscores the critical importance of electricity consumption forecasting in view of modernised grids and increasingly complex usage patterns. The authors' aim is to provide insights to improve future forecasting models. To this end, the review covers a wide spectrum of methods: classical statistical, machine learning, deep learning, fuzzy logic, evolutionary algorithms, and hybrid approaches. These are organised by four forecasting horizons: very short term, short term, medium term, and long term. Per the definition in the paper, medium- and long-term forecasting can both be a year ahead, and thus both will be considered. Their given operational domains cover operational planning and financial planning; thus both are applicable to this study.

The review finds that no single method is best across all horizons. Traditional statistical methods (especially ARIMA) often perform well, particularly in medium- to long-term forecasting when there is less extreme variability and fewer nonlinear effects. In more volatile, nonlinear settings, modern methods (e.g. neural networks, hybrid models) tend to outperform. For single-variable models over medium-/long-term horizons, ARIMA emerges as one of the strongest. The study, like the previous studies, recommends hybrid models and data decomposition strategies to improve forecast quality, combining strengths of different approaches, reducing noise and tailoring models to the nature of the data involved.

5. Rodrigues et.al. (2025) - Medium and Long Term Energy Forecasting Methods: A Literature Review [65]

This paper addresses energy demand, consumption, and price forecasting, organising methods across statistical, machine learning, hybrid, and scenario-driven frameworks, and mapping them to planning horizons. The review documents which variables tend to be used and what modelling approaches are most common in the existing literature.

The study recommends horizon-specific approaches to forecasting model selection. For months to a year ahead, hybrid models and decomposition to manage seasonality is suggested. Most of the studies covered forecasted either demand or electricity price, and no study forecasted electricity consumption for at least a year ahead. The overall methods remain relevant and can be incorporated into the framework development to take place.

6. Klyuev et. al. (2022) - Methods of Forecasting Electric Energy Consumption: A Literature Review [66]

This article provides a detailed and methodical review of electric energy consumption forecasting methods, assessing them against multiple evaluation dimensions such as labour intensity, input data requirements, scope of application, accuracy, and the possibility of applying them to other systems. The authors begin with a historical perspective on forecasting attempts dating back to 1910, arguing that many earlier methods have lost relevance as the complexity of electrical systems has increased. To bring structure to the diversity of methods, the authors propose a universal workflow. This is a stepwise procedure that practitioners can follow to go from data to forecast outcomes. It aims to standardise forecasting practice across contexts, and can thus also be applied within the mining industry.

The study puts emphasis on both strengths and limitations of different techniques. It notes that artificial neural networks (ANNs), while powerful, lack interpretability compared to statistical models, making it difficult to discern cause and effect relationships. Due to this lack of interpretability it recommends against the use of ANNs in applications where the results are used for high-level planning and management. As seen in the other studies reviewed, it finds no universal forecasting method that works well across all types of systems or applications. Each forecasting scenario requires a purposeful choice of model and method. For long-term forecasting, it highlights the rank analysis method as a viable option requiring only past electricity consumption data as input. It also stresses that despite methodological advances, human expert judgement remains critical in forecasting processes.

The criteria of trade-offs between data required, model complexity and labour requirements and result accuracy will be useful in the selection and recommendation of models to use within the proposed framework. As mine electricity consumption forecasts in the context of this study are intended to be an instrument for management, the caution against ANNs for this application will be considered. Lastly, the recommended universal workflow can serve as a baseline process to adapt to ensure rigorous, repeatable forecasting steps.

Findings summary

All these studies note that the field is actively evolving, changing and growing. Suggesting a single method from literature for a framework will result in a short-lived solution, as better options are likely to emerge continuously. The framework will therefore rather provide a workflow with guidance on how to select a forecasting method, in order to remain relevant in a changing landscape. The framework will also favour single-variable forecasting models, as this is recommended for long term forecasting in the evaluated literature [63], [64], [66].

2.5 Electricity consumption forecasting in the mining industry

This section of the literature review will evaluate studies on electricity consumption forecasting in the mining industry, combining all the search terms from Table 2.1 and following the search process as in Figure 2.1. The goal of this is to understand what is already being done in the industry in theory, as Chapter 1 has shown that there is no implementation in practice. Ten relevant studies were identified and evaluated.

The studies found were evaluated according to the following criteria:

- Forecasting of electricity in a mining environment, preferably deep-level
- Forecasting of electricity consumption on a long-term basis (year ahead)
- Forecasting by means of a method that is automated but easily interpretable
- Forecasting in a high frequency, at least hourly
- The creation of electricity consumption profiles
- Costing of created electricity consumption forecasts
- Consideration for the seasonality of datasets

7. Matthee et.al. (2024) - Enhanced Measurement and Verification Practices in Deep-Level Mines: The Current State [67]

This paper examined the state of M&V practices in deep-level mines and identified the need for improved forecasting of electricity consumption. The study emphasised that existing methods are

inadequate for capturing the complexity of energy use in such operations and therefore recommended the development of a technique specifically tailored to forecasting electricity consumption in deep-level mining environments. While this recommendation aligns with the present study's objectives and reinforces the importance of accurate energy prediction as a foundation for effective budgeting, the authors did not propose a methodology or framework to achieve it. Their work highlights the gap the present study aims to fill with the development of a framework.

8. Greyling (2014) - Mine energy budget forecasting: The value of statistical models in predicting consumption profiles for management systems [68]

This mini-dissertation presented one of the first studies specifically addressing forecasting in the mining industry. The author observed that, prior to this work, there was no mine-focussed forecasting literature available. He attributes this observation to the low historic electricity costs compared to high prices for commodities produced by mining activities. There was no financial incentive to manage energy carefully and thus no need for electricity forecasts. The study used two statistical methods to predict electricity consumption based on planned production tonnages. Forecasts were generated at monthly intervals and aimed at supporting long-term planning and load management. This aligns with the current industry practice of budgeting on mines, but not with the goal of the study at hand, to produce budgets that can be used as real-time energy management instruments.

The study demonstrated the value of statistical modelling for mine electricity forecasting applications but did not consider its role in operational improvement. The study's approach lacks the resolution and adaptability that are required for effective electricity budgeting. These gaps highlight the relevance of the current research.

9. Caromba et.al. (2023) - Application of Clustering Techniques for Improved Energy Benchmarking on Deep-Level Mines [49]

The article explores the applications of clustering algorithms to energy benchmarking, a practice similar to electricity consumption budgeting, in deep-level mines. The authors use the k-means algorithm to classify electricity usage patterns among different mining shafts. The clustering enables identification of typical daily load profiles for electricity usage, which are used as benchmarks to spot outliers and potential savings opportunities. The study uses data from similar systems as seen in budgeting practices (compressed air, pumping etc.) and uses the selected algorithms to cluster, and then uses regression models to predict electricity usage per system in daily intervals. The regressions are based on additional non-electricity consumption data like air

and water flow. This method was found to work better than the previous industry standard of aggregated averages, especially in systems with performance deviations.

The study does not create profiles or suggest any methodologies to do so. Its application was only on short-term data, and thus the implications for reusing the method for long-term applications is unknown. The article also does not feature any cost application to the obtained benchmarks. Components of the study may be useful, but it does not provide a full solution to the identified problems.

10. Matrenin et. al. (2021) Recurrent and Ensemble Models for Short-Term Load Forecasting of Coal Mining Companies [69]

The study investigates the use of advanced machine-learning techniques for predicting electricity consumption in mining operations. The authors note a lack of existing research applying modern forecasting models to the mining sector and attribute this gap to the restricted availability of operational data, which is often tightly controlled by mining companies. Their work focusses on developing methods capable of using 24 to 48 hours of historical data to predict the following day's power consumption. Like the study by Caromba [49] it uses the k-means clustering algorithm. This study uses it to group similar profiles before applying recurrent and ensemble forecasting models to the clustered datasets. This approach enables short-term, mine-level load forecasting with improved accuracy compared to traditional statistical methods.

While the study is limited to day-ahead forecasting and does not address long-term or system-specific applications, its methodology provides useful insights for future framework development. The use of clustering to prepare input data for forecasting and the application of existing models to the clustered data shows promise. Although its scope does not extend to full electricity budget development, the study's findings are relevant to the present research in showing how automation, model-based forecasting, and data segmentation can improve mine energy management. These concepts can inform the forecasting component of the proposed framework, particularly in developing scalable and adaptable methods.

11. Laayati et. al. (2022) - Smart Energy Management System: Design of a Monitoring and Peak Load Forecasting System for an Experimental Open-Pit Mine [15]

This paper describes the design and implementation of a smart energy management system on the same experimental open-pit mine. The authors combine forecasting using a fast forest quantile regression with smart energy management. electricity consumption and peak load are forecasted. The designed system is intended for real-time energy management using the

forecasts and available data and visual dashboards integrated with SCADA, enabling monitoring of processes and their performance.

The forecasting is focussed on peak load and short- or near-term demand response, not on long-term yearly budgeting or system-specific cost forecasting. Much of the system implementation is proof-of-concept. Full validation, including how well the forecasts perform over extended periods under varied operational changes, is not yet demonstrated. The work remains highly relevant as it addresses many components the framework aims to address. It also addresses data infrastructure needed to support such an endeavour. The study does not address long-term forecasting or costing of electricity consumption forecasts.

12. El Maghraoui et. al. (2022) - Smart Energy Management: A Comparative Study of Energy Consumption Forecasting Algorithms for an Experimental Open-Pit Mine [70]

The study done in this article is a follow up of the work on the experimental open-pit mine in the previous study [15]. In this article the authors conduct a comparison of four machine-learning algorithms in order to forecast the daily electricity consumption on a mine. The models evaluated are Artificial Neural Network (ANN), Support Vector Machine, Decision Tree, and Random Forest. The study finds the Random Forest model performs the best in this setting. This method is scalable and could be applied to larger and higher frequency datasets than used for the article. Though the authors appear to collect high-interval data from the mine, the forecasts are done in a daily interval.

Because the study is on an experimental open-pit rather than a fully operational mine, its findings may not be applicable to deep-level or production mines. As the study results are based on creating daily forecasts, it is not clear whether the same success with forecasting accuracy would be achieved using high-frequency data. The study is unfortunately also done on a whole mine level, but the methods may scale. Finally, the study does not apply any costs to the developed forecasts. The study provides valuable insights on data pre-processing and several evaluation metrics which can be used to evaluate results obtained from the framework to be developed.

13. Pelser (2021) - Improved energy budgeting process for mines using measurement and verification principles [48]

This paper is one of few to apply electricity forecasting principles specifically to the mining context and, importantly, does so on a long-term basis, developing year-ahead budgets. It addressed a common weakness identified in mine budget practices, namely insufficient accounting for operational changes. It suggests the use of M&V principles to improve existing budgeting procedures due to their ability to account for planned changes. These include defining

measurement boundaries, ensuring sufficient resolution in data collection, maintaining data quality, making routine adjustments and developing a reliable baseline. Through literature analysis it develops parallels between budgeting and M&V and demonstrated that incorporating the M&V principles make the budget a more realistic representation of mine operation.

The budget method developed is applied on a year-ahead basis and uses data at an hourly interval, in compliance with identified best practices in Section 1.2.3. The study gives attention to input data quality and suggests using historically representative electricity consumption data to form budgets. Unfortunately, the methods suggested by the study are time- and data-intensive. These include highly individualised statistical investigations per energy-intensive component in order to calculate routine adjustments needed. This method is not scalable. Additionally, routine adjustments are calculated on weekly bases but then applied to hourly data without considerations for difference between the frequency of data. Finally, while Pelser describes the necessary components for improved budgets, there is no specific forecasting model suggested or described. The study also does not concretely recommend any of its adjustments. It presents a decision tree where using budgets for energy management is optional, not key as identified in Chapter 1.

The study does cover using seasonally representative historical electricity consumption data for forecasts and provides some guidance for costing budgets. The study was used in Chapter 1 as baseline for the best practices developed, but does not contribute additional value towards the development of a framework for budgeting.

14. Esterhuizen (2023) - Forecasting energy consumption on mines using machine learning techniques [71]

This dissertation investigates forecasting of electricity consumption for energy management purposes, specifically in the mining sector. It focusses on the possibility of using machine learning for this forecasting and investigates several methods for this application. The study recognises that linear regression scaling consumption according to production, a commonly used technique, is not accurate enough and therefore seeks an alternative solution. Four machine-learning models, including supervised and unsupervised models, were developed and tested. These models were applied to four case study mines, each with half-hourly data available, to forecast electricity consumption over a one-year horizon. Although these resolutions would have enabled high-frequency forecasting, the study regarded 30-minute intervals as unnecessarily detailed for long-term projections and instead aggregated results at monthly and yearly scales. The forecasting was performed at a high level, per POD, rather than per energy-intensive system, reflecting the current industry trends identified in Chapter 1.

The study produced mixed results and was ultimately inconclusive. Different models performed best on different case study mines and at different intervals. This shows the importance of selecting the right type of forecasting depending on the use case and context. The feed-forward neural network, an unsupervised model, achieved the highest accuracy across most daily and weekly forecasts and may be a candidate for higher frequency forecasts. The study noted a trade-off between accuracy and interpretability: while machine-learning models improved prediction accuracy, their lack of transparency limited understanding of the underlying relationships driving electricity use. The study confirms that machine-learning (ML) models can be used to forecast mine electricity consumption accurately. It also highlights the need for a framework to assist users in selecting suitable models to deliver high-quality budgets.

Findings summary

This section confirms that while there is wide implementation of electricity budgeting in the mining industry, the budgets are low resolution and may not be effective instruments for energy performance evaluation. There are no established and implemented methods within the mining industry for consistent, high-quality electricity cost and consumption budgets. Section 2.7 provides a detailed breakdown and evaluation of the findings of this section in line with the identified barriers preventing the development and implementation of high-quality budgets in industry.

2.6 Long-term high-frequency electricity consumption forecasting models

None of the mine-specific studies suggest a forecasting model that will address all the identified barriers to development of a high-quality electricity budget for a mine as set out in Section 1.2.5.

1. Budget resolution, both in input data and output result.
2. Lack of scalability and adaptability of the budgeting method.
3. Detailed costing, both in the method and the output result presentation.
4. Documentation and traceability of the budgeting process.

Additionally, forecasting methods and models that can handle variable, nonstationary data with seasonal patterns as seen in mines, are required. Methods with simpler approaches were favoured, as less complex approaches have a better track record of implementation in industry [72], [73]. This will aid in developing a framework that is implementable in the mining industry.

The literature search as described in Table 2.1 was repeated using only the first three columns, thus excluding mining from the search, and following the search as in Figure 2.1. The word *framework* was added as an alternative post-modifier. Each study was evaluated for its applicability to the development of a framework to create high-quality, high-frequency budgets.

The method used in each study was considered, including the type of data, preprocessing approach, forecasting model, and implementation strategy. The studies were assessed according to the list of barriers: can the method accommodate high-frequency data input? Can the approach be scaled and ideally automated? Will the process be transparent and reproducible? Can the method accurately forecast non-stationary seasonal data? Costing was not considered as it is well described in utility documentation and can easily be adapted to fit the framework to be developed, as long as the produced consumption forecast is of a high enough frequency.

Many methods not passing these criteria were found. The chief failure identified in models in literature was their adaptability to the mining industry. This was largely due to the complexity of the models suggested. Many models available in literature achieve great accuracy at the cost of very high processing power requirements and expertise in mathematical modelling, which is not freely available in the mining industry. Many models also do not offer adequate transparency on how results were obtained, which is not acceptable for data intended for use as a management instrument.

The following studies were deemed relevant and will be utilised in the creation of a framework methodology:

15. Zhao et. al. (2024) - A hybrid forecasting model for general hospital electricity consumption based on mixed signal decomposition [37]

This paper presents a hybrid forecasting model that is designed to improve the accuracy of electricity consumption forecasts for a hospital through the use of a mixed signal decomposition method. The model decomposes historical consumption data into distinct groups to capture underlying seasonal and operational patterns. This is used to create daily consumption profiles that incorporate seasonality and operational variability. While the application context is a hospital, the structure of electricity use across machinery groups parallels that of energy-intensive systems on mines, making the method conceptually transferable to mining operations.

With regards to the discussed criteria, the study demonstrates a method that can produce high resolution budgets and handle nonstationary and seasonal data well. Decomposition can be applied within the context of mines to prepare data for forecasting, as also seen in two studies in Section 2.5. Unfortunately, the forecasting method is reliant on more than just past consumption input data as is available on mines and can thus not be adapted for application. The method also requires significant computational power, which may be a limiting factor for implementation in practice.

The study method provides valuable insights for framework development in mining electricity budgeting. The concept of mixed signal decomposition can be adapted to group mine electricity data into seasonal and operational components and enable more accurate forecasting at system level. By combining this decomposition technique with more interpretable forecasting models the approach could improve the budgeting process without sacrificing scalability or transparency.

16. Pinsky et. al. (2024) - A Simple Computational Approach to Predict Long-Term Hourly Electric Consumption [74]

This article proposes a computational method for predicting long-term electricity consumption using only historical time-series data as input. The study introduces a single algorithm capable of producing hourly forecasts over extended periods, producing high interval results that are easily interpretable. The simplicity of the approach and its reliance on only historical consumption data as input data make it attractive for application in the mining industry.

In terms of the criteria, the method delivers on budget resolution, providing high-frequency profiles as a result. It is scalable and adaptable and should be relatively easy to automate. The described algorithm is simple and transparent and should also be easily reproducible if documented adequately. Phase 1 of the described approach could be incorporated into a framework to generate baseline consumption forecast profiles.

17. Amin and Mourshed (2024) - Community stochastic domestic electricity forecasting [75]

This paper aims to forecast domestic electricity consumption, an application notorious for its randomness and seasonality. The study identifies a lack of methods in existing literature capable of delivering high-resolution forecasts, specifically on such variable data. It notes that many methods found oversimplify forecasting and therefore lose important behavioural details. To address this, the authors develop a multi-level forecasting framework that first models energy consumption at the household level and then aggregates these results to produce community-scale forecasts. The approach combines two statistical models to capture both typical and irregular consumption patterns, achieving high-accuracy high-frequency results. Although the framework incorporates weather data to enhance prediction accuracy, the core methodology based on grouping user behaviour and statistical modelling can be applied without this component.

Compared to the criteria, the study performs well on budget resolution, producing high-frequency energy consumption profiles. It is scaleable, as demonstrated by the results of the paper, but may not be entirely adaptable to alternative applications. The separation into “use-factors”, however, mirrors the decomposition and clustering seen in other studies, cementing this as an approach to

include in the framework to be developed. The build-up of individual homes to community level forecasting also parallels the individual systems to incoherer setup seen on mines, and thus the study was deemed relevant for inclusion. The method also performs well with stochastic and seasonal data, although it includes atmospheric data in its models to achieve this. Although the study makes annual estimates, the method is not intended to forecast a year ahead.

The developed framework in this paper provides a valuable template for the development of a framework for energy consumption forecasting, even in another industry. A similar structure can be applied to forecast energy consumption for mines.

18. Vassiljeva et. al. (2024) - Profiling and schedule based forecast of electricity usage to improve energy performance of administrative buildings [76]

This article presented a forecasting framework designed to improve forecasting in administrative buildings. Similar to other studies, it developed energy profiles that are intended for energy performance evaluation. The study uses only historical electricity consumption data to do this. The proposed method only forecasts one month ahead, but the methodology could just as easily be used one year ahead. The framework first identifies profiles in data using clustering algorithms, then uses industry knowledge to recombine these into a continuous forecast for the identified future period. While k-means clustering is mentioned as a possible method, the authors recommend DBSCAN due to its superior ability to identify irregular behaviours in energy use without requiring the number of clusters to be pre-specified. The study further advises the use of the elbow method for optimal cluster selection.

The study complies with the criteria for budget resolution, producing high-frequency profiled forecasts. It is also scalable and adaptable, and the clustering and recombination technique is automatable and easy to replicate across multiple systems. The clustering methodology also accounts for seasonality in the input data. The study does not discuss detailed documentation of its methodology, but it can easily be incorporated and would strengthen the methodology, especially with regards to its reliance on the incorporation of industry knowledge for profile recombination.

This method is directly applicable to the mining environment and will require minimal adjustments to be adapted across industries. The methods suggested are also compatible with irregular nonstationary data as is common in the mining industry. Integrating this profiling and recombination method into the forecasting framework to be developed would strengthen the interpretability and repeatability of the process.

19. Liu et. al. (2024) - Energy consumption dynamic prediction for HVAC systems based on feature clustering deconstruction and model training adaptation [77]

This article presented a forecasting method for the electricity consumption of heating, ventilation and air conditioning (HVAC) systems in buildings. The method begins with a decomposition algorithm as preprocessing, sectioning “training data” into distinct groups. It thereafter uses these groups as input into a forecasting model and then assigns weights to the results to compile a full forecast. The methods for decomposition and forecasting proposed are more complex than would be practical in the mining sector, but the concept of using data sectioning as pre-processing and thereafter feeding data into applicable forecasting models presents an opportunity to combine the benefits of clustering and forecasting methodologies into a hybrid methodology.

The proposed method can support high-frequency input and results. The method, as proposed, would not scale well or adapt to the mining industry, but the conceptual methodology of combining clustering and forecasting will. This adds to the ability of any method to handle nonstationary data, and it would be even easier to implement and interpret statistical methods. The concept presented in this study will be transferred into the framework to be developed.

Findings summary

There are solutions available to the identified problems with budget development and implementation in literature. No singular framework that is directly applicable to the identified problem exists, but components of existing solutions can be used to address and overcome the identified barriers. Section 2.7 provides a detailed discussion of the solutions identified in this section and their application to the identified barriers.

2.7 Synthesis of findings

The reviewed literature shows progress in the field of electricity consumption forecasting, both in the mining industry and across other industries.

Mining industry studies

Mining studies as reviewed in Section 2.5 are increasingly acknowledging the need for structured forecasting, especially as it relates to its application in energy management for the mine. These studies are unfortunately limited in scope and did not fully address the identified barriers to high-quality electricity and cost budget development. The following was noted for each identified barrier:

1. Budget resolution, both in input data and output result.

The importance of high-resolution data is mentioned in some studies in the mining industry, but only Pelser [48] truly produced high-frequency results for a full year. The study unfortunately did not recommend producing high-frequency results for all budget applications, and did not produce a method that can practically be used to achieve this. Most studies did find that mines have high-resolution electricity consumption data available. Studies either limited data resolution for simplicity or practicality reasons, highlighting the need for scalable forecasting solutions.

2. Lack of scalability and adaptability of the budgeting method.

Only a few of the studies found mentioned scalability, and even fewer demonstrated methods to achieve it. Some of the applied methods in the identified studies applied methods that they specifically found not to be scalable, and did not recommend them for implementation in practice. The studies by Caromba and Matrenin [49], [69] present potential solutions to the scalability issue, but do not demonstrate it at scale. Neither of the studies are demonstrated on a long-term basis, and thus more research into the methods is required to confirm them for this application. The literature lacks practical, repeatable and adaptable methods for electricity consumption forecasting and budget development.

3. Detailed costing, both in the method and the output result presentation.

Only the study by Pelser [48] addressed costing of budgets or forecasts at all in the literature. None of the reviewed studies present a complete costing methodology to achieve detailed, system-specific cost outputs. This reinforces the need for the electricity budget consumption costing component of the framework to be developed.

4. Documentation and traceability of the budgeting process.

Only Pelser [48] addressed the need for documentation of the budgeting process. The study recommended practices similar to those used in M&V to validate the budget result formally. Five sections of the budgeting process are recommended for documentation for transparency and reproducibility. Several of the other evaluated studies noted the difficulty of interpreting forecasting results, showing the need for detailed documentation with the process, and the need for transparent model usage. Documentation and traceability of the budgeting process is touched on in literature, but will require expansion to include accommodations for the new budget framework suggested. These will be addressed by the framework to be developed.

Across the literature forecasting accuracy and data analytics get the most attention. Limited result resolution, lack of scalability, insufficient costing integration, and minimal traceability consistently

limit the effectiveness of mine electricity forecasting and budgeting. Only isolated elements partially meet the best practice requirements for high-quality budget development. None of the reviewed studies combine all four criteria into a cohesive, implementable framework. These gaps collectively justify the development of a scalable, traceable, and cost-integrated framework for high-resolution, long-term electricity budget forecasting in the mining industry.

Wider industry studies

Outside of the mining industry, as per the studies reviewed in Section 2.6, solutions for the barriers that were not adequately addressed in the mining studies were identified. Across these studies a similar framework pattern for forecasting electricity consumption is seen, despite their application in unrelated industries. The following was noted for each identified barrier:

1. Budget resolution, both in input data and output result.

Budget resolution is addressed more effectively in the studies in wider industry. High-frequency forecasts are the norm, with resolutions in the chosen studies varying from 15-minute to 1-hour intervals. Most studies also present these as daily profiles. All the identified methods can be applied to achieve high-frequency budget outputs that will allow for high-detail costing and near real-time energy management.

2. Lack of scalability and adaptability of the budgeting method.

The methods from the studies show strong potential for scalability and adaptability, primarily due to their use of automated and repeatable processes. The studies suggest methods and frameworks that break up data into representative groups that are then either recombined directly into forecasts or fed into models for forecasting. These methods can easily be adapted to the mining industry and will retain their adaptability to changing datasets, depending on the suitability of the models used for sectioning and forecasting.

3. Detailed costing, both in the method and the output result presentation.

None of the studies covered costing, which is to be expected as it was purposefully not included in the literature search. There is a lack of described costing frameworks in literature, as there is little need for them. Cost breakdown is utility-specific, and each utility provides its own method for costing electricity consumption. The ability of the methods to produce high-frequency outputs, however, will enable the application of high detailed costing, taking into account TOU and seasonal charges. As costing is well described in utility documents, the costing process can also be automated if high-frequency forecasts are available.

4. Documentation and traceability of the budgeting process.

Though the studies discussed here do not explicitly mention their documentation and level of traceability, it is apparent in their clear methodological structures and workflows. The simple, transparent algorithms presented will be easily interpretable and therefore easy to document.

While forecasts and budgets are not exactly the same, forecasting models were found to be largely applicable to the budgeting process of mines. Budgets represent an idealised forecast. Their intent is not to predict exactly what the electricity consumption in reality will be, but rather to provide a guideline for what electricity consumption under normal conditions should be. The mining industry is variable and temporary deviations from budgets are to be expected. This does not represent a failure on the part of the budget or the mine.

2.8 Conclusion

This chapter presented a narrative review of literature on energy forecasting. Energy forecasting and energy consumption forecasting were found to be prominent in literature, so the search was broadened to electricity consumption forecasting in the mining industry. Eight studies on forecasting energy, for budgeting purposes or other, were found and evaluated.

While all the studies were focussed on electricity forecasting in the mining industry, they were not found adequately to address the identified barriers prohibiting high-quality budget development in practice. None of the studies suggested a method that would deliver high-resolution electricity cost and consumption budgets reliably. Methods with potential for scalability and automation were found, but were not used towards this purpose in their respective studies. No methods presented a method for costing high-resolution electricity consumption budgets with system-specific costing. A method for documenting the budgeting process was found, but will need to be adapted and expanded to cover high-resolution budgets with scalable methods.

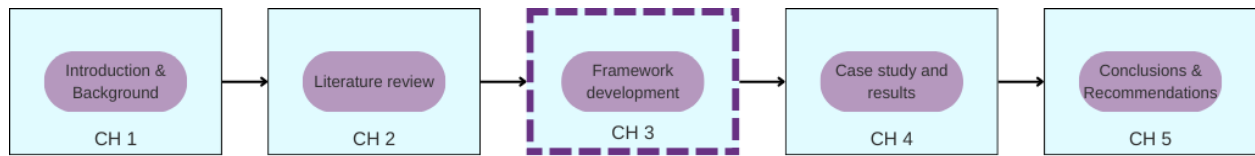
Concluding that studies already done in the mining industry could not reliably overcome all the identified barriers, the search was again broadened. This time, studies specifically pertaining to the lacking aspects of the studies found in mining were selected. This included studies doing electricity consumption forecasting with high-frequency data, with long-term applications and with scalable methods. Studies applied to datasets that are comparable to the electricity consumption datasets in mining, with seasonal and nonstationary data, were favoured. The identified studies were evaluated.

Applicable methods using comparable data to what is available in the mining industry that can be used to overcome the identified barriers were found. These included data-sectioning methods similar to those used in studies in the mining industry by Caromba and Matrenin [49], [69]. The

identified methods further included scalable forecasting methods and energy forecasting frameworks applied in other industries. There was, however, no single method available in literature that can simultaneously overcome all the identified barriers.

The combined insights from this literature review as given in Section 2.7 together with the best practices and barriers identified in Chapter 1 establish a foundation for the development of a framework for high-quality electricity consumption and cost budgeting. The framework to be developed must use the findings from literature to overcome the identified barriers and suggest an actionable method to achieve best practices for each budget component. By integrating proven methods and mining-specific considerations, the framework needs to close the gap between theory and practice and produce high-quality electricity cost and consumption budgets.

CHAPTER 3 FRAMEWORK DEVELOPMENT



3.1 Introduction

Chapter 1 has shown that there is a need for high-quality electricity consumption budgets in the mining industry. Surveys found that there is currently no standard method for budget development being followed industry wide. Industry standard budgets were found not to be in alignment with the best practices from literature and do not produce or implement high-quality budgets that can be used for performance evaluation.

Several shortcomings of the industry standard methods were highlighted. In Chapter 2 a comprehensive literature study was done on electricity consumption forecasting, both in mining and in wider industry. It was observed that there is currently no documented method available to address and overcome these identified shortcomings in the mining industry. There are, however, several electricity consumption forecasting methods available in literature from wider industry that contribute to addressing the barriers to high-quality budget development as defined in Chapter 1, though they do not eliminate the barriers on their own.

These barriers are:

1. Budget resolution, both in input data and output result.
2. Lack of scalability and adaptability of the budgeting method.
3. Detailed costing, both in the method and the output result presentation.
4. Documentation and traceability of the budgeting process.

The methods found in literature addressing these issues can be adapted and combined with the identified best practices for budget development to address the identified barriers collectively. This can then be applied within the mining industry to develop high-quality electricity consumption and cost budgets.

The goal of this section is to construct a framework for high-quality electricity consumption budget creation for mines. The framework will be built according to the best practices developed from literature in the research methodology. It will address the barriers identified in current budget development practices and provide solutions to overcome these barriers. Using information gained from the literature review, forecasting methods will be incorporated into the method where

they can add value and reduce manual work. This approach is based on a mixed methods research methodology and intended to combine theory and practice consistently [60].

The budgets resulting from the implementation of this methodology should be useful instruments for the evaluation of electricity consumption, so that they can aid in the evaluation of energy management initiatives.

The budget best practices in Chapter 1 were presented in three parts: Input, Method and Output. This methodology will be built on this principle. The input section will be kept as is and will cover the identification of the budget objective and data collection and preparation. The method section revealed problems with both budget generation and budget costing. These problems require different techniques and approaches to resolve. The method section will therefore be separated into two distinct sections, an electricity consumption forecasting framework, and a budget costing framework. The output section will be kept as is too and will cover verification, where the validity of the budget consumption and cost results are evaluated, and reporting, where the process of budget creation is documented for presentation to stakeholders, for accountability and for traceability.

Each of the four sections will be further sub-divided into logical steps to address each problem identified and ensure that the result of the framework will comply with the best practices identified.

Figure 3.1 gives a visual guide of the process of the framework.

