

Ensuring long-term energy savings in South African mines by improving energy data

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Abstract

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South African mines experience higher-than-inflation electricity tariff increases, additional expenses such as carbon taxes and mounting environmental obligations. The mining sector is, therefore, forced to maintain long-term energy savings. Over the past 20 years, many mine savings initiatives have been implemented. Unfortunately, studies have shown that most savings deteriorate over time due to limited monitoring and evaluation.

Energy data on South African mines is usually of low-quality and not reliable for decision-making purposes. With the advent of more affordable measurement instrumentation, the amount of data is also increasing. Users are thus often overwhelmed to the point of ignoring data. To gain information from large amounts of data, the data must be of acceptable quality and be processed for presentation in an easily understandable manner.

A method was developed to address the uncertain quality and reliability of mine data. Mine incomers are frequently calibrated and can be verified monthly through Eskom accounts. The data for sub-systems is, however, less reliable. Each sub-system total is a combination of several smaller power meters, resulting in a compounding error. Due to the large number of meters on a mine, calibration or the replacement of inaccurate meters is not financially feasible.

To mitigate this, the total power consumption of the sub-systems is compared to the verifiable consumption measured by the incomer meter. Through normalisation, the difference is then spread over the sub-systems by weight. A validation is also performed on each system to confirm that the resulting values are within the expected performance parameters for the system.

A method was developed to present data effectively for decision making. This involves a process of visualisation and evaluation in order to produce high quality figures. A selection method was developed to identify the best-suited means of visualisation. This includes the identification of relevant data and the preparation of that data for visualisation. The data is checked for outliers and common data quality issues before being visualised. A visualisation evaluation criterion was developed in parallel with this. The visualisation produced by this method will enable a decision-maker to evaluate the performance of energy intensive mine equipment.

This method was implemented on four mines to demonstrate the value thereof. The quality improvement method allowed more accurate energy budgets, saving one mining group R55 million per year. The developed visualisation method enabled the user to evaluate project performance in order to keep energy savings projects on track. With this method implemented, mines could mitigate inefficiencies and achieve energy savings.

This study was successful in developing a method to improve both data quality and presentation. This in turn can be used to achieve and maintain long-term energy savings on mines.

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List of abbreviations

<i>Abbreviation</i>	<i>Description</i>
BAC	Bulk air cooler
COP	Coefficient of performance
EIUG	Energy Intensive Users Group
J	Joule
K	Kelvin
kPa	Kilopascal
KPI	Key performance indicator
kVA	Kilovolt-ampere
kW	Kilowatt
kWh	Kilowatt hour
L	Litre
m ³	Meters cubed
MW	Megawatt
PLC	Programmable logic controller
RPM	Rotations per minute
s	Second
SA	South Africa
SCADA	Supervisory control and data acquisition
VSD	Variable speed drive

1 BACKGROUND & LITERATURE

1.1 Preamble

This section will provide background and context for the study, as well as a literature study that explores relevant research and shortcomings in the field of energy management and energy data visualisation, especially in the mining industry.

Firstly, the need for energy efficiency in South Africa will be explored. Thereafter, the relevance of energy efficiency in the mining industry will be addressed. Literature is presented on mining systems and equipment and the expected energy intensity of these systems. These systems and equipment are further investigated to find systems that can be made more efficient through effective operation. From this, the focus areas for the application of the study will be selected.

The second section investigates the state of data available from mines. As data is a key point of this study, it is vital to have a good understanding of the data one will be working with. Literature on data quality and how data quality adjustments are done in industry is investigated. This will be used to develop a method to improve data quality.

The third section studies how the presentation of data can improve its perception and usability. The importance of how data is presented to users is surveyed. A literature investigation on how data visualisation is used in industry is presented, with the focus on how visualisation is used for performance evaluation. This will later be used to develop a method to visualise data from mines.

All this is combined into a problem statement and list of objectives which the study will aim to answer.

1.2 The need for energy efficiency in the South African mining industry

Identifying the need for energy efficiency in South Africa

South African industries face mounting pressure to be more cost- and environmentally conscious [1], [2]. Costs, particularly those of energy sources such as electricity, have escalated over the past decade [3]. In addition to rising energy costs, industries also face increasing environmental pressure in the form of climate change policies, carbon taxes and stakeholder requirements [4]. This is a global trend and affects several energy-intensive industries and is especially prevalent in developing countries [5], [6].

To assist with effective energy usage in the country, 28 companies from 7 different industries established a non-profit organisation known as the Energy Intensive Users Group (EIUG) of South Africa (SA) [7]. The EIUG comprises technical experts on all energy matters, working towards a sustainable energy consuming industry. Figure 1 presents a breakdown of the industries included in the EIUG.

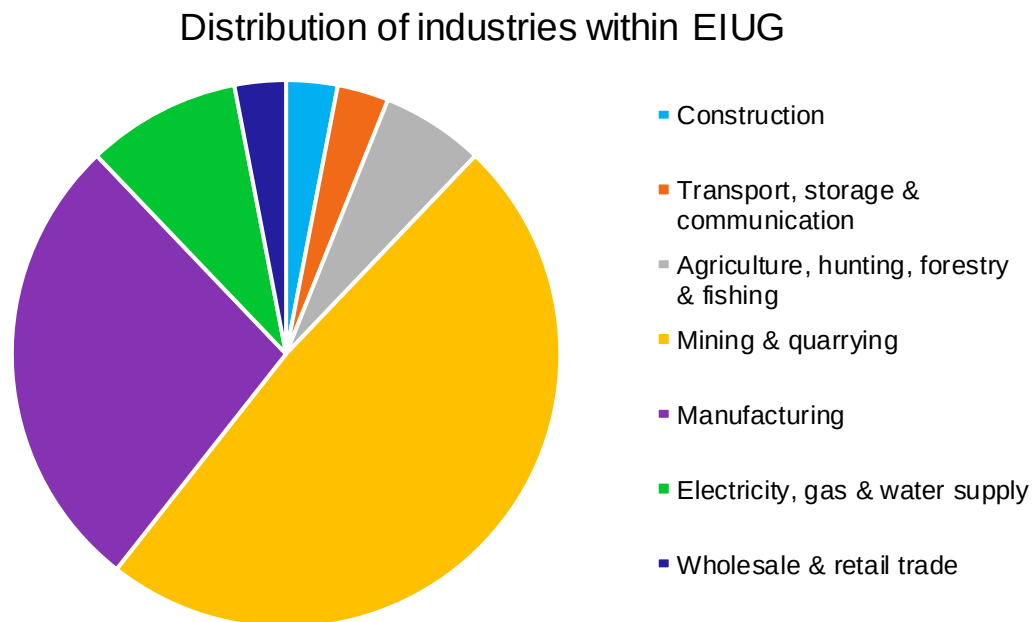


Figure 1: Distribution of industries within the energy intensive user group of South Africa [7]

Of the seven industries included, mining and quarrying industries make up 48% of the EIUG. This indicates that the mining and quarrying industry is a significant energy consumer in South Africa. The mining industry alone consumes 13.9 % of all the electricity produced by the South African electricity public utility, Eskom [8], [9]. This figure highlights the importance of energy efficiency within the mining industry.

Energy efficiency is commonly used to alleviate the pressure of high energy costs. Energy efficiency is the principle of reducing energy usage or energy intensity with the goal of sustainability [10]. Performance evaluation is being used in several industries to bring about energy efficiency [4]. In the mining industry the goal is to minimise energy waste without affecting production [6]. Economically, energy efficiency initiatives may lead to cost savings, and are currently one of the main cost saving measures implemented in industry [3].

Of the companies in the EIUG, 42% EIUG do not currently have any energy efficiency projects implemented. This highlights an opportunity for project implementation and, therefore, ultimately energy savings. There is also potential for energy efficiency initiatives in the mining sector [11]. Operating a mine efficiently has become one of the most important objectives of the mining industry.

It is very important that energy savings are also sustained in the long term. This ensures the continuation of the initial benefit of energy saving. It also reduces the waste of resources to repeat projects.

To sustain savings long term, evaluations of the performance of energy savings projects need to be done throughout. Monthly and annual evaluations will provide insight into the performance of the projects [12].

Long-term sustainability is not frequently achieved in energy efficiency projects. This is largely due to projects not being monitored and maintained [13], [14]. Other contributors to this phenomenon are limited resources and the personnel's resistance to change [13]. This leads to projects having short lifespans and not contributing towards long-term savings. It is also the norm in current energy savings projects to only report on savings in the short term [15]–[18]. This might be due to the high volume of projects being implemented on mines but indicates that long-term savings are not maintained.

Understanding energy efficiency in the mining industry

There are many opportunities within the mining industry to achieve energy efficiency. This section presents a literature survey on attempts to enhance the energy efficiency of systems commonly found on South African mines. Preference will be given to systems that can be optimised through operation only. This is to reduce capital expenditure required to achieve energy efficiency. The identification of energy intensive systems and their functionality will allow for performance evaluation that can lead to energy efficiency.

The South African mining industry represents an estimated 7.0% of SA's GDP [19]. The industry contributes significantly towards employment in the country. The mining industry uses 13.9% of all electricity produced by Eskom [9]. It is vital for the economy that the mining industry remains profitable. To do this, the industry needs to constantly evaluate its performance and be sure to use resources wisely.

The energy efficiency of an entire mine can be determined through a high-level investigation. This can be done by comparing the overall production output with the total energy consumption. Such results may not be informative enough to evaluate project performance

as information can be lost when using aggregated data of such a high level [20]. Analysing the performance of the individual systems or equipment rather than that of the entire mine provides greater insights into the efficiency of the operation.

Performance management can be done using data available to an organisation [21]. Performance evaluation through data has been shown to reduce production costs by up to 50%, and working capital of operations by up to 12% [22]. Implementing this within the mining industry may, therefore, lead to significant cost reductions.

The importance of individual mining systems for energy efficiency

Mines are large and made up of many systems. Focus areas on mines thus need to be selected before any data analysis can be done. Prioritising energy-intensive systems and equipment will ease the analysis process and reduce the resources required for performance evaluation.

According to a report published by Eskom Ltd. in 2010 [8], the following operations and equipment consume the most energy on mines:

- Electric motors
- Pumps
- Fans and ventilation systems
- Compressed air systems
- Lighting
- Refrigeration and cooling systems

This narrows the focus area to only energy-intensive systems of the mine. Strategies to improve the energy efficiency initiatives will have the most significant impact on high consuming systems. Focussing on the improvement of these systems will allow the user to evaluate current performance and to identify possible future initiatives.

Figure 2 represents the usage of energy on mines by these energy-intensive systems. Two typical South African gold mining operations were used for the investigation. Gold mines represent 21% of all South African mines [23].

Note that all small surface operations were grouped under the sub-system “lighting”.

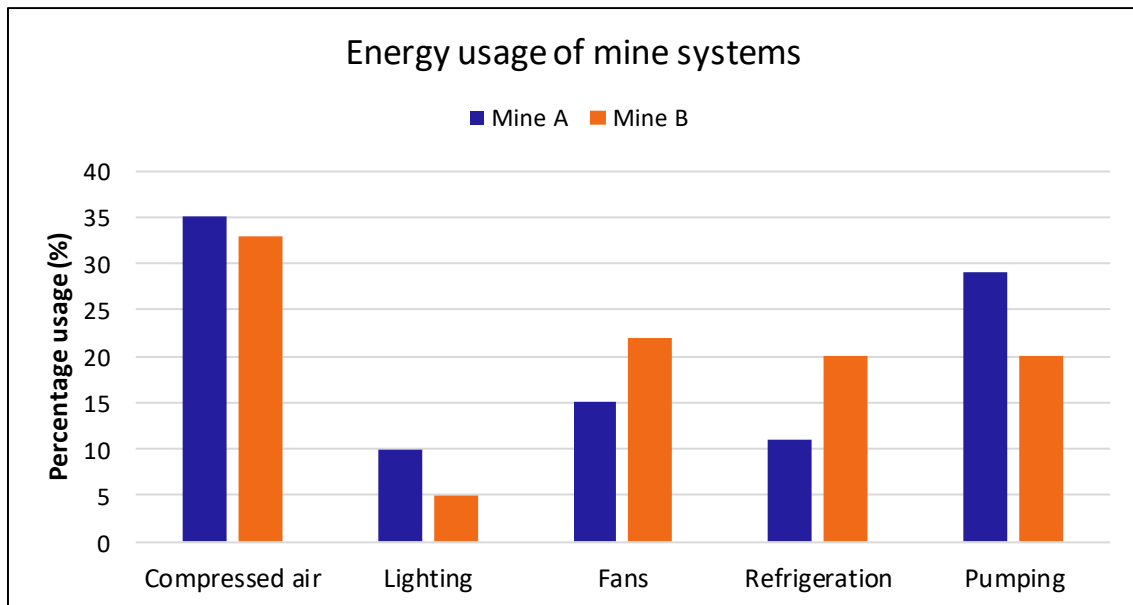


Figure 2: Percentage of energy usage by mine systems

From Figure 2, it can be seen that compressed air systems consume the largest percentage of energy on gold mines. This is expected, as compressed air is used in several mining machines. Second to this is pumping or fans, depending on the mine. Both these systems are driven by electrical motors and are used widely throughout the mining industry.

Refrigeration is also an energy-intensive system, consuming between 11% and 20% of the total energy. Of the systems mentioned in the Eskom report, lighting consumes the lowest percentage of energy on mines [8]. Lighting can, however, not be optimised through operation; but is best optimised through good housekeeping. It will, therefore, not be investigated further. Figure 2 validates the findings of the Eskom report [8].

It is most effective to focus energy savings initiatives on more energy-intensive systems and equipment. This includes refrigeration systems, fridge plants, bulk air coolers, compressors and compressed air systems, and equipment driven by electrical motors like fans and pumps.

The function of each mining system is crucial to ensure that the mine remains operational. These systems provide cooling to ensure legal working temperatures per regulation, circulate air, remove water from working areas, and are used for operations such as drilling. Table 1 provides a summary of the identified energy-intensive mining systems. For each of these systems, the potential for energy efficiency improvement is evaluated. Improvement options are categorised into specification, maintenance, and operation.

Specification implies the installation of appropriately sized machinery, piping, and ducts. Capital expenditure is usually required for this type of energy efficiency initiative.

Maintenance refers to the upkeep of the system. All systems require regular maintenance to function optimally. This includes checking for leaks, cleaning machinery, and examining machinery for faults and signs of wear.

Operation indicates changes to be made to how systems are operated in order to improve efficiency. It involves setpoint changes, the use of variable speed drives (VSDs), and the operation of systems identified as more efficient over others, to name a few.

Table 1: Summary of mine systems and methods to maintain their efficiency

System	General	Specification	Maintenance	Operation
Electric motors [8], [24]	Commonly used to supply power for pumping, ventilation and winder systems. The main purpose of these systems is to move material and resources.	It is suggested that electric motors run at 75% of their full load point for optimal energy efficiency. New high-efficiency electrical motors should be installed when possible.	Regular maintenance of motors is required to keep motors functioning optimally to ensure energy efficiency.	Motors operated according to specification are more likely to have efficient energy consumption.
Pumps [8], [24]–[26]	Pumps that are driven by electric motors are commonly used on mines. They are used to move and pressurise fluids on the mine.	Pumps are most efficient when appropriately sized for their purpose. The efficiency of pumps is also dependent on the layout of the pumping system. Pump systems should regularly be analysed to determine the necessity all pumps.	Regular preventative maintenance is required for pumps to perform optimally.	The most efficient pumps should be operated more frequently to avoid wasting power. The installation of VSDs can make pumping systems with varying flow requirements more energy efficient.
Fans [3], [8], [11]	Fans on mines are also driven by electrical motors. Fans are commonly used for ventilation and extracting warm air from working areas.	Fans should be appropriately sized for their required application. A well-designed ventilation system with appropriate ducts will also improve the efficiency of the fans used.	Regular leak checks, blockage checks and equipment upkeep are important to maintain efficiency in fans.	For optimal operation, fan speed should be controlled in accordance with need for ventilation. This can be done by means of vanes, dampers or VSDs.
Compressed air systems [8], [18], [24]	Compressed air is used widely throughout the mining industry. Pneumatic equipment is used for mining, for the operation of doors and often for cleaning.	High pressure drops make compressed air systems less efficient. It is best if such drops can be avoided. New equipment tends to be more efficient, and correctly sized equipment should be used for optimal operation in order to avoid wasting energy.	Regular maintenance of compressors is required to keep them in peak operational condition. The compressed air lines should also be regularly inspected and maintained, as leakages can cause significant inefficiencies, even if compressors are operating optimally.	Ensure supplied compressed air matches demand. Variable speed drives can be used to deliver pressure according to demand, thus reducing power consumption of the system.
Refrigeration [3], [8], [24], [27]	Due to the high amounts of heat generated by mining operations, refrigeration is required for mines to remain within legal working temperatures. Most mines make use of two refrigeration systems: fridge plants to cool down water, and bulk air coolers to cool down air. Bulk air coolers are reliant on fridge plants as cold water is used to cool down air.	The amount of refrigeration required varies widely between mines. It can be affected by atmospheric temperature, underground temperature, and by the mining operations themselves. Refrigeration systems need to be matched to the cooling load required for optimal operation.	Regular maintenance is required for refrigeration units to perform optimally. Compressors on cooling units can also be upgraded for increased efficiency.	Setpoint changes can lower energy intensity. The most efficient units should be operated more frequently.

From this table it is apparent that the systems and equipment that were identified are all important on mines. Each system works best if it is properly specified and regularly maintained. Most importantly, each of these systems can be made more efficient through operational changes. This includes running equipment at their recommended capacities and ensuring that demand for cooling or compressed air is met and not oversupplied.

This study aims to use data and performance evaluation to drive and uphold energy efficiency initiatives. Systems, as mentioned above, that can be improved through more efficient operation should be investigated, as it will be possible to assess their performance from operational data. These systems are:

- Compressed air systems
- Refrigeration systems
- Systems driven by electric motors

These systems consume a combined portion of approximately 44% of the power of a gold mining and processing plant and 74% of the power on a gold mine [28]. These systems, especially on older South African mines, are often over designed. This is due to historically low prices of energy at the times that the mines were built. This creates even more opportunity for energy savings on these systems [12]

To ensure that energy savings projects on these systems remain sustainable in the long term, their performance must be monitored. To do this, reliable data will need to be presented to relevant personnel on mines. The following section will investigate the availability and reliability of data from mines in SA.

1.3 Literature on energy-related data on mines

Background

The first step of energy management is to analyse historical data available on mines [5]. Unfortunately, on South African mines this is difficult due to the lack of easily interpretable data. Information contained within datasets can assist with cost reductions and process optimisation, and may lead to informed decision making [29]–[31]. This obtained knowledge then leads to more competitive and productive industries [32], [33].

One of the main reasons why industrial energy efficiency lacks momentum is the complexity of systems. Production is of paramount importance on mines. Data from countless measurements is available to track production and ensure that targets are being met, but is not applied in order to save energy [30].

Mines are moving towards a modernised approach to data handling [34]. Data availability has grown considerably in the past few years. Industries are collecting and storing more data than ever before [35], [36]. This sudden abundance of data is due to new developments making data capturing more affordable and accessible [37]. The mining industry is no exception to this trend, collecting exponentially more data every year [30], [32], [35], [37].

Technology for data capturing and storage has become mainstream and relatively inexpensive in the past decade [38]. Data is usually stored without being refined or filtered for future use.

Process variables on mines are measured and resulting data is sent to a Supervisory Control and Data Acquisition (SCADA) system. As the name suggests, this is used to supervise systems and to acquire data. Here data can be viewed by operators through basic and limited visualisations for a restricted time period.

Once the data is outside of the SCADA observational timeframe, it is stored on a historian database. These databases are frequently wiped to make room for new data as long-term evaluations using data is uncommon. Meters are legally only required to be able to store data for 40 days [39]. Numerous mines are, however, implementing cloud storage, which will enable them to store high frequency data long term [30]. Long-term data is most likely to be available in lower frequencies than measured data in order to optimise storage space use.

For the purposes of this study, long term will be defined as a period longer than 30 days.

Data handling and processing errors

Newly available large datasets are often overwhelming. They can be disordered and confusing due to a lack of structure and processing, making them difficult to interpret [33], [40]. Left un-interpreted, these datasets convey little to no information [22]. It is, therefore, important to interpret the available data to obtain the necessary information and be able to act thereon. Interpreting this data will aid in the endeavour to make systems more energy efficient.

When used to its full potential, as discussed above, high-quality data can add value to an operation [21], [41]. Unfortunately, data from industrial operations, such as mines, tend to have quality issues [42]. These issues will need to be addressed before information can be extracted from the data.

The full potential of data does not come without its difficulties. Large datasets present challenges in finding trends and interpreting changes [43]. This is due to the magnitude of resources that are required to process big volumes of data.

Informational overload is cited as a barrier to digital progress by the *Dell technologies digital transformation index* report [44]. This is often why data is not fully utilised. Understanding data is crucial to gain usable information. Unfortunately, mines do not effectively use the generated data for decision making [36].

Quality evaluation is a critical step in any data reporting procedure [45], as high-quality datasets lead to better decision making [46]. If the available data is analysed and amended to form a high-quality dataset, the data can be used for decision making.

Due to the nature of measurement and data capturing equipment, no data can be assumed to be one hundred percent correct [47], [48]. Decisions made using low-quality data will not be accurate [41]. Other risks of low-quality data include calling an entire investigation into question when findings are based on the questionable data. Such mistakes can lead to a loss in revenue [49], [50].

Bantini [51] suggests that errors are specific to the organisation that is the source of the data. As this study focusses on data from mines, data errors specific to mines should be investigated.

Data handling and processing is a challenge on industrial scale operations [42]. This causes issues with the data from these operations [45]. To evaluate the quality of the data at hand, some relevant indicators of data quality must be chosen [52]. The following faults are common in data from mines [53]–[56]:

- Missing data
- “Stuck-at” errors/ static data
- Out-of-bounds errors (exceeds limits, negative values)
- Abrupt errors (outliers)

Missing data is data that is not available when logically it should be. This can be due to sensor faults, storage faults, or other digital issues. A dataset with missing data is not representative of the operation, as the data is incomplete [57]. On mines, missing data can have many causes. Simple meter faults often occur due to meters being exposed to the elements. Meter faults are also often missed due to the sheer number of meters that have to

be monitored and maintained by mines and metering companies. An example of missing data is provided in Figure 3.



Figure 3: Missing data error example

Some fluctuation is expected in measured data. A **stuck-at error** occurs when data remains at a point for longer than is expected. This is considered an accuracy error [41], [58], as the data is misrepresented. Stuck data typically occurs when there are connectivity problems between the meter and the server. Other electronic faults can also cause stuck-at data. Figure 4 presents a visualised example of stuck-at data.

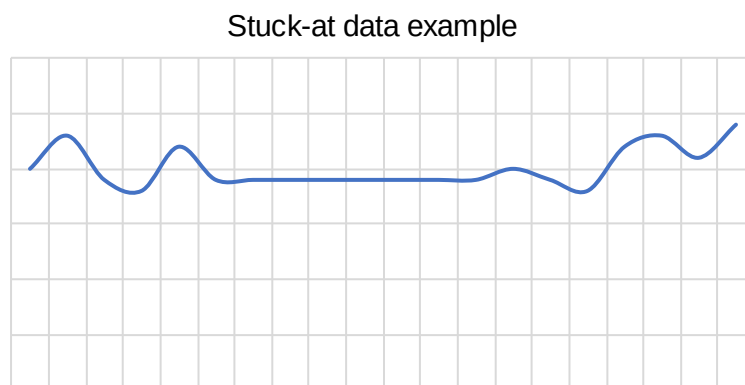


Figure 4: Stuck-at data error example

Out-of-bounds errors are data points outside the expected limits for a dataset [41]. This is a conformity error. Systems will, for instance, always have a positive power consumption when on. All systems involved within this study have a power rating, and systems are not

expected to exceed that consumption. Out-of-bounds errors also cover rule violations. For instance, the temperature of the incoming air at a BAC should always exceed that of the outgoing air. A basic understanding of the system being investigated is required to identify out-of-bounds errors. An example of an out-of-bounds error is given in Figure 5. On mines this can be caused by faulty meters, faulty equipment or unknown connections to meters.

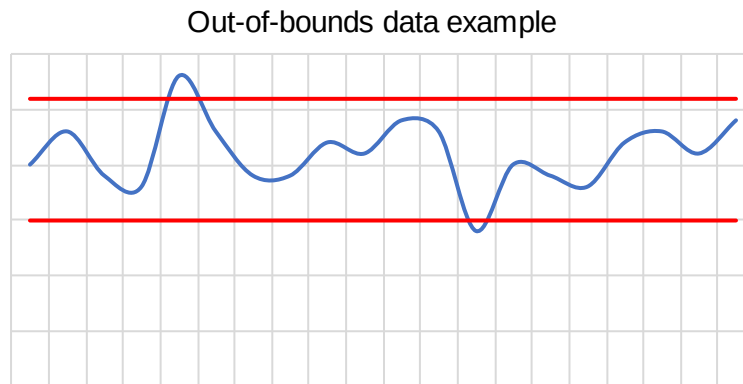


Figure 5: Out-of-bounds data error example

The most common **abrupt errors** are outliers. An outlier is a data point 1.5 of the interquartile range from either the first or third quartile of the data [58]. Excel has a built-in quartile function that can be used to determine the interquartile range and thus determine if a data point is an outlier. Outliers are unexplained accuracy errors [41] and are difficult to identify in real world data. Outlier identification requires context, as low values are possible with electrical systems. Abrupt errors generally occur due to metering errors on mines. This can be caused by interference on the meter, or can be due to start-ups and shut-downs, which generally cause unusual meter readings. A graphical example is presented in Figure 6.

Abrupt error data example

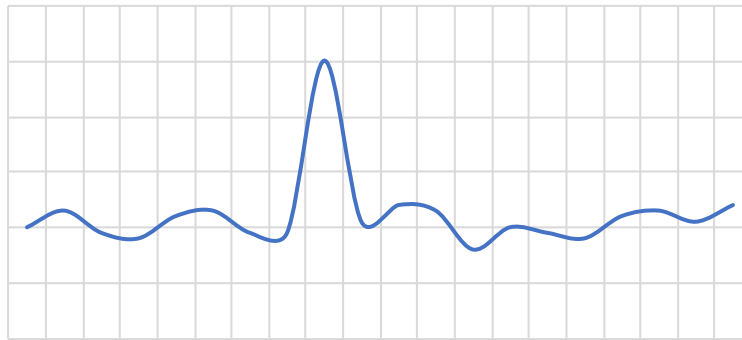


Figure 6: Abrupt error data example

Methods to identify and mitigate these errors will be discussed in Section 0.

Data quality adjustments in literature

As shown in Section 0, data on mines is not often in an acceptable state for use. To use this data, some quality adjustments need to be made. This section investigates whether data quality adjustments are used on mines and discusses and evaluates current data quality adjustments employed in industry, and how they can be applied on mines.

As stated previously, mines primarily focus on production data, as it represents their main source of profit. Data for other resources, like energy, is, therefore, often neglected. This includes the use of less accurate meters and infrequent calibration [59]. Ideally, the metering system should be upgraded. Unfortunately, that is not an economically viable option due to the financial position of most mines. The available data must thus be made usable. This study aims to improve the available data so that it can be used to achieve long-term energy efficiency.

The extent of data quality adjustments on mines address the four common data faults in mining data mentioned in Section 0. This results in data that appears correct to the untrained eye but might not be representative of the true energy consumption. Adjustments to the accuracy of the data are thus required for it to be usable for energy management purposes.

Data accuracy can only be guaranteed from calibrated meters [60]. Unfortunately most electricity meters are only calibrated upon installation and not maintained over time [61]. Electricity meters on mines used for billing purposes must be frequently verified according to

contracts. Meters are required to be verified on a yearly basis [39]. This verification does not necessarily include calibration.

Three studies that address a similar issue were found:

1. A tale of two transformers by Berrisford [62]

Summary:

Berrisford [62] compared smart meter readings on two corresponding entities, a transformer and a group of residential clients within a power distribution network. The goal of the study was to identify possible electricity theft. This was done using voltage data from recently installed smart meters. The study aimed to gain new information using the data available from the new meters. Certain parameters of the transformer and clients were known and available in graphic format. This provided context around the operation and could be used for evaluations.

There was a meter installed on the feed from the transformer as well as on each of the clients' properties. The scenario is illustrated below in Figure 7.

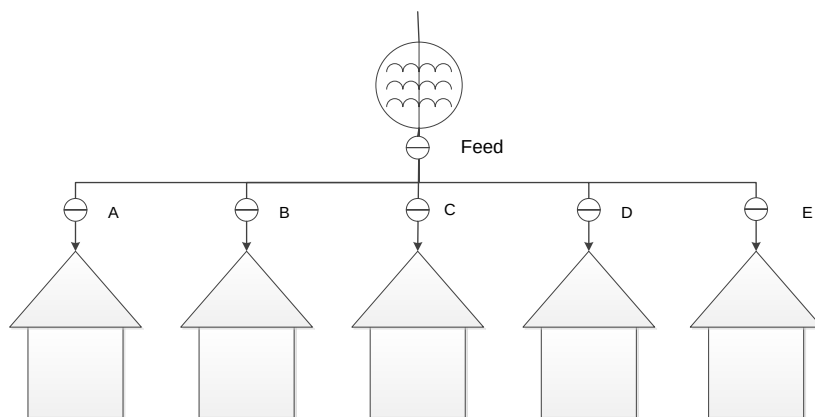


Figure 7 Transformer feeding residential clients

To check for possible theft, the data from the meter of the transformer (Feed) was compared to the data as measured by the meters in each residence (A, B, C, D, E). The results of this balance were used to draw a conclusion about the operation of these systems. The study repeated the method on a second transformer and residence group and proposed a method to automate their calculations.

Applicable solutions:

The following points from the above study can be applied in a mining environment to determine data accuracy from available data.

- Comparison of corresponding datasets to determine data accuracy.
- Use of available data to gain insights into operation.
- Graphical representation of known system layouts.
- Automation of method.

Shortcomings:

The following points from the above study are not applicable to the mining environment and will need to be improved upon before implementation.

- Using voltage data to compare systems.

Voltage data is not commonly available from power meters on mines. Power and energy data is available and can be used instead.

- Using newly installed meters.

Few meters on mines are new, and as discussed earlier, meters on mines frequently have quality issues. Meters that have reliable data must be identified for this method to be effective.

- Using this method to identify possible electricity theft.

Electricity theft is not commonly an issue on mines. Instead, this method can be applied to determine the accuracy of meters.

2. Distribution network topology error correction using smart meter data analytics by Luan [63]

A similar study was done by Luan [63] on a more complex system. The study cites Berrisford's study [62] and applied the method developed therein. The goal of this study was to identify customers that were incorrectly connected to their network. Identifying and rectifying such errors allowed Luan [63] to improve effective asset management.

The study started out with a defined network of customers and transformers. The study highlighted the importance of understanding the metering system at hand before doing an investigation. The data was then used to evaluate the connections indicated. The results

were used to prove the correctness of the existing network layouts. The paper praises this as a cost effective method to identify errors.

Applicable solutions:

As this study applied the same method as that applied by Berrisford [62], similar solutions can be applied to the mining industry. These will not be repeated. The following point from the Luan [63] study can be applied:

- Using this method to identify errors in connections.

Shortcomings:

The Luan [63] study has the same shortcomings as the Berrisford [62] study.

It is important to acknowledge that neither of these studies are addressing quality concerns in uncalibrated meters. Their methods are, however, still valuable and can be applied within the context of this study.

A modified version of this method can be used to verify data on mines. Mine incomers are verifiable as they are used for billing. The data from subsequent unverified meters can thus be compared to the incomer to determine their accuracy, as described by Berrisford [62] and Luan [63]. This method has been applied with great success by the author on South African gold mines [59] to improve data used for energy budgeting.

3. Alternative data structures for improved energy reporting and budgeting on gold mining group operations by Ferreira [59].

The goal of the Ferreira study was to improve data accuracy for use with electricity budgeting. The study validated the data source and did a data balance to check for data accuracy. The study also discussed the identification of a check meter, a common practice in meter verification.

The study suggested an automated method to normalise data to improve the accuracy if a discrepancy had been found. The normalisation involves distributing the error found between the check meter and subsequent meters by weight.

The only validation step in the method is ensuring that the data balances after the calculation has been done. If the two datasets matched, the data was considered accurate. The method successfully improved the accuracy of the data on the mines where it was applied.

Applicable solutions:

The following solutions from the above study can be applied:

- Improving data accuracy through normalisation calculations.
- Identifying a check meter.
- Improving energy data from mines.

Shortcomings:

The Ferreira [59] study had the following shortcomings that will have to be addressed in the implementation of this method:

- Lack of detail regarding normalisation calculations.

The study presented data normalisation as a solution but did not provide enough detail.

- Data quality checks are not applied to resulting data.

The source of the data is validated, but the data resulting from the method was not validated. An additional validation should be added to ensure the correctness of results.

- Lacking validation step.

The validation step presented in the method validated that the method was done correctly, but did not independently validate the resulting data. A validation of the data should be added upon implementation of this method.

Since mines are not able to invest in updated metering systems it would be pointless to strive for perfect data. Mining environments are not conducive to accuracy or perfection. It is important within this study to find the balance between data that is usable for monitoring energy efficiency and data that is perfectly accurate. As long as data is reasonably accurate and fit for use, it can make a difference in maintaining the longevity of energy efficiency projects [45].

1.4 Literature on presentation of energy data

Background

It is difficult to manage systems without information on their operation or condition [64]. With newly available information from datasets, proper evaluation can lead to data-driven decision making. It is therefore important that data is used to its full potential so that it can benefit the operation [37].

Data holds a vast amount of potential in the form of hidden insights [21]. Data analysis and reporting techniques can assist with bringing forth the information contained within datasets [65]. Information gained can be used in two ways:

- To evaluate the performance of ongoing initiatives.
- To identify opportunities for energy efficiency improvements.

This empowers mines by providing them with knowledge and insights that can be used to achieve and maintain energy efficiency. It is important to manage the information and how it is conveyed to ease and enhance the understanding thereof.

It has been established in Section 1.1 of this document that an energy performance evaluation can be used to potentially make a system more efficient. To evaluate the performance of a system, data should be presented in a way that conveys the required information.

The importance of correct data presentation

When relevant data is processed and presented in insightful ways, information may be gained from this data. This information can then be applied to improve energy efficiency. Data and its interpretation alone will not make an industry energy efficient. It can, however, be used to increase one's understanding of an operation, and an increased understanding can lead to an efficiently operated system [66].

The value of data is thus determined not only by the availability or interpretation thereof, but by how it is used [22]. If data is reliable and presented with context, it provides insights which drive action [67].

Information provided to the right personnel on mines may lead to identification of inefficiencies within the operation. This, in turn, can result in optimisation of energy consumption and production [30]. Such effective data usage would give mines a competitive advantage in the industry [37], [65].

Several techniques for data communication exist. These techniques can be divided into three groups, namely **statistical methods**, **mathematical modelling** and **data visualisation**.

Statistical methods are the most basic method of data communication [68]. It is mostly used when interactions between data, such as correlations and associations, are unknown. The data is thus presented without context. Statistical methods can be used to generate hypotheses or to communicate simple data.

In the mining industry, the interactions between data are known. There are clear correlations between input of energy and output of products, whether this is in the form of movement, heat, cooling or compressed air. Statistical models are thus not ideal to be used to communicate data on mines.

Mathematical modelling is used to communicate data where the interactions between parameters are well known. This allows users to make predictions with available data and gain insights from it. Mathematical modelling is widely used in the fields of medicine and agriculture, and can also be applied in fields where chemical reactions are used such as smelting and water treatment [68]–[70].

Although there is a clear correlation in mining equipment between energy input and production, this is not available as scientific rules or formulas. The interactions rely heavily on the type of equipment and the conditions under which it is used. As this is the case, mathematical modelling is not ideal to use to communicate energy-related data on mines.

Data visualisation is a data communication method that is used to identify patterns and trends between datasets that have known correlations [71]. Visualisation differs from most data communication techniques as human interaction is a part of the data analysis process [72]. This allows visualisation to work fast and convey information easily.

The main focus of the mining industry is production outputs. Energy consumed by mines correlates with production, but the correlation is not an exact formula. Visualisation is thus the ideal method to communicate these interactions and patterns between data. The ability of visualisation to convey information directly to humans is also a deciding factor in this selection, as humans play a big role in the mining industry.

Visualisation would, therefore, be an appropriate tool to communicate energy data of mines.

Visualisation is a widely used technique to communicate information from data [73], [74], and can be used to gain understanding of complex datasets [75]. Studies found that pictures in text convey information and that information from visuals are retained longer [76].

Graphic representation has long been used to communicate scientific findings [77]. A study was conducted in 2018 [43] on the application of scientific style visualisation for data communication outside the field of research. It found that visualisation can effectively be used in any field where large datasets are available. Visualisation makes data accessible and understandable to users and can be used for pattern detection in ways that lists and

tables cannot. This allows visualisation to be used in several fields, as it is a powerful decision-making tool.

Graphical visualisation, when used appropriately, can provide a link between data and the interpretation thereof [40]. Visualisation is intended to display as much data as possible as well as provide context, thus making data more “meaningful” [33]. When data is displayed in a user-friendly manner, it can be used to evaluate the performance of the system it represents [78].

Simply displaying a raw dataset will not encourage performance evaluation, as these datasets are difficult to interpret [40]. The challenge is thus to find a way to effectively communicate the information within the data, leading to insights regarding the system.

For effective communication of data, the correct type of visualisation must be used. The goal of this study is to ultimately achieve long-term energy efficiency on mines by improving the data that mines have available. As energy efficiency is measured through comparing energy usage to production output, visualisations that show relationships will be required to present this.

In the pursuit of energy efficiency, the operation of comparable systems must be evaluated. This will allow the identification of more efficient systems that can be studied and used as models for weaker performing systems. For this goal, visualisations that can compare datasets can be used.

To show the relationship between two datasets, scatter charts and bubble charts are best suited [79] [80]. Both these visualisations show the interaction between two datasets; x and y. Scatter plots use a single marker to represent the value of x and y for every data point. Overlap of data points can occur in scatter plots and can hinder correct interpretation of data if not properly visualised.

Scatter plots are especially effective in visualising data with an interaction that can be expressed mathematically, in the form of a polynomial or otherwise. If such a correlation is confirmed, a trend line can be added to a scatter plot to indicate it. An example of a scatter plot is provided in Figure 8.

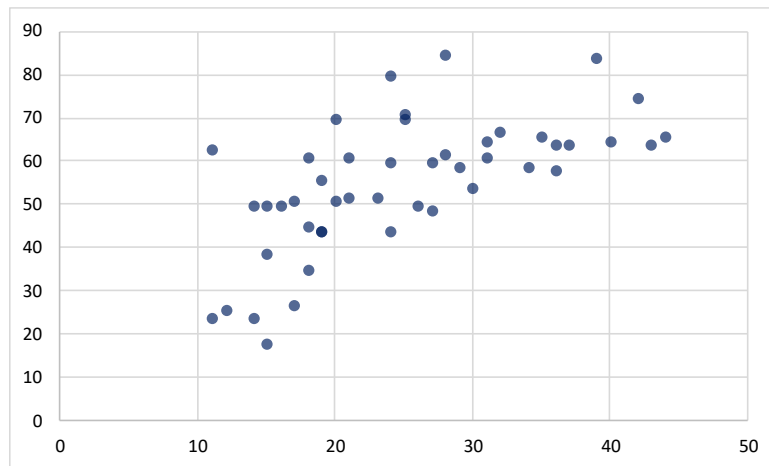


Figure 8: Scatter plot example

Bubble charts are similar to scatter plots in using a marker to represent the values of x and y. Bubble charts add a third dimension by changing the size of the marker used to indicate this [81]. Overlapping data is represented by a bigger “bubble” and data where there is less or no overlap by a smaller bubble or a single dot. Bubble plots are effective in identifying where the most interaction between variables is grouped. An example of a bubble chart is given in Figure 9.

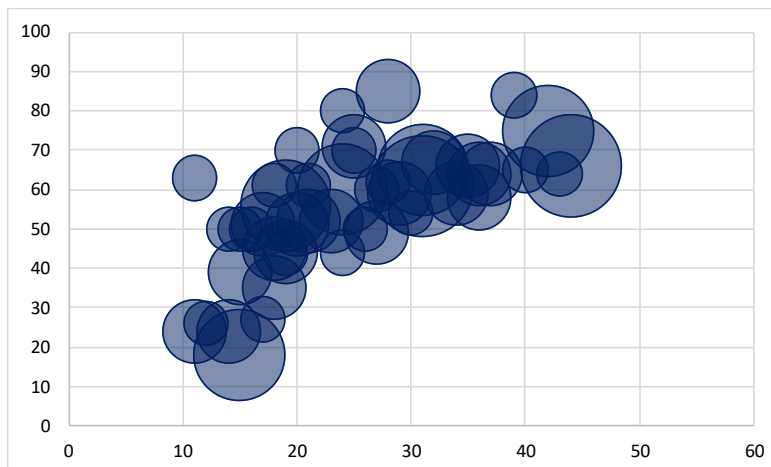


Figure 9: Bubble chart example

Several visualisations can be used to compare datasets. Bar and column charts are commonly used to visualise data that should be compared [82]. Bar and column charts are used for data where the result can be presented as a single number. Bar charts can be used either to compare several variables, or to compare the change in one variable over time.

To compare more complex continuous data, line graphs can be used [83]. Line graphs are ideal for displaying data over time. Line graphs also allow for multiple variables to be displayed simultaneously, therefore allowing comparison of several datasets. Additional data visualisation options are provided in Appendix A.

This section discussed the importance of data presentation. It found that correct data presentation improves data by allowing users to gain insights and information from it. For this study, the insights gained from visualisations will be used to assess performance of mine systems to identify potential for energy savings. The following section presents a literature evaluation of how this is used in industry and how it can be applied within the mining industry.

Data visualisation for performance evaluation in literature

Figure 10 was adapted from concepts by Van Wijk [84], Keim et.al [36] and Holzinger [85]. It illustrates how visualised data, when perceived by a user, becomes knowledge. This knowledge leads to better understanding of the visualised system and can lead to further analysis of the data.

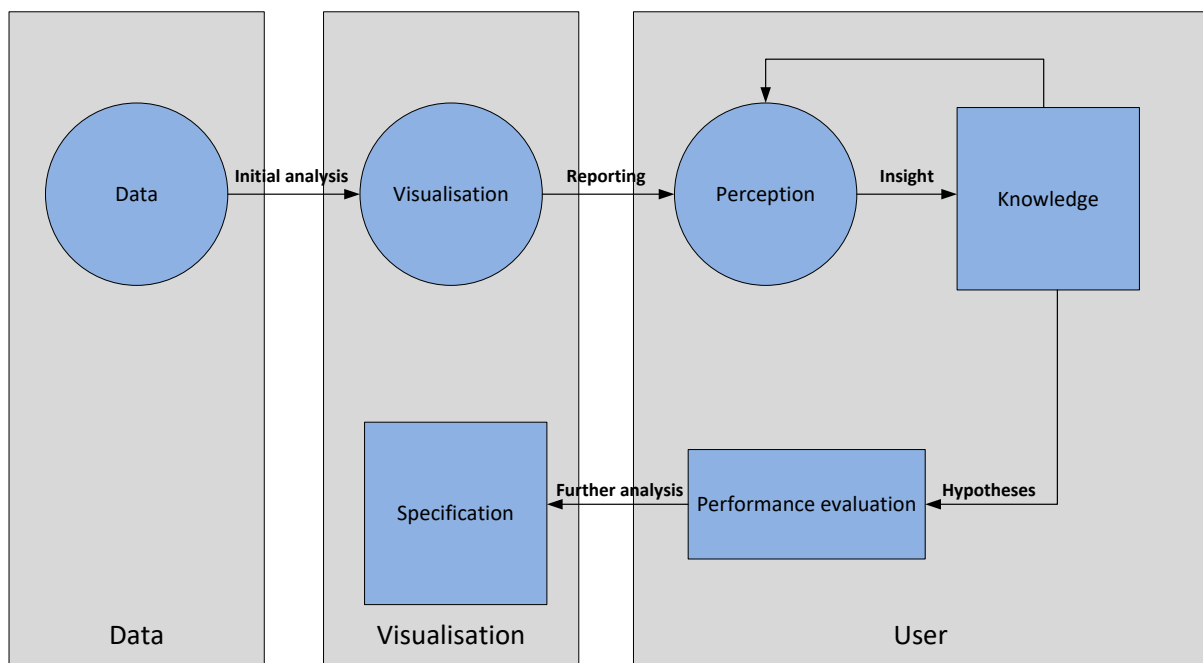


Figure 10: Adapted visual analytics sense-making loop

In Figure 10 there are three components to making sense from data. These are the data, the visualisation and the user. After an initial analysis, data can be presented as a visualisation.

This visualisation is then reported to a user. When the user perceives the visualisation, they gain insight into the data, and therefore knowledge on what the data represents. This knowledge increases the perception of the visualisation.

The knowledge gained by the user should lead to a hypothesis that can be applied to evaluate the performance of the system presented by the data. If required, further analysis can be done from this evaluation to make the visualisation more specific. A specified visualisation will allow the user to gain more knowledge from the data.

It is thus clear that a visualisation can turn data into insights and knowledge. For this to happen, however, the visualisation must be presented to a user with relevant knowledge. A user has the ability to make hypotheses from the gained insights. These hypotheses will lead to an evaluation of the visualised system. Further analysis can then be used to change the specifications of the system, ultimately leading to better performance. This means that a user can evaluate the performance of a mine system through visualisation and use the information for energy efficiency.