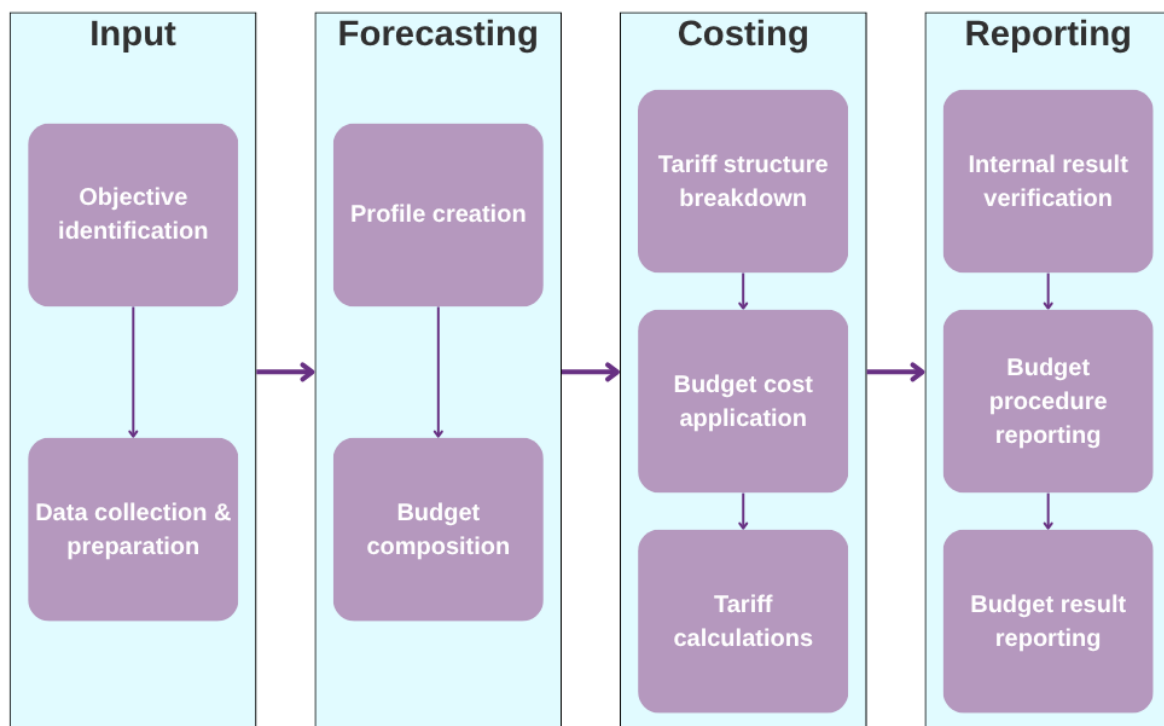


Figure 3.1: Budget development framework flowchart.

In each of these sections, three points will be addressed:

- What problem was identified with this step in the survey presented in Section 1.2.4?
- What effect does this problem have on the desired outcome of a high-quality electricity consumption and cost budget?
- According to the practices detailed in Section 1.2.3, what constitutes best practice?

The proposed framework aims to overcome the identified problem and achieve the best practice. The framework, which can be followed to achieve the best practice, will be described in detailed steps in sub-headings of the sections. Each section is concluded with a checklist of what should be achieved through the implementation of the framework. This needs to be done before the next step can be undertaken. The chapter is concluded with a section verifying the developed frameworks for their ability to overcome the identified barriers.

3.2 Framework: Input data preparation

Problem:

The main problem with the input step of budget development identified was that mines do not consistently use the right type and resolution of data. Many mines focus solely on production data and use it in combination with past electricity consumption data to predict future consumption. This assumes a linear relationship between production and total electricity consumption, which has been disproven in the literature [48]. Mines have several systems operating independently of ore production, and therefore, production data cannot be used to scale all electricity production accurately.

Result:

Many mines do not use high-resolution data to develop their electricity consumption budgets. This is largely due to the processes used for budget development relying on manual calculations. This is already time-consuming on a monthly scale, and prevents the use of higher resolution data due to time constraints and availability.

If electricity data is not used as input, forecasts using historical electricity consumption data cannot be made. The literature section found that electricity consumption forecasts are the most accurate if done using historical electricity consumption data [63].

If high-frequency data is not used as input, there is no way to know usage patterns over a day, and then no way to forecast detailed usage accurately. This also prohibits the detailed costing of

the budget, as the Eskom TOU periods are hourly, and excess reactive energy and demand consumption are calculated half-hourly by the utility [13].

Best practice:

Electricity consumption data should be used, with the exception of production data for systems directly related to ore transport and processing. Data should be high-frequency, at least half-hourly, and be separated into energy intensive systems. Data should be of verifiable quality. The input data should be chosen so that the budget resulting from this data can be used as an energy management tool when compared to actual electricity consumption.

The framework to address these issues will be split into two sections, the first of which focusses on the identification of the objective. At this stage, the goal of the developed budget must be clearly defined. The primary objective of the budget will likely be for long term financial expenditure planning. This framework is however focussed on improving budgets and making them valuable beyond their primary objective. The purpose of a high-frequency budget will be for it to serve as a baseline to be used for performance evaluation and energy management.

In addition, the specific objective should be established by evaluating the mine's existing energy monitoring systems, as the budget is expected to integrate with these tools to enable meaningful performance evaluation. The boundaries of the system under consideration must be identified to ensure that the budget is both representative of the operation and aligned with the intended scope of energy management activities.

The second section of the framework addresses the collection and preparation of data. This involves obtaining the relevant datasets and converting them into a usable format, followed by establishing clear standards for the expected structure and resolution of the resulting budget outputs. Meeting these goals will ensure that the input data used for the next steps will result in high-quality electricity budgets that can be used for performance evaluation of energy management initiatives.

3.2.1 Budget objective identification

Mine data is inherently a non-stationary objective, as both the quality and availability of the data are subject to continuous change. Developments in monitoring technologies and data management practices are rapidly transforming the mining industry, which means that the objective-setting step cannot be a once-off exercise. Instead, it must be repeated each time a budget is developed to ensure alignment with the current state of available data and monitoring capabilities. The goal of this process is to match the budget as closely as possible to the mine's

existing data environment, thereby producing an output that is an effective instrument for energy management.

Step 1: Investigate available data

The framework begins with a thorough investigation of the data currently available from site measurement systems, primarily electricity consumption data as this is most widely used for long term electricity consumption forecasts in literature [64], [74], [76]. This may include supervisory control and data acquisition (SCADA) power meters, as well as records supplied by external metering companies or contractors. Key questions at this stage include:

- At what frequency is the data measured?
- At what frequency is it stored (e.g., in a historian database)?
- What frequency would be most meaningful for energy management?

As a minimum requirement, data must be available at hourly intervals to align with Eskom's billing structures, although higher resolutions may offer additional value. An interval of at least half-hourly frequency that can practically be used for energy efficiency evaluation should be selected.

Outside of electricity consumption data, it can be useful to determine whether the mine has high-frequency records of production data. These can be used in forecasting electricity consumption of production-specific systems such as ore hoisting or processing, but not for other systems where production data is poorly correlated to energy consumption [48]. Additional data for costing calculations will also be required later on. Monthly intervals are available from utility invoices, but if real-time measurements for electrical load and reactive energy are available, they should be collected. Once these aspects have been assessed, the required input data for budget development can be determined.

Outside of the available datasets, a range of additional operational information is required for accurate budget development. In line with best practice, the budget should be compiled by an individual who is well informed on the mine's energy systems, has a clear understanding of the site's data structures, and has access to all relevant datasets. Beyond this, the responsible person must be fully aware of ongoing and planned energy management initiatives, as well as broader operational changes that may influence electricity consumption. Such information includes the seasonality of operations, whether activities remain consistent throughout the year or vary in response to weather patterns, or other fixed events. It also encompasses established operational standards, such as scheduled off-days, routine maintenance windows, or other recurring adjustments to production. Furthermore, knowledge of planned changes to the mine's activities is essential. These may include variations in tonnage mined, the opening or closure of mining

areas, the addition or removal of equipment, and the implementation of planned efficiency projects. Incorporating this broader context ensures that the budget reflects not only historical data but also the anticipated operational realities of the mine.

Step 2: Choose required data resolution

The second step involves selecting the data resolution at which the budget will be constructed. In line with best practice, the highest possible resolution (within reason) should be used to maximise the budget's usefulness for energy management. At a minimum, the resolution must match that applied by the utility company for billing purposes, ensuring comparability and cost accuracy. Identifying the relevant utility provider and tariff structure is essential, as these may differ by country, region, or mine. Engineering and financial personnel typically hold this information and should be consulted to ensure that the budget is aligned with both operational monitoring and billing requirements.

Step 3: Set up systems groups

The final step in objective identification is to define the system boundaries and groupings. For cost purposes, this should start at the relevant utility delivery point. For South African mines this will be the Eskom POD. From this starting point, the measurement practices employed on the mine must be examined. Data may currently be grouped by feeders, systems, or other categories. These can be restructured where necessary to reflect areas of operational significance.

Groups should be established in such a way that efficiency projects or other energy management initiatives are separated and can be accurately tracked. The boundaries must also ensure that the sum of the grouped systems reconciles back to the utility POD. Finally, billing calendars must be taken into account, as utilities may follow calendar months, fixed billing periods or unique custom calendars. This information will be needed when data is later grouped for costing and ultimately for presentation.

Successful completion of this stage yields a clear objective for budget development. Specifically, it defines the resolution at which the budget will be constructed to overcome the boundary of low-resolution budgets, identifies the required input data, and sets up system groupings that are meaningful for both cost allocation and energy management. This provides the foundation for the subsequent stage of the framework, the collection and preparation of data.

Budget objective identification checklist

Before progressing to the next section, the following must be done:

- ☐ Identify data source with high-frequency data available for use.
- ☐ Select required data interval for energy management.
- ☐ Select systems groups for energy management.
- ☐ Identify additional information required for budget development (billing dates, planned changes, etc.).

3.2.2 Data collection and preparation

The previous step has left the user with the knowledge of what data needs to be collected for use as input data in this budget, and in what intervals the data needs to be. This stage of the framework focusses on the collection and preparation of data. The step is necessary because no standard framework currently exists to guide the selection of appropriate data sources or the processes required to prepare them for use in developing electricity consumption and cost budgets. While most mines already perform data cleaning and quality assurance, these efforts are typically applied to monthly datasets. In contrast, high-frequency data that is essential for detailed energy management introduces additional challenges that are more complex to address and cannot be managed effectively through manual methods alone.

To overcome these limitations, this section provides guidelines on both the collection of the correct input data and the procedures required to ensure its quality at higher resolutions. Establishing such practices is critical for enabling the development of accurate, reliable, and high-quality budgets that reflect actual consumption patterns and can be used as effective instruments for energy management.

Step 1: Locate data sources and collect data

The identification of appropriate data sources is a critical step in preparing for budget development, as the sources will vary depending on the type of data required. At a minimum, electricity consumption data covering at least one consecutive year must be collected to ensure a representative baseline. If available, two years should be collected for data verification purposes. Such data should be obtained from the platforms investigated in the previous step, including SCADA systems, historian databases, or external metering contractors.

In addition to active energy consumption, historical load profiles and reactive energy data should also be collected from these sources, or alternatively from utility invoices where direct measurements are unavailable. Where budgets are to be developed for systems with production dependencies, and changes in production volumes are anticipated, production data must also be included. These records are typically accessible through the same channels as electricity data. Importantly, when identical data is available from multiple sources or meters, all versions should

be collected. This enables cross-checking and strengthens data quality assurance, thereby improving the reliability of the dataset used for budget development.

Step 2: Data pre-processing

The next step in the framework is the pre-processing of the collected data to ensure that it is suitable for use in budget development. Data cleaning and preparation are essential, as the accuracy of the final budget depends directly on the quality of the input data [54]. Common procedures include the identification and removal of outliers, the exclusion of known periods of limited or atypical operation such as unplanned maintenance shutdowns, and the correction of obvious measurement errors. The sum of systems or feeders under an incomer can be checked to ensure that it balances.

High-frequency datasets also present unique challenges, as anomalies may not be immediately apparent and cannot be addressed manually at scale. In such cases, automated methods such as filtering techniques, statistical detection of abnormal values, and comparison across redundant data sources should be employed. Studies in the field of energy data analytics and data analytics in general have highlighted the importance of rigorous data pre-processing, as it improves both the reliability of forecasts and the evaluation of the mine's actual operating state [78], [79], [80]. Ensuring high-quality input data is therefore critical, as poor data quality not only reduces the accuracy of consumption and cost forecasts but also limits the usefulness of the budget as a management and evaluation instrument.

Data collection and preparation checklist

Before progressing to the next section, the following must be done:

- ☐ Data identified in previous section is collected.
- ☐ Irregular operation is removed from dataset.
- ☐ Data is checked for errors and approved.

Framework: Input data preparation summary

By the end of the input stage, the framework produces two outcomes. First, the objective of the budget will have been clearly defined, establishing what the result must look like and what it is intended to achieve. Second, a dataset is obtained to meet this objective and has been cleaned and prepared for use. The collected dataset is high-resolution, addressing the first barrier faced when developing and implementing high-quality budgets. Together, these elements form the baseline. It is important to emphasise that the baseline does not yet constitute a budget. Rather, it is a cleaned dataset of historical performance that provides the foundation for further analysis.

The baseline serves as the input for the forecasting process, which transforms historical operational data into electricity consumption budgets.

3.3 Framework: Electricity consumption forecasting

Problem:

The chief problem with the method section of the budget development process as identified in literature is that the methods are not scalable and adaptable to larger, higher frequency datasets. This is due to the reliance on people and manual methods of budget development. The reliance on these methods leads to the use of lower resolution data for budget development. This reduces the usability of this budget as an energy management tool and also prohibits high-detail costing to be done.

Result:

The absence of scalable methods in the budgeting process creates a significant bottleneck. Manual data handling is still widely relied upon, which constrains the ability to use high-frequency data for forecasts. Even where such data is available, budgets are typically still compiled at monthly intervals, because this is manageable through manual processes. Developing budgets at such a coarse resolution results in a considerable loss of detail. Opportunities to filter anomalies, to account for recurring operational variations, and to plan for differences in daily or seasonal activity are also missed. Outside of the operational impacts, reliance on manual methods also carries a higher risk of human error.

This limitation has direct consequences for forecast accuracy. Both consumption and cost estimates are negatively affected, particularly under Eskom's detailed TOU tariff structures, where small changes in operation can lead to significant financial impacts. Additionally, budgets are not always developed by individuals with in-depth knowledge of mine electricity consumption patterns and ongoing energy management projects. This weakens the ability of budgets to reflect the true operation of the mine.

Best practice:

The best practice is for a budgeting method to be adaptable to change, and scalable so that it can accommodate changing systems and increased data frequency. The budget development should be overseen by a knowledgeable person who can take responsibility for the budget results and their effects on energy management and performance evaluations.

Electricity cost budgets should not only serve as financial planning instruments but also as instruments for system performance evaluation, as established in Chapter 1. When the development process is not overseen by personnel responsible for energy management and performance outcomes, the potential of these budgets to enable efficiency monitoring and proactive management is significantly reduced.

The goal of the frameworks put forward in this section is to address these shortcomings using methods available in literature. The goal of the framework is to create budget profiles according to the identified interval required in Section 3.2.1. Per best practices the profiles need to be available per energy-intensive system and take seasonal patterns into account.

The developed framework needs to meet three overarching goals: scalability, repeatability, and traceability. Scalability refers to the ability of the framework to be applied across operations of varying sizes and levels of complexity without becoming excessively time- or resource-intensive. This will address the problem with reliance on manual methods identified in Section 1.2. A scalable approach ensures that both small and large mines can develop high-resolution budgets without the process itself becoming a bottleneck. This ensures that the method developed is adaptable to changes and can incorporate new data sources easily.

Repeatability implies that the method can be applied consistently across multiple budget cycles with comparable results. This reduces reliance on individual expertise and minimises variation introduced by manual development, thereby improving the reliability of the budgeting process. Traceability ensures that every step of the budget development process, from data input to final approval, is transparent and documented. This allows deviations from past trends to be explained, adjustments to be justified, and results to be verified by stakeholders.

While considering scalability and repeatability, it is also important to keep the complexity of the method in mind. Highly complex models, while accurate and adaptable, pose significant challenges in interpretability by users [52]. The framework developed in this section will be kept to a minimum complexity, as it aims to be implemented on mines in practice. Lower complexity models have a better track record of consistent implementation in industry [72], [73].

The forecasting stage of the framework is structured into two distinct segments. The first focusses on profile creation, where the cleaned baseline is organised into meaningful intervals that capture operational and seasonal variations. This is based on the methods found in several of the studies in Section 2.6. Thereafter representative consumption profiles are developed per sectioned dataset to reflect typical patterns of electricity consumption. Secondly, budget composition recombines these profiles into a comprehensive forecast that aligns with the defined objectives of the budget. Together, these three segments provide a systematic approach to transforming the

baseline into an electricity consumption forecast. All the developed methods are grounded in literature, and references to relevant documents are provided in text.

3.3.1 Profile creation

The goal of this section is to adapt methods found in literature to solve the identified problems. As there was no single method found that can be used to create electricity consumption budget profiles that comply with the needs for mines, methods from literature will be combined. The combination of forecasting methods into hybrid methodologies is supported in literature and noted to improve results [37], [81], [82].

Creating profile-based data for electricity consumption budgets is proposed by Pelsier [48] for better performance compared to actual consumption data in the case of high-frequency consumption data. It is also recommended by Goosen [40] to allow for better electricity budget cost calculations. It is clear from literature [66], [71], [74] that the best models for high-frequency electricity cost forecasting use only past electricity consumption as input data, as there are too many variables influencing electricity consumption to consider to create a reliable forecast based on dependent variables. Most often, these variables are also not well monitored and documented. Electricity consumption is exceptionally well measured on mines and thus forms the ideal basis for the budget. This will be adhered to in this framework.

As no ready-to-use methods for electricity consumption forecast profile creation on mines are available in literature, this methodology will suggest a workflow type method, where variations of methods can be substituted in to achieve the desired results [66], [83]. This will allow the user to adapt the method to their needs, skills and resource availability.

Frameworks from literature used two steps, sectioning and forecasting [37], [75]. This section will be presented in two steps, as a hybrid type method. First, a sectioning of data. This is seen in many literature applications as a first step to forecasting. In this step patterns in data are identified and the dataset is decomposed using sorting algorithms and related techniques. Second, future consumption forecasting, which uses the grouped data to create profiles with statistical or machine-learning methods. The combination of these two steps and their methods produce profiles that can be used as instruments for effective energy management.

Step 1: Data sectioning

To ensure accurate and effective forecasting, the dataset must first be sectioned in two ways. First it must be sectioned according to energy-intensive user groups. This involves identifying and isolating major consumers on the mine. This was done in the input framework and should be readily available before the commencement of this step. Second, the data should be sectioned

into matching operational categories within each system. This will allow for pattern identification within systems to be used for forecasting. Sectioning into systems is a manual process, but if done well will only need to be done once and can be used in subsequent years to compile budgets again. Sectioning into operational trends can be automated.

The need for data sectioning, or decomposition, is highlighted in several studies [37], [75], [76], [81], [83].

There are several algorithms and methods that can be employed to section data. This reduces reliance on humans for mass data processing, thus improving the scalability of the approach. These methods will create several datasets representing different operational states of each system. These states can be different due to differing needs for services during different days, different seasons or other operational happenings. Separating these variances with computer-aided methods will allow for improved forecasting to be done with this data. Data grouping by day is most commonly used in literature [75] and is practical for use in the mining environment.

A low complexity option to section data is to separate the data into known operational groups. This could be separating out all days of the week, separating weekdays from weekends, or weekdays, Saturdays and Sundays. This can further be sectioned into seasonal groups, e.g. a weekday in summer. Months, seasons or utility groupings (like low and high season) are all options for data sections. Knowledge of the mine system will be integral to this step. A mine may have known patterns of operation, like working every second Saturday, that can be sectioned and forecasted for. This can be done using simple code or even Microsoft Excel. Amin (2024) presents a good example of low complexity sectioning for electricity consumption forecasting as part of his method development [75].

More advanced methods of data sectioning can make the process less time- and resource-intensive. These methods include the k-means sorting algorithm, empirical mode decomposition (EMD) and DBSCAN [49], [76], [81]. The k-means sorting algorithm partitions data into k clusters through iterative means. Practically, this results in groups of similar operational patterns. It is easily scalable and accessible, as it is available in common Python libraries [84]. EMD adaptively decomposes non-stationary signals into trends and reduces the noise withing groupings [85]. This is applicable as mine data is inherently non-stationary. Both these methods result in well-separated groups that can be fed into the next step to create profiles.

When using k-means sorting, additional methods to determine the number of groups in the dataset may also be required. For this the elbow method can be used. The elbow method is a graphical technique used in k-means clustering to determine the optimal number of clusters (k) for a dataset. The method graphically depicts the distance between points in the groups identified,

with an identifiable angle or “elbow” in the graph at the point where methods have less distinct values. DBSCAN presents a potential advantage over k-means as the user does not need to present a predetermined number of clusters [76].

At the completion of the data sorting step, it is essential for a person who is informed on the electricity consumption patterns and energy management of the mine to review the results. Confirmation is required to ensure that the identified patterns and groupings are realistic and representative of the actual operation of the mine [56] [66]. At this stage, further data filtering may be applied, allowing the removal of groupings that correspond to days not relevant for future consumption budgeting. This validation and refinement of the dataset ensures that only meaningful data is carried forward, providing a solid foundation for the forecasting step to follow.

Step 2: Future consumption forecasting

With data sectioned into usable groups representing different operational states of the energy intensive systems, the next step is to use this data to create a forecast for future consumption, as seen in the studies by Vassiljeva [76] and Liu [77]. Per best practices, this method needs to be easily adaptable and scalable to different data intervals and sizes of operations.

Two broad groups of electricity consumption forecasting methods are available. These are engineering methods, which include artificial neural networks and machine learning. These methods are typically dependent on additional variables for electricity consumption forecasting [63], [75]. Statistical methods are more data driven and rely on historical electricity consumption data to forecast future consumption. Hybrid methods represent a combination of these two types of methods.

As noted earlier and per literature and best practices, only methods using historical electricity consumption data will be considered for use in this step. Step 1 (data sectioning) has prepared groupings of electricity consumption data for input into forecasting models to obtain profiles for use as budgets. Several methods are available for this step, and the selected method will depend on the resource availability and skill available.

The simplest method is the statistical method. Each sectioned dataset can be averaged over the time-series to obtain a representative average electricity consumption profile for the section. Examples of this method are presented in the studies by Pinsky [74] and Vassiljeva [76]. This simple method, in combination with data sectioning, reduces manual input and time spent while maintaining accuracy.

If additional computing resources are available, there are more complex forecasting models available that can use the same sectioned data from step 1 as input and produce high-quality

electricity consumption forecasts as result. These include ARIMA [36], [86], Rank analysis [66], [87] and Monte Carlo simulation [88].

Once again, a person who is informed on the operation and electricity consumption patterns of the mine should review the profiles created for accuracy and realism before the data is adjusted in the next step.

While this method is only focussed on electricity consumption budgets, electrical load and reactive energy are often included in electrical utility charges to mines. These metrics are often more static than electricity consumption and do not require intensive forecasting. Alternatively Al-Suod et.al [41] proposes a method by which these metrics can be forecasted.

As discussed in the literature section, there is no universal forecasting method that is applicable to all electricity consumption forecasting scenarios. The method suggested here in detail is applicable to deep mines in South Africa, as will be demonstrated in Chapter 4. The framework can be adapted to use alternative forecasting methods available, as provided. More complex methods can be used if the available data is significantly higher in frequency than the data demonstrated here. If more processing power is readily available, more complex methods can further reduce the input and time required by the demonstrated method. The workflow suggested, however, remains valid and will achieve the desired outcome if followed correctly. This addressed the identified barrier of lack of scalability in industry standard budgets.

Profile creation checklist

Before progressing to the next section, the following must be done:

- ☐ System datasets sectioned using a sorting algorithm.
- ☐ Grouped datasets reviewed and deemed representative.
- ☐ Grouped datasets used to forecast systems future electricity consumption.
- ☐ Forecast profiles evaluated for relevance.

3.3.2 Budget composition

The final segment for the framework for electricity consumption forecasting involves the recombination of the sectioned, forecasted profiles into a complete, long-term electricity consumption forecast. This is done in three steps. First, future dates must be assigned to the created profile groups, and second, the profiles must be recombined into a preliminary electricity consumption dataset. Third, profile adjustments are made. Created profiles may need to be updated according to planned changes on the mine. This step provides an opportunity to review

and adjust the created profiles to match any future plans or initiatives. On completion of these three steps, a complete electricity consumption budget is created.

Step 1: Assign future dates

Once representative operational profiles have been developed through clustering and forecasting, these profiles must be assigned to future dates within the budget period. This process involves aligning each profile with corresponding conditions such as seasonal variations and known electricity usage patterns. Particular attention should be given to irregular instances such as public holidays, which may have different operational patterns as expected from the weekday they fall on. By systematically assigning the appropriate profiles to specific dates, the forecast can represent variations in day-to-day operation.

Assignment of profiles must be accompanied by clear justification for each selection. This maintains the need for transparency and reproducibility, per the identified best practices. Deviations from regular operation, including scheduled maintenance periods, engineering shutdowns, or the December break commonly observed in South African mining, must be explicitly noted. Documenting these justifications not only strengthens the reliability of the forecast but also enhances the interpretability of the results for later verification and energy management applications.

Step 2: Dataset recombination

After dates have been assigned to each forecasted profile, the profiles need to be recompiled into a long-term forecast. This can be done with any available data processing software. The process should be carried out for each energy-intensive system individually before aggregating results to the POD level.

Step 3: Profile adjustments

In the preceding two steps, data is assigned to future dates and combined into a full time-based dataset. The final step of budget composition is to adjust the created profiles in the case of known planned changes on the mine.

For systems directly related to ore liberation, transportation and processing, linear scaling according to production plans can be done. A linear regression can be used, or percentage adjustments can be made directly. For all other systems, direct power adjustments to the profiles can be made using installed capacity values as well as efficiency estimates.

Budget composition checklist

Before progressing to the next section, the following must be done:

- ☐ Select future dates for each created profile.
- ☐ Use future dates to recombine profiles into year-long datasets.
- ☐ Adjust profiles if required.

Framework: Electricity consumption forecasting summary

By the end of the consumption forecasting stage, the framework produces a time-based high-frequency dataset representing the electricity budget of each identified system. This overcomes the identified barrier of low-resolution budget development in industry. The process by which it is developed is automated and relies on low amounts of user input, largely for approval. This overcomes the identified barrier of low scalability of budget development methods in industry by making the method scalable and adaptable. The developed consumption budget will be used in the next step to calculate costs for the developed budget.

3.4 Framework: Electricity consumption budget costing

Problem:

A key shortcoming in current budgeting practices lies in the approach to costing. Because budgets are seldom developed at sufficiently high frequencies, it is not possible to apply detailed costing methods. As a result, costing is generally only performed at the POD level, with little or no separation of costs between individual systems. This means that costs are not linked to the actual operational profiles of systems and therefore do not reflect the detailed structure of TOU tariffs. Instead, an average TOU split is calculated, either for the mine as a whole or per system and then applied uniformly across the entire month. Such an approach masks operational differences, fails to capture variations in daily or seasonal consumption, and ultimately undermines the usefulness of the budget for both cost forecasting and as an instrument for energy management.

Result:

The problems identified in current budgeting practices directly prevent the achievement of best practice standards and result in the development of sub-par quality budgets. A primary limitation is the loss of detail, particularly when the TOU composition of a given month changes. If these changes are not accounted for, cost forecasts become less accurate and fail to reflect the real financial impacts of energy and cost management measures such as loads shifts and peak

clipping. The budget therefore will be a poor instrument for financial planning and performance evaluation.

When systems are not assigned accurate costs and individualised tariffs, they cannot be held accountable for their actual electricity usage. This lack of accountability obscures the contribution of individual systems to overall electricity costs, reducing the ability of mine management to identify inefficiencies and measure the impact of energy management initiatives. Ultimately, these shortcomings diminish both the financial and operational usefulness of electricity cost budgets.

Best practice:

Best practice requires that the official tariff structures from the relevant utility company be used to assign costs to electricity forecasts. For most South African mines, this entails applying the Eskom Megaflex tariff structure. To ensure accuracy, costing should be carried out at the highest frequency at which the tariff data is available, thereby reflecting the true variation in charges over time. TOU pricing must be explicitly incorporated into the budget development process, as this has a significant impact on the cost outcomes of different systems. In addition, individualised tariffs should be developed for each energy-intensive system. This approach allows for variations in operational profiles to be captured, ensuring that costs are representative of actual usage patterns rather than being averaged across the mine as a whole.

The costing stage of the framework is presented in three segments, each addressing a critical aspect of translating electricity consumption into cost values. The first segment focusses on the tariff structure breakdown, where the relevant utility tariffs are analysed and categorised into their constituent components to enable application. The second segment involves the application of costs, in which these tariff components are assigned to the corresponding consumption data at the appropriate level of detail. Finally, the tariff calculation segment consolidates the applied costs into a complete budget, ensuring that both time-of-use variations and system-level allocations are accurately reflected. Together, these three segments provide a structured and transparent framework for converting electricity forecasts into reliable cost budgets.

Note that this framework is developed based on mines in South Africa using the South African energy utility, Eskom, as reference. Eskom Megaflex tariffs operate on a fixed year ahead TOU system. This methodology does not consider utilities with demand-based costing systems. There is adequate literature available on demand-based cost forecasting to be referenced if needed.

3.4.1 Tariff structure breakdown

This section prepares the utility costing data for application to the electricity consumption data. Costing data is typically not provided as a time series. In order to automate the process of

electricity budget costing, the cost data must be in the form of time-series data. This will be done in two steps: first the identification and breakdown of the relevant tariff structure into its components, and thereafter the dataset creation. These steps can be done using data processing software of the user's choosing.

Step 1: Identify and break down tariff structure

The relevant tariff structure is identified in the framework for input data preparation. Once the tariff is identified and relevant reference documentation is obtained, it must be broken down into its constituent cost components to enable accurate cost allocation in the steps to follow.

The cost components typically include active energy costs, charged per kWh, variable non-active energy costs such as load, demand or reactive energy, and administrative fees which may be fixed or time dependent. Each of these must be identified and isolated. This will aid in producing a detailed cost breakdown when documenting the budget process.

Step 2: Create time-based tariff data

Next, the broken down and isolated tariffs need to be combined into a time-based electricity cost dataset that can be used to automate the costing process. Active energy costs with TOU connections must be assigned to their relevant time slots. It is important that this dataset is set up in the same time-interval as the electricity consumption dataset created by the consumption forecasting framework. Next add all additional active energy based tariffs that are not time dependent to every entry on the dataset. This dataset can be used as a base for every site on the same billing structure.

Once the dataset is representative of the active energy, all other costs need to be determined. Using the broken down costs from Step 1, calculate the known costs for the site in question for the relevant utility billing period (likely monthly). Add these costs up to get a lump sum of non-active energy based costs.

To allocate the non-active energy costs to the time-series, the total energy consumption for the relevant utility billing period is required. This is available from the results of the framework for electricity consumption forecasting. Use this total consumption value to calculate a weighted fixed cost/kWh value. This value can then be added to the cost/kWh active energy dataset. Alternatively, if no consumption is available, a fixed cost per time interval can be calculated and incorporated.

Once the dataset is created, it needs to be adjusted for any known or planned tariff increases in the future budget period. Utilities typically announce tariff increases with the release of new tariffs

once a financial year. Eskom increases for commercial customers take effect every year on 1 April after approval by the regulatory board. Depending on the mine financial year and budget period, increases may need to be estimated. Refer to mine actuaries for estimated increase values. Multiply the tariff dataset with the relevant increase percentage for the after-increase portion of the dataset. The time-based tariff created here will be used to automate the costing process in the next section.

Tariff structure breakdown checklist

Before progressing to the next section, the following must be done:

- ☐ Relevant tariff structure broken down into component tariffs.
- ☐ Tariffs used to set up a time-based tariff dataset in the same interval as the consumption budget dataset.
- ☐ Tariff increases applied where relevant.

3.4.2 Budget cost application

Now that a time-based tariff dataset has been developed, it can be used, in combination with the time series electricity consumption data, to obtain costs. This section is comprised of a single step: multiply the consumption dataset with the cost dataset.

Any data processing software can be used to complete this step. Separate the obtained cost values so that there is time-based cost data, as well as totals for relevant intervals, such as billing periods.