Visualisation is especially useful in communicating large datasets [75]. This means that performance evaluations for energy efficiency can be done over long periods of time, and trends can be observed in this way. Visualisation can be done on four different levels. These levels are **disseminative visualisation**, **observational visualisation**, **analytical visualisation**, and **model-development visualisation** [86]. Each existing level of visualisation fulfils a specific function [71], [86], and each level is more complex than the previous level.

Disseminative visualisations are intended only to display data as is. **Observational visualisations** can be used for quick observations of available data. **Analytical visualisations** can be used for performance evaluation of mining systems. This is due to their ability to display complex relationships between variables. **Model-development visualisation** is the most complex form of visualisation and is used to improve models and algorithms [86].

Table 2: Levels of data visualisation and their uses

Level of visualisation	Use
Disseminative visualisation	Displays data as is.
Observational visualisation	Displays recurring captured data for observation purposes.
Analytical visualisation	Displays data to examine and understand complex relationships.
Model-development visualisation	Displays data to create or improve models or algorithms.

Observational visualisation is at present commonly used on mines for performance monitoring [16], [17], [27]. This is usually done over shorter periods of time and is not sufficient for performance evaluation. Single variable monitoring is typically done over days or even hours [15]–[18]. Opposed to this, long-term evaluations can highlight trends in operation and can be used to evaluate the large-scale impact of inefficiencies.

Three papers are presented to highlight this use of observational visualisation in the mining industry. From them, the shortcomings of observational visualisations and the opportunities for more complex visualisations become clear.

1. Case study: Energy savings for a deep-mine water reticulation system by Liebenberg [15].

Summary

This case study aimed to save energy by improving the operation of a deep-mine water reticulation system. A method was proposed that aims to determine the optimum water reticulation strategy. The study then assessed the effect of this optimised strategy on several individual components of the mine.

The results for this study were presented using observational visualisations. The power consumed by the various water reticulation system components was plotted over a 24h period. This was compared to the baseline power consumption of every system component. The study found that the developed strategy reduces the power consumed by the water reticulation system, and contributes significant cost savings.

Shortcomings

As discussed in the summary, the study only presented results over a 24h period. The results were in the form of a line graph showing the power usage before and after the intervention.

No information was presented regarding the relationship of the power consumed and the cooling provided. The strategy thus only reduces energy consumption, and does not contribute to energy efficiency.

As the results were only presented for a single day, no conclusion can be made of the long-term effects of this intervention. As discussed earlier, long-term savings are seldomly achieved on mines. This study could potentially contribute long-term energy savings, but no data was presented to support this.

2. Novel simulations for energy management of mine cooling systems by Maré [17].

Summary

This study presented simulations to be used for mine energy management, specifically mine cooling. Simulations were presented to highlight opportunities for energy efficiency and cost savings in mine cooling systems. Verification for these simulations was done through comparing the simulations with real mine data.

The study results presented two variables over a 24h period. The difference between the two line graphs represents the potential saving that could be achieved.

Shortcomings

As in the first study, no relationships between the data were presented. Relationships could provide valuable insights into the mechanisms through which these energy savings are achieved.

As the results were presented over such a short time period, the long-term effects of the study remain unknown. Using more of the available data and presenting it over a longer timeframe could indicate whether this strategy could contribute sustained long-term energy savings.

3. Simulating operational improvements on mine compressed air systems by Cilliers [18].

Summary

The Cilliers study presented a simulation method that was used to achieve energy savings on mine compressed air systems. The method reduces air used at refuge bays, leaks and cross sections, and simulates what the resulting impact on energy usage would be. Five compressors were used in a case study to demonstrate this method.

The results from this study were presented using observational visualisation. The actual power consumed was compared to the baseline consumption to confirm the accuracy of the model. This was presented on a 24h plot. The savings simulated were also presented over 24h, comparing the actual power usage to the simulated optimised power usage.

Shortcomings

As no relationships were presented within the results of this study, no information can be gained on the effects of this method on the energy efficiency of the compressors studied. This could also provide an opportunity for the five compressors to be compared and optimised.

As the results were only presented over a 24h profile, no conclusions can be made on the long-term effects of this method on the energy usage of the compressed air system.

The SCADA system used on most mines includes basic visualisations of measurements over a short period of time. These visualisations are in the form of disseminative and observational visualisations as discussed in Table 2. At present, this data is used to trigger alarms and to monitor production. The alarms can be used to trip systems when their measurements exceed safe working conditions [87]. This is used to identify when maintenance on systems is needed.

Visualisation can thus be used to evaluate system performance. This can be used to improve data presentation and provide insights that can then be used to achieve energy efficiency.

Table 3 presents a summary of the most prominent studies cited in this literature study. Four categories are given to summarise the content and focus areas of the study: the discussion of energy savings or energy management, achieving long-term energy savings, methods to improve available data and using data and information to achieve results.

Table 3: Literature study summary

Reference	Discusses energy savings and management	Discusses achieving long-term energy savings	Discusses methods to improve available data	Discusses using data for information to achieve results
[4]	✓	✗	✗	✗
[12]	✓	✓	✗	✗
[13]	✓	✓	✗	✗
[14]	✓	✗	✗	✓
[15]	✓	✗	✗	✓
[17]	✓	✗	✗	✓
[18]	✓	✗	✗	✓
[21]	✗	✗	✓	✓
[22]	✗	✗	✗	✓
[29]	✗	✗	✗	✓
[30]	✓	✗	✗	✓
[31]	✗	✗	✓	✓
[32]	✓	✗	✗	✓
[33]	✓	✗	✗	✓
[36]	✗	✗	✓	✓
[37]	✗	✗	✗	✓
[40]	✗	✗	✓	✓
[41]	✗	✗	✓	✗
[42]	✗	✗	✓	✗
[45]	✗	✗	✓	✗
[46]	✗	✗	✓	✓
[59]	✓	✗	✓	✓
[62]	✓	✗	✗	✓
[63]	✗	✗	✗	✓
[65]	✗	✗	✗	✓
[66]	✗	✗	✗	✓
[67]	✗	✗	✗	✓
[75]	✗	✗	✗	✓

From Table 3 it is clear where there are gaps in the literature. While many studies discuss energy savings (Column 2) and gaining information from data (Column 5), the two fields do not often overlap. Data and the information gained from it are thus not often used to achieve energy efficiency. The studies focussing on the improvement of available data (Column 4) also do not apply this data to achieve energy efficiency. Finally, there is very little research focussing on achieving long-term energy efficiency (Column 3).

1.5 Problem statement

Mines currently fail to uphold long-term energy savings and require ways to use data to highlight available opportunities or risks.

The industry was found to collect large amounts of data that is not utilised for energy efficiency. This data was found to contain information that can be used for performance evaluation. This, in turn, can be used to evaluate ongoing initiatives on a system, or to identify potential for energy efficiency projects.

A large cause of the current problem might thus be the fact that there is currently no method to address data quality issues or for using the resulting data for visualisations.

1.6 Research objectives

The objective of this study is to create a method that can improve the quality and presentation of energy data. This should result in high-quality data and visualisations which can then be used to assess the performance of systems and identify potential for energy efficiency initiatives. This should help to ensure long-term energy savings on South African mines.

The data will first be assessed for quality to ensure that the information resulting from the visualisation is as accurate as possible. The developed visualisations will also be assessed to ensure that they are efficiently communicating the intended message.

1.7 Document overview

Chapter 1 identifies the need for sustained long-term energy efficiency on South African mines. The state of data available on mines is discussed and data quality adjustments from literature are evaluated. The need for proper presentation of data was found, and methods of presenting data from literature are discussed. It was determined that data should be evaluated and adjusted for quality and presented through visualisation.

Chapter 2 explains how two method sections have been developed to address the shortcoming in data from mines as identified in Chapter 1. The first method section provides a way to improve the quality of data available from mines. The second method section focusses on the presentation of data. It provides steps to achieve effective data visualisations with data from mines.

Chapter 3 features two case studies for each of the two developed method sections. Two case studies are used to demonstrate the method developed to improve data quality and

accuracy. Two more case studies are used to test the method to use visualisation for performance evaluation. Each result is verified and discussed to ensure that the goal for the method was met.

Chapter 4 concludes the study. Each chapter is briefly discussed, with some recommendations to improve upon the study provided. These recommendations suggest further, and alternative applications of the methods developed in the study.

1.8 Conclusion

In this chapter a need to maintain long-term energy efficiency in the mining industry of South Africa was established. The industry was found to collect large amounts of data that is not utilised for energy efficiency. This data was found to contain information that can be used for performance evaluation. This, in turn, can be used to evaluate ongoing initiatives on a system, or to identify potential for energy efficiency projects.

The research identified systems where data could be used for performance evaluation. Three systems were chosen: systems driven by electrical motors, compressed air systems, and refrigeration systems.

The energy-related data available from mines was found to be of poor quality. Literature was consulted to find solutions for the problems experienced with energy data from mines.

A need for data presentation to mines to be improved was identified. Possible data presentation methods were investigated and evaluated for use with energy data from mines. Visualisation was selected as the most suitable method for data presentation.

It was found that high-quality data, when visualised, can be used for performance evaluation and can then bring about energy efficiency.

2 METHODOLOGY

2.1 Preamble

The goal of this study was to use data to ensure long-term energy savings. Two opportunities to achieve this goal were identified in Chapter 1. This included improving the quality of available data, and the presentation of that data. The literature study that was conducted suggested that the combination of high-quality data and actionable visualisations can lead to insights that can be used to achieve and maintain energy efficiency.

This chapter is divided into two sections to address the two identified opportunities. Data evaluations are only effective if the data is of high quality [41]. Therefore, data must be analysed before it is visualised.

The first section of this methodology focuses on improving the quality of data that is available on mines. Solutions to common data errors on mines, as identified in literature, are proposed. Thereafter, a method derived from literature to address data accuracy is discussed.

The second section of the methodology focuses on the visualisation of data. This begins with the identification of relevant data. Several visualisation styles are discussed to allow the user to identify a method most suited to the data. An evaluation method is proposed to ensure that visualisations developed through this method are as effective as possible. Finally, the reporting of these visualisations is discussed.

The combination of these two methodology sections provides the user with means to ensure high-quality data and effective visualisations. This will convey information that can be applied toward the energy efficiency of mine systems. When used appropriately, this information will ensure that energy savings are sustained in the long term.

2.2 Improving the quality of data available on South African mines

Preamble

It has been established in the literature review of this study that data from mines tend to have quality issues. For data to be useful for identifying opportunities for energy efficiency and evaluating the performance of current projects, it needs to be of high quality.

The goal of this section was to improve the quality of data available from mines. This was done in three phases, as put forward in Figure 11.

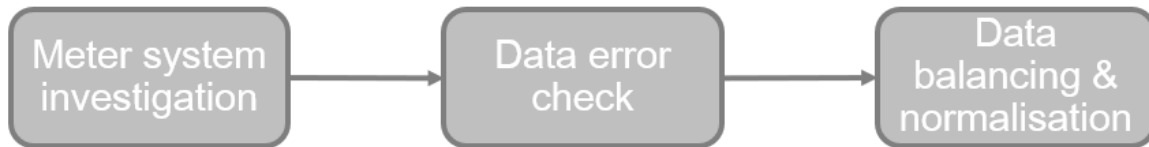


Figure 11: Data quality improvement method schematic

The first step was to investigate the existing mine metering system. This provided useful information and context for the remainder of the study. Secondly, a data error check is presented. This is used to detect and mitigate common errors found on mines. The third step provided a method of data normalisation. This was used to improve the accuracy of available data.

The combination of these three phases will improve the quality of data available to mines. This improved data can be used to achieve and maintain long-term energy savings.

Mine metering system investigation

For this investigation, it is important to understand the mine and metering system before data quality is addressed. To do this, the layout of the mine in question must be obtained and evaluated. From the layout, the specific focus area of the investigation can be determined. An electrical metering layout can be used to identify electrical feeders, systems and sub-systems they connect to. This will help to understand the existing metering system of the mine. From this investigation, data availability can also be established.

If a metering layout is not available, mine personnel should be consulted to gain an understanding of the metering system. Electricians, section supervisors and foremen will be able to assist in this regard. If the mine makes use of a third-party metering company, they should also have valuable information.

Determining the expected accuracy of the relevant meters is helpful for the data quality investigation. Not all meters are expected to be 100% accurate. Knowing how much deviation is allowed on a meter will allow a user to better understand the mine's data.

Once the availability of the data is determined, the data should be collected. The full facility data (total energy usage or total production of the mine) should be easily attainable. Data for sub-systems and individual equipment might be more difficult to obtain, especially if the mine is complex.

Each source from which data is collected should also be verified. Meter verification includes calibration records. Meters are usually calibrated upon installation and should have calibration certificates available. Meters used for periodical billing are calibrated regularly according to their load and should have multiple updated certificates available [88]. This verification will be used later in the process to assess the accuracy of meters.

Common data error check

Data analysis aims to reduce the number of errors contained in data [53]. Data analysis is defined by Chen [33] as the use of proper statistical methods to analyse large datasets, to concentrate, extract, and refine useful information hidden in disordered data. Errors are hard to detect in real-world data, as most error detection methods are based on synthetic errors [53].

In Section 0, expected errors in datasets from mines are discussed. It was found that the most prevalent errors in data on mines are missing data, static data, out-of-bounds data and abrupt errors. This section of the method focusses on data error identification techniques. Once data errors have been identified, the findings can be evaluated to determine whether the errors can be mitigated.

The goal of this first method section is to improve the quality of sub-standard datasets. The resulting data can then be used to monitor and achieve energy efficiency.

Mining data is usually presented as values corresponding to a certain system at a certain time. Errors within this data are presented as deviations from the true value [89]. These types of measurements do not conform to standard error checks, as the true data values are usually unknown.

Several analysis techniques are available to detect and amend the errors identified in Section 0 [53], [54], [57], [58], [90], [91]. These techniques are best applied to data in a usable and uniform format. The highest frequency of available data should be used so that meter errors are not obscured.

All the selected relevant datasets can be compiled into a single data processing program such as Microsoft (MS) Excel. A well-ordered compilation of data will make data analysis much easier [92]. Most error detection methods involve complex automated fault detection software. These software systems are expensive, and generally more complex than is required for the errors described in Section 0.

Due to the simplicity of errors expected within mining data, this study used manual error detection. Using basic graphing software such as MS Excel, data can be plotted over time to identify errors within the data [58]. This enables a user to see missing data, stuck-at errors or static data, abrupt errors and out-of-bounds errors if expected maximums are plotted as well.

Missing data is data that is unavailable when it should have been recorded. Missing data occurs due to metering errors, storage faults or other errors. Three techniques to address **missing data** are suggested by Bennane and Yacout [56]:

- case deletion,
- EM Algorithm, and
- simple imputation (using estimates to fill missing values).

Case deletion is the practice of discarding any incomplete datasets so that only complete datasets are used. A variation upon this is to discard only the missing sections of data if the dataset available is the only one of its kind [56]. Ideally, case deletion should be used to address missing data, as this best preserves the integrity of the overall investigation. Unfortunately, the only available dataset on mines are frequently missing some data points. In these cases, the instances with missing data should be discarded. If an entire variable is missing, it can be calculated using theoretical formulas if enough additional data is available, or estimated through simple imputation.

The EM Algorithm uses an algorithm to estimate the missing parameters. This is best used when working with predictable data [56]. Data obtained from mine equipment is not typically predictable. This technique was therefore not used to address missing data in this study, as the data was not ideally suited. Implementation of the algorithm might also lead to capital expenditure.

Simple imputation is an estimation method that is used to fill data within context. For instance, if one data point is missing within a set, and known to not be zero, the missing data point can be estimated using the data points surrounding it [56]. Simple imputation can only be used if the estimation can be theoretically justified.

Stuck-at data or static data is when a single value is repeated over time where varied data is expected. It is usually an indication of faulty metering. Stuck data points should be discarded if the true value is unknown.

Discarding data will lead to a reduction in the size of the working dataset. Green's method [91] can be applied to ensure that the remaining dataset is still a statistically valid sample size:

$$N \geq 50 + 5p$$

Equation 1: Green's method for sample size

Where:

N is the required number of data points, and

p is the number of predictors.

If the requirements for Equation 1 are met, the dataset is still a valid statistical sample. If the requirements are not met, the dataset is not usable.

A reduction in sample size will not reduce the reliability of the dataset, as long as the data is unbiased [66]. In this way, the quality of the remaining dataset is unaffected. Unless a valid justification exists, out-of-bounds errors must be discarded from the dataset [90].

Out-of-bounds errors occur when a system appears to perform outside of its boundaries. This can be due to incorrect operation or due to errors on meters. The data should be investigated on a case by case basis to determine the cause of this error. Section 0 discusses more mitigation options for these kinds of errors.

Outliers or **abrupt errors** will become more apparent once data is visualised within context. Identified outliers can be removed from the dataset unless they can be justified through theory [54], [55]. Theoretical justifications for outliers involve comparing related data to validate the data point. An outlier is any value that is removed more than 1.5 times the interquartile range of the dataset from either the first or the third quartile [94]. This can be tested through determining the quartiles of the dataset and evaluating the individual data entries.

Table 4 provides a summary of the expected errors in mining data. For each error, an identification method is provided, as well as a way of mitigation if an error is identified.

Table 4: Summary of errors expected in mining data

Error	Identification	Mitigation
Missing data	Fewer data points than expected	Case deletion, simple imputation
Static data	Observation	Discard
Out-of-bounds data	Test data against known boundaries	Discard or justify, Section 0
Abrupt error	Outlier test, logic test	Discard or justify

Not all errors in data will be identified with these methods. The accuracy of data from meters that are not frequently calibrated cannot be guaranteed. These errors are not as apparent, but can inhibit the understanding of the operation of systems. This understanding is critical for achieving long-term energy efficiency.

Once the data errors have been mitigated, the data should be plotted again and re-evaluated. This will ensure that no errors were missed in the first round of mitigations.

The next section will address how the accuracy of meters that cannot be verified can be improved.

Data balancing and normalisation

Section 0 discussed some of the most prevalent errors in data from mines. Unfortunately, not all problems with data from mines fall into the four given categories. Small inaccuracies can frequently be observed on mine metering systems. These errors compound over time and can prove costly to mines.

This section aims to develop a method to improve the accuracy of available data from mines without requiring any capital expenditure. This will be adapted from methods found in literature, as discussed in Section 0.

The studies from literature each began with two entities or groups of sub-systems that lined up in a power grid. The same were selected for this study. It should be noted that the goal of this method is to improve data quality, not to eliminate all data quality errors. One of the meters identified should have data that is of verifiable quality (calibration records, invoiced data etc.). The verified meter is hereafter referred to as the *check meter*.

The method developed during this phase was simplified into four sections, with a total of seven steps. These steps establish the system on which the normalisation calculation will be done. A balance check is suggested to determine the accuracy of the available data.

Depending on the results of the balance check, the data was left as is, or normalised. If normalised, a step to evaluate the resulting data was provided. All of this can be seen in Figure 12.

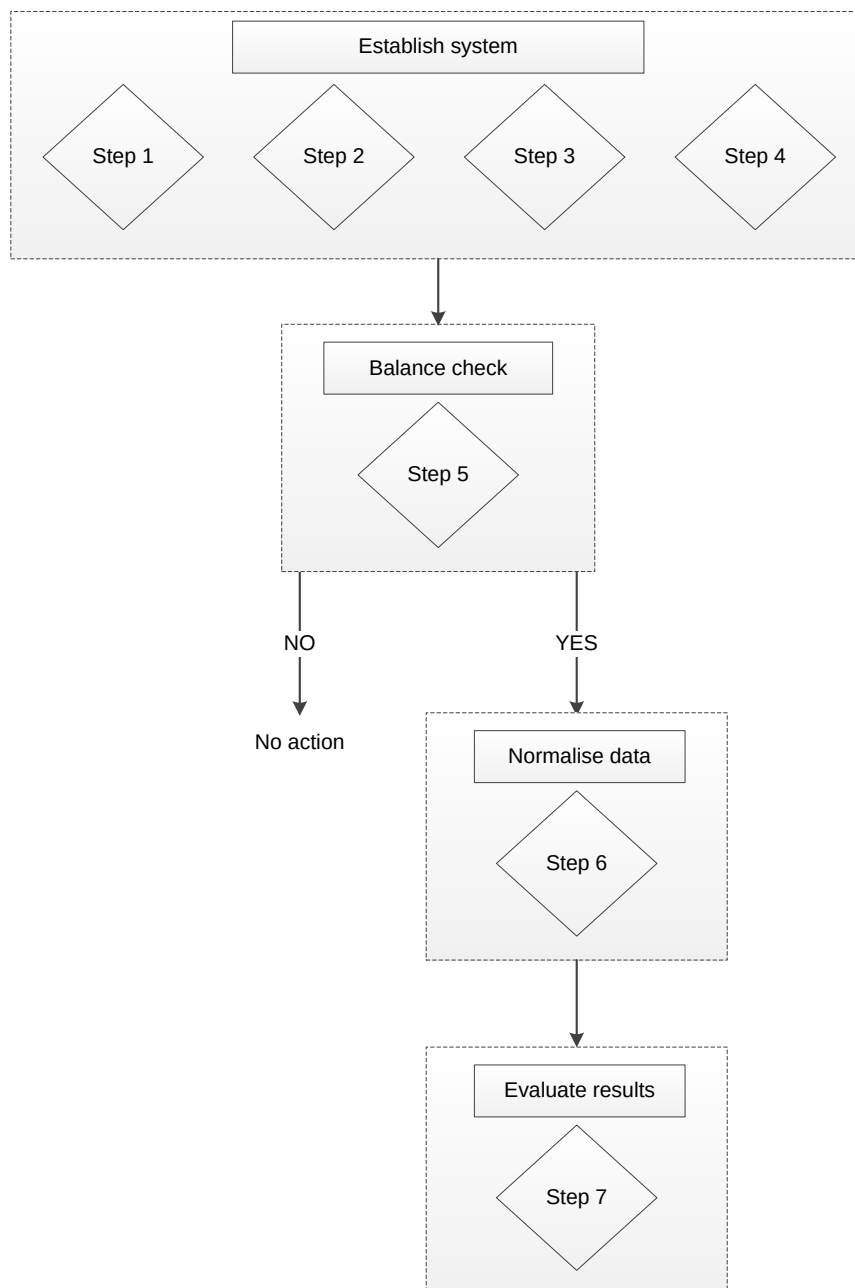


Figure 12: Data normalisation method schematic

The steps given in Figure 12 are explained below.

Step 1: Determine the boundaries of the investigation.

The collection of what falls within this determined boundary is referred to as the *system*, which consists of the *check meter* and *sub-systems*. It is important that all the meters within the system have data available at a comparable frequency.

The next step is to identify the check meter within this boundary.

Step 2: Identify a check meter.

The check meter needs to have data that is verified, or that can be verified with available information. As this meter is correct, the goal is to have the measurements of the sub-systems add up to that of the check meter.

As in the literature studies, the next step is to determine the exact layout of these systems. Understanding the connections within the system enables effective comparison between data from these sources.