After this step, the user should have a time series dataset with exact cost budget for every time interval. This can be aggregated to calculate total cost per system per month, total cost budget for the mine per month, and total yearly budget cost. This step addresses the identified barrier of lack of scalability of industry standard budget development methods.

Budget cost application checklist

Before progressing to the next section, the following must be done:

- ☐ Budget cost calculated per system using created budget consumption and tariff datasets.

3.4.3 Tariff calculations

The final section of the budget costing framework involves the calculation of tariffs from the time-series cost and consumption datasets developed in previous stages. This step converts the

detailed cost forecasts from the previous section into interpretable tariff values that represent the cost of electricity over time.

Tariff summaries per system and per billing period are required for reporting purposes. Effective tariffs can also be used to evaluate expected cost performance of systems, and in cost systems with TOU is especially useful for identifying unplanned consumption.

This is achieved by aggregating the cost and consumption forecasts over the relevant period and dividing the total cost by the total consumption for a cost/kWh value. This result represents an effective tariff and can be used for high level reporting and billing period evaluations.

Tariff calculation checklist

Before progressing to the next section, the following must be done:

- ☐ Budget tariff calculated per system per month using created budget consumption and cost datasets.

Framework: Electricity consumption budget costing summary

By the end of the costing stage, the framework produces a complete electricity budget that integrates both consumption forecasts and detailed costs and tariffs. These components provide a cost budget that is consistent, traceable, and aligned with best practice standards. This overcomes the identified barrier of lack of detailed costing of budgets by producing a high-frequency, detailed cost dataset that accounts for TOU. Before the budget can be used it must undergo verification to ensure its accuracy, reliability, and suitability as a decision-making tool. The next section therefore addresses the verification of the developed electricity consumption and cost budget, and its final reporting.

3.5 Framework: Budget verification and reporting

Problem:

Few problems were noted with the verification processes of mine budget practices. Still, budgets may be subject to human error, and it is good practice to verify any data that will be used for management purposes.

The reporting of the budget process was identified as a barrier to the development of high-quality budgets in practice. Budgets are developed but no detailed information on the process, the input data, or any considerations made to arrive at the final dataset is documented. There is thus a lack of proper process reporting as part of the budget creation process.

Result:

If budgets are not subjected to a thorough verification process, the risk of inaccuracies in financial and operational planning increases. Errors introduced during budget development, whether through incorrect data handling, inappropriate assumptions, or simple human oversight, may go unnoticed. Such inaccuracies compromise the reliability of the budget as both a financial forecasting instrument and an energy management tool.

Unverified budgets may also misrepresent system performance, leading to incorrect electricity performance evaluations. Over time, this reduces confidence in the budgeting process, diminishing its value as a management tool. The absence of verification removes an important layer of accountability, as nobody assumes responsibility for the accuracy of the developed budget. The result is a budget that lacks credibility and that cannot be used as an instrument to evaluate performance of energy management initiatives.

Without detailed reporting of the budgeting process, the validity and accuracy of the budget can easily be called into question. A lack of reporting significantly reduces the reproducibility of a budget, leading to inconsistencies long term, as every budget cycle may be calculated in a different way. Transparent and standardised reporting is critical to maintain the integrity and the reproducibility of budgets.

Best practice:

The best practice for budget verification dictates that budgets need to be checked and verified by an informed person before presentation and usage. This ensures the quality and reliability of the budget for use. As budgets are an integral part of mine financial management, accuracy and verifiability of results are very important.

For reporting and documentation, best practice is to document the process and steps followed in creating the budget for traceability and repeatability. This is followed by presenting the data in a concise and informative manner to relevant stakeholders for use.

The framework is presented in three sections. First, internal result verification, where steps will be given to check the developed budget against historical figures to ensure accuracy and quality. Second, a procedure for reporting the budget to ensure repeatability and transparency will be given. This section includes suggestions from the study by Pelser on the subject [48]. Finally, a section discussing the presentation of the results to different stakeholders is presented, ensuring that the budget is effectively communicated to each group.

The combination of these three sections will provide a structured method to overcome the identified barrier of improper budget reporting, while also ensuring accuracy and reliability of the budget. Proper visualisation and presentation of final results will tailor the results to the needs of different users.

3.5.1 Internal result verification

This section presents a method to verify the electricity cost and consumption budget created in the preceding framework sections. The verification process provides a high-level evaluation of the overall budget to ensure consistency and accuracy. As the individual profiles have already been verified in the consumption forecasting framework section, this section focusses on verification of the aggregated results. Verification of the monthly totals serves as a secondary check on the integrity of the system level components that comprise the budget. This will be done in two steps, one to check the consumption budgets, and one to check the cost budgets. All verifications must be done by a person well informed on the operation and on the energy management of the mine and its systems. It is advisable for verification and review to be done independently of budget development.

Step 1: Check the consumption budget

This step involves checking the consumption budget to confirm its consistency with historical actual data and the assumptions and adjustments made during the forecasting process. Visual comparisons enable a reviewer to compare several data points over time easily. Aggregated data, such as monthly intervals, can be checked, and higher frequency can be used if anomalies are noted. A clustered bar chart is recommended to compare the developed budget to either the input dataset or to past developed budgets.

Any deviations between the two datasets must be reviewed in the context of the development process. Deviations may be attributed to data cleaning or to adjustments made between the input dataset and the final budget. Unless large adjustments have been made, the budgets are expected to be in the same order of magnitude. This confirms that the budgets represent realistic operation and ensures that the developed budget is defensible.

Step 2: Check the cost budget

This step verifies the results of Section 3.4 to confirm that it represents a realistic budget result. First, costs and consumptions can be compared to ensure that the results follow the expected pattern of offset between these values. The developed cost budget can thereafter also be compared to historical actual cost values, or historical budget values. In this case the tariff increases between the years, as well as any adjustments made to the consumption budgets, need

to be considered when comparing. Any noted differences should be explainable by these known changes.

Further validation of the costing process can be done by evaluating the system level effective tariffs. Tariff values can be plotted to confirm that they remain within expected ranges, and that they show variation where expected, for instance lower tariffs for systems with load shift projects reducing consumption in more expensive operating times. These visual comparisons provide a practical and transparent means of verification of the costs before they are reported for use.

Internal result verification checklist

Before progressing to the next section, the following must be done:

- ☐ Consumption budget checked and verified.
- ☐ Cost budget checked and verified.

3.5.2 Budget procedure reporting

The next component of the framework focusses on reporting the procedure followed to create the final budget. In this step all data sources, assumptions and adjustments made as well as methods used in the creation of the budget are documented for transparency and repeatability. This section is completed in three steps, one reporting on each of the first three framework steps to create the budget. Each follows a similar structure, addressing what was used (data or methods), what was done, and that it was verified. The exact procedure will differ based on the budget developed, but the workflow of reporting addresses the identified barrier of lack of reporting budgeting processes in industry.

Step 1: Input procedure reporting

This step focusses on reporting on the work done during the input framework of the budget development process, as in Section 3.2. The following should be documented:

- Input data type.
- Input data source.
- Input data time interval.

This can include information on groupings available, why the groupings and time intervals were chosen, if multiple data sources were available, and why the specific source was selected. Recording this information establishes a foundation for reproducibility and allows subsequent

users of the framework to trace how the input data relates to both the operational structure of the mine and the forecasting outcomes.

In addition to the documentation above, any changes made to the input data selected should be well described. This includes any data cleaning and preparation applied to the datasets. The mechanism for making changes should also be reported, manual or automatic, and any code used should be recorded and kept in a dedicated digital archive. Any additional steps taken to verify and accept the collected data for use should also be documented.

Step 2: Consumption forecasting procedure reporting

This step focusses on creating an account of the methods used to forecast electricity consumption as described in the second framework, Section 3.3. The following should be documented:

- Data grouping method and resulting groups.
- Data forecasting method and resulting profiles.
- Adjustments and assumptions made.
- Future date assignments.

All codes, algorithms and datasets created need to be recorded and kept for future reference in a dedicated digital archive. Timeline for data retention varies between operations, but at least two years is recommended, to allow year-on-year comparisons. Justifications for methods selected and adjustments and assumptions are recommended for optimal transparency. This systematic reporting approach promotes transparency, repeatability, and confidence in the forecasting component of the budgeting framework.

Step 3: Cost forecasting procedure reporting

The final step for budget procedure reporting is focussed on documenting the process resulting from the third framework presented, Section 3.4. The following should be documented:

- Tariff structure used.
- Tariff increases applied.

Documenting the relevant tariff structure and its source ensures that future budget cycles can replicate the budget with the appropriate variations if any tariff changes occur. All created datasets should be securely stored for future reference or possible re-use. The basis of assumptions made around tariff increases, if the budget is developed before official announcements, should be given. Documenting these assumptions ensures transparency in cost forecasting and provides a reference point for future verification.

Any steps taken to verify the created datasets and the resulting cost budgets should also be documented for future reference. As in the previous steps, all this information should be kept in a dedicated digital archive for at least two years. This ensures transparency, reproducibility, and accountability of the costing phase of the electricity budgeting framework. This step addresses the identified barrier of lack of detailed reporting and documentation of the budget development and implementation process.

Budget procedure reporting checklist

Before progressing to the next section, the following must be done:

- ☐ Input procedure documented.
- ☐ Consumption forecasting procedure documented.
- ☐ Cost forecasting procedure documented.

3.5.3 Budget result reporting

The final section of this framework focusses on budget result reporting, ensuring that the developed budgets are effectively communicated to all relevant stakeholders. Reporting results appropriately is important for providing actionable information and facilitating understanding of the presented data, as visualised data is better interpreted and understood [89].

This stage is intended to bridge the gap between budget development and practical application of the developed budgets. This section is presented in four steps. First, relevant stakeholders are identified, and thereafter their specific needs are determined. The relevant data is then visualised or processed appropriately and finally presented for approval and use. Effective result reporting aligns different levels of the organisation and ensures utilisation of the developed budgets.

Step 1: Identify relevant stakeholders

The first step in budget result reporting is to identify and evaluate the key stakeholders who will use the developed budget. Several levels of an organisation may be interested in the developed budget. Typical stakeholders include those responsible for energy management, the management and engineering teams of each mine, and financial planning departments. These roles may vary depending on the structure of the organisation and the identified purpose of the budget. Clearly defining the stakeholders will ensure that their needs are all addressed by tailoring results for each relevant group.

Step 2: Determine stakeholder needs

Once stakeholders are identified, the next step is to determine their specific budget requirements. Each group may have different needs depending on their end goal with the budget. The budget may therefore be required in different levels of detail and different time intervals by different groups. For use as an instrument for energy management, the budgets will need to be presented in the highest possible interval, and digital datasets may need to be made available for use with smart energy management software. Financial departments may only require monthly cost figures. Results for evaluation and approval by management may need to be visualised to be presented to all relevant stakeholders.

Step 3: Visualise or prepare developed budget data

With stakeholder needs identified, the third step is to transform the developed budgets into visual representations and representative datasets according to needs. Effective visualisation improves understanding and allows complex information to be interpreted quickly. The choice of visualisation method should be guided by the audience's level of technical expertise and the specific application. Detailed profile charts are appropriate for operational and technical staff who require insight into consumption patterns. Simplified graphs and summary tables are more suitable for management and financial teams focussing on overall cost and consumption values.

When selecting visualisation and presentation strategies, it is important to consider what insight each audience should take away from the data. Doing so will allow for budget data to be presented in a way that is informative and supports decision-making across organisational levels.

Step 4: Present developed budgets for approval and use

The final step of the budget reporting process is to present the budgets that were prepared and visualised in the previous step. This ensures that the budget outputs are communicated to the right stakeholders in the formats and intervals they require to perform their functions. Users can then approve the budgets and begin implementing them in practice.

Budget result reporting checklist

Before progressing to the next section, the following must be done:

- ☐ Relevant budget stakeholders identified.
- ☐ Stakeholder needs determined.
- ☐ Data prepared and visualised for presentation.
- ☐ Data presented to relevant stakeholders.

Framework: Budget result reporting summary

By the end of this stage of the framework, all the developed budgets will have been verified, approved, documented for traceability and future reference, and presented to relevant stakeholders. This ensures that the budgets are accurate and accepted by the mine, and available for use to all who require it. The identified barrier of low-resolution budgets was addressed through the presentation of high-resolution budgets. The identified barrier of lack of output of detailed costs was addressed. The identified barrier of lack of reporting of the budget process was addressed through the steps provided, ensuring that all data and critical decisions made during the process are recorded and kept.

3.6 Summary of developed framework

Figure 3.2 gives a detailed summary overview of the developed framework, including the steps and checklist items for each section. A full checklist, for reference, is provided in Appendix B.

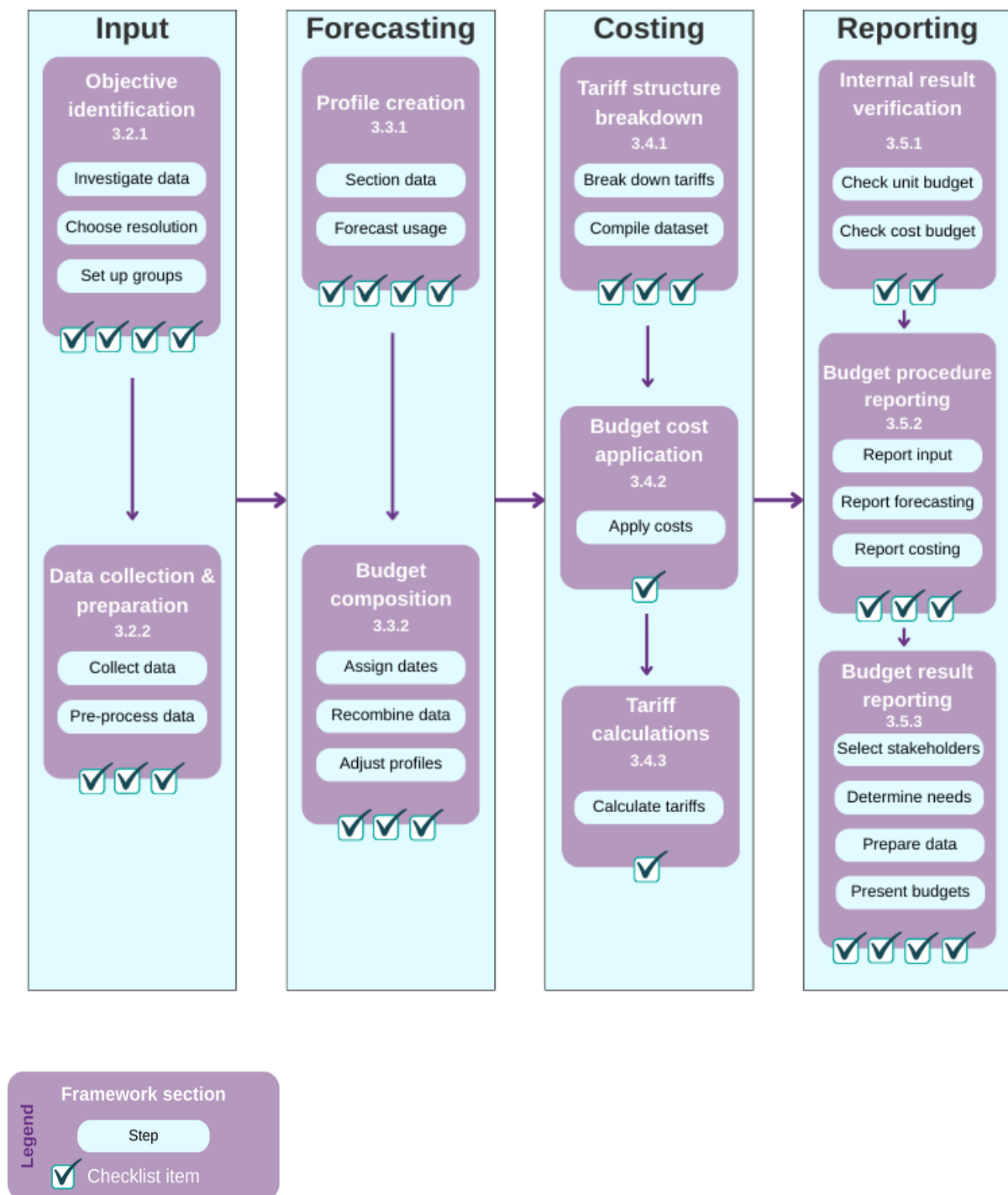


Figure 3.2: Detail summary of the developed framework.

3.7 Developed framework verification

In Section 1.2.5 of this study, the following four barriers to the development of high-quality electricity and cost budgets on mines were identified:

1. Budget resolution, both in input data and output result.
2. Lack of scalability and adaptability of the budgeting method.
3. Detailed costing, both in the method and the output result presentation.
4. Documentation and traceability of the budgeting process.

The goal of the developed framework is to provide approaches to develop budgets that address and overcome each of these barriers. This section provides a verification that each of the identified barriers have been addressed and that the application of the framework will aid a user in overcoming them. A summary of how and where the barriers are addressed is given in Table 3.1.

Table 3.1: Verification of developed framework.

Barrier	Section addressed	Workflow	Result
1. Budget resolution, both in input data and output result.	Sections 3.2.1, 3.2.2, 3.3.2, 3.5.3.	Appropriate budget resolution is identified, input data of the appropriate resolution is collected, and budget results are reported in the identified appropriate resolution.	A high-resolution budget that can be used for near real-time energy management.
2. Lack of scalability and adaptability of the budgeting method.	Sections 3.3.1, 3.3.2, 3.4.2.	Data sectioning and forecasting are combined to relieve the manual inputs of industry standard budget development. The methods can be automated and only need approval by an informed person.	A budgeting method that can scale to large and high-frequency datasets and adapts easily to changes.
3. Detailed costing, both in the method and the output result presentation.	Sections 3.4.1, 3.4.2, 3.4.3, 3.5.3.	Detailed costing is done using high-frequency consumption data. By breaking down tariffs into a time-based dataset, systems can be costed independently and automatically.	Costs that are individualised per system, reflecting differences in TOU and total cost.
4. Documentation and traceability of the budgeting process.	Section 3.5.2.	All inputs, methods, calculations, procedures, assumptions and results are noted and stored in a dedicated digital archive. Reports are to be kept for at least two years.	A process that is traceable and repeatable, enhancing the reliability and transparency of the budgeting process.

The table shows that each of the identified barriers are addressed by at least one of the framework steps provided. The “checklists” at the end of each framework sub-section provide a summary of what is achieved throughout the implementation of the framework. This additionally shows that the developed framework is in compliance with the developed best practices in Section 1.2.3.

The method addressed the problem with industry standard budget development as given in Section 1.2. The developed methodology combines existing methods and solutions from both the mining industry and wider industry, as given in Sections 2.5 and 2.6, with available data on mines and the developed best practices. The result is high-frequency budgets, developed through a method that is scalable and adaptable, with representative costs that account for TOU, that are

well reported and thus repeatable and traceable. This is a high-quality budget that can be used effectively as an instrument for improved energy management.

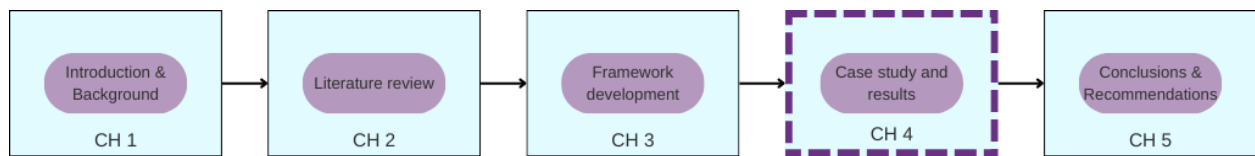
3.8 Conclusion

The framework developed in this chapter provides a structured approach to develop electricity cost and consumption budgets for mines. The framework addresses the four barriers identified in Section 1.2.3: budget resolution, scalability and adaptability, detail costing, and documentation and traceability. It does so in four sections. In each section, the problem identified earlier in the study and the effect of the problem on the resulting budget is compared to the best practice outcome. The proposed framework is then given, which should lead a user to develop a budget that complies with the developed best practices.

The framework for input data preparation guides the user through identifying the objective of the budget and collecting and preparing the input data accordingly. The framework for electricity consumption forecasting provides a workflow method to create electricity consumption profiles in a scalable and adaptable way and compose a budget with the developed profiles. The framework for electricity consumption costing provides steps to break down and analyse tariffs, use them to develop a time-based tariff dataset and to apply costs and calculate tariffs. The framework for budget verification covers methods to verify obtained budget results, how to document the budget procedure for transparency and reproducibility, and how to report the result appropriately.

The framework combines manual and automated processes, utilising technical experts for key checks and approvals, and not for time-intensive data processing. This improves the scalability of the budgeting process by automating some of it, without sacrificing the credibility of the resulting budget. The framework was verified and found to address all the identified barriers. The framework therefore can produce budgets that will be useful instruments for continuous improvement and energy performance evaluation. The framework developed in this methodology will be subjected to a test on a case study mine to evaluate and validate the effectiveness of the framework.

CHAPTER 4 RESULTS AND DISCUSSION



4.1 Preamble

This chapter presents an application of the framework developed in Chapter 3 to demonstrate its practical implementation and evaluate its effectiveness in addressing the identified barriers to the development of high-quality electricity consumption and cost budgets in the mining industry. The section will evaluate and validate the results produced by the application of the developed framework for their ability to overcome the identified barriers. It was elected to use a single case study to demonstrate these attributes, as the goal of the framework is qualitative improvement, not quantitative. Recommendation for evaluation of other metrics of this framework can be found in Section 5.4.

To demonstrate the practical application of the proposed framework, a suitable case study site was selected. A mine with high-quality, high-frequency consumption data and adequate data availability was approached. The mine and its operations are known to the author, and the author could act as a person with knowledge on the current and future operations of the mine for the budget development process. The mine operates on a single Eskom POD, simplifying the costing for demonstrative purposes. The mine also has many sub-systems that have varying daily and seasonal operational patterns, which will demonstrate the strength of the forecasting methods selected for the framework. The chosen site provided reliable historical electricity consumption and cost data as well as historical budget data, enabling a comprehensive comparison of budgeting practices.

Data from the period January 2023 to December 2023 was used as the input dataset. These data points were captured in the relevant Eskom billing intervals applicable to each month, thereby ensuring that the budgets developed in this study align with actual billing practices. Using this dataset, two distinct electricity cost budgets for the year 2024 were constructed. To keep comparisons accurate, exactly the same dataset was used as input for both budget development methods.

A budget was developed following the framework established in Chapter 3 of this study. This framework incorporates best practices identified from the literature review and addresses

shortcomings identified by the survey analysis, with the aim of producing budgets that are of higher quality and resolution.

The budget developed according to the new framework will be evaluated in comparison to a budget developed according to the industry standard method. This method and its development can be seen in Appendix C. Both budgets are developed using exactly the same input data to provide a fair comparison of the methods. The following barriers to high-quality budget development in industry, as identified in Chapter 1, are used as metrics for the evaluation:

1. Budget resolution, both in input data and output result.
2. Lack of scalability and adaptability of the budgeting method.
3. Detailed costing, both in the method and the output result presentation.
4. Documentation and traceability of the budgeting process.

The developed 2024 budgets were then evaluated against the actual consumption and cost data for the year 2024. This was done to ensure that the implementation of the new framework delivers budgets that are at least as accurate as budgets developed through industry standard methods. To ensure robustness of the evaluation, the results of both budgets were compared using Mean Absolute Percentage Error (MAPE).

The results are presented in two stages. First the budget developed according to the proposed framework is presented, illustrating how the developed framework will function in practice and what output it will produce. Second, an evaluation will be presented in order to validate the results, and thereby, validate the developed methodology. In this section the two budgets are evaluated against each other and against the 2024 actual data. This sequential presentation allows for a clear comparison between the two approaches and highlights the potential improvements achievable through the application of the proposed framework.

4.2 Application of the developed framework

4.2.1 Preamble

This section will apply the developed framework to the identified case study mine. The steps as given in Chapter 3 will be implemented and the process and obtained results will be presented.

4.2.2 Implementation of framework: Input data preparation

4.2.2.1 Identify objective

Step 1: Investigate available data

The case study mine had multiple available sources of electricity consumption data. The most dependable source of data was from a third-party metering company. This data is routinely used by the mine for electricity consumption performance evaluations and was available in half-hourly intervals, which aligns with the minimum requirement for best practice. This data was also stored for at least 3 years, making historical data for comparisons easily available. The case study mine did not have high-interval historical production data available.

The author is well informed on the case study mine and has information about the seasonality of the operation of systems on the mine. Information on planned changes on the mine during the budget period was collected. Additionally, information on the mine billing calendar was also collected for use during the costing framework. The mine is not billed on calendar months, but on custom billing months that span across calendar months and vary significantly in length.

Step 2: Choose required data resolution

The identified historical data to be used as input for this case study was available in half-hourly intervals. No further changes to the data resolution were required. This data will be used to develop a half-hourly interval electricity consumption budget.

Step 3: Set up systems groups

The data available from the metering company is grouped into the following systems:

- Pumping
- Mining (underground operations)
- Surface refrigeration
- Underground refrigeration
- Surface general operations
- Hoisting

The mine does not have a dedicated compressed air system. The mine receives ventilation from a nearby shaft and is not responsible for the efficiency monitoring thereof.

All the systems feed from the same POD, where the utility (Eskom) also has a meter. This is illustrated in the flowchart given in Figure 4.1.

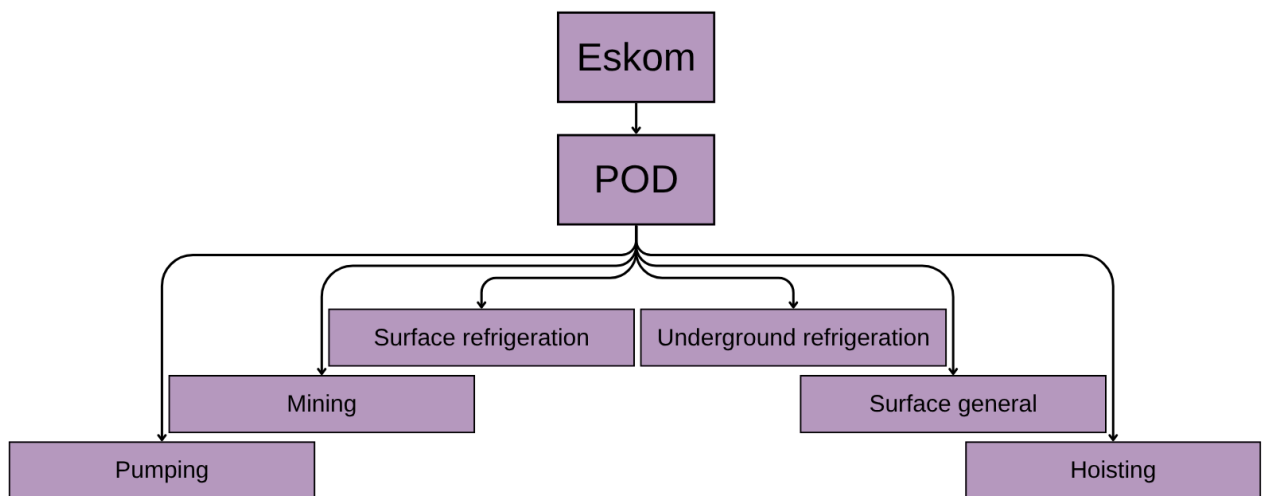


Figure 4.1: Case study mine system layout simplified.

The mine is interested in monitoring the efficiency and performance of each of these systems. A high-frequency dataset of historical data of one year for each of these systems, as well as the POD, is available. The Eskom metering point data is only available in monthly intervals.

All four checklist items for “identify data” have been met, thus the next step of the framework can commence.

- ☑ Identify data source with high-frequency data available for use.
- ☑ Select required data interval for energy management.
- ☑ Select systems groups for energy management.
- ☑ Identify additional information required for budget development (billing dates, planned changes, etc.).

4.2.2.2 Collect and prepare data

Step 1: Locate data sources and collect data

Data was available from long-term storage servers of a third-party metering company providing electricity metering services to the case study mine. Time based half-hourly electricity consumption data separated by energy-intensive system was collected.

Step 2: Data preprocessing

The collected data is confirmed to be from calibrated meters, and have undergone basic pre-processing for data loss and common metering errors by the third-party metering company. The data has also been verified in use, as it has been used for data management evaluations. The data was reviewed by the author and no evidence of data loss, extreme outliers, or metering errors was identified. As a result, the dataset was deemed suitable for direct use in the development and testing of the proposed framework.

Additional steps were taken to ensure that the baseline dataset was representative of normal mine operating conditions. Days with atypical events such as safety days or unplanned shutdowns were excluded from the dataset. Due to the sensitive nature of the information and for the anonymity of the mine, the days and events will not be noted. Most of the exclusions were in the first half of the year. These exclusions were required to ensure that the budget will represent business-as-usual on the mine. Figure 4.2 gives an example of an outage on the underground fridge plants that was excluded. The figure represents one year of data; however dates are hidden for confidentiality.

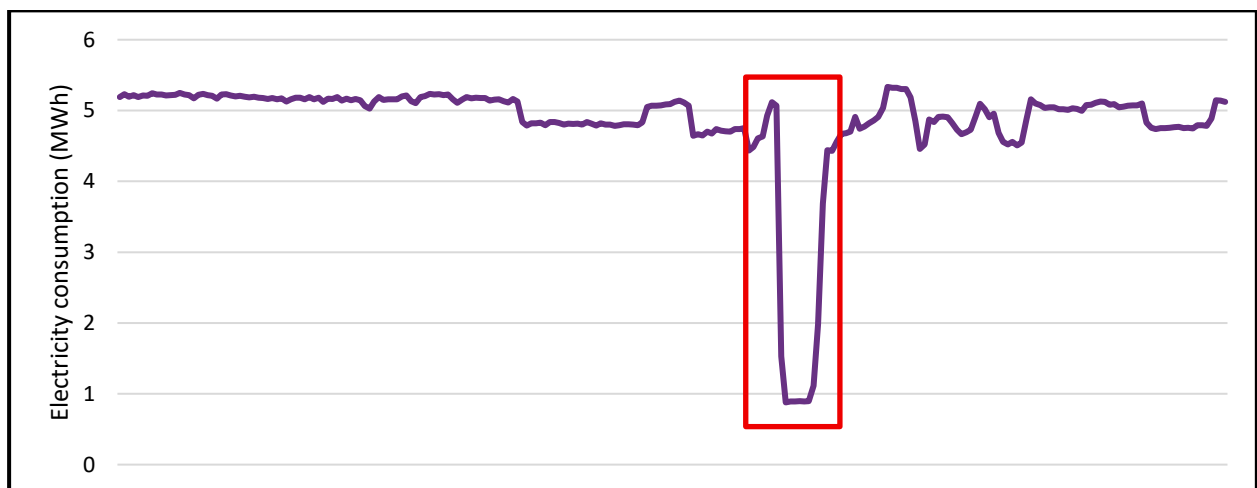


Figure 4.2: Data filtering example on underground refrigeration system.

All three of the checklist requirements for this section have been met, thus the next step of the framework can be done.

- ☑ Data identified in previous section is collected.
- ☑ Irregular operation is removed from dataset.
- ☑ Data is checked for errors and approved.

4.2.3 Implementation of framework: Electricity consumption forecasting

4.2.3.1 Profile creation

Step 1: Data sectioning

As a first step to data sectioning, all the collected datasets were separated into two seasonal groups, high-season and low-season, according to Eskom Megaflex tariffs. Operation of most systems is expected to differ between these seasons.

To identify recurring patterns within the datasets, a k-means sorting algorithm, given in Equation 1, was applied. As described in Section 3.3.1, this algorithm partitions the dataset into a specified number of clusters with corresponding operational patterns. The elbow method was used to identify the ideal number of groups for the k-means algorithm to sort the data into. The combination of these methods allowed each seasonal system dataset to be sorted into groups based on their consumption profiles, thereby separating different consumption patterns to be used in the forecast.

Equation 1: k-means sorting algorithm.

$$J = \sum_{i=1}^k \sum_{x \in S_i} \|x - \mu_i\|^2$$

Where J represents the within-cluster sum of squares, k represents the number of clusters, S_i is the i_{th} cluster, x is the data point in cluster S_i and μ_i is the mean of cluster S_i . The $\|x - \mu_i\|^2$ operator represents the Euclidean distance between the data point and the cluster's mean. The algorithm separates the dataset into k distinct, non-overlapping clusters by minimising J [90].

Figure 4.3 shows the result of the elbow method application to the low-season dataset of the pumping system, where three clusters were selected as the optimal amount. This was repeated for each dataset and each system using an automated script. If no clear elbow was discernible through the method, a default of three was selected, to represent the expected operational differences between weekdays, Saturdays and Sundays.

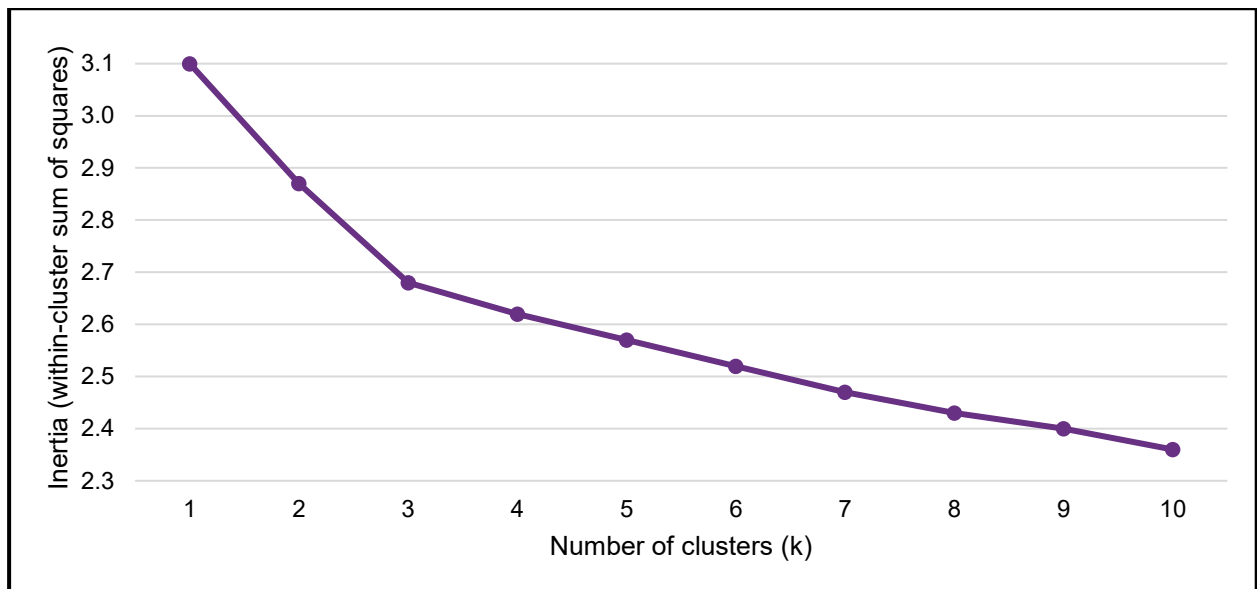


Figure 4.3: Example of elbow method application.

Through application of this method, several representative datasets were compiled. The datasets were reviewed and accepted for use. Figure 4.4 gives the operational patterns of electricity consumption that were identified in the surface refrigeration system as an example. Figures for all other systems are given in Appendix D. Numbers 0-4 represent identified and isolated clusters of consumption trends, with the profiles showing the average electricity consumption of each of these clusters.

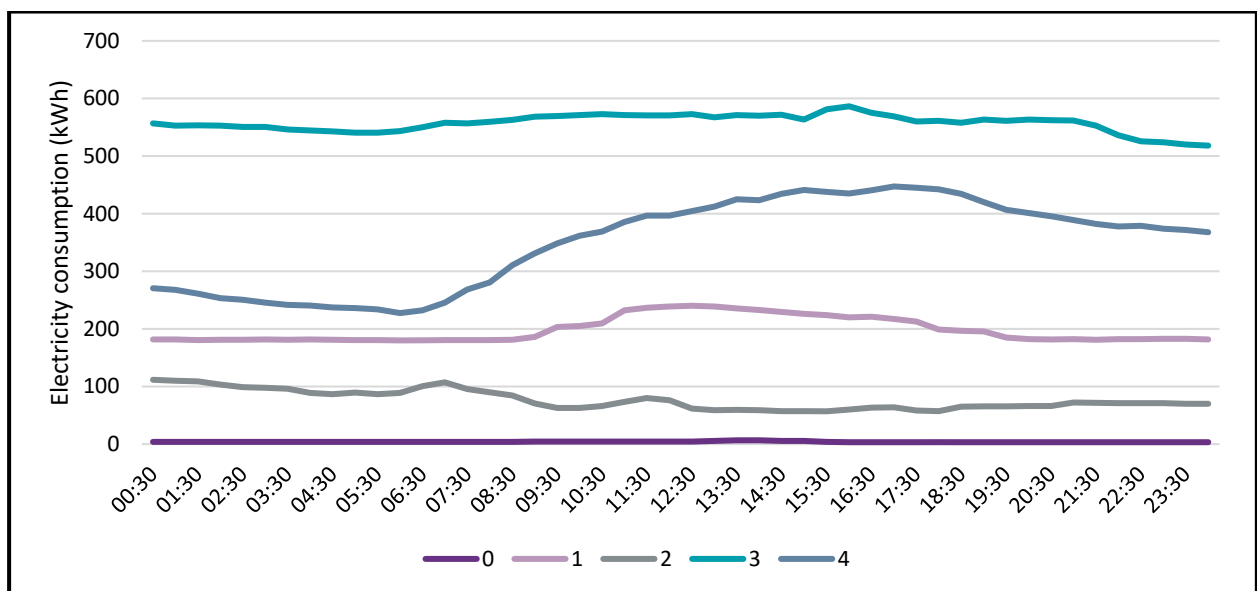


Figure 4.4: Identified electricity consumption patterns in surface refrigeration system.

Step 2: Future consumption forecasting

As limited processing was available to produce the forecasts in this case study, the simplest method suggested in the methodology was applied. This involved using an average of each grouped dataset as its profile for the forecast. The groupings were then evaluated for application to future dates. The following was considered:

- Prevalence of certain groupings on specific days.
- Prevalence of certain groupings during specific times of the year.
- Known operational situations that cause different groupings.

Several operational and context specific considerations were incorporated into the development of the final budget profiles to ensure that they accurately reflected expected future operation. For example, where a notable increase in consumption was observed later in the baseline year in the surface refrigeration system (Figure 4.4 cluster group 3), this trend was expected to continue into the budget period and beyond. Only the corresponding group profile was used to forecast the surface refrigeration. This ensures that the budget captured the most recent operational behaviour.

Seasonal operational adjustments were also considered. A lower consumption grouping was identified and applied to most systems for the period between Christmas and New Year, when the mine has a planned shutdown.

Weekday specific operational trends were also identified and incorporated. Certain groupings or combinations of groupings were found to occur predominantly on certain weekdays, reflecting known operational routines. Together, all these considerations ensured that the final profiles captured both recurring operational patterns and planned changes in mine electricity consumption for the budget period.

All four checklist considerations were met, and the forecasted profiles are now ready to be used in the next step.

- ☑ System datasets sectioned using a sorting algorithm.
- ☑ Grouped datasets reviewed and deemed representative.
- ☑ Grouped datasets used to forecast systems future electricity consumption.
- ☑ Forecast profiles evaluated for relevance.

4.2.3.2 Budget composition

Step 1: Assign future dates

Following the development of representative profiles, the profiles need to be assigned to future dates to generate a full dataset. Each created profile per system was aligned with corresponding future dates according to the identified designations in the previous step.

Step 2: Dataset recombination

The identified corresponding profiles and dates were combined into year-long time-based datasets per system using data processing software. Figure 4.5 gives the year-long dataset for the surface refrigeration system. Figures for all other systems are given in Appendix D.

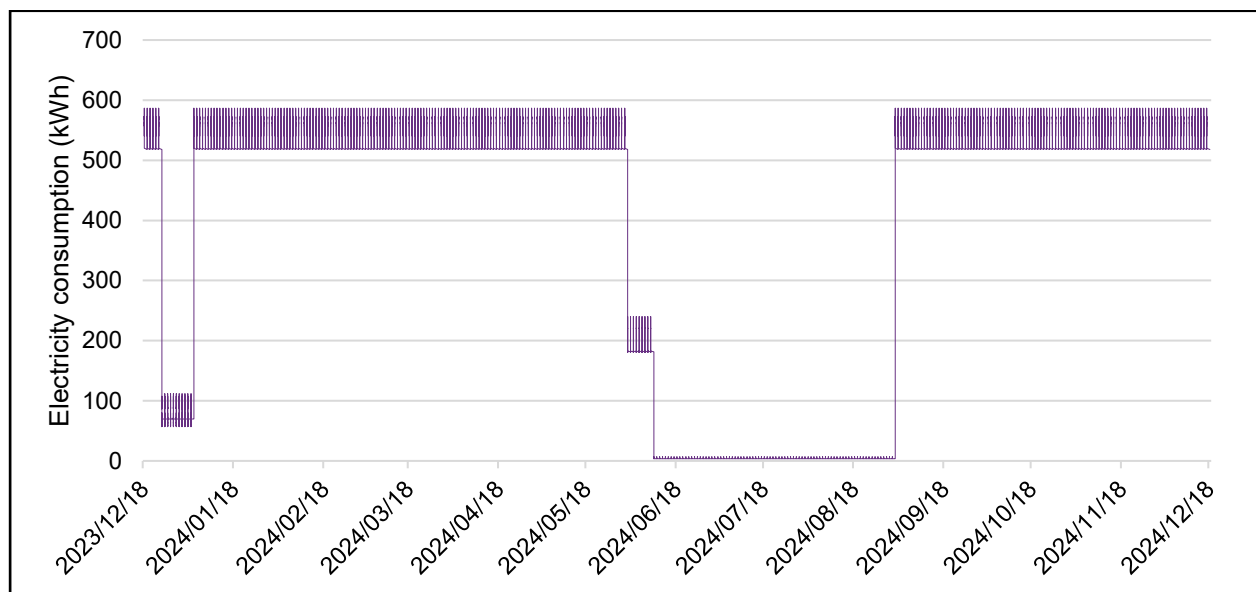


Figure 4.5: Combined yearly electricity consumption budget for surface refrigeration system.

Step 3: Profile adjustments

Information on planned operational changes were collected during the input framework step. The mine planned to have a 9% reduction in ore production starting in July 2024. The hoisting system budget consumption was adjusted 9% down from July 2024, as ore hoisting will be directly affected by this reduction. The mining system was also reduced by 9% from July 2024, as the system is primarily made up of machinery used for mining and ore movement underground. Per best practice, no other systems were reduced as the reduction is not anticipated to affect them.

An efficiency upgrade was made to the underground conveyors on the mining system. The equivalent effect, according to the mine, should be a 2% reduction in electricity consumption year

on year. For this, the electricity consumption budget of the mining system was adjusted down 2% from January 2024.

All checklist items for this section of the framework have been met. The dataset can now be used to calculate the cost of the developed budget.

- ☑ Selected future dates for each created profile.
- ☑ Used future dates to recombine profiles into year-long datasets.
- ☑ Adjusted profiles if required.

4.2.4 Implementation of framework: Electricity consumption budget costing

4.2.4.1 Tariff structure breakdown

Step 1: Identify and break down tariff structure

The Eskom Megaflex tariff relevant to the case study mine was evaluated and broken down for this step. The following active energy charges, billed in R/kWh, were identified:

- TOU consumption charges separated into peak, standard and off-peak and two seasons.
- Ancillary service charge
- Rural network subsidy
- Affordability subsidy

The following variable, non-active energy charges, were identified:

- Transmission network charge (R/kVA/m)
- Network capacity charge (R/kVA/m)
- Network demand charge (R/kVA/m)
- Excess reactive energy charge in high season (c/kVArh)

The following fixed charges were identified:

- Service charge (R/POD/day)
- Administration charge (R/POD/day)

Tariff values for each of these were obtained. A tariff increase of 12.74% on 1 April 2024 was announced for all tariffs except the Affordability subsidy, which increased by 25.24% [91].

Step 2: Create time-based tariff data

The broken-down tariffs from the first step were used to create a time-based cost dataset. This was done in half-hourly intervals to align with the consumption budget dataset that was constructed.

Active energy was first assigned to each half-hourly interval according to TOU and season, with other non-TOU active energy charges added.

The total cost of non-active energy charges was calculated using the known notified maximum demand (NMD) load of the mine. Due to a past NMD exceedance, the network capacity and network demand charge were levied on the same fixed load. The total fixed costs per month were also calculated for each month. The combined cost of these for each month was divided by the forecast electricity consumption for the month to obtain an effective R/kWh charge for the non-active energy and fixed charges. This value was added to the half-hourly active energy charges resulting in a budget tariff dataset. The relevant tariff increases were applied to relevant dates to finalise the dataset. Figure 4.6 gives a detailed breakdown of the developed tariffs for each season and TOU charge. The tariffs for February and July of 2024 were used for this figure.

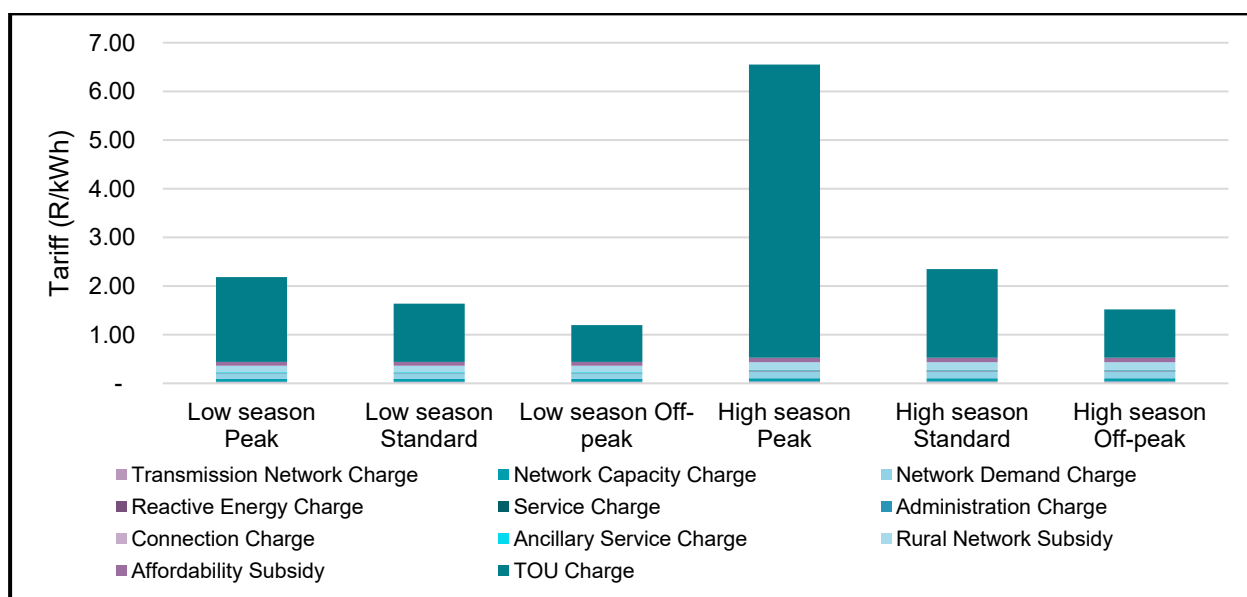


Figure 4.6: Budget tariff dataset example.

The figure clearly shows the importance of separating costs per TOU, especially in the high season where the TOU charge can be over 90% of electricity costs during peak times.

All checklist requirements for this section, as given in Section 3.4.1 were met. The budget tariffs can now be used in combination with the budget consumption to calculate the budget costs.

- ☒ Relevant tariff structure broken down into component tariffs.
- ☒ Tariffs used to set up a time-based tariff dataset in the same interval as the consumption budget dataset.
- ☒ Tariff increases applied where relevant.

4.2.4.2 Application of costs

Cost application was automatically done using data processing software. The budget consumption per system was multiplied with the tariff budget dataset to obtain a time-based cost dataset. Figure 4.7 gives the yearly cost dataset in half hourly intervals for the surface operations system. Figures for all other systems are given in Appendix D.

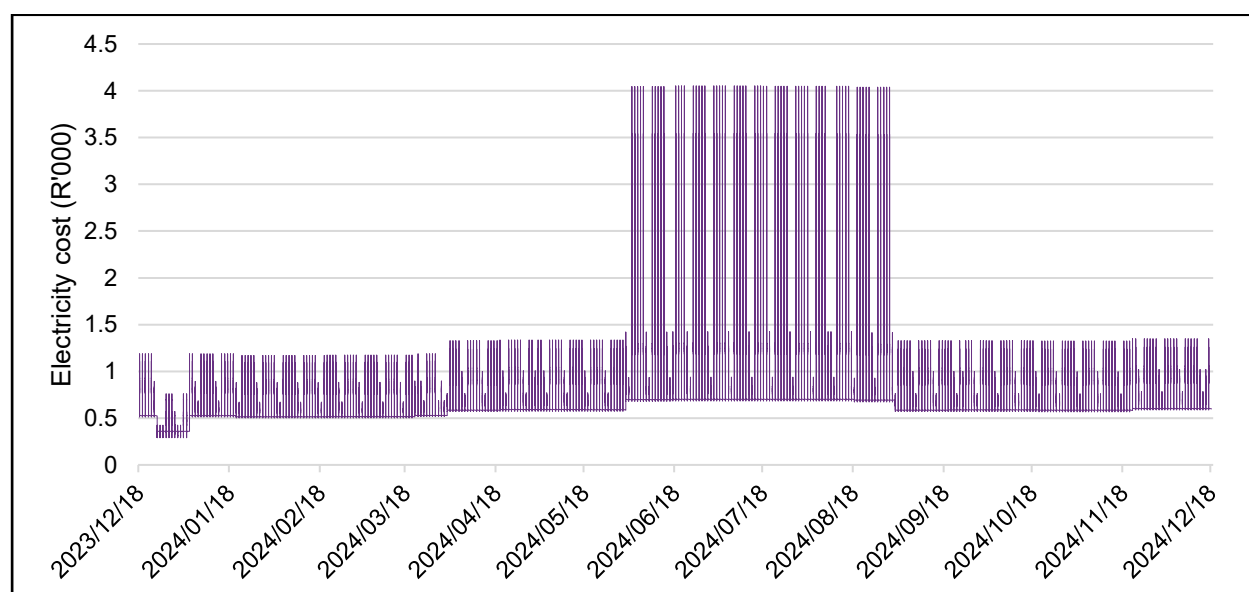


Figure 4.7: Combined yearly electricity cost budget for surface operations system.

This results in individualised costs per sub-system, as different operational profiles, will result in different TOU proportions. The total monthly cost per system and the total cost of the POD were calculated, as reporting the monthly costs is part of the baseline budget requirement.

The checklist action for this section has been completed the next step can be done.

- ☒ Budget cost calculated per system using created budget consumption and tariff datasets.

4.2.4.3 Tariff calculations

For this section, effective tariffs per system per month were calculated. This was done by dividing the monthly costs per system, as calculated, by the monthly budget electricity consumption as per Equation 2.

Equation 2: Monthly effective tariff equation.

$$\text{Monthly effective tariff} = \frac{\text{Electricity cost per month (R)}}{\text{Electricity consumption per month (kWh)}}$$

The result is an individualised effective tariff per system that can be used for performance evaluation.

The checklist action for this section has been completed and a full cost budget is now available.

- ☒ Budget tariff calculated per system per month using created budget consumption and cost datasets.

4.2.5 Implementation of framework: Budget verification and reporting

4.2.5.1 Internal result verification

Step 1: Check the consumption budget

All developed consumption budgets were checked according to the framework instructions. The created profiles per system grouping was already reviewed and approved in Section 4.2.3.1. This section covers higher level approval, ensuring that month totals are in expected ranges and that planned changes are visible. For illustration, the verification done for the pumping system is given in Figure 4.8.

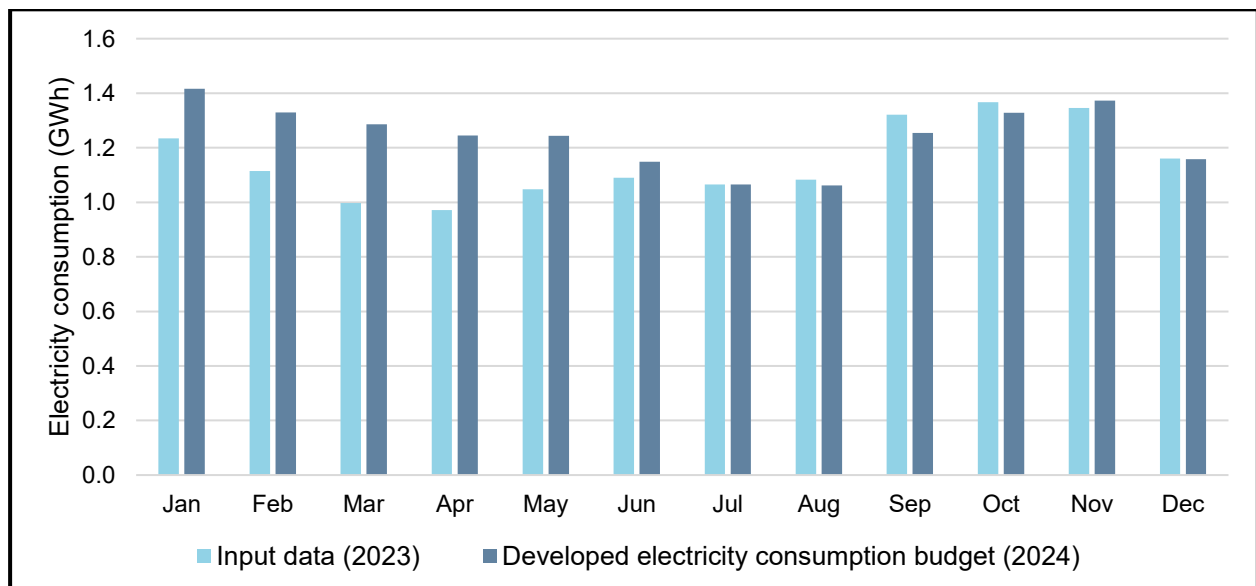


Figure 4.8: Pumping consumption budget verification.

The developed budget for pumping is markedly higher in January – May of the budget year than the input data. This corresponds to data cleaning that was done to remove days without operation in those months. The months’ consumption is comparable to that of September – November, also summer months which should have similar usage profiles. Variations between months are as expected, as the billing months for the mine are not of equal length, with a six-day difference between the shortest and longest month.

The developed budget, both displayed here and not, was considered verified and approved.

Step 2: Check the cost budget

The developed cost budgets were checked according to the instructions in the framework. The tariffs and tariff datasets are already confirmed and verified in Section 4.2.4. This section presents a high-level check of the results of the costing framework. Figure 4.9 presents a comparison of the total budget for electricity consumption through the incomer meter, both cost and consumption.

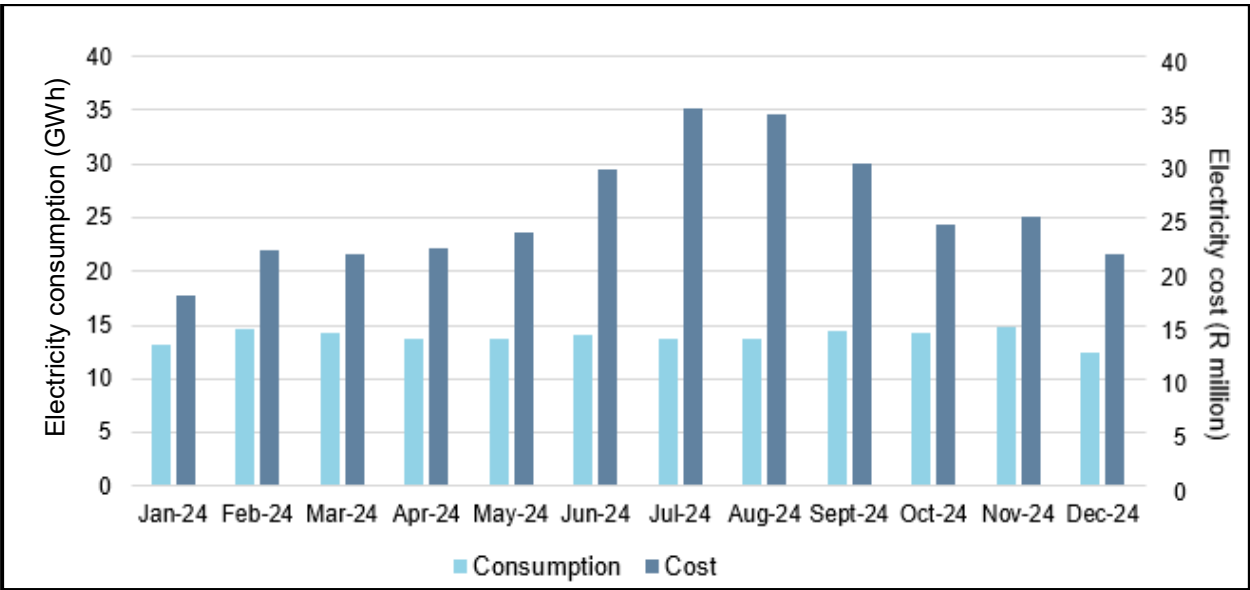


Figure 4.9: Incomer meter electricity consumption cost verification.

The costs in the figure are higher than the consumptions, as is expected due to the electricity tariffs, which varied between R1.20/kWh and R6.55/kWh for this period. In periods with comparable tariffs, costs increase or decrease proportionally to the electricity consumption (such as January vs February, or November vs December). The high-season months have higher costs, and the costs after April increase, as is expected due to the annual tariff increase. The cost budget is verified.

Figure 4.10 presents a comparison of the effective tariffs for every system for the budget period.

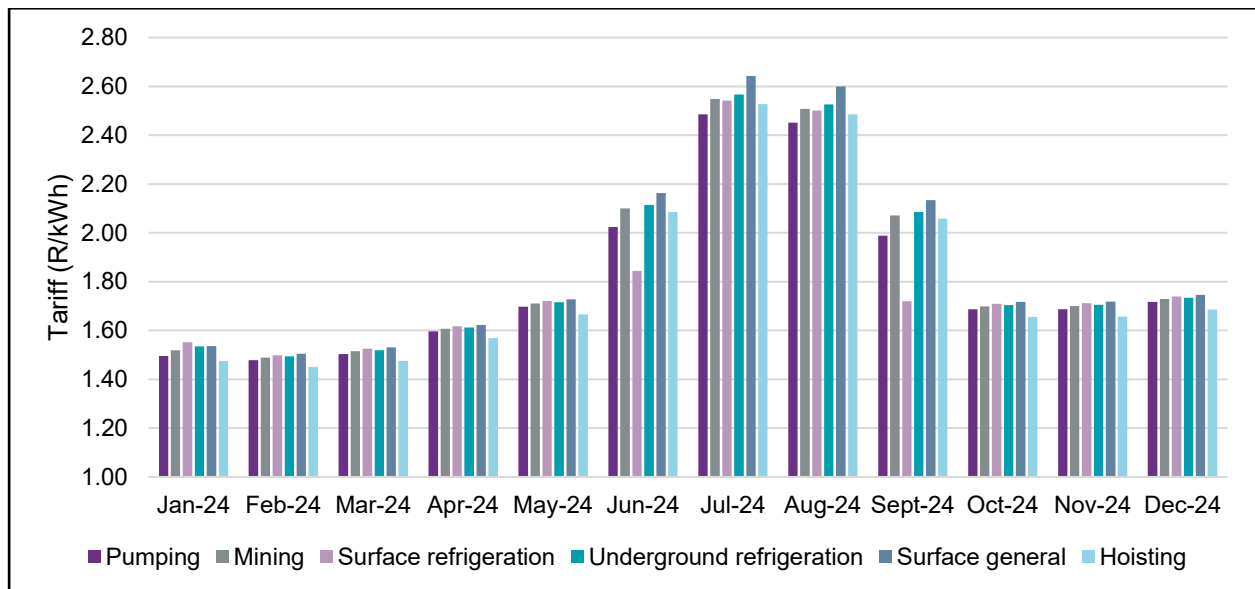


Figure 4.10: Systems effective tariff verification.

This analysis demonstrates how incorporating TOU costs in costing and applying costs to high-frequency data influences the resulting effective tariffs. The pumping and hoisting systems consistently have lower effective tariffs than other systems, corresponding with load shifting efforts on those systems. Surface refrigeration, which operates overwhelmingly in low-season months, has a significantly lower effective tariff in June and September compared to other systems. This is due to the bulk of electricity consumption on this system occurring on the low-season days in the June and September billing months.

Following these verifications, the checklist steps for internal result verification have been completed and the next step can be done.

- ☒ Consumption budget checked and verified.
- ☒ Cost budget checked and verified.

4.2.5.2 Budget procedure reporting

The case study result section shows the configuration of the case study budget in detail. In practice the procedure is not written up in this way, and thus the framework is required to ensure that all relevant information is documented and kept for transparency and traceability of the budget.

4.2.5.3 Final budget result reporting

As this budget was only developed to test the framework, there are no relevant stakeholders for the development of the budget. There are no needs to be identified either. The framework does provide a guide as to who the relevant stakeholders may be and what their needs are.

The final budget results will be evaluated in Section 4.3 as part of the case study results evaluation and will therefore not be repeated in this section.

4.3 Result validation

This section will demonstrate how the budget developed using the novel framework developed in Chapter 3. This study adheres to the developed best practices and how it addresses and overcomes the barriers identified in Section 1.2.5. To do this, each framework result intended to overcome one of the barriers will be evaluated against the industry standard method of budget development. The comparison will illustrate the practical improvements achieved through application of the developed framework and demonstrate its effectiveness in producing high-quality budgets that can be used as tools for improved energy management.

4.3.1 Budget best practice validation

Table 4.1 presents an evaluation of the budget developed through use of the framework based on the best practices and best practice evaluation survey presented in Section 1.2.3. The results are compared against the industry budget development standards.

Table 4.1: Developed budget best practice evaluation.

Question		Industry standard	Framework result
1.	To what level of the operation is the budget separated?	Pass	Pass
2.	What is the resolution of the budget?	Fail	Pass
3.	Is the quality of the input data ensured?	Pass	Pass
4.	What input data is used in the budget creation process?	Pass	Pass
5.	How are planned changes budgeted for?	Fail	Pass
6.	Who is responsible for budget development?	Pass	Pass
7.	Are adjustments made to account for changes in TOU in the future budget period?	Fail	Pass
8.	Is costing done using the official Eskom tariff structure?	Fail	Pass
9.	How time consuming and labour intensive is the current budgeting process?	Fail	Pass
10.	Is the budget output validated before use?	Pass	Pass
11.	Is costing split into beyond POD level according to TOU?	Fail	Pass
12.	Are changes to the budget baseline documented?	Fail	Pass
13.	Is the budget adequately presented for use?	Pass	Pass

The budget developed through the implementation of the developed framework satisfies all the best practices and can therefore be considered a high-quality budget that will be an effective instrument for electricity performance evaluation.

4.3.2 Budget resolution validation

The first barrier identified in Chapter 1 is that the industry standard is to develop budgets using low-frequency data, usually in monthly intervals. Using this data not only results in low-frequency budget outputs but also reduces the level of detail in which data can be cleaned and prepared. Low-resolution budgets are not useful tools for evaluating energy efficiency.

The developed framework addresses the identified barrier in the following ways:

- Evaluates budget objective to develop a suitable budget.
- Evaluates available data to determine frequency of input data required for best results.
- Uses high-frequency data as input.
- Suggests scalable methods that can process high-frequency data.
- Produces high-frequency results.

The effect of these interventions is a budget result that is in a practical frequency for near real-time energy efficiency evaluation for the purposes of energy management. Consider the budget developed for the mining system, as presented in Figure 4.11. The budget is presented as a profile, in aggregated half-hourly intervals, measured in MWh electricity consumption.