Step 3: Determine the layout of the system.

An example of a simplified layout is presented in Figure 13. This was used throughout the method development as an example.

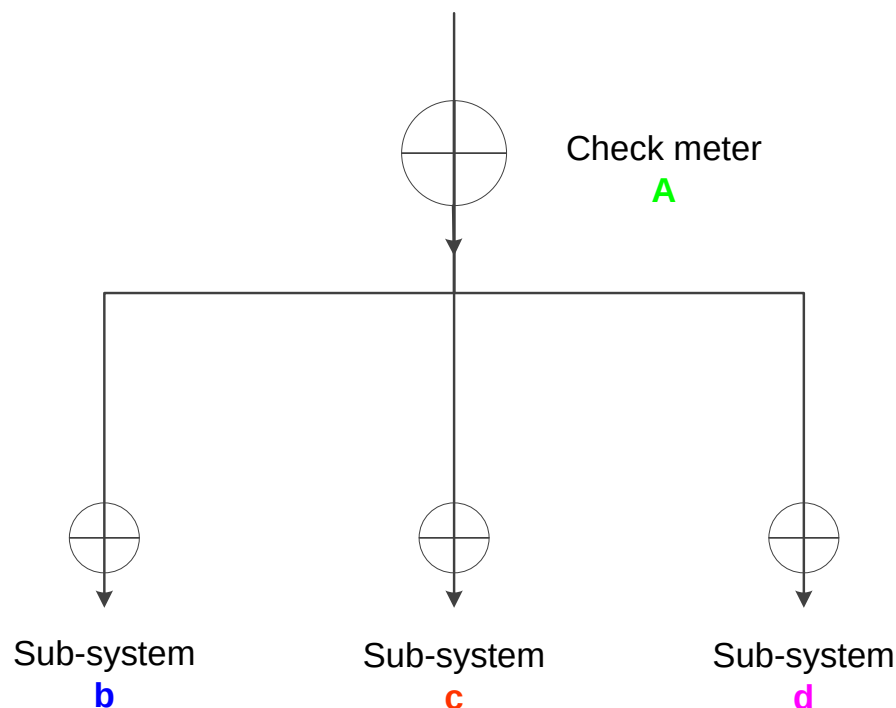


Figure 13: Example system diagram

The example system layout in Figure 13 shows a check meter A in line with three sub-systems, b, c and d. This was used to explain the equations for normalisation that was developed. Once the layout of the system is known, information about the components of the layout must be gathered.

Step 4: Determine specifications of all relevant equipment.

In the study by Berrisford [62], the transformer used had a known rating. This provided users with an understanding of the parameters of its operation. For the purposes of this study, available information on the equipment within the system was important and was collected. This assisted with a logic check, and to determine whether the data received was within expected boundaries. Information like installed capacity, overload ratings, maximum theoretical power draw and KPIs can be obtained to assist with the investigation.

Once the specifications are determined, the comparison method as seen in the literature studies of Berrisford [63] and Luan et al. [64] are applied. In this case, the electricity meter readings from the check meter were compared to the meter readings of the corresponding sub-system meters.

If the sum of the readings are equal, the meters can be considered accurate and the data can be used for further evaluations to achieve energy efficiency. If the sum of the readings are not equal, it indicates an error in the data of the unverified meters. Additional steps are required to improve the accuracy of the data before it can be applied for further use. These are represented by Steps 5 – 7.

Step 5: Perform data balance check.

Using Figure 13 as reference, the balance check is represented in Equation 2:

$$\sum A \text{ vs. } \sum b, c, d$$

Equation 2: Example data balance check

When comparing A with the sum of b, c and d, ideally, the result would be a system that balances, ie. no difference noted between the sum of the sub-systems and the check meter. This is visualised in Figure 14.

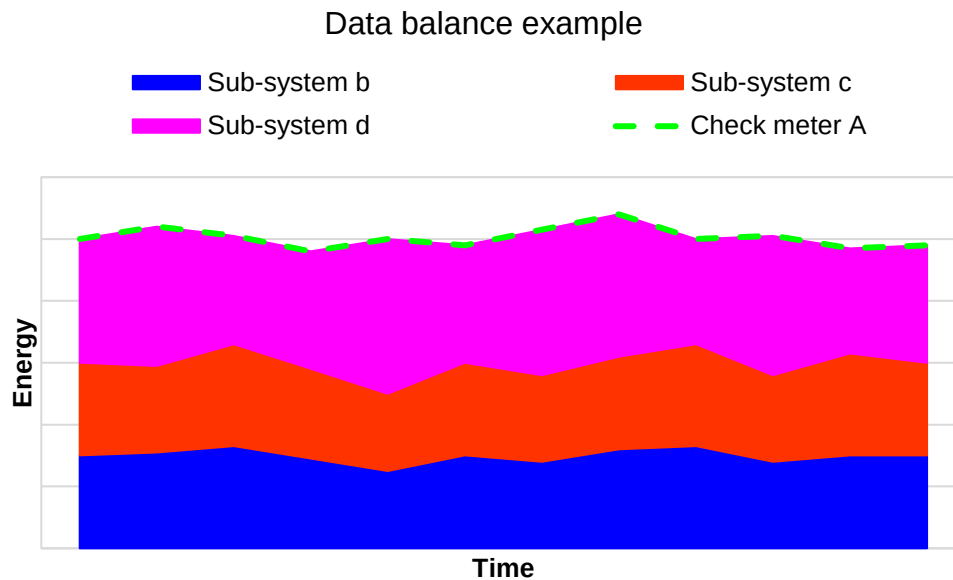


Figure 14: Data balance example - Accurate data

In Figure 14, it can be seen that the sub-systems b, c and d added up to the check meter A. This indicates that the data from the sub-system meters were accurate and could be used for further analysis.

Unfortunately, data will not always balance. The remainder of this method development will discuss how to improve the quality of data that resembles Figure 15.

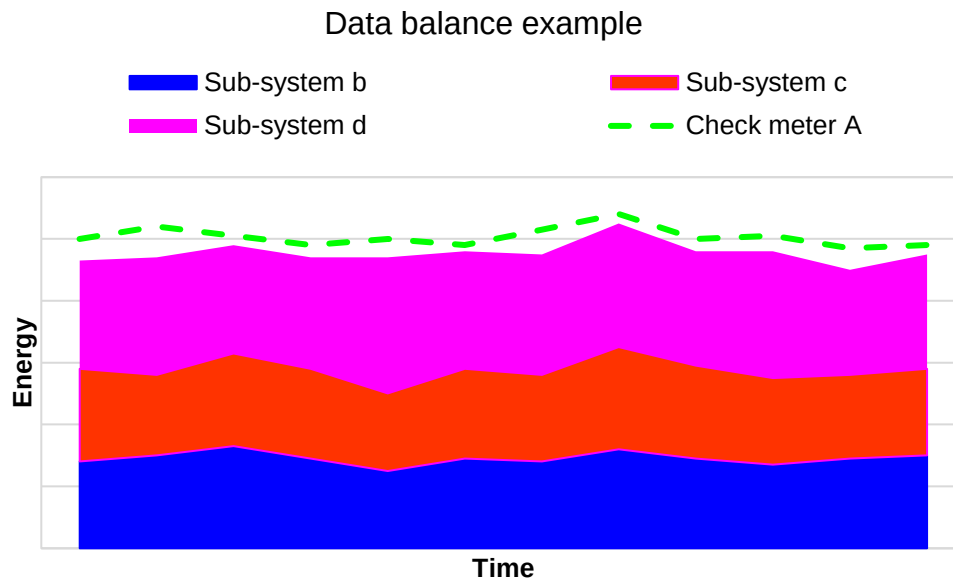


Figure 15: Data balance example - Inaccurate data

Figure 15 provides a realistic example of how data might present if the sub-system meters have errors or are faulty. The sum of the sub-systems does not add up to the check meter. In the given example, the sum of the sub-systems was lower than the check meter value, but metering errors can also cause the opposite error.

If the data does not balance, it should be adjusted to correspond to that of the verified meter. While this might not result in perfect data, the adjusted data will be more representative of the system, and can thus be more accurately used to achieve energy efficiency.

Step 6: Normalise data.

This is done in the following manner:

- Determine the weight of each sub-system.
- Determine the difference between the sum of sub-systems and the check meter.
- Allocate the difference to the sub-systems according to the determined weight.

Figure 16 is an adaptation of Figure 13 where the weights of the sub-systems have been added. This was used to provide reference for the upcoming equations.

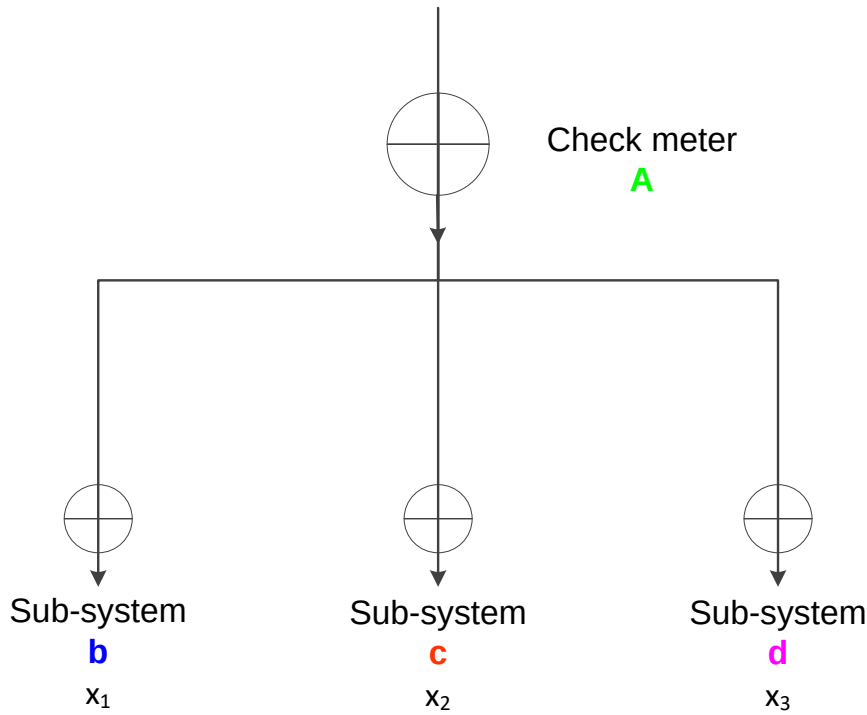


Figure 16: Example system diagram with weights

Each weight as shown in Figure 16 represents the percentage size of the sub-system relevant to the sum of all the sub-systems.

The goal of the normalisation is to have the sub-systems add up to the check meter as in Equation 3. Normalisation should be done at the highest frequency where data is available to maintain maximum accuracy.

$$A = \sum b_n, c_n, d_n$$

Equation 3: Normalisation goal example

Where A is the power consumption measured at the check meter as in Figure 16, and b_n, c_n, d_n represent the normalised power consumptions of the sub-systems.

For Equation 4 and Equation 5, let x_1 be the weight of the sub-system b , as in Figure 16, so that

$$x_1 = \frac{b}{\sum b, c, d}$$

Equation 4: Example data normalisation sub-system

and

$$b_n = b + \left[\left(A - \sum b, c, d \right) * x_1 \right]$$

Equation 5: Example data normalisation sub-system

Thus

$$A = \left\{ b + \left[\left(A - \sum b, c, d \right) * x_1 \right] \right\} + \\ \left\{ c + \left[\left(A - \sum b, c, d \right) * x_2 \right] \right\} + \\ \left\{ d + \left[\left(A - \sum b, c, d \right) * x_3 \right] \right\}$$

Equation 6: Example data normalisation
full system

Equation 6 describes the full normalisation calculation. A correction factor was calculated for each sub-system. This was done by multiplying the difference between the sum of the sub-systems and the check meter by the weight of each sub-system, respectively. Each correction factor was added to the original sub-system value, resulting in a normalised value. The sum of the normalised sub-systems added up to the check meter.

This result is visualised in Figure 17.

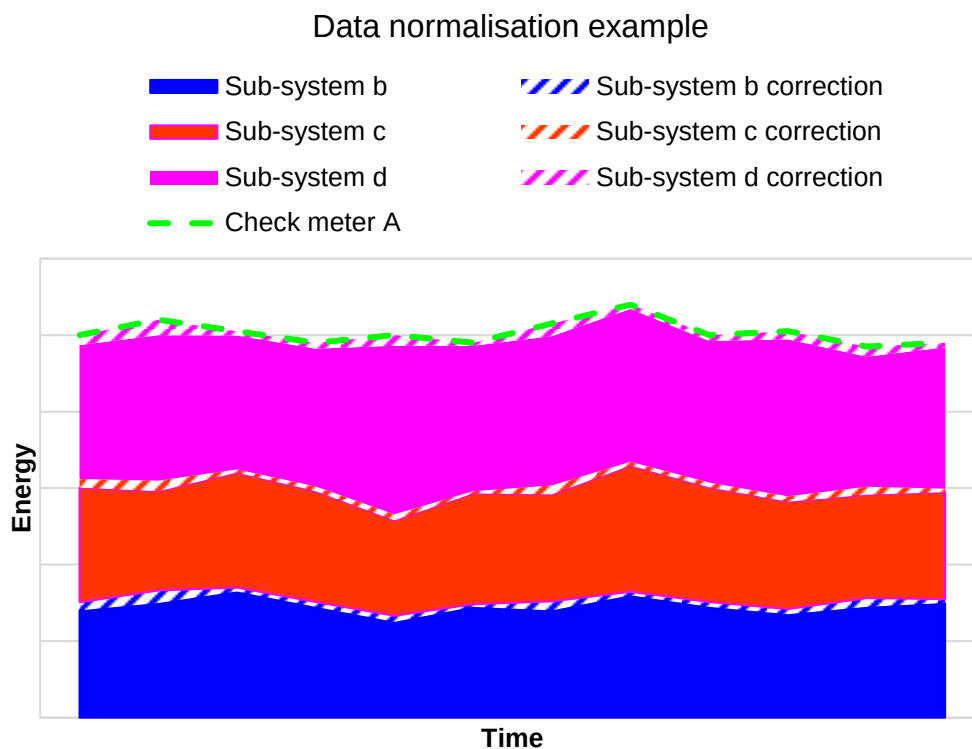


Figure 17: Data balance example – Normalised data

Figure 17 presents each sub-system and its corresponding correction factor that was calculated through normalisation. It can be seen that the three normalised sub-systems now added up to the check meter.

Step 7: Evaluate resulting data.

The final step uses the information gathered in Step 4 to determine whether the newly normalised data is within the expected boundaries for each sub-system. This result evaluation is done using the specifications for the systems.

The new data should be compared to the expected operation for the system. If the normalisation pushes the data outside of these established boundaries, the data that resulted from the normalisation calculations should be rejected. In such a case this method will not be able to improve data. This might be indicative of large data errors, and replacement of faulty meters should be considered.

If the data is within the boundaries, it can be accepted and used further. This data should then be more accurate than the raw data that did not add up to the incomer meter total.

This method is intended to correct small meter deviations within mine metering systems. If the data fails the test put forward in step 7, an in-depth investigation into the source of the error should be conducted. Once these steps are completed, reliable values should be available for every sub-system in the mine metering layout.

This method improves the accuracy of unverified data. While the method does not guarantee absolute accuracy, it provides a way to measurably improve overall accuracy with no capital expenditure. As discussed in literature, results of efficiency studies and calculations are of more value if they are done with accurate data [21], [41].

The goal of improving data in this study was to achieve long-term energy savings. The availability of accurate, high-quality data allow for accurate conclusions to be made from the data. These conclusions can be used to evaluate performance and be employed towards achieving energy efficiency. As this method can be applied on any available data, it can be used to improve the quality of past data and perform evaluations on longer time periods.

The method presented in this section is summarised in Figure 18.

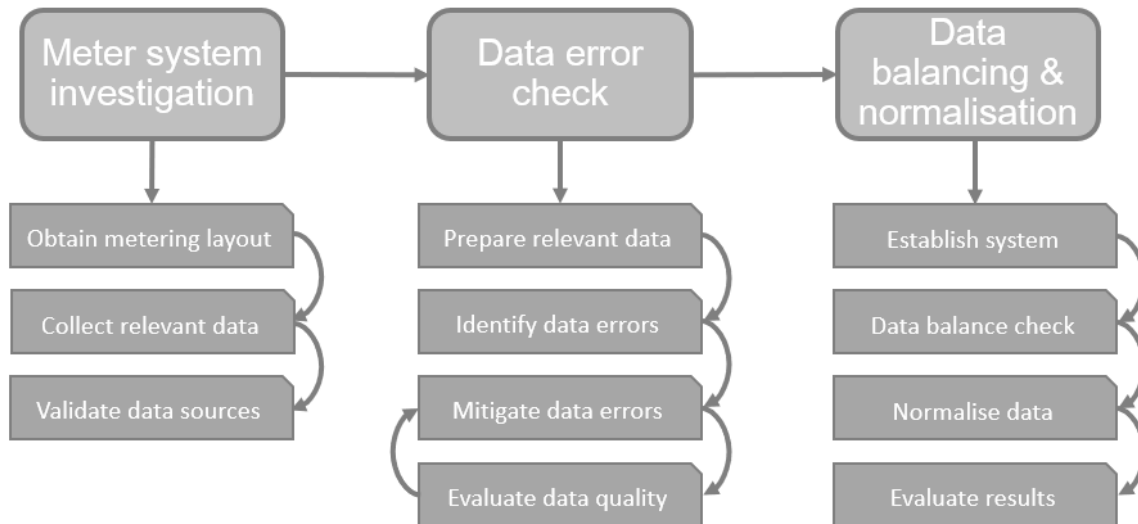


Figure 18: Detailed schematic for data quality method

2.3 Data visualisation for mine system performance evaluation

Preamble

The second section of the methodology developed for this study is discussed in this section. It discusses how to best visualise and report data to be used in order to achieve long-term energy efficiency.

Visualisation was identified in Section 0 as a method to use data to gain information that can be applied to evaluate system performance and achieve energy efficiency. Visualisation is thus another method of improving insights gained from available data so that it can be used to achieve energy savings. Visualisation also allows for the evaluation of data over long time periods and the comparison of data over time. Visualisation can thus be applied to identify opportunities for long-term energy efficiency.

Figure 19 presents a flow chart of the method that is developed in this section.

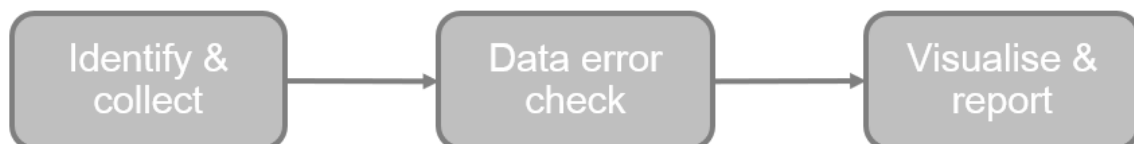


Figure 19: Data visualisation method schematic

The method is presented in three phases. The first phase entails identifying the relevant data for the study. The second phase repeats the data error check developed in the first method. This ensures that the data is of acceptable quality to move on to the visualisation phase. The final phase provides steps to visualise and report data with the goal of using the results for performance evaluation.

Identify and collect relevant data

This method starts with the selection of relevant data. This ensures a relevant outcome so that the generated information is useable for performance evaluation. This can be done by first choosing the scope of the intended investigation [41].

Three energy-intensive systems on mines were identified in Section 0. These included:

- a) electrical motors,
- b) compressed air systems and
- c) refrigeration systems.

In order to identify relevant data for the systems mentioned above, it is important to have knowledge of certain parameters within the system [52]. This will assist with the intuitive selection of relevant data. It is important to carefully establish which data to use, as poorly selected data could potentially bias the results [95].

The following four questions can be used to choose data relevant to the investigation:

1. *What is the goal of the system?*

The goal of the system is the intended function it serves. To ensure that the system is performing as intended, information on the goal it is expected to meet will be required.

2. *What are the operational specifications of the system?*

Each system has a rated capacity where it is intended to operate. Knowing this will ensure that a system is evaluated according to its capabilities and compared to other systems with similar specifications.

3. *What are the performance indicators of the system?*

A system is typically evaluated according to a set of key performance indicators (KPIs). The data used to evaluate the performance of the system should align with the KPIs of the system. These KPIs can be used to measure whether a system is meeting its goal.

4. What data is theoretically available from the system?

All systems have, depending on its goal and KPIs, certain data that should theoretically be available. Knowing what data may be available provides an opportunity to plan how the evaluation will be done. It also provides a starting point for data acquisition. It is important to note that some important variables are not measured by some mines, as their focus is on production and not system performance.

Once available data has been collected, these questions will help assess whether the data can be used for performance evaluation. Enough data from each KPI of the system and its energy carrier is essential for the investigation to proceed.

For the purposes of this method, each of the questions is addressed for each of the systems identified in Section 0. This information is summarised in a table at the end of this section.

2.3.1.1 Relevant data identification: Electrical motors

Many electrical motors are present on mines. For the purposes of this discussion, electrical motors were limited to pumps and fans, as these were identified in Section 1.1 as the most energy intensive.

1. What is the goal of the system?

On mines, fans are used for ventilation within the mine [11], while pumps are used to move and pressurise fluids. These two systems have a common goal to displace a fluid by using electrical energy.

2. What are the operational specifications of the system?

Operational specifications will vary according to each specific system. The following points are examples of common specifications found on electrical motors:

- the flowrate it is designed to deliver,
- the rotations per minute (RPM) it can achieve, and
- the installed capacity (kW).

3. What are the performance indicators of the system?

The performance of pumps and fans is measured by the volume of fluids they can displace and by the pressure they supply. All this should be done using as little electricity as possible. Both pumps and fans have curves that show how they should perform in terms of pressure and flow.

4. *What data is theoretically available from the system?*

The following data should be available for fans:

- power consumption of motor powering fan,
- initial air flowrate,
- delivery air flowrate, and
- fan speed.

The following data should be available for pumps:

- power consumption of motor powering pump,
- initial fluid flowrate,
- delivery fluid flowrate,
- initial head, and
- delivery head.

It is clear from this section that these two systems are very similar. Pressure, flow, and power data is required to continue the investigation on pumps. Flow and power data is required for fans.

2.3.1.2 Relevant data identification: Compressed air systems

Compressed air systems are present on most mines and have various applications. The pressurised air they provide is used to power mining equipment, particularly in underground mines.

1. *What is the goal of the system?*

The goal of a compressed air system is to pressurise air using electrical energy.

2. *What are the operational specifications of the system?*

Operational specifications will vary according to the size and brand of the compressor. The following specifications should be considered:

- installed capacity (kW) and
- delivery pressure.

3. What are the performance indicators of the system?

Compressors are evaluated according to the pressure they can deliver, as well as by the flow produced. This is often expressed in a combination known as the fluid power, calculated using the following equation [96]:

$$P_h = \frac{QdP}{3600}$$

Equation 7: Fluid power equation

Where:

P_h is the fluid power produced by the compressor in kW,

Q is the flow through the compressor in m³/h, and

dP is the pressure produced by the compressor in kPa.

4. What data is theoretically available from the system?

The following data should theoretically be available from a compressed air system:

- air pressure before compressor,
- delivery air pressure,
- power consumption of the motor,
- initial air flow,
- delivery air flow, and
- percentage blow off.

To continue with an investigation on a compressed air system, power consumption data, flow data, and pressure data must be available. The performance of the compressor can then be evaluated by comparing the fluid power produced to the power consumed.

2.3.1.3 Relevant data identification: Refrigeration systems

The underground mining environment tends to have increased temperatures due to increased geothermal heat. Mining activities involving people can only occur within legal temperature limits. Therefore, cooling is required to achieve the desired working conditions as per regulation. Refrigeration systems on mines consist of fridge plants and bulk air coolers (BACs) as part of a system of pumps, pipes, and dams.

1. What is the goal of the system?

The goal of a mine refrigeration system is to provide cooling, either for water or air, by using electric energy.

2. What are the operational specifications of the system?

Operational specifications will vary between systems. The following are examples of possible specifications within refrigeration systems:

- installed capacity (kW),
- design flow of fluid through system, and
- design cooling capacity.

3. What are the performance indicators of the system?

The performance of a refrigeration system is evaluated by the amount of cooling it provides.

The cooling duty can be calculated by means of Equation 8:

$$Q_c = mC_p\Delta T$$

Equation 8: Cooling duty equation [96]

Where:

m is the flow of the fluid being cooled in L/s,

Q_c is the cooling duty produced by the evaporator side of the fridge plant in kW,

C_p is the specific heat capacity of the fluid being cooled in J/K, and

ΔT is the resulting change in temperature of fluid being cooled in °C.

4. What data is theoretically available from the system?

The following data may, in theory, be available from refrigeration systems:

- flow through the refrigeration system,
- temperature of fluid entering the system,
- delivery temperature of fluid,
- power consumed by main compressor,
- power consumed by auxiliaries, and
- ambient temperature.

To adequately evaluate the performance of a refrigeration system, flow data, temperature data and power data is required. The temperature and flow data can be combined into a cooling factor and compared to the amount of power used to generate the cooling. Table 5 provides a summary of the answers to the four relevant data identification questions for each of the energy-intensive systems identified in Section 0.

Table 5: Summary of relevant data identification for energy intensive systems

System		System goal	System specifications	Performance indicators	Theoretical data
Electric motors	Pumps	To pressurise and displace fluid	Flowrate, installed capacity	Delivery flow, delivery head, power consumption	Power consumption, initial and delivery flowrate, initial and delivery head
	Fans	To displace fluid	Flowrate, RPM, installed capacity	Delivery flow, power consumption	Power consumption, initial and delivery flowrate, fan speed
Compressed air systems		To pressurise air	Installed capacity, delivery pressure	Delivery pressure, delivery flow and power consumption	Initial and delivery pressure, initial and delivery flow, power consumption, blow off
Refrigeration systems	BACs	To reduce air temperature	Installed capacity, design flow, cooling capacity	Cooling factor, power consumption	Initial and delivery flow, initial and delivery temperature, power consumption, ambient temperature
	Fridge plants	To reduce water temperature			

The performance of each identified system is reliant on an energy carrier and a driver. An energy carrier is what provides energy to the system. This can be electricity, fuel, heat etc. Electrical energy is the energy carrier of all the selected systems. The energy driver of a system is what is delivered by the system from the energy that is consumed. This can be heat, cooling, compressed air etc. The driver of each system is its “product” and will vary depending on the system in question. Answers to the questions stated above should reveal the driver of the system.

Once relevant data is identified, it must be collected from a reputable source. The collected data should be compared to the theoretically available data and KPIs to determine relevance. This leads to a dataset that is ready for analysis.

This concludes the identification and collection phase of the method. Once the four set questions are answered regarding the specific system, one is able to determine whether the available data is enough for an investigation and which of the available data is relevant for performance evaluation. This will ultimately provide sufficient information of the system to evaluate its performance.

Common data error check

The importance of data quality and the state of data quality of mines were discussed in detail in Section 1.3. It is important for any data to undergo a quality assessment and error check.

The method developed in Section 0 should be used for any data that has not yet undergone a quality check. The method provides ways to prepare relevant data that was collected. It advises to plot the available data so that commonly expected data errors on mines can be identified.

Descriptions of all these errors are provided, along with possible causes for the errors and proposed mitigation strategies. The method ends with a re-evaluation step to ensure that no errors were missed.

Visualise and report data

There is a need for mines to obtain information from data for system performance evaluation to achieve energy efficiency [66]. It was found that visualisation can be used to extract this information from data [40], [75]. The goal of this phase of the methodology is to devise a method that will produce a visualisation that can convey knowledge through perception, to ultimately be used for performance evaluation.

The visualisations resulting from this method should present data in a decision-oriented manner. These visualisations should make the interpretation and application of said data easy. If the data is not well represented, the value of the original data may be lost [33]. Therefore, this methodology included a checklist to ensure that the resulting visualisations are effective in communicating relevant information from the data.

A five-step method for effective visualisation is suggested by McKay in the *Encyclopaedia of Ecology* [75]. Although this method was designed for ecological analysis, it can easily be adapted and applied to the mining industry. The five steps are discussed in the following paragraphs (a-e).

a) Identify the best visualisation for the message you want to convey

Regardless of what data is visualised, the visualisation chosen should be suited to the communicated information. This step is relevant to the mining industry and needs no adaptation. It can, however, be split into two steps: (i) to determine the goal of the visualisation; and (ii) to select a visualisation that conforms to this goal. Visualisations that can be used were discussed in Section 0.

b) Determine relevant scales

The scales on which data exists within the mining industry does not vary dramatically. This step is relevant in ecology where exponential growth is expected but is not relevant in the mining industry. This is therefore removed from the adapted version.

c) Adapt the visualisation to the data distribution

In ecology, data often appears in orders of magnitude due to growth present in ecological studies [75]. Mine system data exists between a set minimum and maximum, and not much variation is expected. This step can be removed as it does not apply to the mining industry.

d) Consider the constraints of the visualisation environment

Visualisations can be used in several environments. These may vary from presentations, digital reports, or printouts. The constraints of each occasion should be considered when a visual is made. This consideration is valid in the mining industry and does not need adaptation.

e) Consider the tools and expertise available

Specialised visualisation software can be used for the visualisations in this study. It is, unfortunately, not widely accessible and may not be available on mines. Available tools and the ability to use them are relevant to this study and, therefore, this step can be used.

The following method adapted from the ecological steps discussed above can thus be used to effectively visualise mine system data:

1. Determine the information you want to convey

The goal is to visualise the performance of the selected system with a focus on energy efficiency. This study focussed on the evaluation of energy-intensive systems on mines, and thus the energy consumption of the system in question must be clear from the visualisation. The KPIs of the system must also be evident from the visualisation. The ideal visualisation

will thus indicate the relationship between the power consumption and the KPIs of the selected system.

The visualisations produced by this study were intended for a person who is well informed about the system the visualisation pertains to. This person should get enough information from this visualisation to draw conclusions regarding the system and make informed decisions based on it. An analytical visualisation is required so that complex relationships can be communicated and understood [86].

2. Choose a visualisation that will best display this information

The visualisation chosen depends heavily on the information that has to be displayed. Earlier in this study it was determined that an analytical visualisation [86] should be used for the intended level of communication. The combination of data assessment and analysis should make the choice of data visualisation technique more clear [29].

Section 0 contains a discussion on different available visualisations. Analytical visualisations have the ability to convey a relationship between two variables. Suggested visualisations to best display a relationship include scatter plots, histograms, and multi-series plots. Other complementary visualisations can be used to show change over time and trends within the data.

3. Consider the medium of the intended visualisation

Visualisations resulting from this study may be used in several different situations. Each setting may require an entirely different set of considerations. Colours that could be difficult to discern by colour-blind people should be avoided.

In printed media, black and white is often the only colour scheme used. Different datasets can be identified using patterns. In digital media, colours can be used for this distinction. Animations may be used in digital media to show the passage of time, or to compare different datasets.

Other situations may require entirely different considerations. It is important that this be taken into account for every visualisation made.

4. Consider the availability of tools and expertise

It is important to keep in mind, while visualising data, who the visualisation is intended for. Information should be included to enable the intended recipient to interpret the data [43], [74]. Visualisations can be done with any available software. In the case of sharing data and

visualisations for an investigation, one should ensure that all parties involved have access to, and can use, the chosen software.

5. Visualise data according to the considerations above

Once all these considerations have been taken into account, a visualisation can be constructed. The resulting visualisation should be evaluated to determine whether it is effectively communicating the intended information.

All visualisations are not created equal. The visuals generated must be effective [84]. Kelleher and Wegener [97] provide ten guidelines to assess the effectiveness of a visualisation, of which only the following seven were deemed relevant to this study:

- Use the simplest possible graph that still conveys the necessary information.
- Focus on visualising patterns and details relevant to the purpose of the plot.
- Use meaningful axis ranges.
- Indicate the density of overlapping points in scatter plots.
- Simplify large datasets in a meaningful way.
- Use similar axes and ranges when comparing data.
- Use an appropriate colour scheme.

Asada *et al.* [98] also developed a list of questions to evaluate a visualisation. The following questions are relevant to this study:

- Is the graph necessary?
- Does the graph encourage a comparison between variables?
- Is the type of graph suited to the information communicated?
- Is the data well-represented?
- Are auxiliary elements complimentary to the visual?
- Are titles, labels, legends, and captions clear and informative?

All these considerations were taken into account and condensed into the following checklist. If a visualisation passes this check, it can be considered effective. If a visualisation fails, the five steps of visualisation must be redone with special consideration to the failed criteria.

Table 6: Visualisation effectiveness checklist

Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?		
Is the visual in its simplest form?		
Is an appropriate colour scheme used?		
Does the visual encourage comparison?		
Does the graph choice suit the information to be conveyed?		
Is the graph clear?		
Are the legends, titles and labels clear and self-explanatory?		
Are the legends, titles and labels well-positioned?		

The only remaining step, once a visualisation has been confirmed to be effective, is to report the visualisation. Reporting is an often overlooked step in the visualisation process, but a visualisation has to be perceived by a user for it to truly convert data to information [84]. Human interaction allows a visualisation to add value.

In order for a visualisation to be effective, it has to be seen and interpreted by someone with the ability to use the information [74]. If the produced visualisation can be used to evaluate the performance of a system on a mine, the visualisation can be considered successful.

A summary of the method developed to visualise data for performance evaluation is presented in Figure 20.

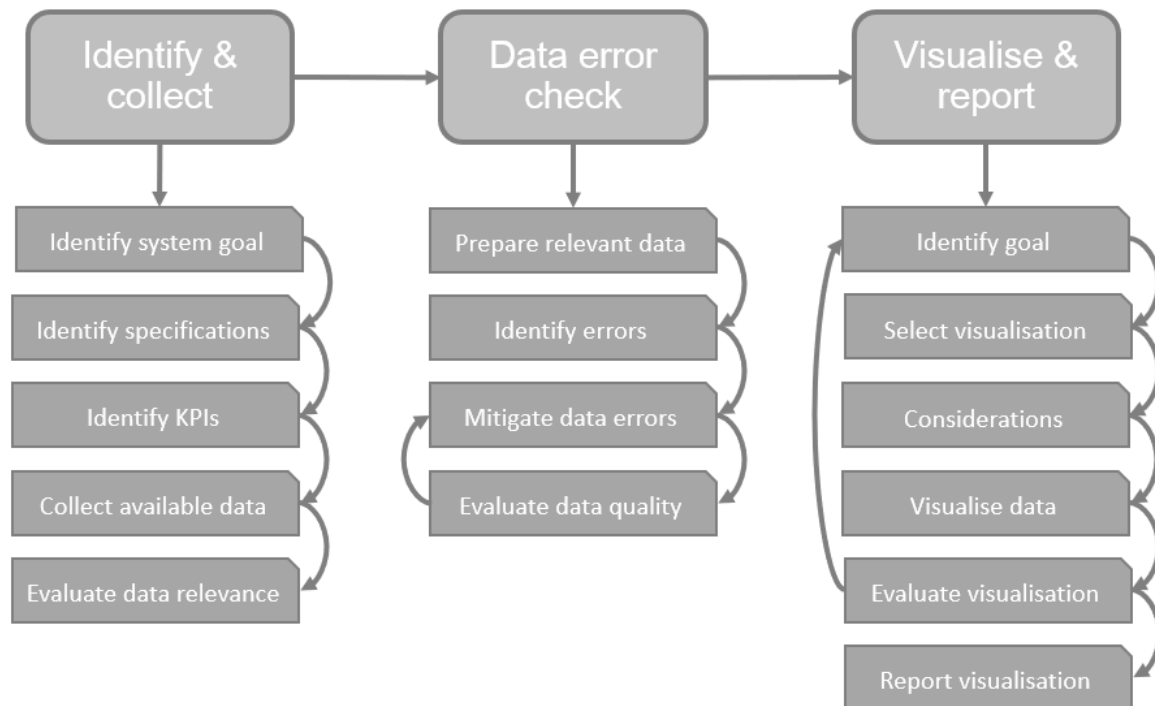


Figure 20: Detail schematic of data visualisation method

2.4 Conclusion

Two methodology sections were presented in this chapter. The aim of the first section of the methodology was to improve data quality, and the aim of the second was to improve data presentation. The results of both of these sections of the method can be applied to achieve and maintain long-term energy savings in the mining industry.

The first methodology section provided three phases in which data quality were assessed and improved. The first phase focussed on investigating the existing metering system of the mine. This provided information and context for the remainder of the study.

The second phase of this methodology section provided a list of commonly occurring errors within mining data. Identification and mitigation methods for each of these errors were suggested. This allows for common errors to be removed from a dataset before it is used.

The final phase provided a seven-step method to normalise data in order to improve its overall accuracy. This method establishes the system, checks the available data against a check meter, normalises the data and then evaluates the results.

The second method section aimed to provide a step-by-step guide to turn data into information that can be used for mine system performance evaluation. This should be done in three phases. Firstly, relevant data has to be identified through a series of questions. This relevant data could then be collected.

Once obtained, the data must be checked for quality, as only high-quality data would yield useful information. Quality indicators for data on mines were identified, and identification and mitigation strategies suggested. This process should result in a high-quality dataset.

After the first two steps, the data should be ready to visualise. The visualisation is intended to communicate the performance of the relevant system. Several considerations should be taken into account before the visualisation is made, to ensure an effective visualisation.

Additionally, a visualisation effectiveness checklist was developed. This can be used to determine whether the visualisation communicates the intended information in an effective manner. The combination of these three steps turns data into useful information that can be applied to evaluate the performance of a system.

These two method sections will allow a user to turn the abundant data available on mines into useful information. The first section addresses the quality issues known to occur on mines, and will result in data of an improved quality and accuracy. The second section addresses the shortcomings in data presentation on mines by providing a step-by-step visualisation approach to produce quality visuals that can add value. This methodology will thus enable mines to improve the data they have available. This improved data can, in turn, be used to achieve long-term energy savings.

3 RESULTS AND DISCUSSION

3.1 Preamble

This chapter explains how the developed methodology (Chapter 2) was applied on four practical case studies. Two case studies are presented for each of the two sections of the developed methodology.

The first and second case studies were used to demonstrate the method of data normalisation developed in Section 2.2. The goal of this section is to improve the quality of available data from South African mines without the need for capital expenditure. The mechanism of this method is given in Figure 21.

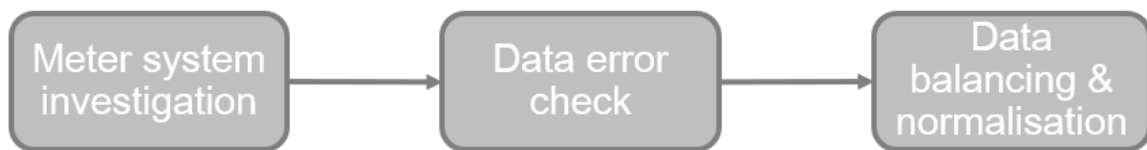


Figure 21: Data quality improvement method schematic

This method is demonstrated through Case studies 1 and 2.

The third and fourth case studies used the method developed in Section 2.3. This method uses the data available from mining operations to evaluate systems performance through visualisation. The mechanism used is presented in Figure 22. Validation of this method is presented in the form of an article by the author of this dissertation [59].

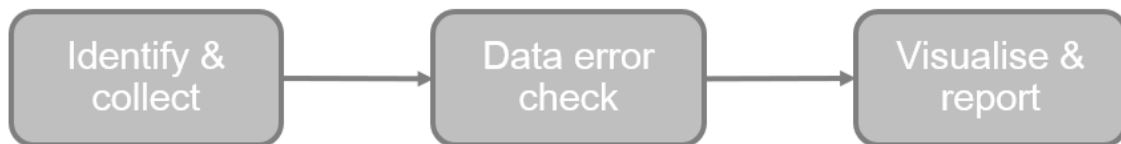


Figure 22: Data visualisation method schematic

This method is demonstrated by Case studies 3 and 4.

The results of the first section of the methodology were validated by determining the reduction in accuracy error that is found in the data. This is also presented as a Rand value.

The results of the second section of the methodology were validated through the visualisation evaluation checklist provided in Chapter 2, and subsequently reported. The evaluation was done by engineers working primarily in the mining industry. These evaluations were used to determine the overall effectivity of the method for delivering a visualisation informative enough for performance evaluation.

3.2 Data normalisation: Case study 1

Introduction

The first case study was based on a small gold mine in South Africa with a maximum demand of 12 000 kVA. This mine is referred to as Mine α . The mine forms part of a parallel operation with another mine. The two mines share resources such as pumps, cooled air and compressed air. The mine investigated is primarily responsible for pumping water throughout the mining complex as well as hoisting mined rock from underground. The mine also houses fans, refrigeration equipment and compressors that act as a backup for the equipment on the parallel mine. This case study aimed to implement the developed method to improve the quality of data from this mine.

Data for one billing month spanning 30 days was used for this case study.

Metering system investigation

The first step of this case study was to gain an understanding of the mine. To do this, a full electrical layout of the mine was obtained and studied. The full layout is available in Appendix B. From this layout, a simplified electrical layout (Figure 23) was compiled.

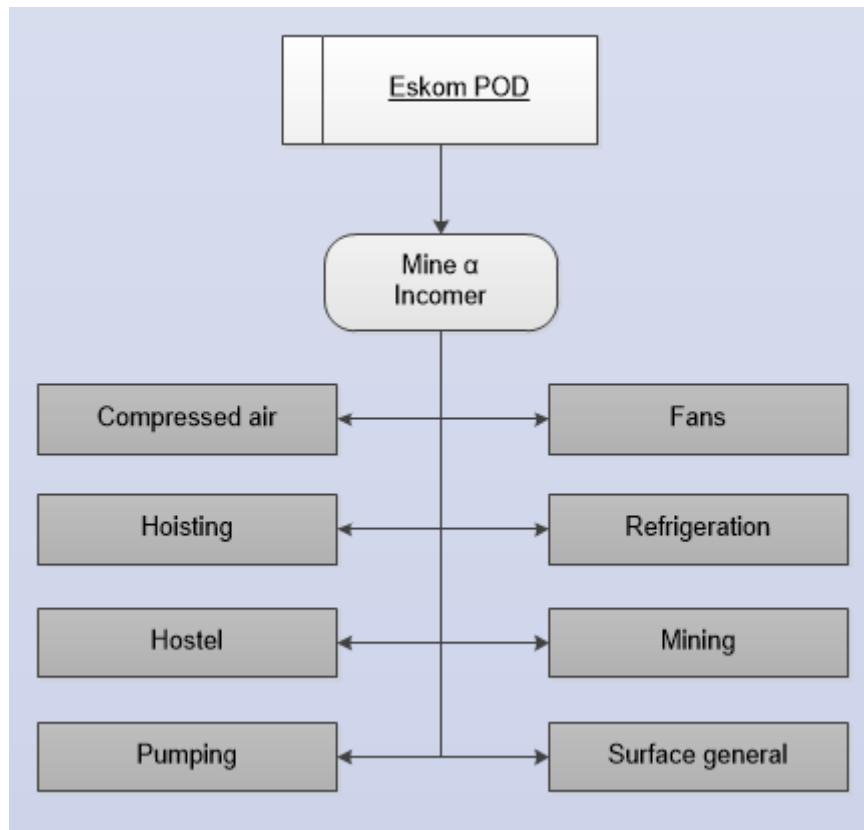


Figure 23: Simplified electrical layout for Mine α

All blocks in Figure 23 represent electricity meters. The incomer and Eskom point of delivery (POD) meter both measure all the power consumed by the mine. If the meters are accurate, both of these should deliver the same reading.

There are eight sub-system groups feeding from the mine incomer. A meter is available for each of these sub-system groups. The sub-systems further comprise multiple individual machines. Meters are not available for all equipment pieces on this level.

The sub-system groups for compressed air, fans, refrigeration, hoisting and pumping are relatively self-explanatory. Each represents a group of the equipment it is named for. The mine has a single compressor, three ventilation fans, three fridge plants, four winders used for hoisting, and four pumps responsible for moving water from underground to the surface.

The group called mining represents several conveyors, underground lighting and other mining equipment. The surface general sub-system contains all site offices and lighting on surface. The hostel sub-system represents all personnel housing on site and is made up of general usage, lighting and water heating.

Mine personnel do not have direct access to the Eskom POD meter. Data from the Eskom POD is only available once a month from accounts received by the mine. All other meters in Figure 23 are installed and maintained by a third-party metering company. This data is available to the mine in 30-minute intervals and can be accessed at any time.

Data available from each of these meters was collected for one 30-day period. The Eskom POD meter is regularly calibrated as it is used for billing. It can thus be used to validate the incomer meter if the measurements from the meters correspond. All other meters were calibrated upon installation. The meters were installed several years ago, thus this calibration is of little to no value.

The following two sections evaluate the integrity of this data and attempt to improve the quality thereof, if needed.

Common data error check

This section takes a look at the quality check of the data collected from Mine α . This was done according to the method developed in Section 0. For this method, data was visualised in its original form and inspected for common errors expected in data from mines.

This was done for the data from the incomer and each sub-system. The data from the Eskom POD was only a single total value for the billing month and could thus not be inspected for errors.

Visualisations to check data were done as daily and monthly views. The monthly view can be used to inspect the data for the full investigation period. The daily view of the data was provided to the user to gain an understanding of the patterns observed in the monthly view.

For Mine α , data from the pumping sub-system was used to demonstrate the method. Results for the incomer and the other sub-systems can be found in Appendix C.