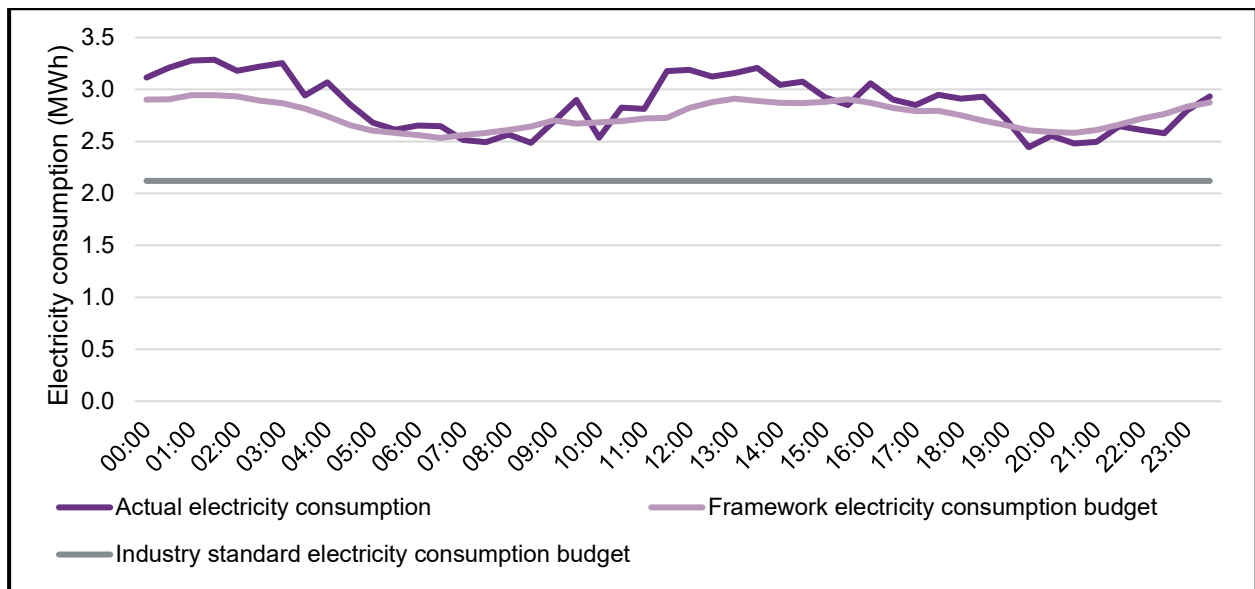


Figure 4.11: Mining actual electricity consumption vs budgets.

A 24-hour profile of the electricity consumption of the mining system is compared to two budgets, the framework budget and the industry standard budget. As the industry standard was developed on a monthly interval, the budget is not profile based. This flat line budget does not provide any insights. The budget developed according to the framework matches the actual data consumption pattern and can be used to evaluate the performance of the system.

The resulting budget is high-resolution and can be used effectively as an instrument for energy performance evaluation, as it provides a budget value per actual consumption time interval against which to check performance. This allows the mine to act in near real-time for proactive energy management.

4.3.3 Method scalability and adaptability validation

The second barrier identified in Chapter 1 is that the methods used to develop electricity consumption and cost budgets in industry do not scale well and are not very adaptable to changes in datasets. The budgets in industry are typically developed manually and cannot accommodate large datasets with high-frequency data. This manual element of budget creation created a bottleneck in the budget development process, prohibiting the use of high-resolution data and preventing high-detail costing.

The developed framework addresses the identified barrier in the following ways:

- Suggests clustering and forecasting methods using simple code and algorithms to relieve the bulk of the manual element of budgeting while accommodating high-frequency data.

- Suggests a spectrum of methods catering to many situations, datasets and resource availabilities.
- Relies on a technical expert only to review and accept the results, instead of large dataset processing and budget creation, thus reducing input required and making the process less time intensive.

The effect of these interventions is reduced time spent on the development of the budget by the person developing, while producing a higher-quality budget result. The case study result is encouraging, but a larger-scale rollout with evaluations and feedback from industry will be required to confirm the effectiveness of this intervention.

4.3.4 Detail costing validation

The third barrier identified in Chapter 1 is that the methods used to develop electricity cost budgets deliver low-detail results that do not consider all relevant costs and do not adequately account for TOU. The industry method does not produce a time-based budget tariff and does not deliver distinctive effective tariffs between systems. This reduces the ability of the mine to evaluate the costs of systems in near-real time. Mines are also not able to evaluate the cost performance of a system independently, which is critical if energy management projects are implemented for cost savings.

The developed framework addresses the identified barrier in the following ways:

- Guides the user to develop a time-based budget tariff.
- Uses high-frequency, profile-based consumption data in combination with the developed tariff to produce a high-frequency cost profile.
- Produces a cost value per system, based on the individual performance of the system and TOU.
- Produces an effective tariff per billing period per system, based on the individual performance of the system and TOU.

The effect of these interventions is a cost budget that is high-resolution and based on detailed calculations including system specific TOU. This enables evaluation of cost performance per system, as opposed to incomer level evaluations done with industry standard budget results. Figure 4.12 presents the time-based budget tariff developed through the framework compared to the incomer-wide effective tariff value that remains constant throughout the month, produced by the industry standard budget method.

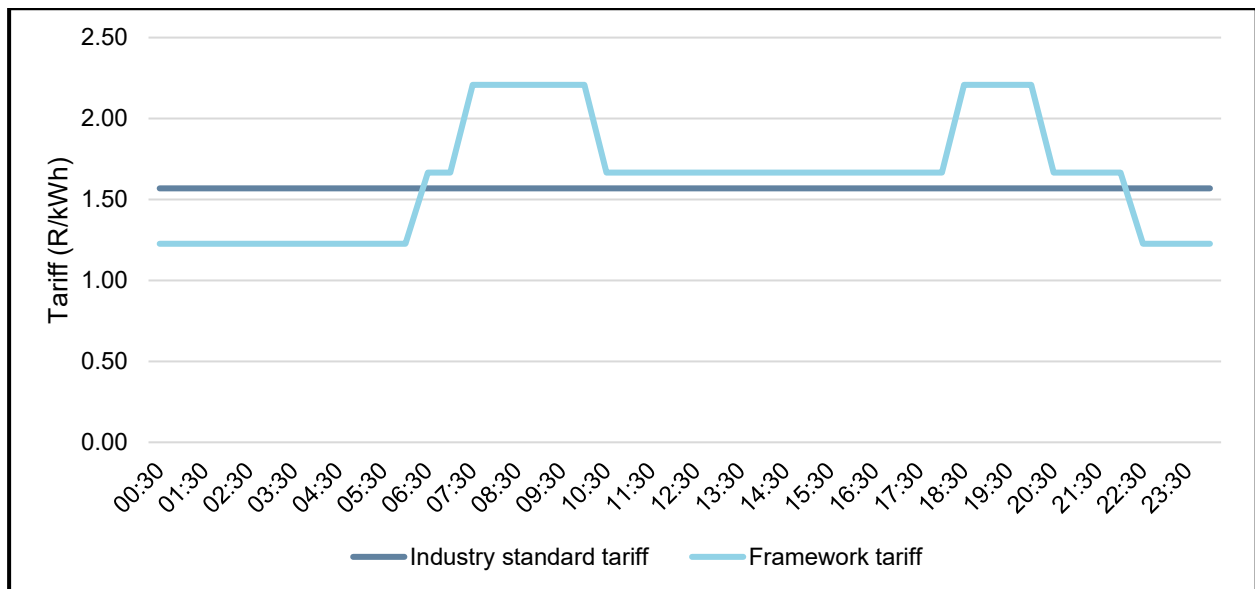


Figure 4.12: Framework vs industry standard tariff comparison.

The time-based tariff developed through the framework accounts for peak, standard and off-peak TOU on a half-hourly interval. This allows for detailed costs to be calculated, instead of presenting a single cost value per month. Figure 4.10 presented in Section 4.2.5.1 supports the finding, showing varied effective tariffs per system based on their individual profiles.

4.3.5 Result documentation process validation

The fourth and final barrier identified in Chapter 1 is that the methods used to develop budgets in practice are not well documented. The results produced by existing methods are not repeatable or traceable, and there is no system of accountability for the source of the budget. Lack of documentation undermines the credibility of the budgeting process and makes it difficult to verify results or identify causes of discrepancies.

The developed framework addresses the identified barrier in the following ways:

- Relies on models and algorithms that produce repeatable, traceable results
- Suggests a protocol for reporting input used and changes made to input data
- Suggests a protocol for recording the development of the budget profiles
- Suggests a protocol for reporting how profiles were assigned to future dates
- Suggests ordered visualisation and presentation of the results for approval and to ensure optimal communication of results to relevant stakeholders

The effect of these interventions is a digital archive documenting the budget process and all data used and produced. This provides improved transparency, traceability and reproducibility of the developed budget, thereby improving the credibility and reliability of the produced budget values.

Reliable, traceable values are easily defensible when used as instruments for energy management.

4.3.6 Improvement in accuracy of consumption forecast

In addition to the improvements on the identified barriers, the accuracy of the developed budget was evaluated. To do this, actual data from the case study mine for 2024 was collected and compared to the framework budget and the industry standard budget.

To evaluate the accuracy of the developed budgets, MAPE was used. This method is frequently used to evaluate the accuracy of long-term forecasts [92]. The formula for this method is given in Equation 3 below [93]:

Equation 3: Mean Absolute Percentage Error.

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right|$$

Where $\hat{Y}$ is the forecast value of n predictions and Y represents the actual value. This method evaluates the absolute distance from the actual value for every forecasted value. The difference in MAPE over a year between the new framework budget results and the industry-standard budget results is presented in Table 4.2.

Table 4.2: MAPE difference between new framework budget and industry standard budget.

System	MAPE difference
Underground refrigeration	6%
Surface refrigeration	-3%
Mining	2%
Pumping	2%
Hoisting	11%
Surface operations	-5%
Incomer	2%

The budget developed through the framework had a 2% improvement in MAPE over the industry standard budget on the incomer level, with the largest improvement being 11% on the hoisting system.

The total absolute percentage difference between the forecasted electricity consumption over the budget period through each method is presented in Table 4.3. This evaluates only the total

cumulative budget value for the whole mine as opposed to the individual point evaluation of MAPE.

Table 4.3: Electricity consumption budget accuracy yearly.

Industry standard total consumption budget error	Framework total consumption budget error
8.05%	3.05%

The framework method improved the accuracy of the budget over the period of a year and forecasted a result 5% closer to the actual consumption than the industry standard method. This represents a difference of just over 8 GWh.

Figure 4.13 presents a graph with the monthly results of each forecasting method and the actual electricity consumption for the year 2024 in the case study mine.

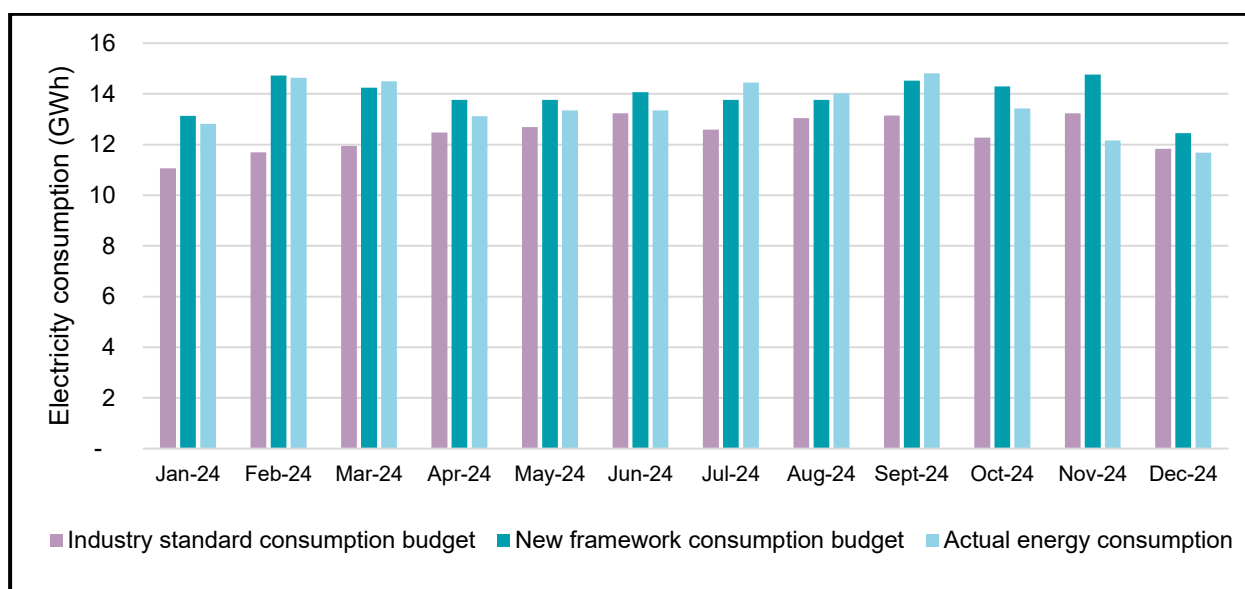


Figure 4.13: Electricity consumption budget accuracy monthly.

The framework budget forecasted the actual consumption well as noted in Table 4.3. Notable exceptions are in June, July, November and December. Cooler weather allowed the mine to halt refrigeration systems earlier than planned in June, reducing the total electricity consumption. Unplanned events in November shut the mine down for a few days, significantly reducing the power consumption. The December break was extended past its planned length, slightly reducing electricity consumption in December.

The framework budgeting method demonstrated an improvement in forecasting accuracy over the industry standard approach. The alignment between the forecasted and actual values indicates that the framework effectively captures operational and seasonal trends in mine electricity use. The developed framework can therefore be considered successful in producing an

accurate electricity consumption budget suitable for use in energy management and performance evaluation.

4.3.7 Improvements in accuracy of cost forecast

As done with the electricity consumption budget, the accuracy of the developed cost budget was evaluated. Actual costs from the invoices collected in 2024 were compared to the developed cost budget using the framework, and the industry standard budget that was developed as a baseline.

The total absolute percentage difference between the forecasted electricity cost over the budget period through each method is presented in Table 4.4.

Table 4.4: Electricity cost budget accuracy yearly.

Industry standard total cost budget error	Framework total cost budget error
5.80%	1.73%

The framework method improved the accuracy of the cost budget over the period of a year and forecasted a result 4.08% closer to the actual consumption than the industry standard method. This represents a difference of just over R12 million. The industry standard method underestimated the cost by R17.4 million, and the new framework overestimated the cost by R5.1 million.

Figure 4.14 presents a graph with the monthly results of each forecasting method and the actual electricity cost for the year 2024 on the case study mine.

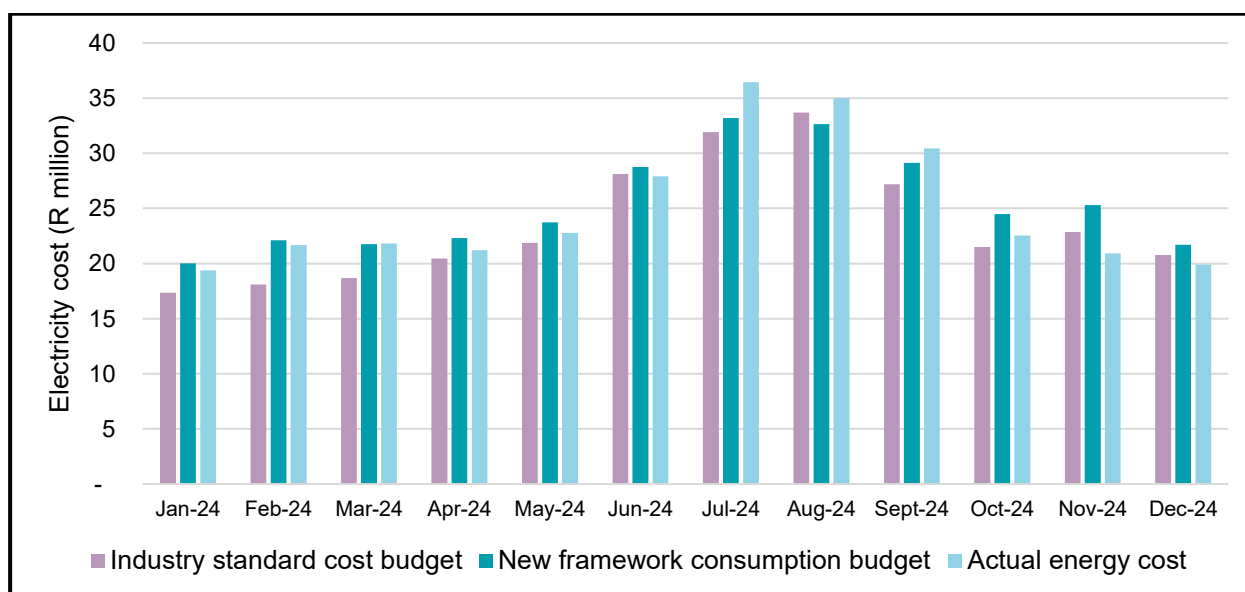


Figure 4.14: Electricity cost budget accuracy monthly.

The framework budget forecasted the cost of electricity for the budget period well, especially for the first five months of the budget period. As with the consumption, unplanned events affect the accuracy of the budget. July and August specifically had incidents where excess pumping was required, deviating from load shifting plans and significantly increasing electricity costs for those billing periods. This is not a reflection on the performance of the budget, and the budget still represents the planned operation and can be used to evaluate performance. The framework costing method demonstrated improvements in the accuracy of cost forecasting.

4.4 Discussion

The goal of this section was to apply the developed framework methodology to a real-world case study mine to evaluate its performance and practical applicability. By implementing the framework in an actual mining environment, the study aimed to determine whether the proposed methods could overcome the identified barriers.

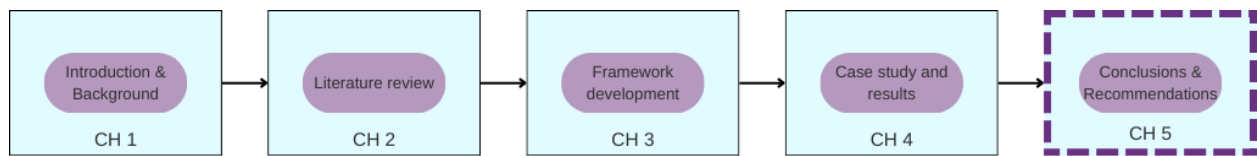
A case study mine that could be used to test the developed framework was identified. The four framework sections of the developed methodology were applied to the case study mine's historical electricity consumption data. An electricity consumption and cost budget was developed by following the steps provided in the framework. The resulting budget was then systematically evaluated against the four previously identified barriers to high-quality budget development: budget resolution, scalability and adaptability, detailed costing, and documentation and traceability.

The application of the developed framework to create a budget for the case study mine successfully produced the intended results. Implementing the framework led to the development of a high-resolution electricity consumption and cost budget. The framework worked as expected, demonstrating its ability to scale to large volumes of data while still producing accurate and scalable results. The method was also easy to apply in practice and took as long as the industry standard to develop, while producing much more detailed results. This outcome confirms that the framework is both technically sound and practically feasible.

The result validation section evaluated the framework and its results according to criteria based on the four barriers preventing the development of high-quality budgets in the mining industry. The framework produced high resolution results that could be used to evaluate actual electricity consumption performance. The electricity consumption budget developed was also found to be more accurate than the industry standard method. The method was found to be scalable but will need to be tested further and by a more varied group to evaluate it fully and determine its limits. The cost results produced were according to best practice and produced costs and tariffs per system. The costs forecasted were also found to be more accurate than the industry standard

method. The result verification and documentation sections provided sound guidelines that will reduce errors and make the budgeting process more reliable and traceable.

CHAPTER 5 CONCLUSION AND RECOMMENDATIONS



5.1 Summary

This thesis addressed the need for improved electricity consumption forecasting and cost budgeting in the mining industry. Electricity budgets play a critical role in evaluating energy performance. With the increase in smart energy management systems and the prevalence of real-time electricity data availability, the demand for detailed, high-quality budgets has grown significantly. Current budgeting practices were found not to be making full use of the available data and produced budgets that were not effective instruments for energy management. Since high-quality energy management depends on high-quality budgets, improving the budgeting process is essential for mines to improve their efficiency.

A narrative literature review was used in Chapter 2 to explore electricity consumption forecasting in the mining industry and wider industry. No specific methodologies addressing the combined barriers were found in mine-specific literature. Individual solutions, however, could be identified in studies in other industries.

A set of best practices for electricity budgeting was developed to establish a benchmark for evaluating the quality of mine budget development processes and resulting budgets. These best practices were used as the basis for a survey that was used to evaluate budgeting processes of 41 mine business units. The survey results were analysed to determine the extent to which best practices are being implemented in industry. Four barriers preventing the development of high-quality electricity cost and consumption budgets in industry were identified. These were used as the foundation for the development of a framework in Chapter 3 to improve mine budgeting practices.

Research objectives were formulated to guide the development and evaluation of a solution to the identified problem. A hybrid research methodology was implemented, combining multiple approaches to address the problem. Literature findings together with the survey results and best practices were used to develop a framework for high-quality budget development. The framework was developed in four sections, addressing input data collection and preparation, electricity consumption forecasting, budget costing and budget validation and reporting.

The developed framework was implemented on a case study mine in Chapter 4 and evaluated for its ability to overcome the identified barriers, its achievement of the best practices and was also evaluated against actual consumption and cost data for accuracy. The developed budget complied with all the best practices, and the framework was found to overcome each identified barrier effectively. The developed budget also resulted in accuracy improvements in cost and consumption over industry standard methods.

5.2 Objective validation

Three objectives to guide the development and evaluation of the framework presented in this study were presented in Section 1.3. Each of the objectives was addressed in a chapter of the study.

Objective 1: Evaluate available literature on electricity consumption forecasts inside and outside the mining industry was addressed in Chapter 2. A narrative literature study was presented, evaluating studies on energy forecasting, energy consumption forecasting, and electricity consumption forecasting for mining. No adequate solutions to the barriers preventing the development of high-quality budgets in industry were found in mining specific literature. A broadened literature review found methods that could be adapted to the mining industry to address and overcome the identified barriers.

Objective 2: Develop framework based on research findings to overcome the identified barriers was addressed in Chapter 3. A framework was developed based on a combination of theoretical and industry knowledge. The developed framework was validated in Section 3.7 and found to address each identified barrier effectively.

Objective 3: Evaluate the developed framework based on its ability to overcome the identified barriers was addressed in Chapter 4. A case study mine was identified and a budget was developed by implementing the developed framework. A companion budget was developed in Appendix C using industry standard methods. The budgets were evaluated on their ability to overcome the identified barriers to show the improvements gained by the new method. The framework budget was found to comply with best practices in Section 4.3.1 and was effectively found to overcome each barrier in Section 4.3.

5.3 Evaluation of presented novelty

The novel contributions of this study were presented in Section 1.4. The study succeeded in developing a framework for improved electricity and cost budgeting for mines. This section gives the two novelties achieved through this study with a discussion of the process and findings throughout the study.

Compilation of best practices for mine electricity consumption and cost budgeting process, evaluation of the industry process and identification of barriers preventing implementation of best practices.

Through literature evaluations and industry observations, this study found that there was no recognised set of best practices for budgeting in the mining industry. Mines in practice were found not to be producing budgets that were effective instruments for energy performance evaluation and energy management. There was no existing evaluation metric to determine whether a budget was high quality, and there was no literature on what is preventing mines from developing high-quality budgets.

A set of best practices was developed in Section 1.2.3 and used to develop and conduct a survey, with results presented in Section 1.2.5. The survey results were analysed and four consistent barriers preventing the implementation of best practices and the achievement of high-quality budgets were identified.

The identified barriers were used as a foundation for a literature survey to find solutions to overcome these barriers. Building on the barriers and best practices, a framework could be constructed to help develop high-quality budgets in industry.

Development and application of framework for the creation of electricity consumption and cost budgets that comply with the identified best practices.

There was no framework for the development of electricity cost and consumption budgets on mines. Barriers preventing the development of high-quality budgets in industry were identified, but there was no literature found with a single solution to address all the identified barriers and produce high-quality budgets. There were few high-quality budgets developed in industry, indicating a need for such a framework.

Following a literature review, solutions to the individual barriers preventing high-quality budget development were found in wider industry. Theory, best practices and survey results were combined to develop a step-by-step framework to address and overcome each identified barrier and to produce best practice budgets.

The developed framework was validated for its effect on each barrier in Section 3.7 and found to address each adequately. The framework was applied to a case study mine to evaluate its performance in relation to both the identified barriers and the best practices. The results of the implemented framework were evaluated against a budget developed using industry standard method. The budget resulting from the application of the framework was found to comply with

best practices in Section 4.3.1. The developed budget was found to overcome each of the identified barriers in Section 4.3.

5.4 Recommendations

Throughout the study, several points for future improvements in the field of electricity forecasting in mining were observed. The following is recommended for future work.

The literature survey in Chapter 2 found few forecasting methods that could accommodate both high-frequency data and long-term forecasting. There is a gap for the development of specific models that can accommodate both these parameters.

The developed framework was found to be scalable and adaptable to large, high-frequency datasets, but the effect could not be quantified. A broader industry test with more participants is required to prove the scalability and adaptability of the developed method, especially to evaluate the effect on time spent on budget development.

The developed framework does not give detailed instructions for the handling of multiple interconnected PODs, for the handling of multiple utilities servicing one mine, or for integrated renewable energy systems. The base framework will be applicable, but case studies on special cases may contribute to the knowledge base.

The developed framework is focussed on the mining industry but may be applicable to other heavy industries as well. It is recommended that the framework be tested for application in other industries.

There is scope for automation of the developed framework. As most of the methodology is computer based and only requires select inputs and approvals from informed persons, the framework could be turned into a “budgeting system” to simplify the budgeting process further.

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Article

Electricity Cost Forecasting in the South African Mining Industry: A Gap Analysis

Andrea Cronje ^{*}, Jean H. van Laar ^{*}, Johann F. van Rensburg and Jan C. Vosloo

Centre for Sustainable Mining, North-West University, Potchefstroom 2531, South Africa; jvanlaar@nwmu.ac.za (J.H.v.L.); johann.vanrensburg@nwmu.ac.za (J.F.v.R.); jcvosloo@nwmu.ac.za (J.C.V.)
^{*} Correspondence: andcronje01@gmail.com

Abstract: Despite the rapid improvement in the availability and resolution of real-time electricity data, budget development processes in mining have remained relatively unchanged. Currently, there is no standard for the evaluation of mine electricity cost budgets. This study aims to determine whether forecasting processes used by mines produce budgets of sufficient quality and resolution to be used as a tool for daily energy- and cost management. A literature review was conducted to determine a set of best practices for electricity budgeting on mines. These findings were used to develop a survey to evaluate the current state of budgeting processes on South African mines. Surveys were conducted at 41 mine business units. Survey results were processed and analyzed and found that there are significant shortcomings in complying with the identified best practices. The majority of mines produced forecasts in lower resolutions than actual available data, thereby reducing their usefulness as energy management tools. The methods currently employed by mining sites are not scalable and are vulnerable to human error. Only 7% of participating business units' budgets passed the identified best practices. Adherence to best practices, identified in this paper, will assist mines in improving electricity cost forecasts for more proactive- and sustainable energy management. This will also assist the industry in aligning with the UN Sustainable Development Goals (SDGs) of Affordable and Clean Energy (SDG 7), Industry, Innovation, and Infrastructure (SDG 9), and Responsible Consumption and Production (SDG 12).

Keywords: electricity cost forecast; mine energy management; electricity budgets; data quality



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1. Introduction

1.1. Background

Electricity costs in South Africa are generally much higher than other developing countries. The average electricity cost in South Africa is \$0.19/kWh compared to an average of \$0.12/kWh for neighboring countries [1].

With the cost of electricity increasing at rates above inflation, and complications in the national energy supply [2], energy management has become vital for South African mines. Mining, especially deep mining which is prevalent in South Africa, is incredibly energy-intensive, with up to 30% of mine operating costs attributed to various forms of energy use [3]. Mining companies implement energy efficiency projects to reduce their electricity usage, thereby reducing their operating costs [4].

Eskom, the sole South African national energy utility provider, uses a time-of-use (TOU) pricing structure to bill clients. Tariffs for electricity purchased from Eskom are based on the period and season of electricity usage [5]. The tariffs are higher during high

demand periods, which includes peak hours on weekday mornings and afternoons, and high season winter months. The planning of when electricity will be consumed and how much electricity will be used is thus equally important for cost management.

Mines in South Africa largely use the Eskom Megaflex tariff structure. The Eskom tariff booklet [5] describes Megaflex as a “TOU electricity tariff for urban customers with a notified maximum demand (NMD) greater than 1 MVA”. Charges include active energy charges subject to electricity consumption and TOU, and less flexible transmission, distribution, administration and service charges, as well as subsidies.

Figure 1 shows the hourly distribution of the Eskom TOU peak-, standard- and off-peak periods for the two billing seasons, namely high demand (June to August) and low demand (September to May).

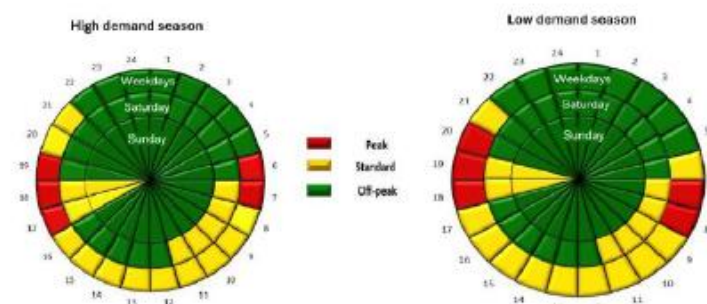


Figure 1. Eskom TOU time periods [5].

Figure 2 below summarizes the Megaflex tariff charges (in ZAR currency). These tariffs were effective as of 01 April 2025. Active energy charges are applied to all kWh units utilized by the consumer. This includes the TOU charge according to time and season, as well as legacy, ancillary service, rural network subsidy and affordability subsidy charges. Additional network charges are applied to the whole point of distribution (POD) for kVa load consumptions and allowances, and additional administrative charges are applied to the POD on a cost per day basis.

		Active energy charges [c/kWh]										
Transmission zone	Voltage	High demand season [Jun-Aug]			Low demand season [Sep - May]			Legacy charge	Ancillary service charge	Rural network subsidy	Affordability subsidy	
		Peak	Standard	Off-peak	Peak	Standard	Off-peak					
≤ 300 km	≥ 500 V & < 66kV	669.92	366.73	111.15	276.78	155.62	111.15	22.2	0.39	4.94	4.69	

Additional network charges [R/kVA/month]			
Generation capacity charge	Transmission network charge	Network capacity	Network demand
8.09	10.25	35.98	24.17

Administrative charges [R/POD/day]	
Service charge	Administration charge
1118.46	19.37

Figure 2. Eskom Megaflex tariffs (taken from [5]).

Costs are grouped by transmission zone (distance from nearest distribution center) and by voltage.

Electricity budgeting is a form of energy-and cost forecasting commonly used on mines in South Africa. Mines and other industries use budgets to plan for future electricity consumption and related costs [6]. South African mines are under significant financial pressure, thus the focus on accurate cost forecasting is greater than ever [7].

Utility companies bill mines monthly for their electricity usage. Historically, monthly budgets are configured for each POD using these billing values. These budgets are often not sufficiently adjusted for year-on-year changes in operation and TOU, do not include detailed budget profiles, and lack detailed tariffs.

The electricity usage of a mine is evaluated at month-end with the use of the developed budget [8]. These evaluations are used for planning but fall short as a comprehensive energy management tool.

In recent years, there have been noticeable improvements in the quality and availability of data on mines [9,10]. Mines are realizing the value of good information, not just data, and are investing in the gathering, storage and processing thereof. Most South African mines now have real-time data available for energy intensive systems. This data is often used for performance monitoring and impact assessment in energy savings initiatives. There is an opportunity to use this real-time data to assist with proactive energy management.

To gain insight from real-time data, context is important. Electricity budgets are used to contextualize data and provide an electricity consumption forecast for operations. High resolution electricity budgets would allow for energy management to take place on a half-hourly basis, rather than monthly.

1.2. Problem Statement

Industry observations point toward a discrepancy between the quality of actual electricity consumption data and electricity cost forecasts. Budgets and actual data need to be of comparable frequency and quality to allow for real-time electricity cost and usage evaluations. Currently, no standard exists for the evaluation of deep mine electricity cost budgets, and no previous studies have evaluated the effectiveness of the budgets.

1.3. Aim & Scope

This study aims to evaluate whether current budgeting practices used by the mining industry in South Africa are delivering budgets that are effective tools for electricity usage and cost evaluations. To achieve this, a novel set of best practices for the process of electricity cost budgeting on deep mines will be constructed from literature and compared with survey results from a variety of mining operations.

The difference between best practices and industry standards will be discussed, along with the benefits of developing a framework and standards for high-frequency, high-quality budgets. The results will highlight potential areas for development for future studies on improved mine electricity cost forecasting.

2. Literature on Mine Electricity Cost Forecasting

2.1. Search Strategy

The aim of this review section is to identify and evaluate existing electricity budgeting practices in both the South African mining sector and other heavy industries globally to understand the importance of electricity cost forecasting and to identify important criteria for successful electricity budgeting.

Figure 3 details the search strategy employed to find relevant literature.



Figure 3. Literature search strategy.

2.2. Existing Electricity Cost Budgets

The aim of this review section is to evaluate existing electricity budgeting practices in both the South African mining sector and other heavy industries to identify important criteria for successful electricity forecasting.

Shortcomings of current electricity budgeting practices in mining are identified and improvements are proposed in the following section to improve current mine electricity budgeting practices.

This review considered studies related to the forecasting of electricity usage and the forecasting of electricity cost. Studies on the impact of renewables on these parameters were excluded as it is not relevant to the study topic.

Mysatakidis et al. [11] provides a comprehensive review of the critical role of electricity forecasting in energy management. It enables both utilities and consumers to plan for and balance energy generation and consumption. The study finds that there is growing complexity in the techniques available for forecasting in the energy sector. This reinforces the need to evaluate whether available techniques from literature are being applied within the South African mining industry.

Several industries employ energy budgeting as a financial forecasting method such as education [12], city planning [13], healthcare [14] and mining [15]. Electricity consumption forecasting is done both by consumers, to anticipate costs, and by producers to anticipate future demand [13,16–20].

From these studies, several trends in the practice of electricity cost forecasting emerge. Previous usage patterns are used to predict energy usage in future. Most studies recommend contextual grouping of historical data, for instance separating by season and by use type. Several of the studies noted above also use complex models such as machine learning and deep neural networks to match previous usage to forecasted future scenarios.

Studies [13,16–20] forecasted energy usage for electricity production planning, not for electricity consumption. Krishnamurthy et al. [21] investigated advanced methods for production planning in South Africa and found that there is need for smart energy resource management. The study is focused on providing grid stability through forecasting to eliminate practices such as demand side management. While the broader method of forecasting is applicable to the topic of this study, the application of the studies is not as mines are primarily electricity consumers and not producers.

Studies [16–18,20] only focused on improving electricity demand and production prediction through several advanced forecasting methods. The studies did not mention the cost of electricity, which is important to the scope of this study.

Zhao et al. [19] forecasted electricity cost in systems where electricity cost is variable, driven by user demand in real-time and not predetermined as is the case in South Africa.

Vassiljeva et al. [22] developed an electricity usage forecasting method for administrative buildings that combines detailed consumption-based profiles with schedule-based predictions.

Most of the studies are focused on creating a model for electricity forecasting, but not on the implementation of the model in practice.

Two studies attempted to improve the current budgeting and electricity costing processes used by mines. Pelser [23] put forth a methodology likening the steps of budget development to measurement and verification (M&V) methods, and proposed improvements to the steps. Goosen [24] suggested improvements to the budget costing methods used by mines. The study implemented TOU and the Megaflex costing structure from Eskom which resulted in improved cost estimations.

Table 1 outlines six steps, distilled from the studies discussed to this point, for developing electricity cost budgets in heavy industries, including mining

Table 1. Steps of the budgeting process according to literature [23].

Step Number	Details
1. Inform	Identify boundaries and select resolution
2. Data	Obtain data
3. Evaluate	Calculate expected changes
4. Develop	Construct the operational budget
5. Convert	Convert the developed usage budget to cost
6. Report and approve	Approve and sign off developed budget

These steps are a simplification of how electricity budgets are developed. However, they will be used to structure the literature review. Each of the steps in Table 1 were evaluated, and literature was used to determine how each of these can best be applied for the goal of electricity usage forecasting.

Literature on existing cost budgets found that electricity cost forecasting is widely used and that industry puts emphasis on the importance of electricity cost budgeting. Few studies focused on mining, and none evaluated the application of available literature in industry. In this section, the literature on cost forecasting in budgets will be evaluated and expanded upon to identify criteria for evaluation of the quality of budgets used on South African mines.

2.2.1. Step 1: Inform

The first step of budget creation is boundary selection. For boundary selection, Pelser [23] produces a decision tree to choose between a whole facility evaluation and a component isolation. Energy management and performance evaluation is not taken into consideration for the choice. The ideal boundary on which to develop an electricity budget is per energy intensive system. This is due to energy management evaluations being focused on isolated energy intensive systems rather than the full facility or individual components [25,26]. Meters are mostly installed on feeders rather than on individual components so that operation can switch between components as required, allowing for outages and maintenance without data loss.

The decision tree uses two conditions to decide the budget resolution. First, whether the budget will be used for performance evaluation, and second, whether the component has varying operation throughout a day. As this study aims to improve budgets so they can always be used for performance evaluation the developed budget resolution should be at least as high as that of the available operational data.

Using the electricity budgets to evaluate performance in real-time is priority for this study, as well as improving daily associated budgeting costs. Eskom TOU tariffs are separated by the hour and notified maximum demand (NMD) is evaluated half-hourly. Hourly is thus the lowest possible resolution on which budgets can contain accurate cost information [5]. The ideal resolution for an electricity budget is therefore hourly or higher to account for the different tariffs throughout the day, and half-hourly for accurate semi real-time cost forecasts.

2.2.2. Step 2: Data

The second step of budget creation is data acquisition and evaluation. The data should be traceable to a calibrated meter, evaluated for consistency and additionally checked for outliers or unplanned events.

It is important that the input data is of the highest possible quality. Ideally this data should come from a calibrated meter and should undergo some data analysis before being used. Using poor input data for forecasting results in poor prediction accuracy [27].

Electricity usage data should be used as the main input to the electricity budget. There is little correlation between production and electricity used by the mine [23]. This is due to several energy-intensive processes operating independently of the mining of material. Production tonnages (tons mined) should rather be used to plan for rock hoisting and processing estimates, as these activities are directly correlated to the material mined and treated [28]. Electricity usage data is therefore the most suitable input for electricity budget development while production data can be used to develop budgets for systems directly related to material processing or hoisting.

2.2.3. Step 3: Evaluate

In the evaluate step of the budgeting process, adjustments are made to the established baseline. Planned operational changes and energy savings initiatives should be included in the electricity budget. Historic electricity consumption can be adjusted according to planned future interventions. When budgeting, relevant data should be used to plan for these expected changes. Increases and decreases should be planned for according to equipment additions or removals, using the rated capacities, running hours and schedules of the relevant equipment. Knowledge of equipment additions and removals, new mining areas and up- or downscaling is required. All this data is available to mines and should thus be used. Deviations between previous developed budgets and actual electricity usage can be used to identify areas where adjustment may be required.

Scaled increases using production values can be used for processing plants and for hoisting systems [28].

This step requires thorough year-ahead planning and specialized knowledge of the operation. This could pose problems for budget development if projects and initiatives are not planned that far ahead, or if the budget developer is not involved enough in future planning for the operation.

2.2.4. Step 4: Develop

In the development step of the budgeting process, information gathered in the previous three steps is combined. It is important that budget development be done by someone with adequate knowledge of the mining operations. As discussed in Step 3, a minimum level of knowledge of planned mine changes and energy efficiency initiatives are required to develop an accurate electricity budget.

Real-time data is available to most mines [29]. TOU tariffs can thus be accounted for in the electricity budget development. Changes in TOU between the baseline period and future budget period, for instance leap day or the number of weekends in a billing month, should be considered during the budget development phase, and consequently adjusted for as they may have impacts on planned operation.

The method of budget development should be scalable so that high detail budgets can be developed regardless of the size of the operation. The scalability and adaptability of the budgeting method is important when electricity forecasting is done, especially with large data sets [30,31].

2.2.5. Step 5: Convert

This step entails assigning a cost to the budget developed in Step 4. Costing of an electricity budget must be done according to the relevant Eskom costing structure used by the mine, typically Megaflex [24]. To use the Megaflex tariff structure, budgets should be developed per utility POD, as this is the measurement used for billing. Electrical feeders for energy intensive systems on a mine are typically downstream of the POD and the sum of the electricity usage of the feeders should add back up to the electricity usage of the POD. Developing a budget per energy intensive system is possible in this configuration.

The Megaflex tariff structure is comprised of a set of active energy costs, per kilowatt hour (kWh) used, reactive energy charges, demand charges and fixed costs, independent of electricity consumption [5]. Active energy costs can be directly applied to electricity consumption. Fixed costs can be added to systems by weight to ensure that the sum of the systems and total mine are equal. The resulting costs should be itemized according to the Eskom structures for maximum transparency.

For the proposed electricity budget, costing of active energy should be done per system. Not all systems have the same usage patterns but still needs to be incorporated into the electricity budget to account for all operating conditions. For example, systems with load shifting projects that operate outside of peak periods have significantly lower costs than systems that operate consistently during peak periods.

Consequently, the forecasted costs can be divided by the forecasted electricity usage to determine the effective tariff (R/kWh) for each system.

2.2.6. Step 6: Report and Approve

The final step of the electricity budgeting process is reporting and approval. This entails documenting the budgeting process and its outcomes, and validation of the resulting budget.

It is essential that the developed budgets undergo a validation process to ensure the development was done accurately and transparently. Past budgets and actual data can be used to check that the budget is within the expected boundaries. It is also important that the results from the electricity budgets are traceable. Deviations from past usage patterns, as well as changes due to TOU should be documented.

Final approval of the developed budgets is critical and needs to be presented to a wide variety of personnel across multiple disciplines. Results should be presented in a concise format and should also be visualized for easy and effective reporting [32].

This literature study provides an analysis of current budgeting practices, combined with actual data and resource availability. The electricity cost budget is designed to be an effective tool for proactive energy management. This literature review of electricity budgeting processes identified shortcomings that, when addressed, could enhance the efficiency of electricity cost budgets in mining operations and improve overall energy management.

2.3. Summary of Literature

Six steps for budget development relevant to mining operations in South Africa were identified from literature. These steps provide a realistic framework for the development of high-quality budgets, but existing implementation falls short of the quality and availability of real-time data in mining. For budgets to be relevant and comparable to real-time data, they should have various inputs.

One such input is data representing the electricity consumption of an energy-intensive system on the mine, in at least hourly intervals. This data should also be traceable to a verifiable source.

With this data, the following method should be followed:

- Adjustments to the baseline electricity usage data should be made using knowledge of planned increases in electricity consumption by each energy-intensive system. Adjustments should also be made to account for changes between the TOU of the baseline period and the future period being budgeted for. All this should be overseen by a person with in-depth knowledge of the electricity usage patterns of the mine. This method should ultimately be easily scalable. Costs should then be assigned to the electricity budget using the relevant utility costing structure.

The resulting electricity cost budget should then be verified and finalized in the following manner to produce a usable output:

- The developed budget should be validated using past data and knowledge about planned future changes to ensure its accuracy. Changes made to the input data should be well documented. The validated budgets and supporting documents should thereafter be approved by a responsible entity. The budget should be reported in an easily accessible manner using visual mediums.

The steps identified from literature fit into three components, namely:

- Input: The collection and evaluation of all data and information required for the budgeting process.
- Method: The processing of the data collected in the “Input” into electricity profiles and costs.
- Output: The presentation of the results of the “Method” to relevant parties.

Each step also involves a measure of quality control. Within each component, certain criteria must be met to ensure a high-quality budget that is usable for energy management. Criteria for each of these steps, and survey questions to determine whether best practices are met, are presented in the following section.

3. Methods

This study used a mixed methods approach to determine the best practices for electricity cost budgets on mines in order to establish criteria for efficient mine budgets. Qualitative and quantitative methods are combined in the form of a literature review, survey design, and interviews. The resulting data is analyzed and discussed in Section 4.

3.1. Determining Best Practices for Electricity Cost Budgets on Mines

This section uses the information gathered in the literature study to determine a set of best practices for electricity cost forecasting on mines. The identified best practices are used to compile a survey to determine the quality of budgets currently used on mines.

The steps of budget development as discussed in the literature review, can be divided into three components: Input, Method, and Output. Table 2 below shows how the literature sections fit into each component.

Table 2. Electricity budget component contents aligning with the criteria from literature.

Literature Section	Contents	Budget Component
1. Inform	Boundary selection	Input
	Data collection	Input
	Output boundary selection	Output
2. Data	Data quality evaluation	Input
3. Evaluate	Adjustments for planned changes	Method
4. Develop	Profile creation	Method
5. Convert	Costing	Method
6. Report and approve	Result validation	Method
	Result documentation	Output
	Result presentation	Output

A few additional points are highlighted under each component to effectively evaluate the current budgeting methods applied in practice. These points are gathered from literature and industry standards, evaluated in the literature study. This is done to ensure accurate, traceable and scalable electricity budgets are developed which can be applied for effective energy and cost management in the mines.

The application of this methodology is limited to the budgeting processes of South African mines, as well as to the relevant personnel involved in the processes.

3.1.1. Input

The budget input provides a starting point, where data to construct the budget is gathered and where a boundary is selected. A successful budget should employ the following best practices for its input:

- (a) Budgets should be developed per energy intensive system.
- (b) Input data should be in a half-hourly resolution.
- (c) Input data should be of verifiable quality.
- (d) Electricity usage data should be used for most systems. Production data can be used for systems directly related to processing or hoisting.
- (e) Relevant data should be used to adjust the historic electricity usage baseline.

For the input, direct questions can be asked to determine the boundary and data resolutions. This covers the boundary and resolution of the output as well. For data quality a checklist of possible data quality interventions can be used. A checklist can also be used to evaluate the input data, as there is only a set number of possibilities. How planned changes are currently budgeted for should also be discussed as this will provide the surveyor with insight of the methods used and how to evaluate them. A combination of multi-answer and single-answer questions will be used to evaluate each.

3.1.2. Method

The method section of the budget includes the compilation of the input data into a budget, adjustments for planned changes in operation and the costing of the electricity budget. The following best practice steps should be employed:

- (a) Budgets should be developed by a person with established knowledge of the energy management systems of the mining operation.
- (b) Time-of-use should be accounted for in the development of the electricity budget.
- (c) Tariff structures from the relevant utility company should be used to assign costs to electricity forecasts. In the case of most South African mines this is the Eskom Megaflex tariff structure.
- (d) The budgeting method should be scalable and adaptable.
- (e) Developed budgets (electricity and cost) should be validated before being presented for use.

For the method section, a checklist can be used to determine the person responsible for budget development. Whether TOU is used and whether the budget is validated are binary yes or no questions. How costing is done is again a question that needs to be discussed. The surveyor needs to gain an understanding of the whole process as well as the tariffs and breakdowns used. To gain an understanding of the adaptability and scalability of the budget is difficult, as it is not easily quantifiable. The survey can ask how time intensive the budgeting process is, or how tedious the process is. Budgeting processes that take a lot of time and are tedious are unlikely to easily scale to large systems.

A combination of empirical and open-ended questions will be required to gain a well-rounded understanding of the mine budgeting method.

3.1.3. Output

The output section of the budget outlines how the budget should be checked, approved and presented. The following steps are the best practices according to literature for the output of a mine electricity budget:

- (a) The developed budget should be available per energy intensive system.
- (b) The developed budget should be available in at least an hourly resolution.
- (c) Costs and effective tariffs should be available per energy intensive system and should have different tariffs according to their operation.
- (d) Planned deviations from historic electricity usage patterns should be well documented for traceability.
- (e) Developed budgets should be presented in a concise manner and visualized in an appropriate way for the intended audience.

The three components of budget development are therefore now linked. High quality input data is required for all steps in the method, and a high-quality result from the method is required for a high-quality output to be achieved.

Some of the output points can be deduced from questions in the input section, namely the resolution and boundary of the budget. To determine if costing is split and how, the question should be followed up by options to ensure that the costs are not just split by percentage usage. To determine what records are kept on budgeting and how budgets are reported on, the survey can ask for an example on how the budget is presented. This will determine whether a record of changes was given, whether visualizations were used, and if the presentation is varied according to the recipient.

The output section of the survey will be comprised of binary yes or no questions, single-answer questions, and discussion questions to understand the final budget result.

3.2. Survey Development

The identified best practices were converted into survey questions to be used to determine mines' adherence to the established best practices.

The initial survey was composed in a narrative format, following the flow of the input, method, and output best practices as identified in this section.

Empirical and binary questions were included, where the participant is expected to select only one answer. Open-ended questions are included to allow for discussion of budget practices and to promote a better understanding of the budgeting process for the interviewer. Accepted answers within the open ended questions are provided, and multiple answers may be selected.

The initial survey (Appendix A) comprised 15 questions, five per section. The questions in Table 3 represent an edited version of the questionnaire that was distributed to obtain the results in Section 4. The questions were condensed where results overlapped to present the most concise set of results without losing the detail of information that was obtained. Letters in brackets () refer to the best practices from Sections 3.1.1–3.1.3 addressed by each question.

Participants were selected from a mine energy management company who represents several large mining groups in South Africa. After obtaining informed consent, the surveys were sent to the participants and the data collected over a period of two months by the first author. The surveys were performed in the form of interviews between the participants and the first author. Participants were guided through completion of the questionnaire during the interview.

Survey participants were selected according to the following criteria:

- At least two years of experience with mine budget cycles.
- Have some knowledge of the entire budget development process.

To prevent bias, the survey aimed to present the participants with clear, neutral questions based only on the findings from the literature. All results were collected anonymously.

The complete survey is presented in Appendix A.

Table 3. Survey question allocations to evaluate electricity budget quality.

	Question	Budget Component Evaluated
1.	To what level of the operation is the budget separated?	Input (a), Output (a)
2.	What is the resolution of the budget?	Input (b), Output (b)
3.	How is the quality of the input data ensured?	Input (c)
4.	What input data is used in the budget creation process?	Input (d), Input (e)
5.	How are planned changes budgeted for?	Input (f)
6.	Who is responsible for budget development?	Method (a)
7.	Are adjustments made to the input data to account for changes in TOU between the baseline period and future budget period?	Method (b)
8.	Is costing done using the official Eskom tariff structure?	Method (c)
9.	How time consuming and labor intensive is the current budgeting process?	Method (d)
10.	How is the budget output validated before use?	Method (e)
11.	Is costing split into beyond POD level, and if so, how?	Output (c)
12.	Are changes to the budget baseline documented?	Output (d)
13.	How is the budget presented?	Output (e)

4. Industry Performance vs. Best Practice Results

The survey constructed in Section 3 was used to evaluate whether the budgeting procedures of 41 mine business units deliver a high-quality budget that is comparable with available real-time electricity usage data. The mining operations used to evaluate the industry performance form part of the leading mining companies in South Africa and play an important role in the country's Gross Domestic Product (GDP).

Representatives of several South African deep-level gold and platinum mines were identified to participate in this survey. All representatives are involved in some capacity in the electricity cost budgeting process of the business unit they represent. The problem being investigated by this paper was discussed briefly with each participant before commencing with the survey. After answering the questions, deviations from the literature best practices and reasons for their occurrence were discussed.

Findings of the application of this survey are presented in the next three sections.

4.1. Input

This section discusses the outcomes of the application of the Input questions of the survey developed in Section 3. Both multiple choice, single answer and discussion questions were used to evaluate the data utilized as input for development of electricity cost budgets on the relevant mines. The results per identified best practice as presented in Section 3 are discussed below.

- (a) Most of the mines surveyed (78%) develop budgets per energy intensive system. The remaining sites develop them per feeder or for the whole POD. To pass, the input data should be split at least per feeder, as 85% of the mines have done.
- (b) The utilization of monthly input data during the budgeting processes was most prominent. Only seven mines used half-hourly data as input for their budgeting process. Input data needs to be half-hourly to align with best practices.
- (c) The surveys found that the input data used to develop electricity cost budgets on mines is generally of high quality. All the mines surveyed contract third party metering companies where data quality is a contractual obligation. For half of the business units, data is from calibrated meters. For best practices, at least two data quality checks should be present in the process.
- (d) The majority of sites (78%) used electricity usage data to account for planned changes. Some of the surveyed sites (9/41) uses production data as the only input for their budget development and did not align with best practices.

- (e) 78% of the surveyed sites utilized planned electricity usage increases to plan for future changes, while 9 of the 41 sites relied on production scaling. Production scaling for systems other than hoisting and processing is not in line with best practices.

Figure 4 shows the detailed results of the Input section of the survey. Questions (a)–(e) and answers A–E can be found in Appendix A.1.1. Results were analyzed and consolidated into pass/fail, shown in Figure 5.

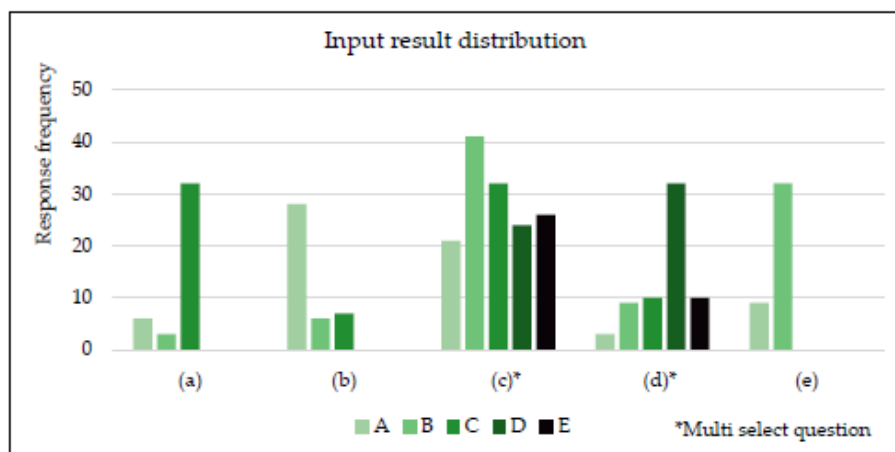


Figure 4. Input survey results distribution.

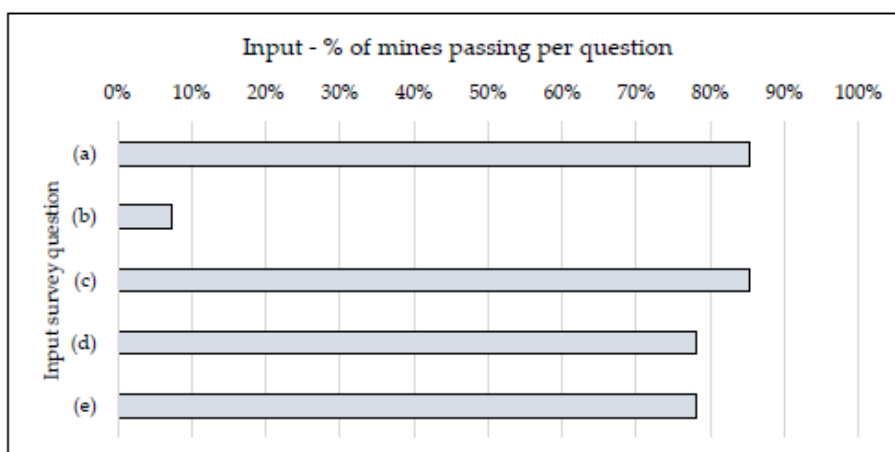


Figure 5. Input survey results—percentage passing.

Although the right type of data is used, on the right boundary and with high quality data, the input will not deliver a high-quality budget unless the data is also in a high enough resolution. Monthly budgets are not an effective energy management tool when contrasted with real-time data. Monthly budgets also cannot be costed as accurately as higher resolution budgets allow, as the Eskom Megaflex costing structure is billed half-hourly.

The survey questions from the methodology were effective in gathering all required data from the participants.

All the sites surveyed had at least hourly data available for systems where energy management is required. Approximately 61% of the operations have this data available in real-time and could thus employ effective energy management if budgets were of a high

enough resolution. When the data is not used, it is largely due to time constraints. If the time constraints could be overcome, half hourly data can be used as input for electricity cost budgets for mines. This would allow for high quality and high-resolution budgets that can be used for energy management to be developed.

4.2. Method

This section discusses the outcomes of the application of the Method questions of the survey developed in Section 3. A combination of single answer, yes/no, multiple choice and discussion questions were used to better understand the steps taken by the mines to develop an electricity cost budget.

- (a) For most mines, electricity cost budget development is done by the engineering department. The remaining mines had budgets developed by their respective financial departments, or by third party companies involved in the energy management of the mines. For best practices, the mine's engineering department should be either fully responsible for, or at least heavily involved in, the development of the budget.
- (b) As 68% of mines only used monthly data as their input, they could not account for TOU in detail using Megaflex tariffs to determine the cost of their budgets.
- (c) The mines interviewed all use similar methods to cost their developed electricity budgets. This involves using historical percentage splits for the TOU of active energy charges. The charges are then combined with historical fixed charges and multiplied with the expected tariff increase for the year. Only 6 of the 41 sites did account for TOU in the costing of their budgets using the official Eskom tariff structure. This could only be done because they started the budget process with at least hourly data.
- (d) On average, those surveyed rated their budgeting process as 9/10 in terms of how time consuming and tedious the process is. This is an indication that the methods are not scalable and would not easily adapt to a larger scale or other systems. There is a positive correlation between the sites who find the process less time-consuming and the sites that outsource the development of budgets.
- (e) Most budgets are validated before they are used. The majority of sites (85%) used at least two forms of validation. The most applied method was to compare the developed budget to past actual data and past budgets. Both internal and third-party validation is used. It is important to note that despite validation and checks being in place, errors in budgets do still occur. This is largely due to human error, amplified by the large volumes of budgets that often need to be developed in a short period of time, and due to the bulk of budget development being done in Excel, thus there are no built-in checking mechanisms.

The questions developed in Section 3 proved effective in gaining enough information to evaluate the methods used by mines to develop electricity cost budgets. Figure 6 shows the detailed results of the Method section of the survey. The complete set of questions (a)–(e) and answers A–E can be found in Appendix A.1.2. Results were analyzed and consolidated into pass/fail, shown in Figure 7.

Several mines have electricity budgets developed by financial departments who do not have the expertise to plan for changes in planned mining activities. While most mines use the Eskom tariff structures, few account for TOU in their costing. The methods currently used by mines were also found to not be very scalable, contributing to the lack of high-resolution budgets available.

From the Method survey results there is a clear shortcoming in the level of detail used when costing electricity forecasts. This is a knock-on effect, due to the low resolution of input data used. As all costs are known, costing in high detail can easily be automated

to improve this. Costing done with high resolution data will yield better quality results, especially if changes in electricity usage patterns are planned.

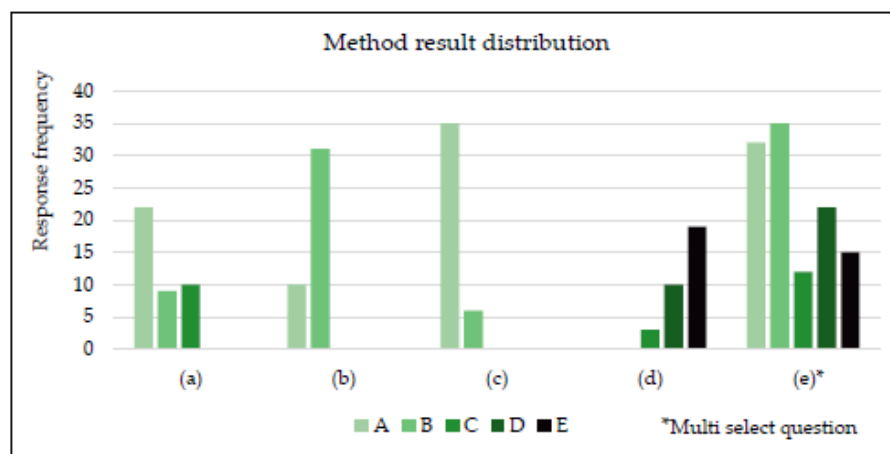


Figure 6. Method survey results distribution.

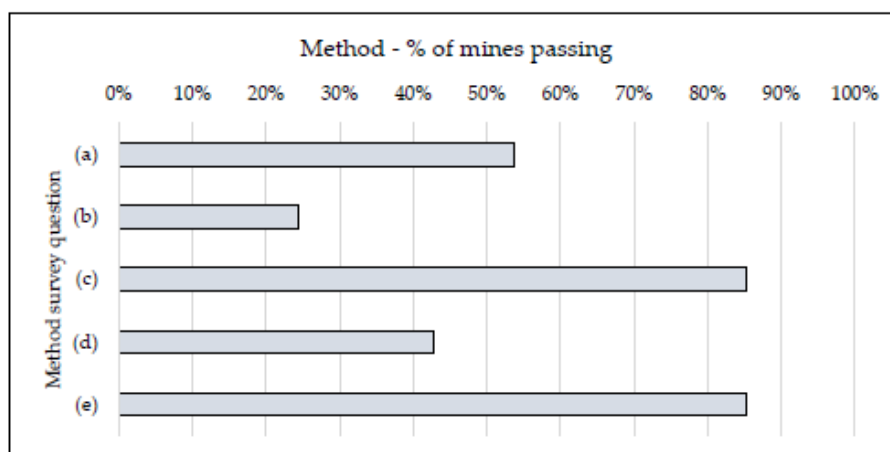


Figure 7. Method survey results—percentage passing.

4.3. Output

This section discusses the outcomes of the application of the Output questions of the survey developed in Section 3. Yes/no, multiple choice and discussion questions were used to determine the quality of the output produced by the budgeting methods employed by the mines surveyed.

- In line with the inputs, most budgets were developed per energy intensive system or feeder (85%).
- The budgets developed by the mines surveyed were mostly available in a monthly resolution due to the monthly inputs used. All mines presented their budgets in a monthly format, even if it was also available in higher resolutions. Some sites used daily data only for data cleaning, and still developed a monthly budget. Ten sites developed daily budgets, and three sites developed half-hourly budgets.

- (c) Most sites split their budget cost beyond the POD level. Unfortunately, most do this by just splitting the cost by percentage, not using TOU. 6/41 sites used TOU and have individual tariffs per energy intensive system.
- (d) Only 29% of mines surveyed formally reported on specific changes made to base-line input data. There is a correlation between mines who formally document the budgeting process and mines using third party companies to develop their budgets.
- (e) All surveyed mines used visualization to present developed budgets, and most had various types of formats used to present the budgets, depending on who it is presented to. Effective reporting requires a combination of values and visuals, as done by 82% of participants.

Figure 8 depicts the detailed results of the Output survey. The complete set of questions (a)–(e) and answers A–E can be found in Appendix A.1.3. Results were analyzed and consolidated into pass/fail, shown in Figure 9.