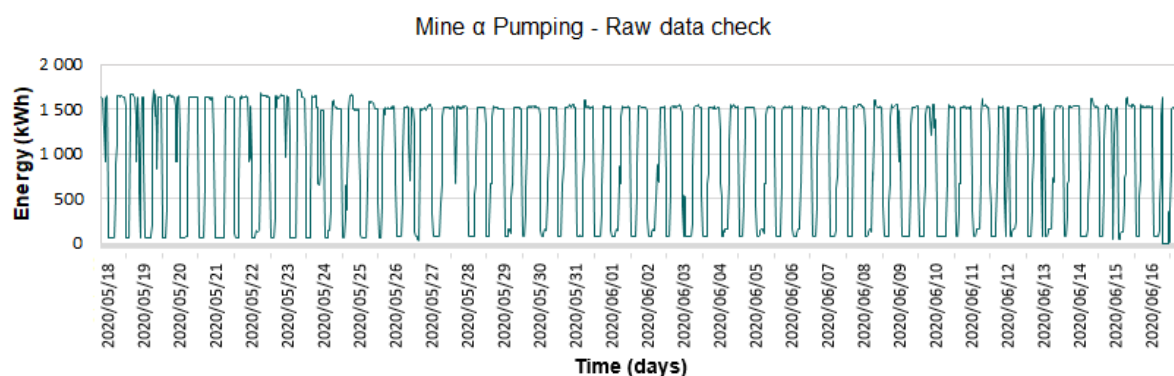


Figure 24: Mine α Pumping - Month profile

Figure 24 shows a one-month view of the data from the pumping sub-system on Mine α . The data was plotted in half-hourly intervals, which is the highest frequency available from the mine. On the graph, a small reduction in daily power consumption can be seen about a quarter into the month. Mine personnel suggested that this could be due to a pump switchover. Of the four pumps underground, only 2 are used at once under normal circumstances.

On the last day of the month, the power dropped to zero. This was due to a power failure experienced by the mine and is visible on the profiles of every sub-system, as well as that of the incomer.

The power consumption of the pumps moved to near zero twice a day. Figure 25 provides a closer look at this.

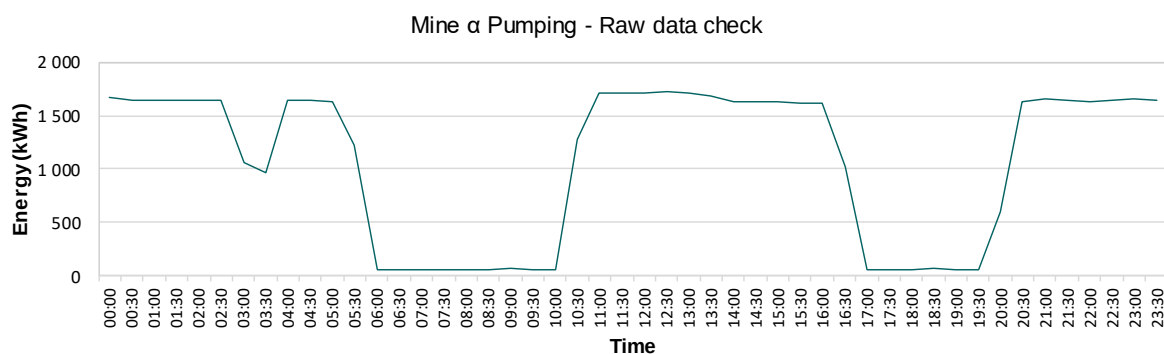


Figure 25: Mine α Pumping - Day profile

A clear twice-daily reduction in power consumption can be seen in Figure 25. This is observed every day over the 24h period. The downtime corresponded with the twice daily Eskom time-of-use peak times. The mine plans its pumping so that minimal power needs to be consumed by the pumps while electricity is at its most expensive. This explains the up and down patterns seen in the monthly profile.

During the downtime, the electricity consumption did not reach zero. This indicates the presence of auxiliaries on the pumping group meter. This should be kept in mind when evaluating the data. The four data checks defined in Section 0 are discussed in the following paragraphs.

- *Check for missing data*

No data was missing for the 30 day period investigated. In Figure 24, a drop in power consumption could be seen for the last day. This was due to a power failure and was not excluded from the data.

- *Check for stuck-at errors*

No stuck data was noticed within the dataset. Small variations were present in the data where there appeared to be straight lines.

- *Check for out-of-bounds errors*

The pumping system at Mine α consists of two 1 500 kW pumps and two 1 250 kW pumps. According to mine personnel, only two of the four pumps are operated simultaneously. The pumping system is thus expected to use a maximum power of 3 000 kW at any given time.

Energy consumption data from the mine is available in half-hourly intervals and measured in kWh. The measurements should thus not exceed 1 500 kWh, provided that the measurement represents only those pumps. Figure 26 provides a visual check for this boundary.

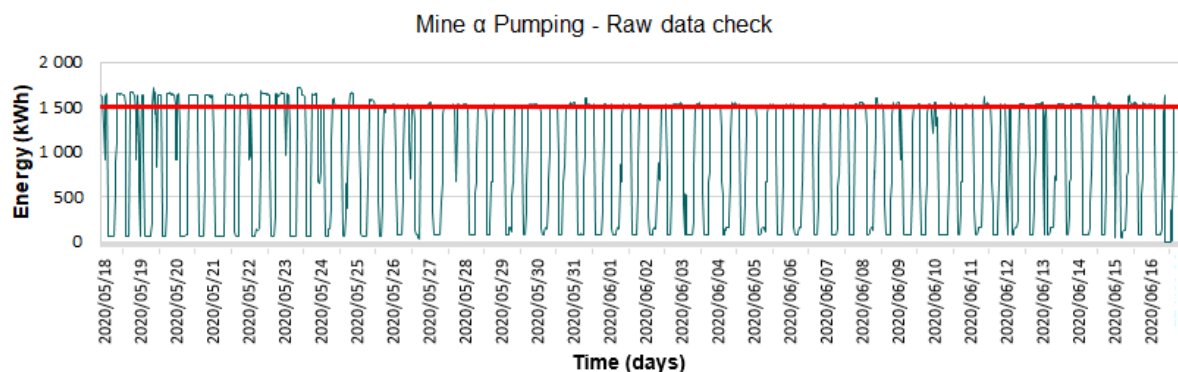


Figure 26: Mine α monthly profile for data boundary check

From Figure 26, it can be seen that the pumping system operated outside its boundaries for a few days, and from there on had been right on the maximum line of expected energy consumption. This could be due to auxiliary systems also feeding on the meter attached to the pumping system, or to faulty meters.

Mine personnel was consulted about this, and suggested that the installed capacities of the pumps might not be accurate. Some work had been done on the motors driving the deeper

level pumps (1 500 kW). Their current estimated capacity had therefore increased to 1 780 kW as is indicated by the red line in Figure 27. The maximum capacity is thus 3 560 kW, and not 3 000 kW. This is presented in Figure 27.

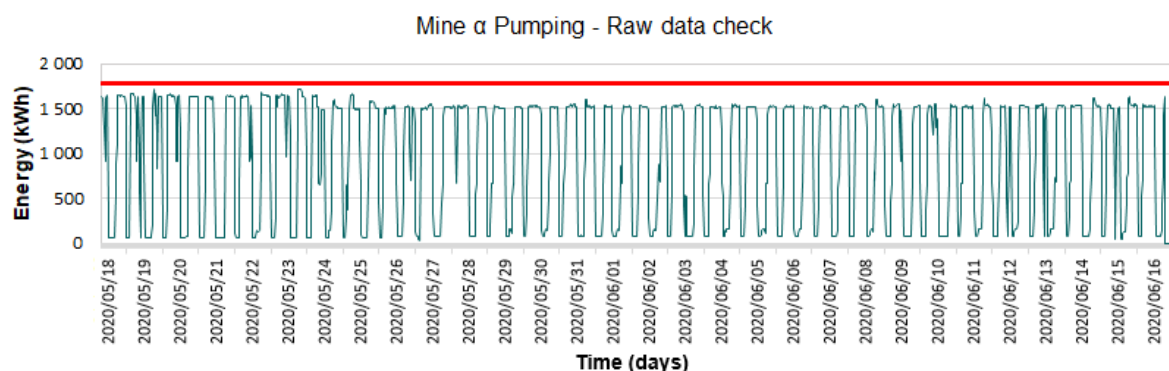


Figure 27: Mine α updated monthly profile for data boundary check

From Figure 27, it can be seen that the pumps were operating within their expected boundaries. There is thus no cause for concern.

- *Check for abrupt errors*

No abrupt errors were noted from Figure 24.

These data quality checks were repeated on all the data available for Mine α . The investigation of these systems can be found in Appendix C. The following was noted:

The compressor was infrequently used during the documented 30-day period. The compressed air for Mine α is provided by its parallel mine and thus the compressor on Mine α is not frequently used.

Fans were only switched on for one day out of the 30-day period that was investigated. While this may appear to be an outlier, the data was still well within its expected boundaries. The fans on Mine α are used as a standby for those on its parallel mine, and are not frequently used.

The refrigeration system of Mine α was used as needed during the documented period. The system is only used to pre-cool water for the parallel mine, thus the full capacity of the fridge plants is not used. The fridge plants performed within the expected boundaries and did not have any missing or static data.

Hoisting on Mine α is dependent on the mining activities. If more rock is mined, the winders have to operate more. Due to the low mining activity at Mine α , the hoisting group did not consume large amounts of energy. The winders performed within their boundaries and did not have any missing or static data.

As discussed, all mining activities occur at Mine α 's parallel mine. The mining sub-system is responsible for some lighting and rock conveyors underground. Very little energy is used by this system. No boundaries were available for this data, and no missing or static data was noted.

For the systems of surface general and hostel, no boundaries were available. The systems performed as expected, with high consumption in the hostel due to cold weather during the documented period. No missing or static data was noted.

All figures pertaining to these systems are available in Appendix C.

Data balancing and normalisation

The previous section evaluated the available data from Mine α for common data errors on mines. The data had now been rid of errors, but the accuracy of the data had not been established. For the sub-systems, the accuracy could not truly be established, as no up-to-date calibration certificates were available.

The method developed in Section 0 is intended to improve the accuracy of such datasets. The method uses seven steps to adjust data towards meters with known accuracy. The seven steps were applied to Mine α as described in the following paragraphs.

Step 1: Determine the boundaries of the investigation

For a normalisation calculation, it is important that all data sources have data available on the same intervals. This disqualifies the Eskom POD from being a part of the selected system, as it is only available monthly. The normalisation investigation thus focussed on the incomer meter and eight sub-system meters.

Step 2: Identify a check meter

The incomer meter was be used as a check meter. Unfortunately, the incomer meter is not calibrated. The incomer meter is, however, on the same line as the Eskom POD, which is calibrated. If the monthly total of the incomer meter matches up with the Eskom account, it can be verified. The energy consumption from the incomer was compared to the reading on the Eskom POD. The results are presented in Table 7.

Table 7: Mine α check meter verification

Mine α Incomer	Mine α Eskom POD	Difference
1 964 781	1 964 362	0.02%

From Table 7, it is clear that the mine incomer meter reading was nearly an exact match for the Eskom POD. The difference between the two meters was negligible. The incomer meter can therefore be used as a check meter as it had been proven to be accurate.

Step 3: Determine the layout of the system

The layout identified in the metering system investigation (Section 0) was adapted to only include the meters selected to be a part of this method. The adapted layout is given in Figure 28.

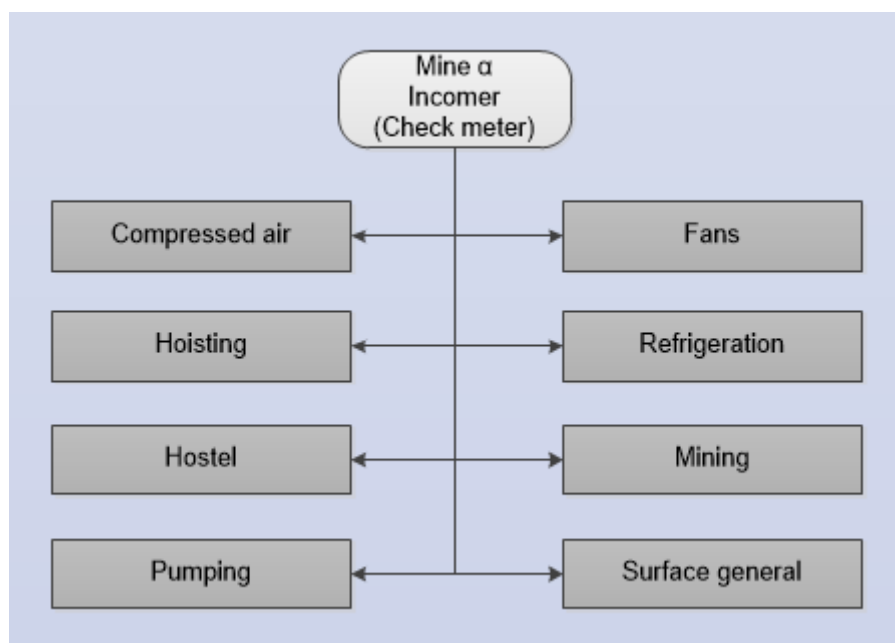


Figure 28: Mine α layout for normalisation calculations

Figure 28 presents the altered layout for Mine α used for the normalisation calculations. The check meter has been indicated on the figure.

Step 4: Determine specifications of all relevant equipment

Information on the specifications of sub-systems was collected from mine personnel and is summarised in Table 8.

Table 8: Mine α sub-system specifications

Sub-system	Specification
Compressed air	1 × 4 800 kW
Fans	3 × 2 100 kW
Hoisting	2 × 3 600 kW, 2 × 4 000 kW
Refrigeration	2 × 500 kW, 1 × 600 kW
Hostel	No specifications available
Mining	No specifications available
Pumping	2 × 1 250 kW, 2 × 1 780 kW
Surface general	No specifications available

These specifications were used to evaluate the results of the normalisation calculations. Ideally, the altered values should fall within the bounds of the expected system performance.

Step 5: Perform data balance check

The next step in the method is to compare the energy usage of the incomer check meter to the energy usage of all the sub-systems. This was then used as an indicator of the accuracy of the sub-system meters. A 30 day period of energy usage was used. The results are indicated in Table 9.

Table 9: Mine α data balance check

Description	Energy usage (kWh)
Incomer	1 964 781
Compressed air	2 760
Fans	1 048
Refrigeration	18 983
Hoisting	137 040
Hostel	295 313
Mining	2 229
Pumping	1 381 989
Surface general	39 089
Sum of sub-systems	1 878 452
Difference	86 329

From the values in Table 9, it is clear that the data for the selected system did not correspond with the check meter reading. There was a difference of 86 329 kWh or 4.4%. As the incomer meter had been verified, this indicates that the error lay on the sub-system meters.

This is further illustrated in Figure 29. For visualisation purposes, the sub-systems of mining, hostel and surface general were combined into “other systems”.

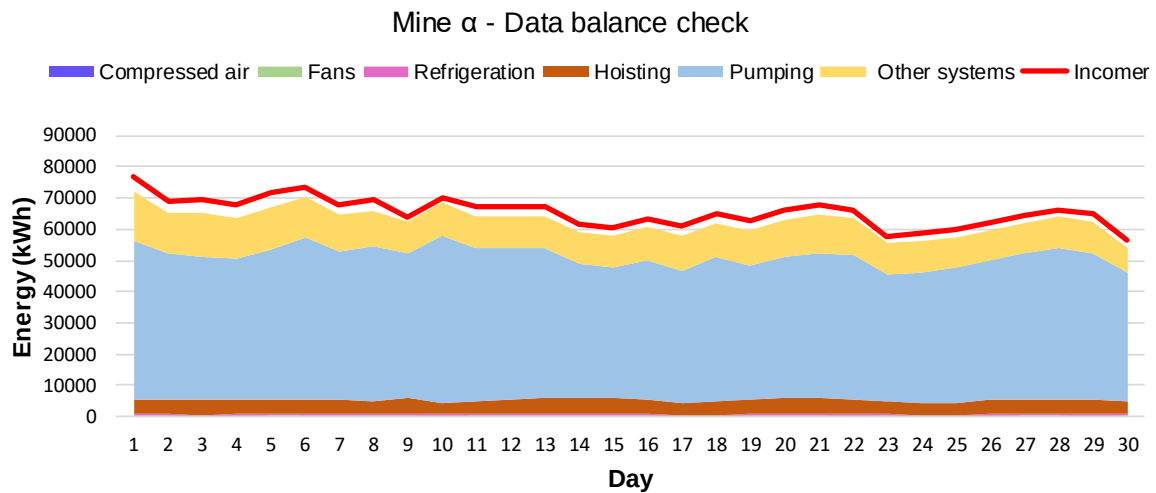


Figure 29: Mine α data balance check

A clear gap between the sub-system’s energy consumption and that of the incomer can be observed in Figure 29. This indicated scope for improving the accuracy of the sub-systems data.

Step 6: Normalise data

As scope for normalising the available data had been identified, the data could be normalised to match the incomer meter. The method described in Section 0 (Equation 6) was used. As data was available half-hourly, the normalisation calculation was carried out half-hourly and added to every single non-zero data entry.

This resulted in the following data, given in Table 10.

Table 10: Mine α normalised data breakdown

Description	Raw energy usage (kWh)	Adjustment (kWh)	Normalised energy usage (kWh)
Incomer	1 964 781	-	1 964 781
Compressed air	2 760	128	2 888
Fans	1 048	47	1 094
Refrigeration	18 983	864	19 847
Hoisting	137 040	6 262	143 302
Hostel	295 313	13 872	309 186
Mining	2 229	102	2 331
Pumping	1 381 989	63 244	1 445 233
Surface	39 089	1 811	40 900
Sum of sub-systems	1 878 452	86 329	1 964 781

In Table 10, it can be seen that the normalisation adjustment was proportional to the size of the sub-system. The normalised sub-systems now added up to the check meter. The normalised data is visualised in Figure 30. As in Figure 29, the sub-systems of mining, surface general, and hostel were combined into “other systems”.

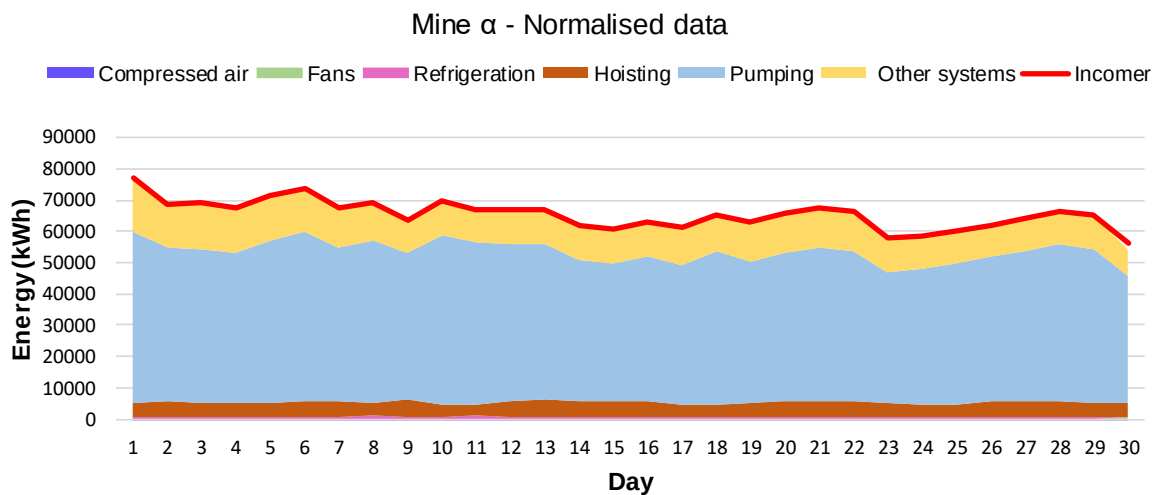


Figure 30: Mine α normalised data

Figure 30 illustrates the effect of the normalisation over the documented period. The normalised data now added up to the incomer on a daily basis.

Step 7: Evaluate resulting data

The developed method suggests evaluating the data resulting from the normalisation against the specifications for each sub-system. Data that passes this test should be accepted and used in place of the raw data.

As with the data error check in Section 0, the data of the pumping sub-system was be used to demonstrate the method. The data evaluation was also done on all other sub-systems, which can be found in Appendix C. Figure 31 presents the normalised data of the pumping sub-system against the earlier established boundary for operation of the pumps.

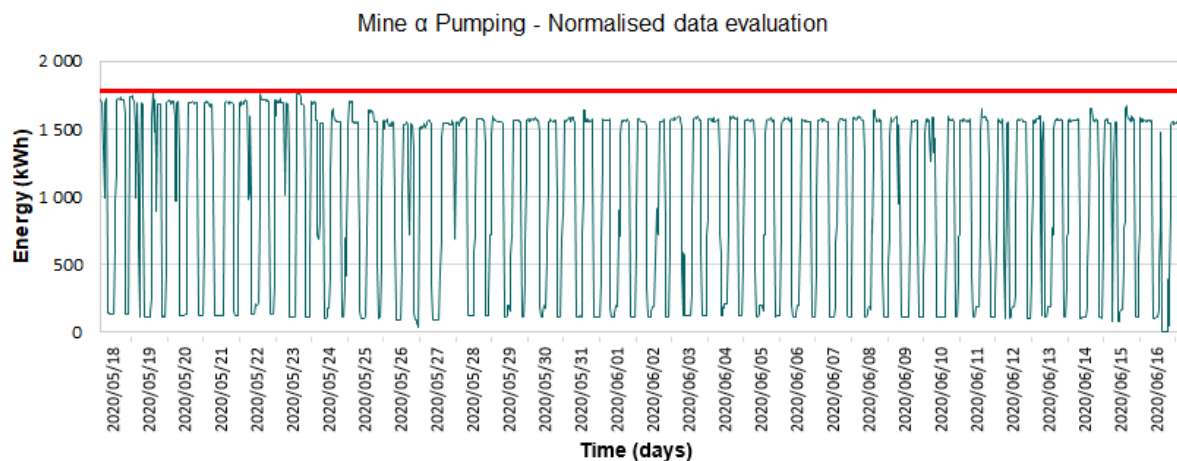


Figure 31: Mine α pumping normalised data evaluation

Predictably, the energy consumption of the pumps had been increased by this calculation, as the energy consumption of the incomer was higher than that of the sum of the sub-systems. The normalised usage was just under the expected usage.

This normalisation method can be used for this method, but it is not the best suited because of how the weights of this system are distributed.

This concept can be explained using the compressed air sub-system as an example. See the normalised data of the compressed air system in Figure 32.