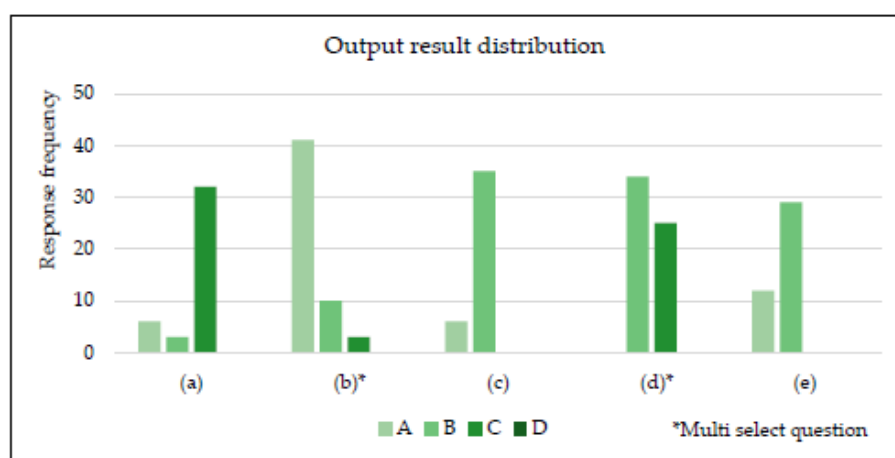


Figure 8. Output survey results distribution.

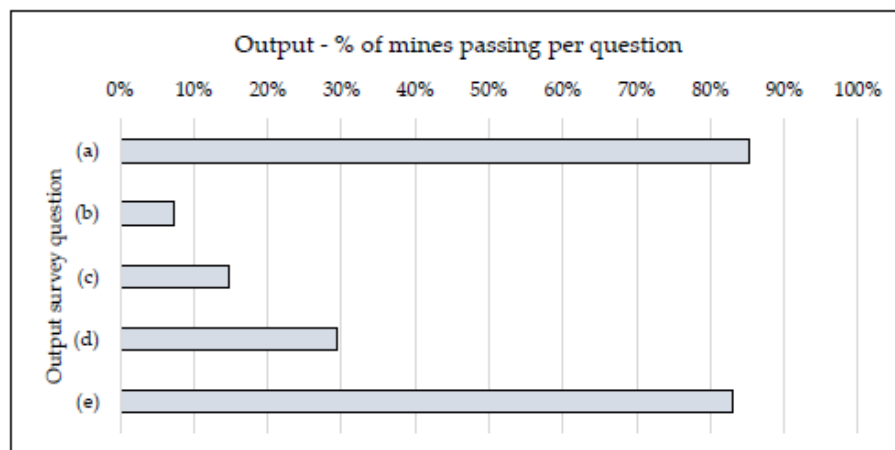


Figure 9. Output survey results—percentage passing.

The developed survey questions were successful in determining whether the budget outputs developed by mines adhere to best practices. The developed budgets are mostly are separated by energy intensive system, as in the input, adhering to best practices. The

resolution however remains a problem, as the input was not of a high enough resolution to produce a high-resolution output. Costing issues arising from the Method section of the survey led to budgets that are split beyond POD level, but without accounting for TOU. This results in inaccurate cost estimations per system. Changes to the baselines are not frequently formally documented. Most mines do however employ effective visualization and presentation strategies to communicate the developed budgets.

5. Discussion

5.1. Results Summary

The study shows that the monthly budgets produced by mines in South Africa would not be useful tools for real-time energy management. The novel research question was answered by the methods developed in this study. Because most sites only split their costs by percentage, even the monthly cost values for each energy intensive system would not be useful for evaluating the cost performance of the system. Budgets in high resolutions and with costs representative of their TOU can be used to track electricity and cost performance progressively throughout a month, enabling proactive energy management by identifying and rectifying issues without having to wait for month end to compare to the budget.

Formally reporting on the electricity cost forecasting process legitimizes it as an energy management tool. Having transparency on the targets set for operations will assist with compliance to meet these targets.

5.2. Next Steps

This study has shown that literature frameworks for mine electricity cost budgets, while available, are quite sparse. The study further found that the established methods from literature are not practically implemented on South African mines in a way that enables the mines to use the budgets for proactive real-time energy management.

A framework incorporating the findings from this study could assist in the practical implementation of existing electricity forecasting and costing methodologies and would result in higher-quality budgets that can be used for real-time energy management.

Table 4 highlights the focus areas to improve practical implementation of electricity cost budgets on mines.

Table 4. Identification of focus for future studies.

Problem	Section	Focus Area	Performance
Mines are not implementing methods for accurate electricity cost forecasting available from literature in practice.	Input	(a) Budgets should be developed per energy-intensive system.	>80%
		(b) Input data should be in at least an hourly resolution.	<50%
		(c) Input data should be of verifiable quality.	>80%
		(d) Electricity usage data should be used for most systems.	50–80%
		(e) Production data can be used for certain systems.	50–80%
		(f) Relevant data should be used for adjustments to the baseline.	50–80%
	Method	(a) Budget should be developed by an informed person.	50–80%
		(b) TOU should be accounted for.	<50%
		(c) Relevant tariff structure should be applied.	>80%
		(d) Method should be scalable and adaptable.	<50%
		(e) Results should be validated.	>80%
	Output	(a) Result should be per energy intensive system.	>80%
		(b) Result should be in at least hourly resolution.	<50%
		(c) Cost and tariff should be separate per system.	<50%
		(d) Deviations from historic patterns should be documented.	<50%
		(e) Results should be well presented and visualized.	>80%

Future studies should focus mainly on the method and output of the budget, as they have the most questions with under 50% of mines passing. A framework should be developed to ensure that a scalable and adaptable method is applied to budget development, meeting the criteria from literature, and delivering the desired output.

5.3. Alignment with Sustainable Development Goals (SDGs)

- Affordable and Clean Energy (SDG 7): The focus on improving electricity cost forecasting and energy management supports the goal of ensuring access to affordable, reliable, sustainable, and modern energy for all.
- Industry, Innovation, and Infrastructure (SDG 9): Enhancing the budgeting processes and adopting best practices in electricity management contributes to resilient infrastructure, promoting inclusive and sustainable industrialization and innovation.
- Responsible Consumption and Production (SDG 12): By improving energy management and reducing inefficiencies, the study supports sustainable consumption and production.

By aligning the recommended best practices for electricity forecasting with these SDGs, mining companies can improve their operational efficiency, minimize energy wastage, and contribute to the broader sustainability goals.

6. Conclusions

This study aimed to determine whether the electricity budget development methods currently employed in the South African mining industry results in high quality electricity cost budgets that can be used for meaningful, real-time energy management. A gap in the literature was identified: there are no existing evaluation criteria to determine whether a developed electricity cost budget will serve as an effective tool for energy management.

Key steps for the development of electricity budgets were identified from literature. Each step was evaluated for relevance within the context of mine electricity cost budgets. Subsequently, a set of best practices were developed to evaluate the quality of the electricity cost budget development process of mines. The best practices are grouped to evaluate the input, method and output of a budget development process.

A survey was compiled based on the best practices identified. A total of 41 mine business units participated in the survey, representing several major South African mining companies. The surveys found that there are significant shortcomings in the budgeting processes of most of the mines. Only 3 of the 41 mines surveyed produced budgets in a half-hourly resolution, as required by the identified best practices. Budgets in lower resolutions than half-hourly do not accurately represent expected patterns in electricity consumption and the related cost implications of TOU.

Surprisingly, most mines surveyed do have high-resolution electricity usage data available for budget development. The barriers to producing high-resolution, high-quality budgets are largely dependent on time, effort and resources available.

The identified barriers hindering the implementation of each best practice should be isolated, investigated and addressed in order to overcome them. From the study results, the following key areas should be addressed:

- Input data resolution.
- Improvement will allow improved costing by allowing TOU costing. This will improve the cost results as well.
- Improvement will result in a high-resolution result.
- Budget method scalability.
- Currently, manual methods are relied on.

- Investigations into advanced forecasting methods, their applicability and scalability are recommended to identify suitable solutions.
- Process and result documentation.
- Improvement of documentation practices throughout the process will improve the quality and traceability of the budgets and allow for repeatability of methods.

Overcoming each of these will enable the development of high-quality electricity cost budgets that can be used as effective tools for energy management. The development of a framework for the budget development process based on the identified best practices is recommended.

By improving the electricity forecasting methods, these energy-intensive mining companies can contribute to SDG 7 by optimizing energy use and reducing costs, SDG 9 by promoting technological innovation and resilient infrastructure, and SDG 12 by minimizing energy wastage and supporting sustainable production practices.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

GDP	Gross Domestic Product
M&V	Measurement and Verification
NMD	Notified Maximum Demand
POD	Point of Delivery
SDG	Sustainable Development Goal
TOU	Time-of-Use
UN	United Nations

Appendix A

Appendix A.1. Budgeting Process Questionnaire

Key: Single answer (s), multi-answer (m), discussion (q)

Appendix A.1.1. Input

- (a) To what level of the operation is the input data separated? (s)
- Incomer/POD
 - Feeders
 - Systems
 - Components

- (b) What is the resolution of the input data? (s)
 - A. Monthly
 - B. Daily
 - C. Half-hourly
 - D. Other
- (c) How is the quality of the input data ensured? (q, m)
 - A. Calibrated meters
 - B. Independent checks
 - C. Incident tracking
 - D. Outlier elimination
 - E. External validation—data used for reporting etc.
- (d) What input data is used in the budget creation process? (m)
 - A. Historic tonnes with fixed kWh/t
 - B. Planned tonnes with fixed kWh/t
 - C. Historic energy budgets
 - D. Historic actual energy data
 - E. Combination of tonnes and energy data
- (e) How are planned changes budgeted for? (q, s)
 - A. Using increased tonnes (rate kWh/t)
 - B. Using increased energy
 - C. Not budgeted for
 - D. Other

Appendix A.1.2. Method

- (a) Who is responsible for budget development? (q, s)
 - A. Engineering department
 - B. Financial department
 - C. Third party company
- (b) Are adjustments made to the input data to account for changes in TOU between the baseline period and future budget period (for example when the baseline month has more weekdays than the future budget month)? (s)
 - A. Yes
 - B. No
- (c) Is costing split into systems? (s)
 - A. Yes
 - B. No
- (d) On a scale of 1–10, where 1 is very quick and 10 is very time consuming, how time-consuming is the current budgeting process? (q, s)
 - A. 0–2
 - B. 3–4
 - C. 5–6
 - D. 7–8
 - E. 9–10
- (e) How is the budget output validated? (q, m)
 - A. Compare to past actual data
 - B. Compare to past budget data
 - C. Internal validation process

- D. Third party validation process
- E. Validated in use

Appendix A.1.3. Output

- (a) To what level of the operation is the budget separated? (s)
 - A. Incomer/POD
 - B. Feeders
 - C. Systems
 - D. Components
- (b) What is the resolution of the created budget? (m)
 - A. Monthly
 - B. Daily
 - C. Hourly
 - D. Half hourly
 - E. Other
- (c) Are the final costs split into systems according to TOU? (q, s)
 - A. Yes
 - B. No
- (d) How is the budget presented? (q, m)
 - A. Values only
 - B. Values and visual medium
 - C. Values, visuals and summary of changes
 - D. Other
- (e) Is the budget process formally documented? (q, s)
 - A. Yes
 - B. No

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APPENDIX B FRAMEWORK CHECKLIST

Framework: Input data preparation

Budget objective identification

- ☐ Identify data source with high-frequency data available for use.
- ☐ Select required data interval for energy management.
- ☐ Select systems groups for energy management.
- ☐ Identify additional information required for budget development (billing dates, planned changes, etc.).

Data collection and preparation

- ☐ Data identified in previous section is collected.
- ☐ Irregular operation is removed from dataset.
- ☐ Data is checked for errors and approved.

Framework: Electricity consumption forecasting

Profile creation

- ☐ System datasets sectioned using a sorting algorithm.
- ☐ Grouped datasets reviewed and deemed representative.
- ☐ Grouped datasets used to forecast systems future electricity consumption.
- ☐ Forecast profiles evaluated for relevance.

Budget composition

- ☐ Select future dates for each created profile.
- ☐ Use future dates to recombine profiles into year-long datasets.
- ☐ Adjust profiles if required.

Framework: Electricity consumption budget costing

Tariff structure breakdown

- ☐ Relevant tariff structure broken down into component tariffs.
- ☐ Tariffs used to set up a time-based tariff dataset in the same interval as the consumption budget dataset.
- ☐ Tariff increases applied where relevant.

Budget cost application

- ☐ Budget cost calculated per system using created budget consumption and tariff datasets.

Tariff calculations

- ☐ Budget tariff calculated per system per month using created budget consumption and cost datasets.

Framework: Budget verification and reporting

Internal result verification

- ☐ Consumption budget checked and verified.
- ☐ Cost budget checked and verified.

Budget procedure reporting

- ☐ Input procedure documented.
- ☐ Consumption forecasting procedure documented.
- ☐ Cost forecasting procedure documented.

Budget result reporting

- ☐ Relevant budget stakeholders identified.
- ☐ Stakeholder needs determined.
- ☐ Data prepared and visualised for presentation.
- ☐ Data presented to relevant stakeholders.

APPENDIX C INDUSTRY STANDARD BUDGET DEVELOPMENT

It is established in the article by the author in the journal *Mining* [51] that there was, prior to that study, no established industry standard or best practice for electricity consumption and cost budget development on mines. In this section an electricity consumption and cost budget for a case study mine will be developed according to the current industry standard for budget development, as identified in Chapter 1 of this study. This represents the status quo and provides a baseline against which improvements can be measured. This method is given in Figure 1.2 and discussed in the results of the survey in Section 1.2.5.

Data from the calendar year of 2023 will be used to develop a budget for the calendar year of 2024. The same input data as used for the results in Chapter 4 was used.

Input

In this section, input data and information on the mine is gathered for the development of the industry standard budget. The data is verified for use before the method section can be applied.

Boundary selection

The industry standard is to develop a budget in monthly intervals, per energy-intensive system. 68% of surveyed mines develop their budgets in monthly intervals [51]. 78% of mines group budgets according to energy intensive system. Operations on the selected case study mine can be grouped into the following energy-intensive systems:

- Pumping
- Mining (underground operations)
- Surface refrigeration
- Underground refrigeration
- Surface general operations
- Hoisting

The mine does not have a dedicated compressed air system. The mine receives ventilation from a nearby shaft and is not responsible for the efficiency monitoring thereof.

The abovementioned sub-systems add up to a single Eskom POD on the Megaflex costing structure. The POD is billed in custom months. For the anonymity of the case study mine, details on the exact billing dates will remain hidden.

The selected boundary this budget will be developed on will be a single monthly budget value per system per month. This will be rolled up to a mine total budget per billing month.

Data collection

The following data for the case study mine was collected for the development of the industry standard budget:

- Actual operational electricity consumption data.
- Utility invoices (Eskom) from January 2023 to December 2023.
- The electricity consumption budget developed and used by the mine for 2023.

Electricity consumption data was available in half-hourly intervals. This data was rolled up to one month intervals according to the mine's custom billing periods. Invoice data is intended for use to check the accuracy of the collected consumption data. Budget data was collected as the industry standard is either to re-use the previous budget (if it performed well) or to use the actual values as a budget. The combination of collected datasets will be the baseline for the industry standard budget development.

Data quality evaluation

The data collected for the study are from reputable sources. All electricity consumption meters used to collect data belong to a third-party metering company, contracted to do energy monitoring on the mine. The company collects, analyses and cleans the data. This data is also actively used in daily electricity monitoring and management systems, both by the mine and third-party energy management contractors providing services to the mine.

The collected data stems from calibrated meters and are installed on the same line as the Eskom incomer meters so that the data used can be double checked for accuracy monthly. Two checks were performed on the collected dataset to ensure accuracy. First, the incomer meter values were compared to the billed electricity consumption by Eskom. This step verifies the incomer data as correct. Second, the now verified incomer data was used to verify the sum of the feeders under the incomer.

The verified actual data collected for this study can now be used to evaluate past budget performance, as is the industry standard, to select baselines for budget development.

Method

Consumption budget creation

One of the common budget development methods observed in industry during the survey is to re-use either past budget values or past actual consumption values as future budgets [51]. This method will be applied here. For each system, the 2023 budget value per month will be evaluated against the 2023 actual value for that billing month. If the budget value came within 5% of the actual consumption value, the past budget value will be re-used as the future budget value. If the past budget value was not within 5% of the actual consumption for the system, the actual consumption value is used as the future budget value. The result of this evaluation is given in Table C.1, with values equal or under 5% marked in green and values over 5% marked in red.

Table C.1: Industry standard budget consumption evaluation.

	Jan-23	Feb-23	Mar-23	Apr-23	May-23	Jun-23	Jul-23	Aug-23	Sept-23	Oct-23	Nov-23	Dec-23
Pumping	4%	9%	12%	14%	15%	9%	19%	14%	6%	12%	8%	10%
Mining	11%	13%	20%	21%	14%	22%	11%	10%	6%	5%	5%	10%
Surface refrigeration	3%	33%	21%	89%	8%	74%	171%	8%	604%	25%	21%	17%
Underground refrigeration	47%	30%	12%	2%	7%	1%	2%	11%	10%	6%	7%	11%
Surface general	8%	10%	13%	15%	6%	2%	14%	0%	3%	4%	6%	9%
Hoisting	62%	27%	22%	13%	11%	3%	0%	8%	10%	3%	5%	1%

Results of this method were evaluated and a monthly baseline budget value for each system was selected. Very few of the past developed budgets came within 5% of the actual electricity usage of 2023. The selected values must now be subject to changes planned between the two years of operation. The result of this will be the final consumption budget.

Consumption budget adjustments

The following information was gathered on planned changes for the case study mine between the baseline and future budget period:

- More efficient conveyor belts were installed underground. This is expected to reduce the power consumption of the mining system by 2% from January 2024.
- Some production areas of the mine will close in July 2024. This is expected to reduce production by 9%.

The underground conveyor belts upgraded run on the mining system. The mining system will therefore be reduced by 2% from the baseline.

30% of mines surveyed were found to scale all underground utilities according to production to plan for known changes [51]. As no information on specific effects on individual systems were available to the author, this method from industry was applied. The mining, underground

refrigeration, pumping and hoisting systems will all be reduced by 9% from baseline from July 2024 due to anticipated reduction in mining activities.

This information was used to adjust the baseline budget created in the previous step. To obtain a POD level budget, the sum of the systems' budgets per month were added up. The resulting industry standard consumption budget is given in Table C.2.

Table C.2: Industry standard consumption budget.

	Jan-24	Feb-24	Mar-24	Apr-24	May-24	Jun-24	Jul-24	Aug-24	Sept-24	Oct-24	Nov-24	Dec-24
Pumping	1 234 430	1 114 900	997 865	971 696	1 047 401	1 090 668	969 034	986 043	1 143 927	1 243 940	1 224 844	1 055 958
Mining	3 359 008	3 804 581	3 818 237	3 854 087	3 808 678	4 159 560	4 003 487	3 857 517	3 740 032	3 435 509	3 546 331	3 290 087
Surface refrigeration	777 972	625 396	685 002	360 250	455 640	261 580	4 588	6 172	9 473	336 542	560 086	594 433
Underground refrigeration	4 764 493	5 098 023	5 450 942	6 220 152	6 220 152	6 434 640	6 381 280	6 838 274	6 878 591	6 050 706	6 654 228	5 835 791
Surface general	548 806	593 400	559 057	600 130	648 986	732 839	706 786	778 692	775 610	674 992	710 227	591 481
Hoisting	376 154	456 175	433 266	471 881	505 230	559 050	525 693	578 481	596 935	525 693	542 651	457 862
Incomer	11 060 865	11 692 475	11 944 369	12 478 196	12 686 087	13 238 338	12 590 867	13 045 179	13 144 568	12 267 382	13 238 367	11 825 613

This consumption budget will be used to develop costs for the industry standard budget.

Budget costing

The industry standard budget costing method most prominent in the survey results was to use the TOU percentage split from the previous year and apply it forward. This is done on a POD level with utility TOU data. Table C.3 gives a summary of the percentages from the Eskom invoices of 2023.

Table C.3: Utility level TOU split 2023.

	Jan-24	Feb-24	Mar-24	Apr-24	May-24	Jun-24	Jul-24	Aug-24	Sept-24	Oct-24	Nov-24	Dec-24
Peak %	13.97	13.70	15.01	12.81	13.22	14.59	13.81	14.76	13.85	14.54	14.32	14.29
Standard %	36.22	36.21	38.16	34.50	36.33	37.14	35.69	37.20	35.76	36.98	36.52	36.18
Off-peak %	49.80	50.09	46.82	52.69	50.45	48.28	50.50	48.04	50.39	48.48	49.15	49.52
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

The values from Table C.3 were multiplied by the incomer budget consumption to calculate the budget electricity consumption for each TOU. This was then multiplied by the known active energy costs for each TOU. A tariff increase of 12.74% on 1 April 2024 was announced for all tariffs except the Affordability subsidy, which increased by 25.24%. This was applied to all cost values from 1 April.

Next, fixed charges were calculated. Due to a past notified maximum demand exceedance by the case study mine, the demand charge for the mine is a fixed value and does not need to be estimated. The notified maximum demand charge was calculated with the known NMD for the site, as it is not likely to change within the budget year. For excess reactive energy, the consumption values for 2023 were used and multiplied with 2024 tariffs. Other fixed charges and administrative charges that are not dependent on usage were calculated for their respective time

periods. The case study mine has additional custom connection charges. These are not subject to tariff increases and remain constant year on year, and were added to the fixed charges.

The total cost for the mine was calculated by adding the total active energy charges and the total fixed charges per month. System specific costs were calculated by splitting the total POD cost, as calculated, by weight of consumption per system. The results of this calculation are given in Table C.4.

Table C.4: Industry standard cost budget per system.

	Jan-24	Feb-24	Mar-24	Apr-24	May-24	Jun-24	Jul-24	Aug-24	Sept-24	Oct-24	Nov-24	Dec-24
Pumping	R 1 936 416	R 1 727 373	R 1 561 324	R 1 593 494	R 1 806 711	R 2 317 388	R 2 456 757	R 2 545 947	R 2 367 345	R 2 180 995	R 2 115 734	R 1 854 346
Mining	R 5 269 183	R 5 894 636	R 5 974 260	R 6 320 355	R 6 569 766	R 8 837 991	R 10 149 899	R 9 960 048	R 7 739 960	R 6 023 464	R 6 125 756	R 5 777 655
Surface refrigeration	R 1 220 384	R 968 959	R 1 071 799	R 590 778	R 785 955	R 555 790	R 11 631	R 15 936	R 19 604	R 590 057	R 967 464	R 1 043 872
Underground refrigeration	R 7 473 928	R 7 898 633	R 8 528 894	R 10 200 489	R 10 729 428	R 13 671 947	R 16 178 234	R 17 656 315	R 14 235 177	R 10 608 680	R 11 494 181	R 10 248 114
Surface general	R 860 897	R 919 385	R 874 736	R 984 158	R 1 119 465	R 1 557 093	R 1 791 889	R 2 010 569	R 1 605 118	R 1 183 461	R 1 226 811	R 1 038 688
Hoisting	R 590 063	R 706 776	R 677 917	R 773 843	R 871 494	R 1 187 837	R 1 332 772	R 1 493 628	R 1 235 351	R 921 696	R 937 349	R 804 042
Incomer	R 17 350 872	R 18 115 761	R 18 688 930	R 20 463 118	R 21 882 819	R 28 128 046	R 31 921 181	R 33 682 443	R 27 202 556	R 21 508 352	R 22 867 295	R 20 766 717

Effective tariffs were calculated by dividing the consumption by the cost to obtain a R/kWh value. Due to the process of cost splitting, all systems have the same effective tariff.

Result validation

The industry standard method for result validation is to check developed values against past actual consumption and cost values, as well as past budget values. All developed values were plotted against past actuals and past budgets. An example of this, with the comparison for the full mine, is given in Figure C.1. All observed variations could be explained by the choice of baseline data used, planned changes and price increases.

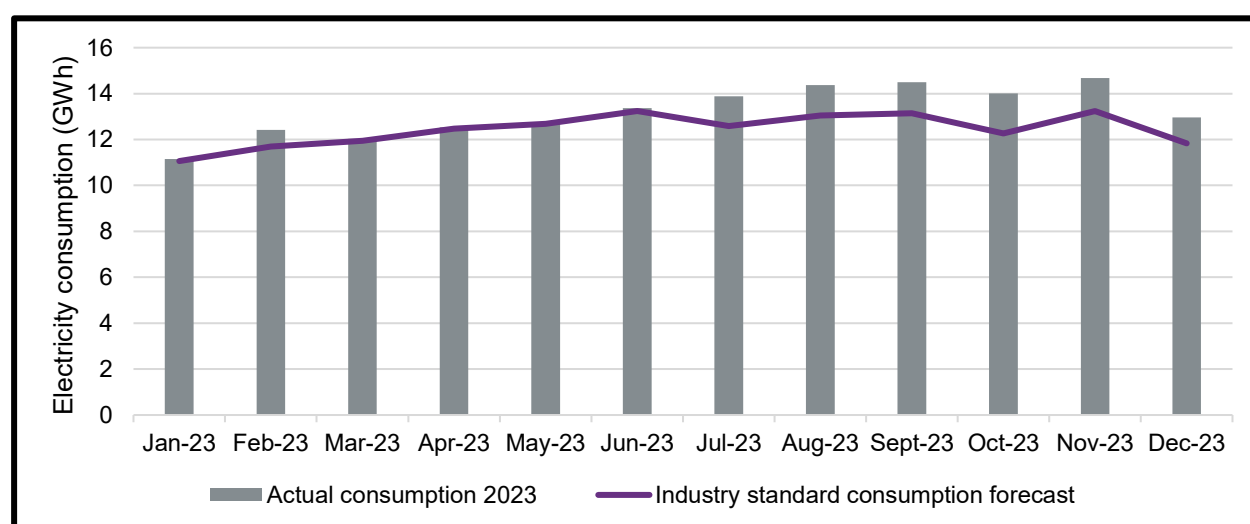


Figure C.1: Industry standard incomer consumption forecast result validation.

The developed budget is approved through this step of validation and can now be presented for use.

Output

Boundary selection

The boundary for the output of the budget development remains the same as the boundary set in the input section for the budget development. The budget will be presented as monthly values of both consumption and cost for each energy-intensive system identified on the mine.

Result documentation

From the survey results in 1.2.5, documentation of the budgeting process was not found to be commonplace. For the purpose of this study the process of developing the budget was documented to show the difference in development strategy between the industry standard and the developed framework.

The following is documented in the text:

- Baseline used as input data.
- Justification for the choice of input data.
- Adjustments made to the baseline data.
- Assumptions made during the costing process.

Result reporting

The results from this case study do not need to be reported for use. If they were reported, industry standard is to report the following:

- Total electricity consumption per system per billing month.
- Total electricity cost per POD per month.
- Effective tariff per POD per month.
- Visualisations of each of the noted parameters.

Appendix D ADDITIONAL RESULTS

This section presents additional visualisations and result discussions from the case study application as given in Chapter 4. Underground refrigeration has the highest consumption, which is common in deep-level gold mines. The case study mine is over 2 km deep and has a large interconnected underground network, thus requiring large amounts of cooling which is extremely energy-intensive.

Clustered profile results

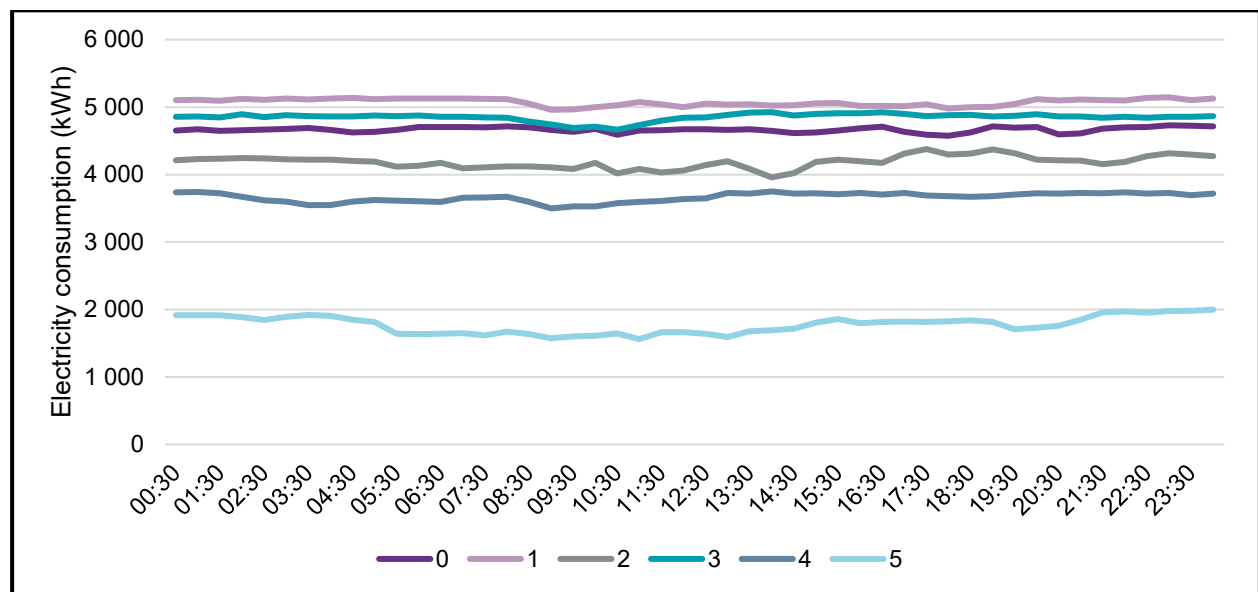


Figure D.1: Identified electricity consumption patterns in underground refrigeration system.

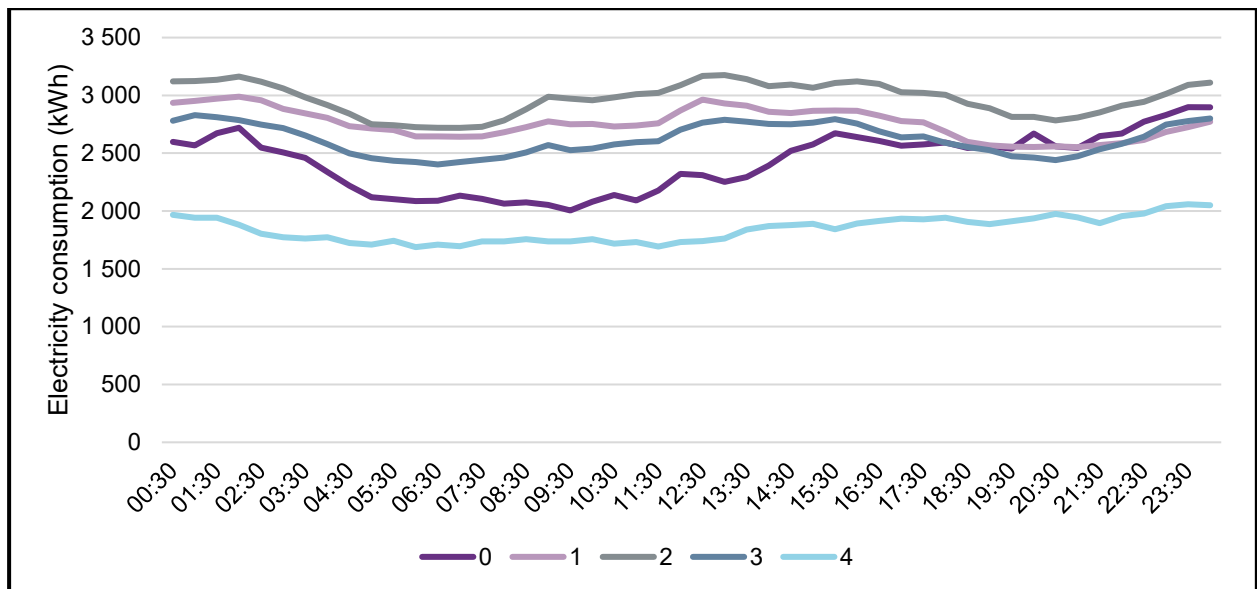


Figure D.2: Identified electricity consumption patterns in mining system.