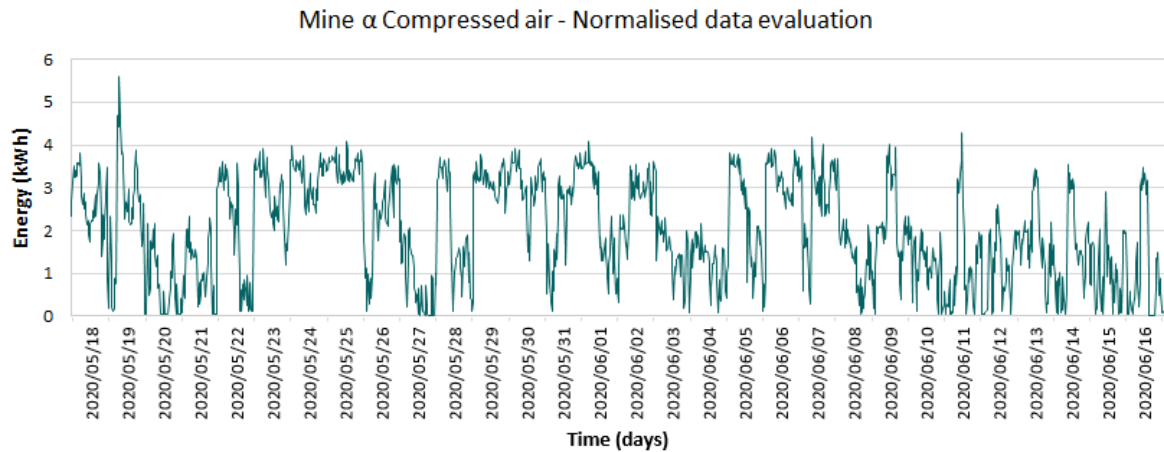


Figure 32: Mine α compressors normalised data evaluation

The compressor appears to be operating far below its rating. The compressor has a power rating of 4 800 kW and could thus use about 2 400 kWh in the half-hourly intervals measured. The energy consumption seen in Figure 32 represents auxiliary systems on the compressed air system, as it is known that the compressors were not in operation at the time of the investigation. Figure 33 presents the usage of the compressed air system to its operational limit.

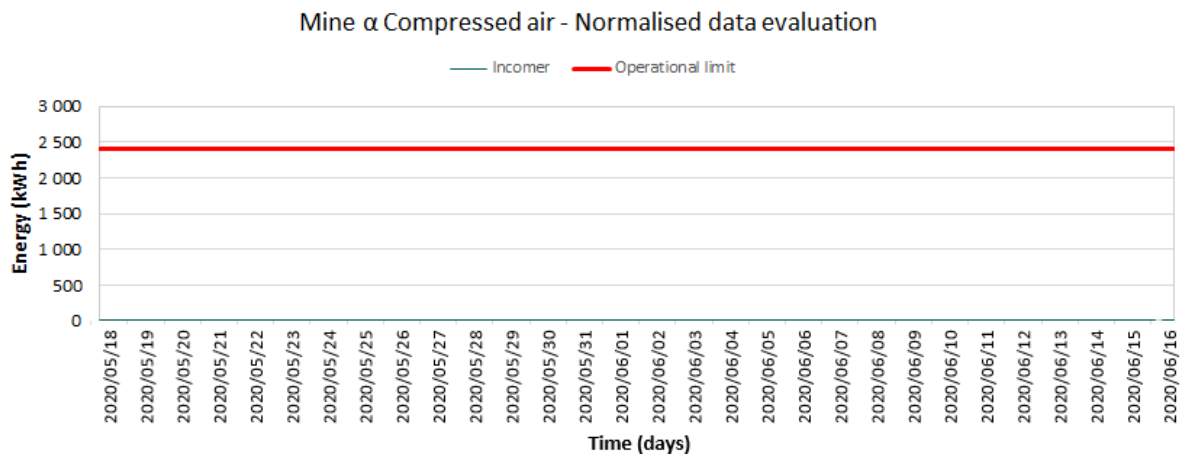


Figure 33: Mine α compressors normalised data evaluation with operational limit

A meter intended to measure the energy consumption of the compressor should be most accurate in the range where the compressor is expected to operate. A similar situation was found with the fans, refrigeration sub-system and the hoisting sub-system.

Mine α should consider new meters for systems that are underperforming, or downscaling equipment where large equipment is no longer needed. The normalisation method has still reduced the relative error from 4.4% to 0.02%. This is a significant improvement in the accuracy of the data. The method thus successfully met the goal of improving the quality of the data.

This improved the accuracy of the system as a whole, but would be more effective on a system where all sub-systems are fully operational. This improvement equates to R82 000¹ in uncertainty monthly, or R984 000 per year. The improved data could be used for better sub-system level budgeting.

3.3 Data normalisation: Case study 2

Introduction

This case study focussed on a medium-sized South African gold mine with a maximum demand of 24 500 kVA. The mine, which is referred to as Mine β , forms part of a cluster of 4 shafts. The mine is supplied of cooled water by one of the other shafts and does thus not have its own refrigeration system. The mine has fans that are only used during summer months. During winter months, adequate ventilation is supplied by the other shafts. The goal of this case study was to improve the quality of the data available from the mine.

Data for one billing month spanning 30 days was used for this case study.

Metering system investigation

Following the method as given in Section 2.2, the first step was to investigate the mine metering system. A full electrical metering layout was obtained from the mine, but it is large and impractical to display in this format. It is included in Appendix B for reference. For reference, a simplified layout was drawn up from this, and is given in Figure 34.

¹ Assuming an effective tariff of 95c/kWh

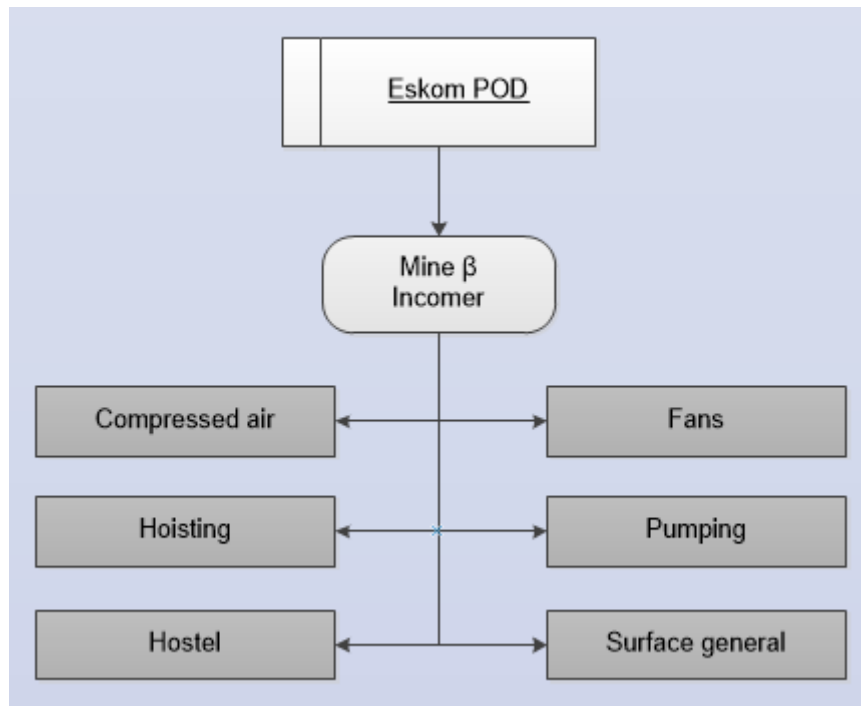


Figure 34: Simplified electrical layout of Mine β

As with Mine α, Mine β receives energy from an Eskom POD. The electricity feeds through an incomer meter to six sub-system groups. If all the meters were accurate, the group of six sub-system meters should add up to the incomer meter, which should be equal to the meter located at the Eskom POD. If this is not the case, the data has to be adjusted in an attempt to increase the accuracy of the various meters.

The compressed air system at Mine β is made up of four compressors, two larger (4 800 kW) and two smaller (3 800 kW). One large and one small compressor are operated at any given time on the mine. Loss of compressed air is detrimental to underground operations. When switching compressors, three compressors are operated at once to ensure that no pressure is lost.

As mentioned, the fans at Mine β do not operate during winter months. The data for this case study was captured during winter, thus the fans had no part in this case study.

The hoisting sub-system at Mine β is made up of two rock winders. They are responsible for bringing mined ore to the surface. The ore is later processed at a nearby gold-processing plant.

Pumping of water from underground is done at two levels. Several pumps are available on each level, but each level only operates one pump at a time.

The hostel sub-system is accommodation for mine personnel. The hostel on Mine β is large as it houses personnel from the other mines that form a part of the mining cluster as well. Energy is used by the hostel primarily for cooking, lighting and water heating.

The final sub-system grouping is the surface general group. This group accounts for all offices on the mine, as well as some conveyors and lighting.

Data for all these sub-systems, as well as the incomer, is available from the mine at half-hourly intervals. The meters were installed and are maintained by a third-party metering company. The Eskom meter is not accessible by mine personnel. A single monthly reading in the form of an Eskom account is the only information available from this meter.

Data from all the systems in Figure 34 was collected. The following step in the method was to verify the sources of the collected data. The accuracy of the Eskom meter could be verified, as meters used for billing must be calibrated frequently. All other meters were not calibrated since installation. Most of these meters are a few years old, thus this calibration is not an indication of accuracy.

Common data error check

This section uses the method developed in Section 0 to identify and mitigate common data errors, especially those prominent in data from mines. The data collected in the previous step was visualised in the original form available to ensure that no errors were missed.

The method is demonstrated with one of the sub-system groups. All visualisations for the other sub-systems and the incomer meter are available in Appendix C. For Mine β , the compressed air system was used to demonstrate the method. Figure 35 presents the raw data from the compressors over the 30-day period for which data was collected.

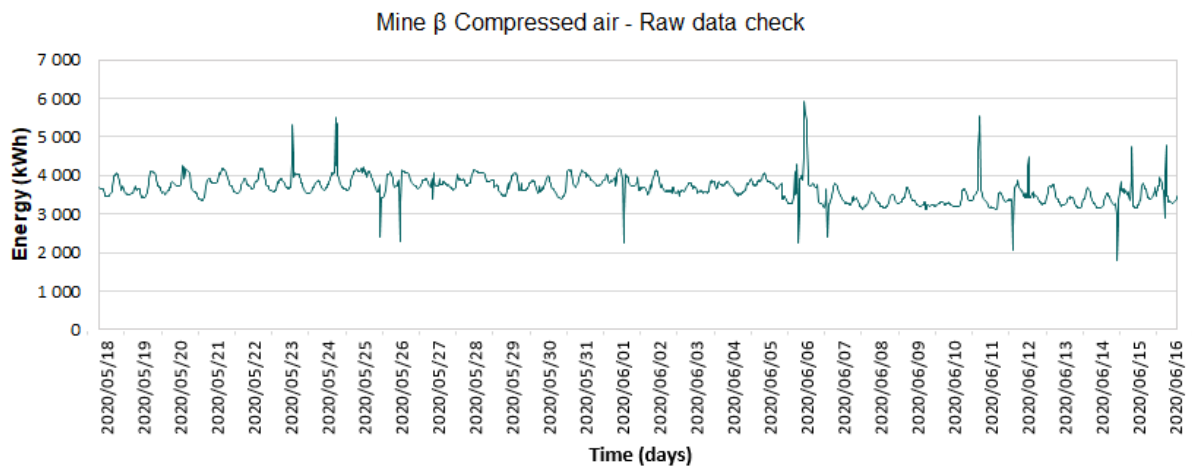


Figure 35: Mine β Pumping - Month profile

From Figure 35, it can be seen that the compressed air system usually uses between 3 000 kWh and 4 000 kWh every half hour. There are a few exceptions, where the power spikes up or down. Figure 36 provides a closer look at such a case.

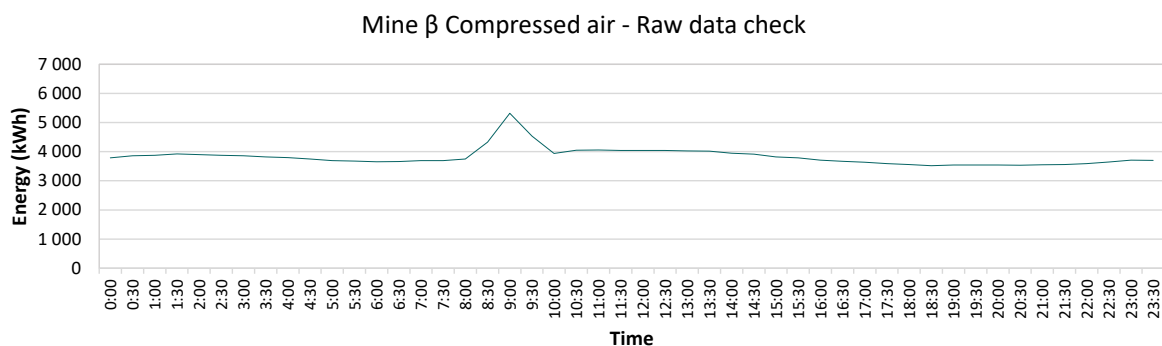


Figure 36: Mine β Compressed air - Day profile

The compressors followed a gentle up-and-down profile, apart from the spike. The spike in consumption was due to guide-vane control being used on the compressors. This is a typical profile of a compressor switchover, where an additional compressor is switched on, and only once it is running the other compressor is switched off. There were thus three compressors running for a short time. The dips in Figure 35 could either indicate compressor failures, or unsuccessful compressor switchovers.

- *Check for missing data*

No missing data was observed over the investigation period.

- *Check for stuck-at errors*

No stuck data was observed in the data of the compressed air system.

- *Check for out-of-bounds errors*

The compressed air system at Mine β is made up of four compressors. Two of these are rated 3 800 kW, and two are rated 4 800 kW. One of each is operated at any given time, apart from switchover events. The sub-system was expected to not use more than 8 600 kW at any given time, excluding switchover events.

As this was compared to half-hourly measurements in kWh, the maximum was expected to be 4 300 kWh unless a switchover was happening. Figure 37 provides a visualisation for this comparison.

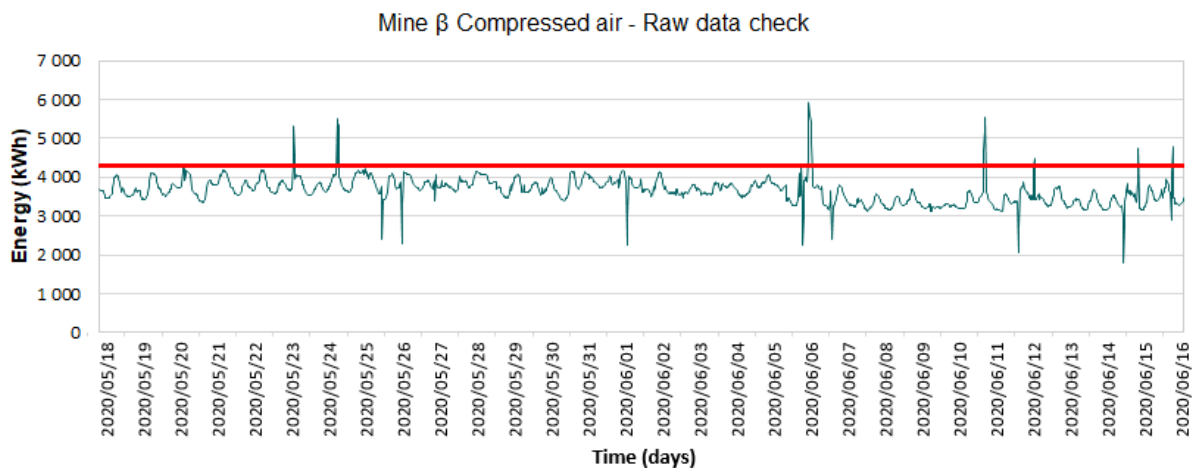


Figure 37: Mine β Monthly compressed air profile for boundary check

Figure 37 shows the operation of the compressed air system compared to the operational limits of the compressors. The operation did not exceed the boundary apart from at switchover events. For the first half of the observed time period, the data appeared to be closer to the boundary. It is not ideal for the compressor to be operating so close to its limits. This might indicate a slight error in the meter.

- *Check for abrupt errors*

Apart from the discussed switchover events, no abrupt errors were noted from Figure 35.

These data quality checks were repeated on all the data available for Mine β . The following was noted:

No systems had any missing data.

No data appeared to be stuck.

The hoisting and pumping sub-systems were operating close to their expected boundaries. Both the hoisting and pumping systems did not move to zero when not in operation. Mine personnel noted that some small auxiliary systems were connected to both these sub-system feeders. These systems included some underground lighting, conveyors, and small pumps for potable water. This “base-load” can be estimated from visualising the data, and should be accounted for when evaluating the data boundaries.

All relevant figures for these systems are available in Appendix C.

The data collected from Mine β appeared to be of acceptable quality. The following section explains how the data was tested to determine its accuracy.

Data balancing and normalisation

Section 0 explains how the data collected from Mine β was tested to identify any common data errors. The data was deemed to be of acceptable quality. This section aimed to improve the data further by normalising it to a source with confirmed accuracy.

A method to do this was developed in Section 0. The method uses seven steps to determine if there is any need for normalisation, to apply it, and to test if the results obtained are valid. The following paragraphs discuss the data balancing and normalisation for the compressed air system using the seven steps.

Step 1: Determine the boundaries of the investigation

It is important for a normalisation calculation that all the data sources used are in the same format. All data collected from Mine β , apart from the Eskom POD data, was available in half-hourly intervals. As the fans are non-operational during the winter months, the fans sub-system was excluded. The investigation thus focussed on the incomer meter and the remaining five sub-system meters.

Step 2: Identify a check meter

On Mine β , all the sub-systems feed from the incomer. The sum of the sub-systems was compared to the energy consumption of the incomer meter. The check meter was unfortunately not calibrated, and therefore was not confirmed to be accurate.

The incomer meter and Eskom POD are installed in line. As the Eskom POD is confirmed to be accurate, it can be used to confirm the accuracy of the incomer meter.

Table 11: Mine β check meter validation

Mine β Incomer	Mine β Eskom POD	Difference
8 203 306	8 178 939	-0.30%

From Table 11, it is clear that the difference between the incomer meter and the Eskom POD was very small (0.3%). The incomer meter could thus be used as the check meter, as its data was accurate.

Step 3: Determine the layout of the system

The layout for this section could be adapted from the layout in Figure 34. The changed boundaries from Step 1 were taken into account to create Figure 38.

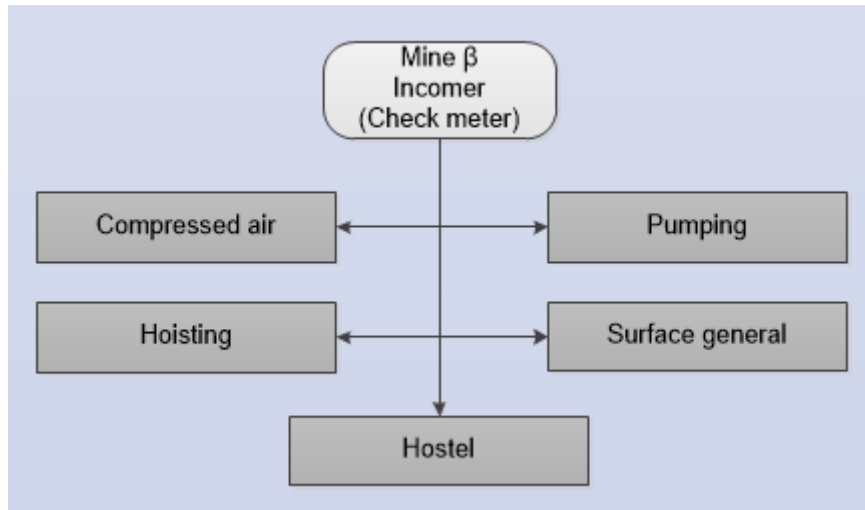


Figure 38: Mine β layout for normalisation calculations

The normalisation calculations that follow used Figure 38 as reference for the system layout.

Step 4: Determine specifications of all relevant equipment

Information on the specifications of the sub-systems were collected from mine personnel and is summarised in Table 12. The values provided are the rated capacities of the instruments.

Table 12: Mine β sub-system specifications

Sub-system	Specification
Compressed air	2 × 3 800 kW, 2 × 4 800 kW
Pumping	1 × 1 250 kW, 1 × 1 750 kW
Hoisting	2 × 1 750 kW
Surface general	No specifications available
Hostel	No specifications available

It is important to note that, although there are four compressors, only two are expected to run at any given time, with the exception of switchover events. It is unclear exactly how many pumps on each of the underground levels were in working order. Of these pumps, only one of each size is ever expected to run at once.

These specifications were used in Step 7 to evaluate the results of the normalisation calculation.

Step 5: Perform data balance check

Now that all relevant information around the system had been collected, the normalisation phase of this method was next. Firstly, it is important to check if any normalisation is necessary. To do this, the energy usage of the sum of the sub-systems was compared to that of the incomer meter. The results of the balance check is presented in Table 13.

Table 13: Mine β data balance check

Description	Energy usage (kWh)
Incomer	8 203 306
Compressed air	5 259 941
Hoisting	1 066 752
Hostel	500 967
Pumping	810 820
Surface	154 547
Sum of sub-systems	7 793 026
Difference	410 279

From Table 13, there is a clear difference between the sum of the sub-systems and the incomer meter. The difference was 410 279 kWh, which is 5.0%. The incomer meter was considered accurate, which indicated that the error lay within the sub-system meters. The error between the sub-systems and the incomer has been visualised in Figure 39.

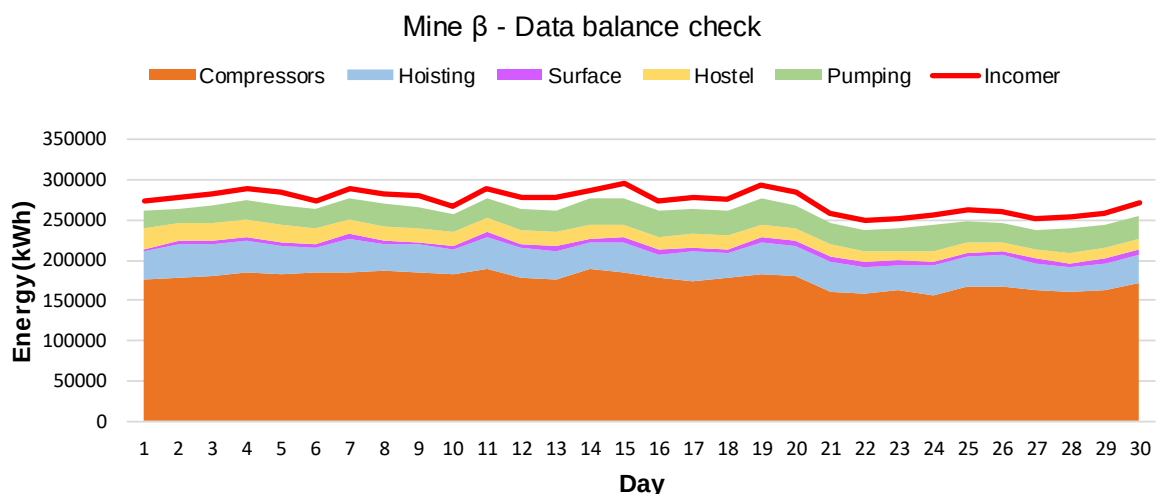


Figure 39: Mine β data balance check

The gap between the combined sub-systems and the incomer meter is easily visible in Figure 39. Due to this error, it was assumed that the sub-systems meters were not accurate, and that normalisation may improve their accuracy and bring their measurements closer to the truth.