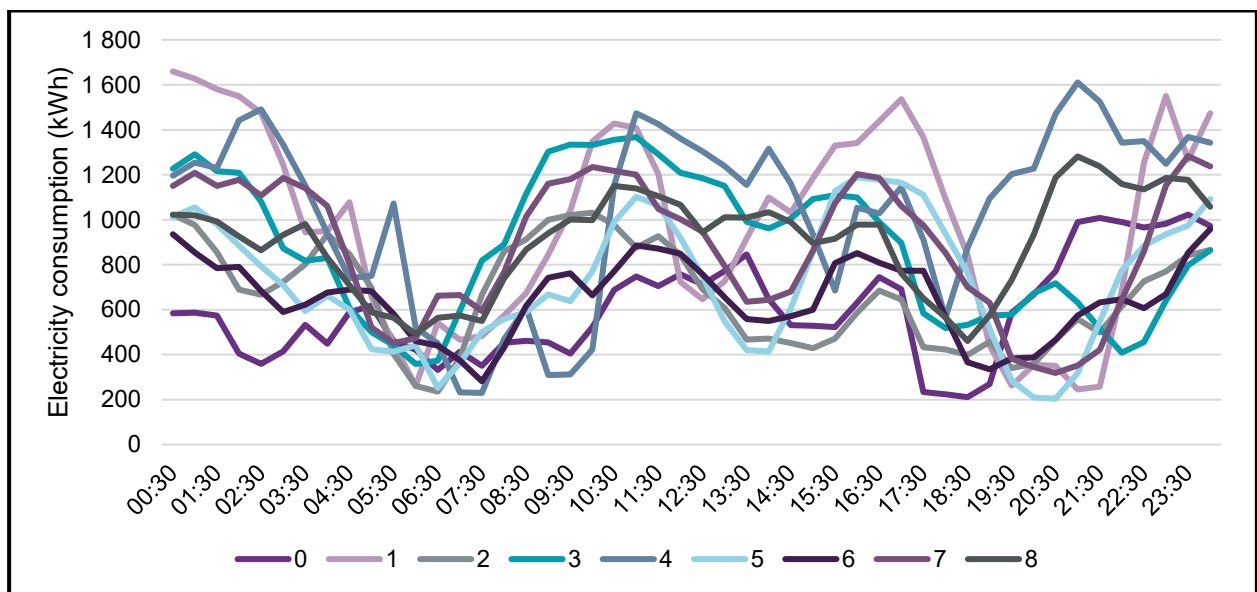


Figure D.3: Identified electricity consumption patterns in pumping system.

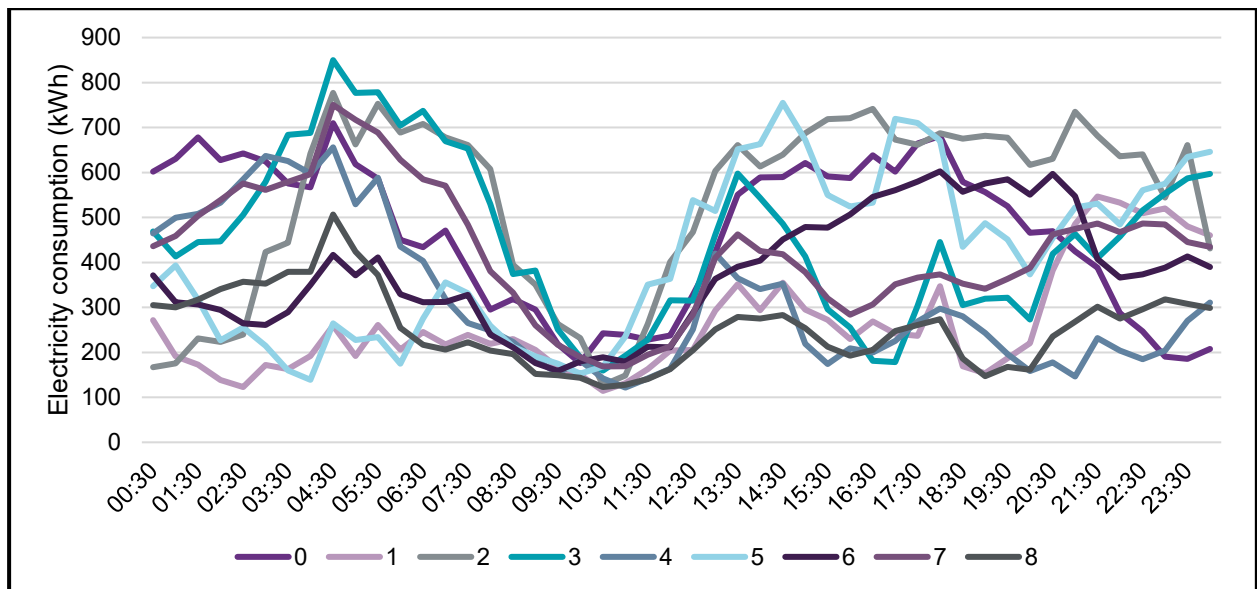


Figure D.4: Identified electricity consumption patterns in hoisting system.

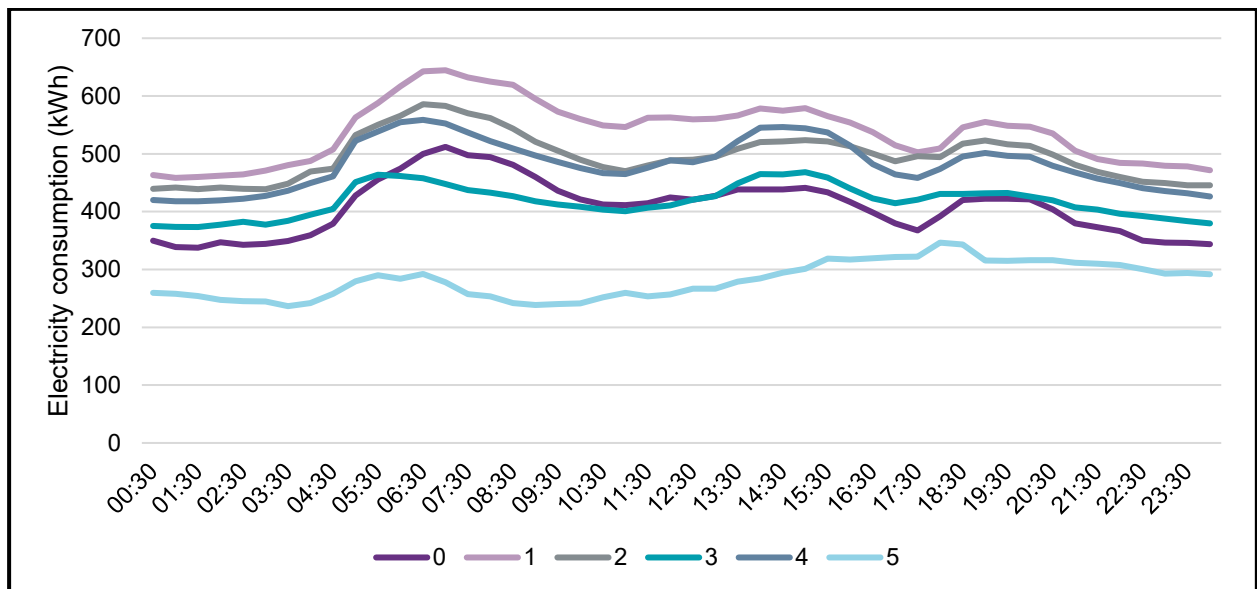


Figure D.5: Identified electricity consumption patterns in surface operations system.

The following section presents the combined yearly profile consumption results. underground refrigeration has the highest consumption, which is common in deep-level gold mines. The case study mine is over 2 km deep and has a large interconnected underground network, thus requiring large amounts of cooling which is extremely energy-intensive.

Yearly consumption profile results:

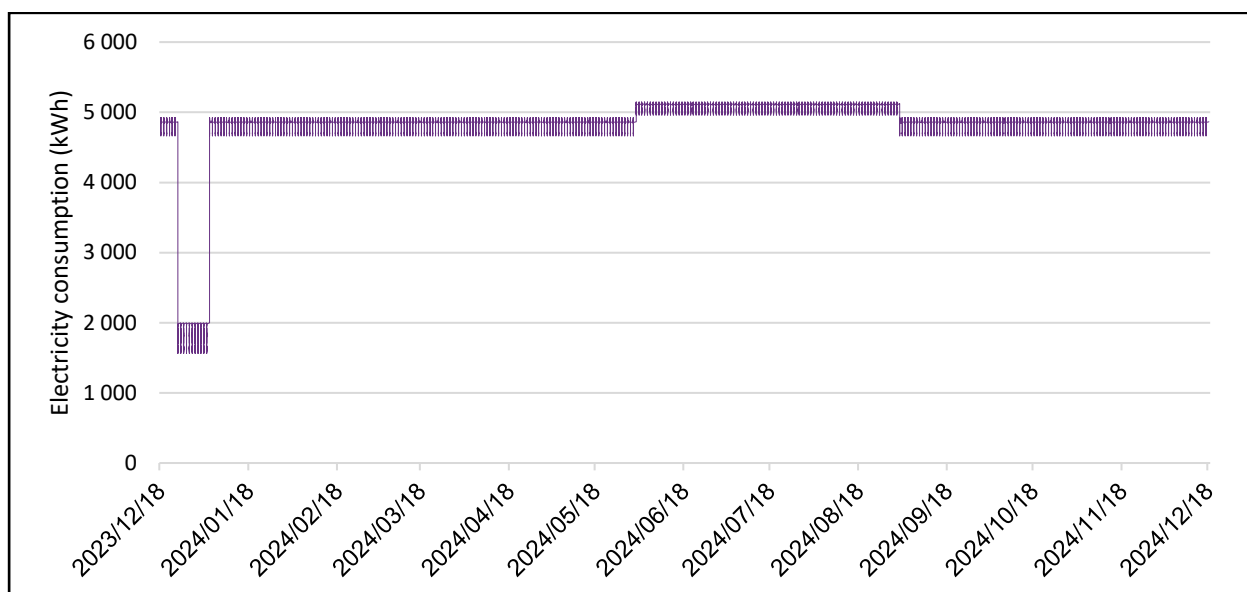


Figure D.6: Combined yearly electricity consumption budget for underground refrigeration system.

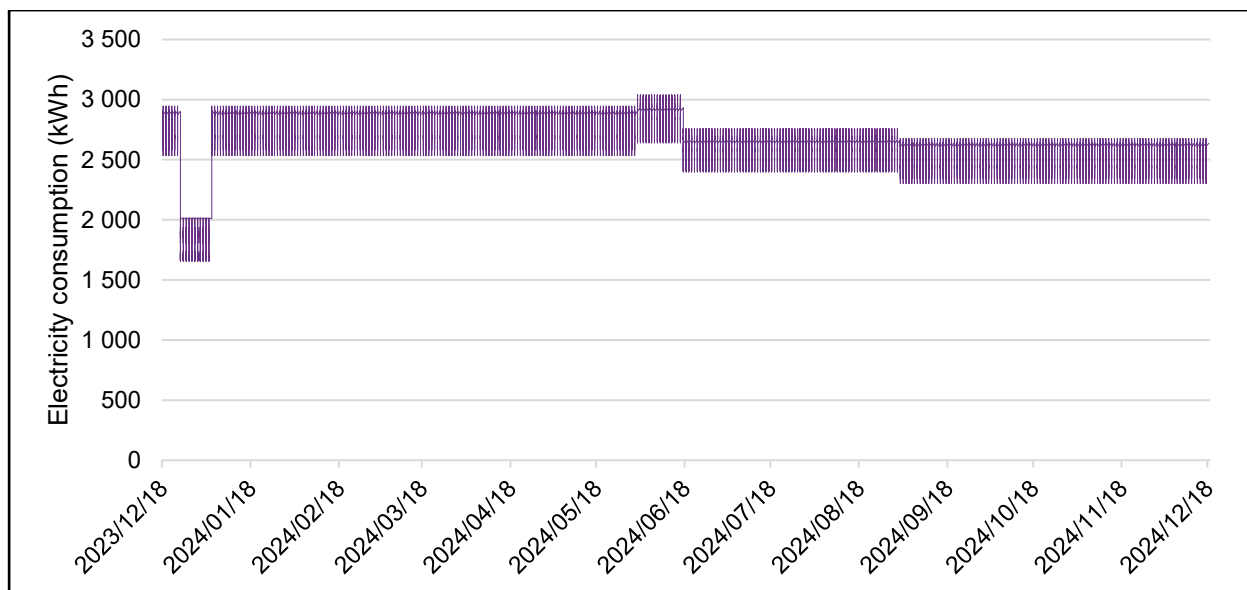


Figure D.7: Combined yearly electricity consumption budget for mining system.

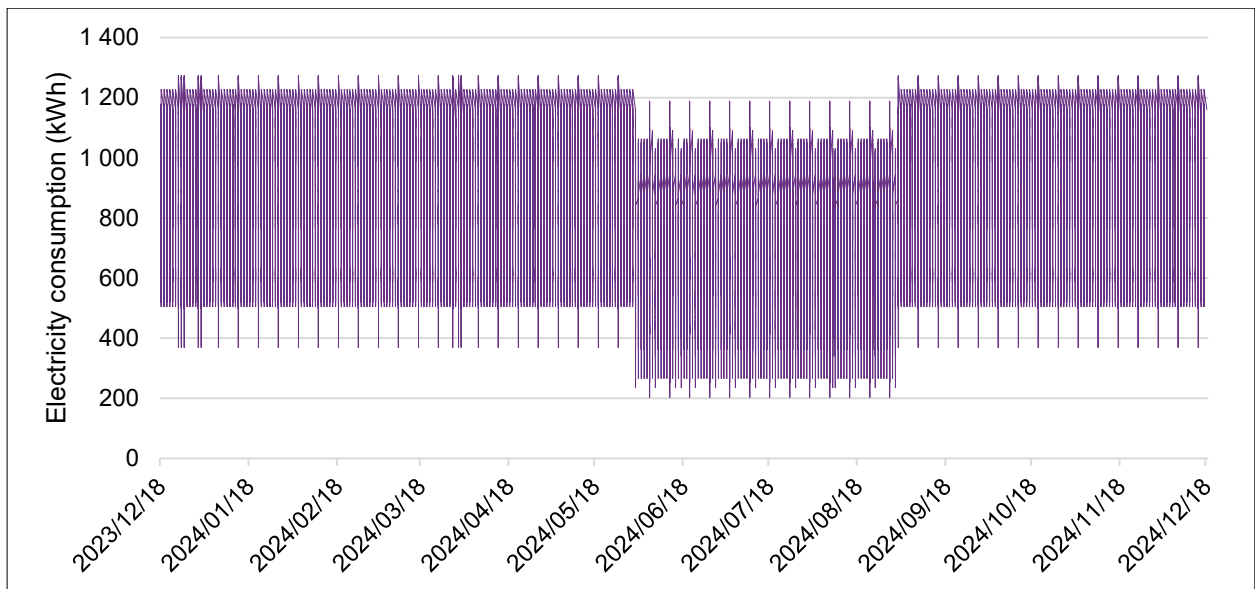


Figure D.8: Combined yearly electricity consumption budget for pumping system.

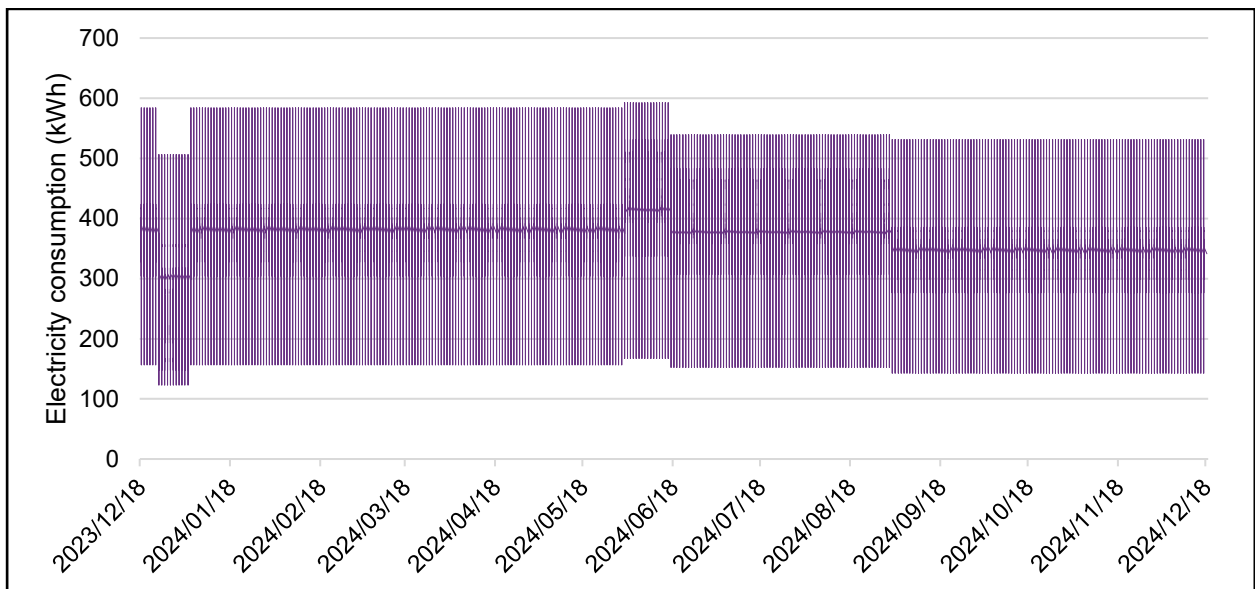


Figure D.9: Combined yearly electricity consumption budget for hoisting system.

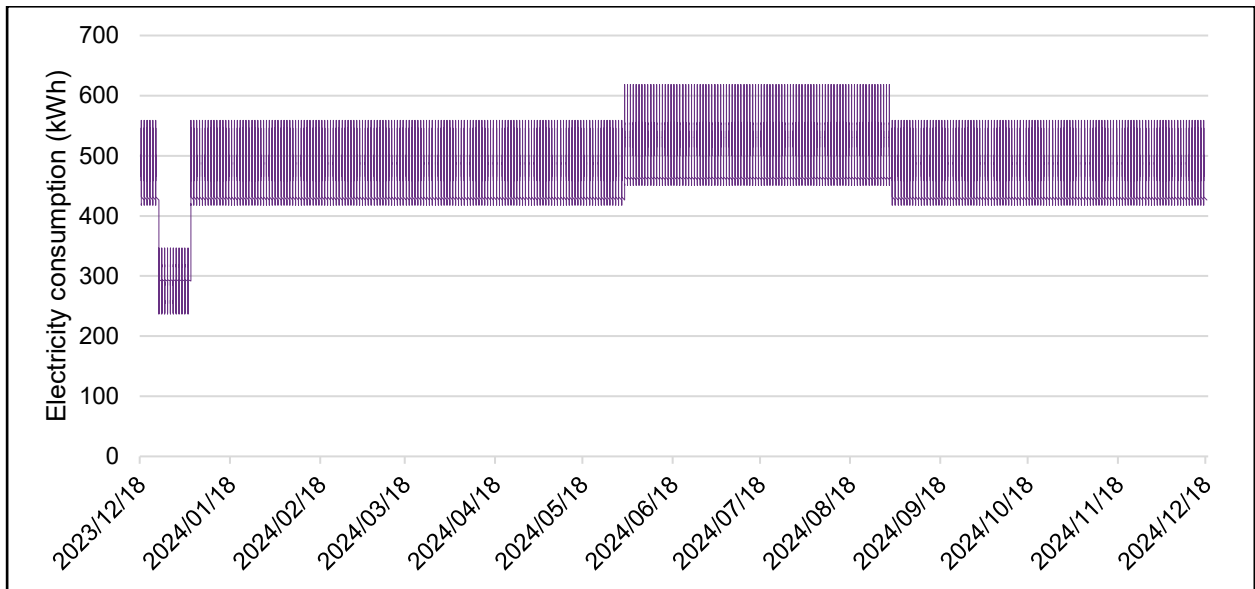


Figure D.10: Combined yearly electricity consumption budget for surface operations system.

Yearly cost profile results:

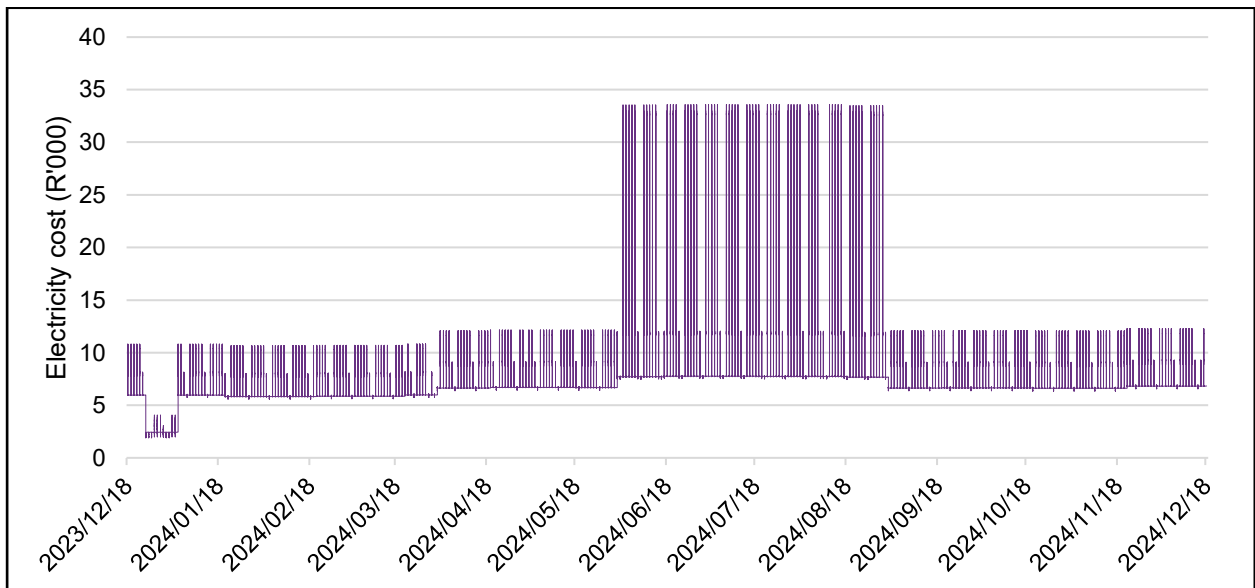


Figure D.11: Combined yearly electricity cost budget for underground refrigeration system.

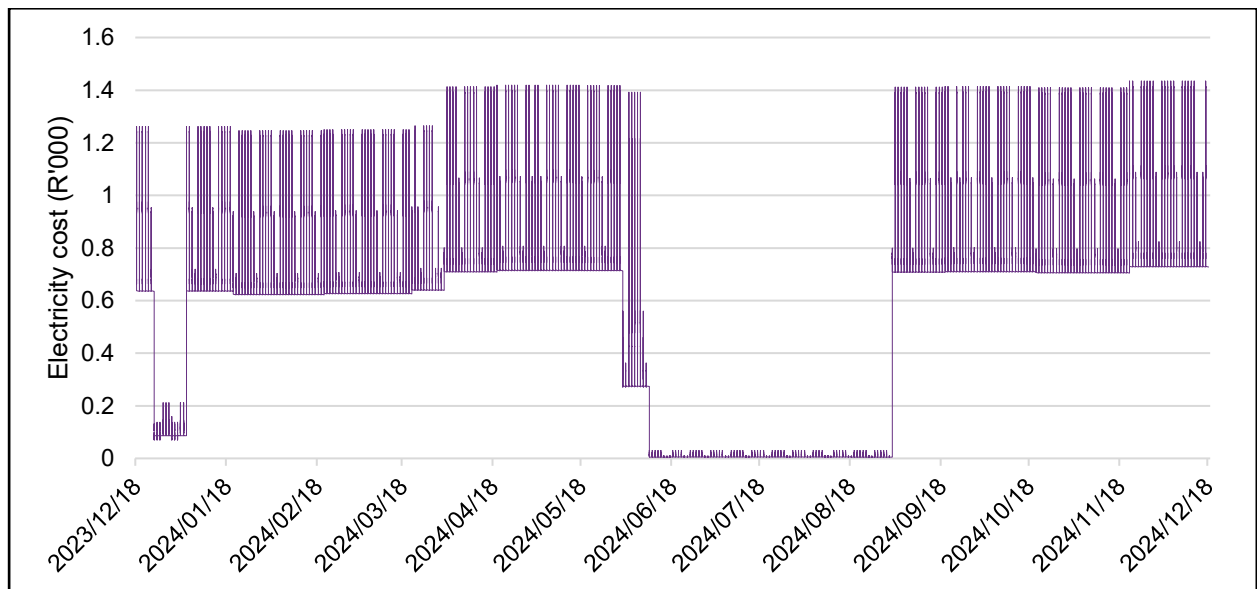


Figure D.12: Combined yearly electricity cost budget for surface refrigeration system.

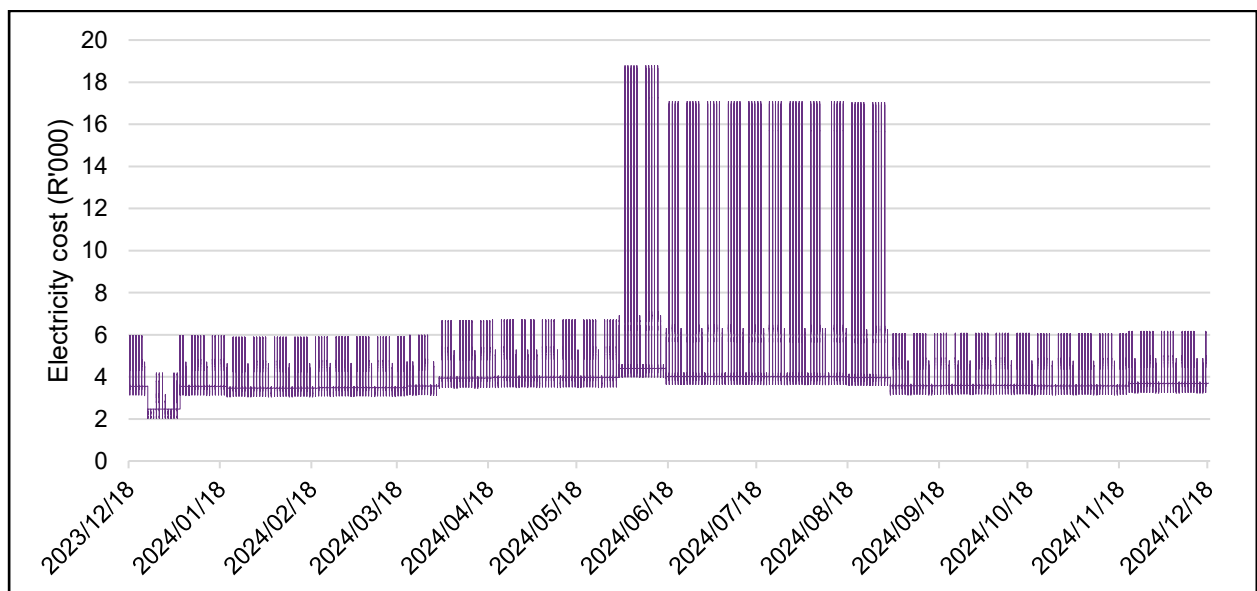


Figure D.13: Combined yearly electricity cost budget for mining system.

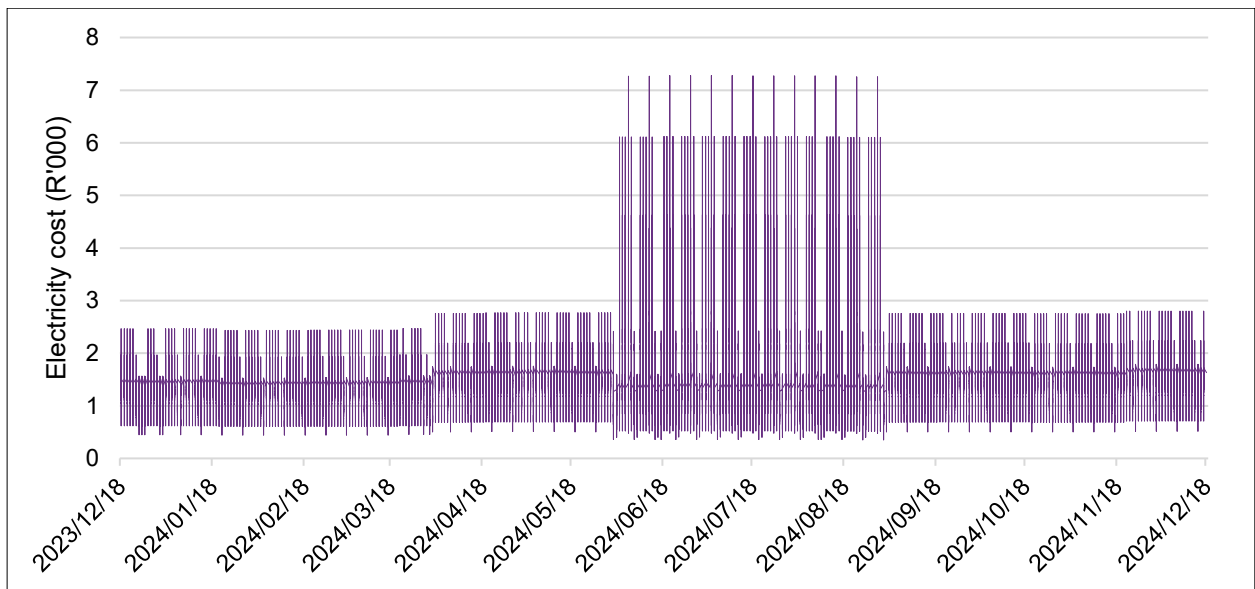


Figure D.14: Combined yearly electricity cost budget for pumping system.

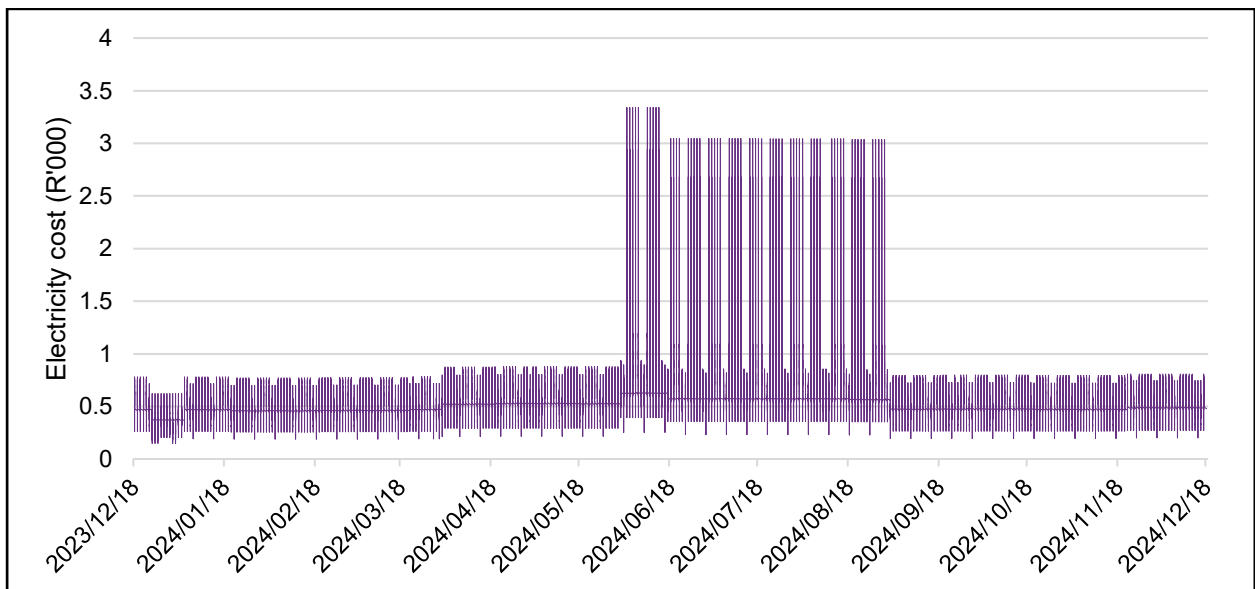


Figure D.15: Combined yearly electricity cost budget for hoisting system.