The next step used the formulas developed in Section 0 to normalise the sub-systems to the incomer meter.

Step 6: Normalise data

The following normalisation calculations were done according to Equation 6 from Section 0. The average difference between the incomer meter and the sub-systems was calculated on a daily basis, and scaled so that it could be added to every half-hourly data point.

The resulting data is presented in Table 14.

Table 14: Mine β normalised data breakdown

Description	Raw energy usage (kWh)	Adjustment (kWh)	Normalised energy usage (kWh)
Incomer	8 203 306	-	8 203 306
Compressed air	5 259 941	276 623	5 536 564
Hoisting	1 066 752	56 483	1 123 235
Hostel	500 967	26 184	527 151
Pumping	810 820	42 845	853 665
Surface	154 547	8 144	162 691
Sum of sub-systems	7 793 026	410 279	8 203 306

In Table 14, the adjustment and how it affected the overall energy usage of each sub-system is shown. The normalisation was successful as the sub-systems now added up to the energy usage of the incomer meter. The normalised results are visualised in Figure 40.

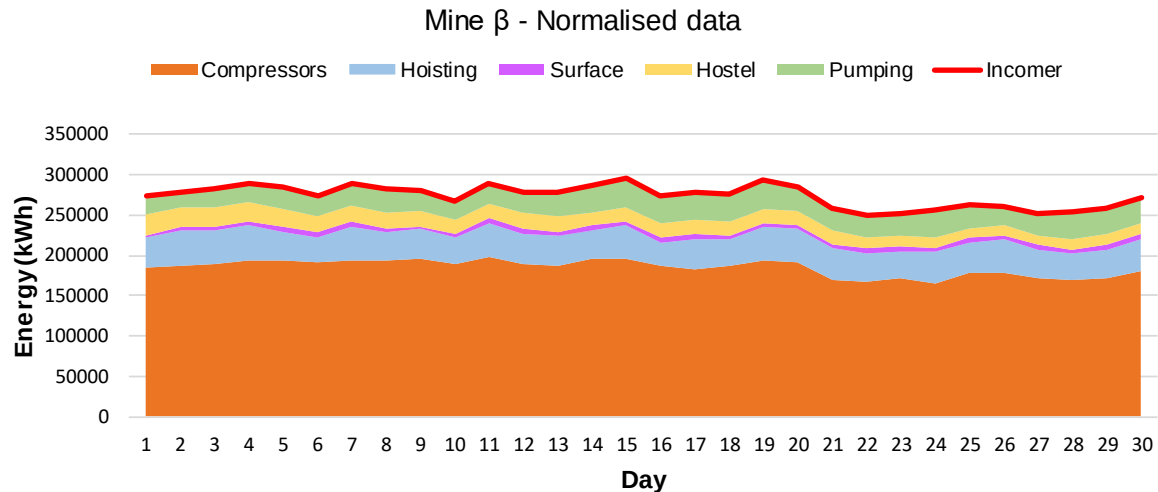


Figure 40: Mine β normalised data

Figure 40 illustrates the effect of the normalisation over the 30-day data period selected for this study. The normalised sub-system data now added up to the incomer on a daily basis.

Step 7: Evaluate resulting data

Before the normalised data could replace the raw data collected from site, it had to be evaluated. The true readings of the data could not be obtained without additional capital expenditure. Fortunately, their installed capacities were obtained. This could be used as a rough measure to ensure that the data had not been adjusted to outside its expected operational boundaries.

As with the common data error check in Section 0, the compressed air system will be used to demonstrate this step. All other sub-systems were also evaluated and are available in Appendix C. Figure 41 shows the normalised compressed air data compared to the rated capacity of the compressors.

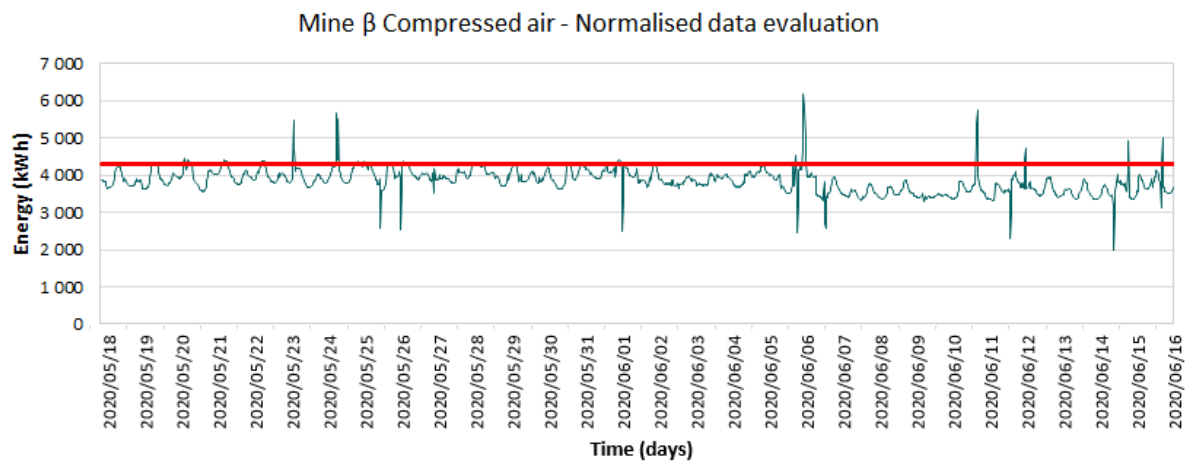


Figure 41: Mine β compressed air normalised data evaluation

From the figure, it can be seen that the compressors were mostly operating as they are expected to, and were not exceeding the boundaries for sustained periods of time. The same was found for the pumping and hoisting sub-systems, where the operation according to the normalised data was still well within the expected range.

Effectively, this normalisation procedure had now reduced the error on the system as a whole from 5% to 0.3%. This was a significant improvement in accuracy. The goal of the method section to improve the quality of the data had thus been met. Though the accuracy of each sub-system was still not verified, the entire system had been brought closer to its true measurements. This is especially useful for budgeting purposes to ensure that day-to-day measurements of usage add up to what is billed.

If this data was used for budgeting, the uncertainty of 410 279 kWh would cost about R 390 000 per month, or R 4.68 million per annum². All additional visualisations from this method can be found in Appendix C.

3.4 Data visualisation: Case study 3

Introduction

This section features a compressor cluster on a South African platinum mine. This mine will be referred to as Mine A. The method developed in Section 2.3 was applied for this case study. The pressure setpoint of these compressors was lowered for non-peak periods, and an increased energy efficiency was expected.

² Assuming an effective tariff of 95c/kWh.

The goal of the method is to create visualisations to improve the data that the mine already has available. This can then be used to evaluate system performance and achieve long-term savings.

Identify and collect

The goal of the system is to provide compressed air to a system of five mine shafts where it is used for various mining applications. This system was selected due to its high power consumption and constant use.

With the goal of the system known, the specifications of the system needed to be defined. This provided insight into which parameters to include in the performance evaluation. The layout of the system can be seen in Figure 42. The compressed air system on Mine A consists of nine compressors. Six of these are located in Compressor house 1 (2 x 1 MW, 1 x 4 MW, 3 x 5.1 MW), with the remaining three located in Compressor house 2 (2 x 4 MW, 1 x 5.1 MW). There is a pressure meter (indicated on the figure in red), flow meter (in yellow), and a power meter on every compressor.

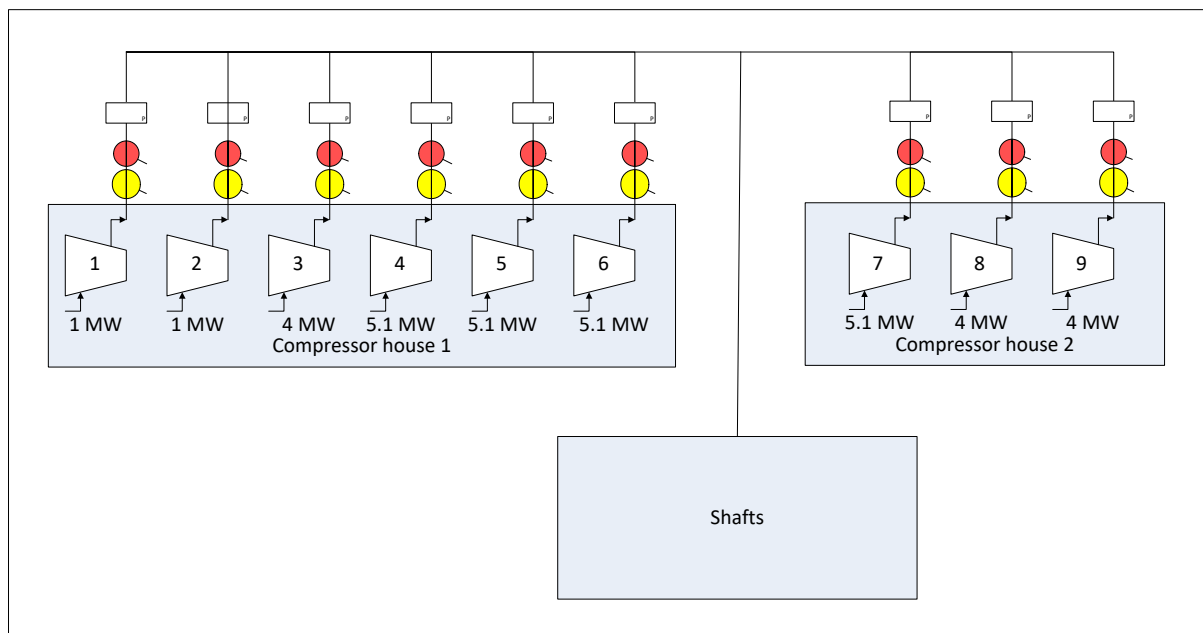


Figure 42: Simplified Mine A compressed air system layout

This study focussed on the four 5.1 MW compressors located on this mine, i.e. Compressors 4, 5, 6, and 7. These compressors were selected as they are the largest, and thus consume

the most power. Gaining insights on these systems could enable users to evaluate their performance and highlight opportunities for energy efficiency.

Next, the KPIs of the system had to be identified. The performance of compressors is generally indicated by the pressure and flow they generate. This can be combined into a fluid power which is evaluated against energy consumption to evaluate performance. Using these and other available data will give a good indication of how the compressors are performing.

Theoretically, the following data should be available from compressed air systems: volumetric flowrate, pressure, power consumption, and blow off. All four of the required measurements were available for each compressor. The data was available from the historian database as daily averages. The collected data should now be prepared and analysed to ensure that it is usable and of high quality.

Common data error check

For data to be visualised, it has to be in a usable format and error free. Four steps are used to get the data to this point. Firstly, the relevant data identified in the first phase is prepared. Thereafter tests are performed to identify possible errors in the data. Identified errors must be mitigated, after which the data should again be evaluated for quality.

As this case study required a calculation with the data, single raw variables were checked first. Once they were analysed for quality, the calculations were performed, and the calculated values were then quality-checked.

Daily data from the mine is available for a period of two years. The frequency of the available data (daily intervals) is sufficient due to the constant nature of operation. A higher frequency is not required. This investigation was done on a daily data interval. All the data was obtained from a single source. Standardising the format to make the data usable was thus not necessary. The obtained data was consolidated to a single sheet for easy data analysis.

Data analysis was performed on all the variables to ensure high-quality data. If compressors were not operated for the full 24-hour period, the values are not representative of operation. To mitigate these effects, only days when the compressor was operating for 24 hours were included in the performance evaluation.

Data quality for the single variables was checked first. The following figures show the flowrate through Compressor 6 before (Figure 43) and after (Figure 44) data preparation

over the two year period for which data was collected. The steps taken to analyse the data will be discussed following the figures.

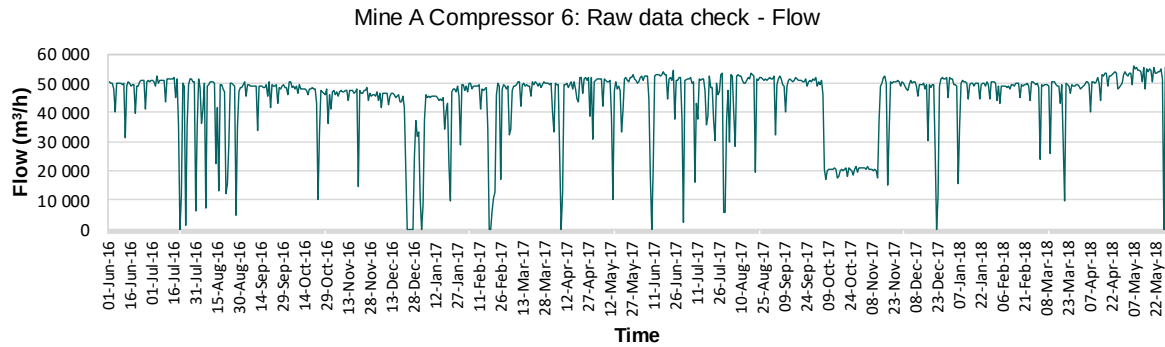


Figure 43: Mine A Compressor 6 - Raw flow data error check

Figure 43 shows the flow through Compressor 6 before any data analysis. Several drops in flowrate were observed over the timeline. These instances were probably due to the compressor not operating for a portion of those days. Such data points could be removed as they were not useful in determining efficient operation. A large drop in flow over a significant amount of time in the second half of the timeline was observed. This was investigated and will be discussed.

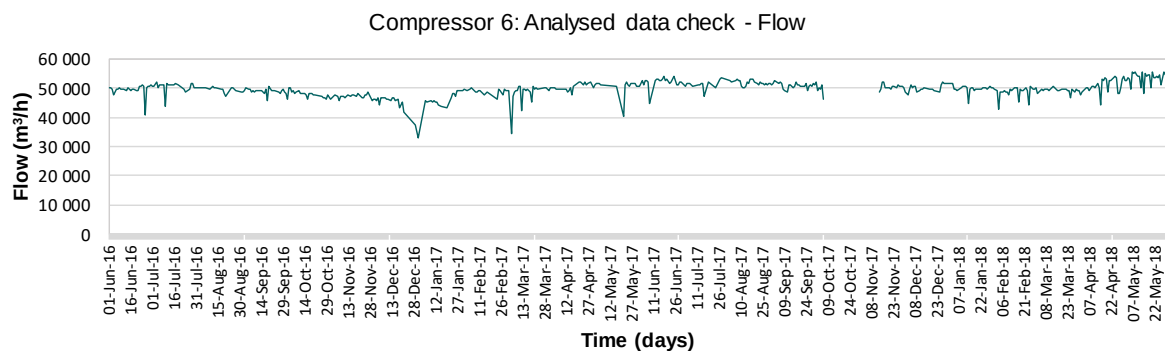


Figure 44: Mine A Compressor 6 - Analysed flow data check

In Figure 44, the effect of the data error checks and mitigation is clearly visible. All questionable data had been removed. The checks and mitigations are explained step by step.

- *Check for missing data*

For certain days, pressure data was unavailable. These days correspond with days when the status and energy input was 0. The system apparently does not record pressure data when the compressor is off. This is possibly due to the meter being on the same power line as the compressor.

- *Missing data mitigation*

A few of the days with missing pressure data could be discarded, as discussed in Section 0 of this study. Missing data for when the compressor was not operating was excluded from the dataset. The remaining points were included in the analysis.

- *Check for stuck-at errors*

No stuck data was noticed within the dataset.

- *Check for out-of-bounds errors*

One of the most accessible boundaries to check is to compare the power consumption against rated power. The compressors used for this investigation are rated 5.1 MW. As the measurements provided are in kWh, measured daily, this had to be converted. The maximum power usage that can be expected from this compressor is 122 400 kWh (5.1 MW x 24 h). From Figure 45, it can be seen that the power used by the compressor exceeded its rating. Meters used on compressors are expected to have up to a 2% error, as per contract with the metering company. The power data was, therefore, within expected bounds, and no mitigation was necessary.

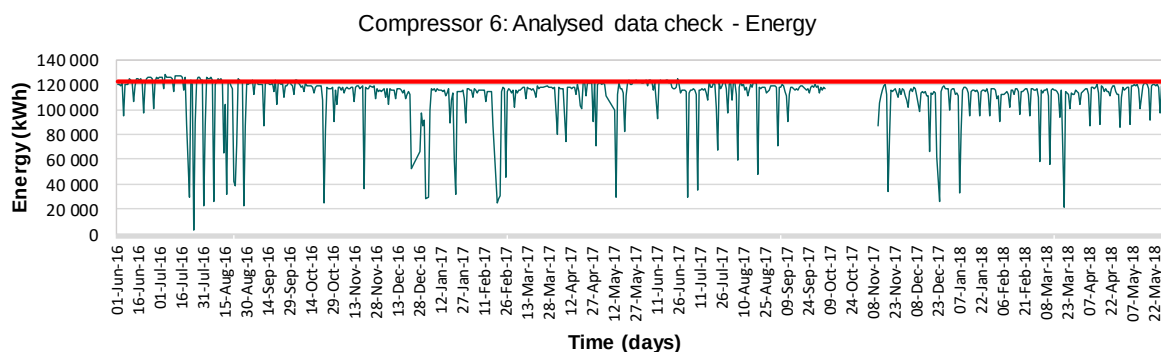


Figure 45: Compressor 6 - Analysed energy data

- *Check for abrupt errors*

A clear drop in flowrate was observed for the second year of this case study, for about a month, as can be seen in Figure 43. A reduced flowrate is possible but would correspond with low energy and pressure. The flow was plotted against these variables in Figure 46 to confirm the accuracy of this data. No other abrupt errors were found.

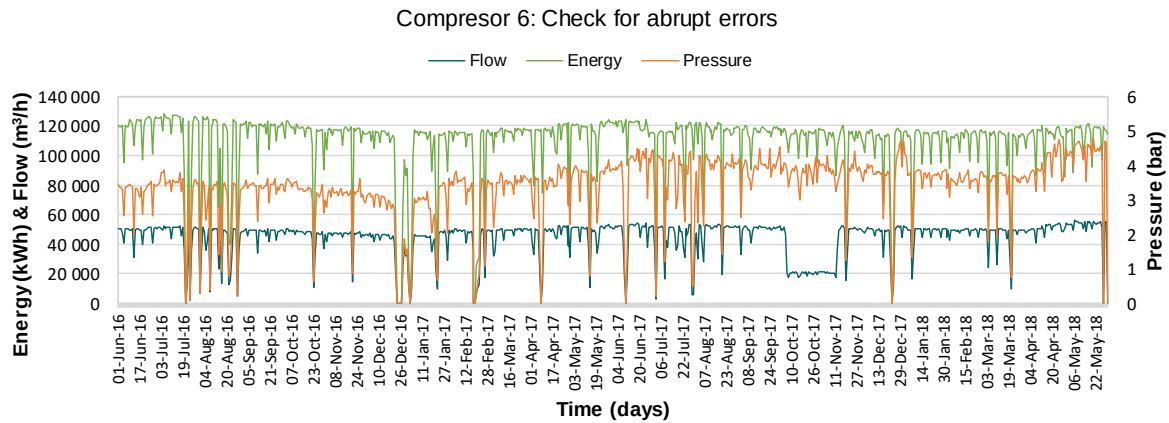


Figure 46: Check for abrupt errors

- *Abrupt error mitigation*

It is clear, from the comparison in Figure 46, that there was no reduction in energy or pressure. Without reduction in energy or pressure, there should be no reduction in flow. The reduced flowrate data and the corresponding pressure and energy data were therefore discarded to protect the integrity of the overall dataset.

Using Green's method for sample size (Equation 1), the remaining data was checked to ensure that the sample was statistically significant. Assuming that the variables energy, flow, and pressure are each predictors, the minimum sample size is 65 data points. Year 1 and Year 2 respectively had 251 and 268 data points remaining out of an initial 365. This sample thus passes the test for statistical significance.

Once the suggested data fixes were implemented, fluid power was calculated using Equation 7 from Section 2.3.1.2.

Data quality checks were repeated on calculated values and no anomalies were found. The data left after analysis was of an acceptable quality and would yield insights if effectively visualised.

Visualise and report

When visualised, the obtained data is intended to convey information regarding the performance of the compressors in relation to their energy usage. To do this, a visualisation that displays relationships should be used.

It was found that scatter plots can be used to effectively display relationships between data (Appendix A). Scatterplots were, therefore, used to visualise the data. This visualisation was displayed digitally or printed in colour. This visualisation was developed to use colour to distinguish between the two time periods in this case study. All visualisations for this study were done in MS Excel to maintain simplicity and accessibility.

The analysed data for two financial years was compared for all four compressors. Figure 47 compares the two years' performance for Compressor 6. All results for the other compressors can be found in Appendix C. Energy in kWh is provided on the y-axis, and the calculated fluid power in kW on the x-axis. This visualised the relationship between energy used and fluid power achieved.

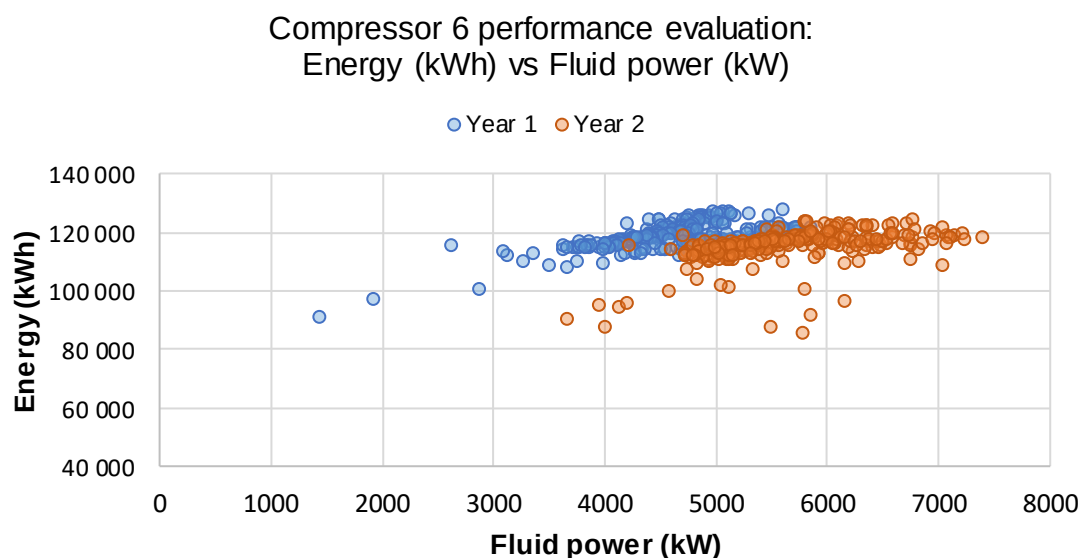


Figure 47: Compressor 6 performance evaluation visualisation

From Figure 47, a clear shift can be observed from Year 1 (blue) to Year 2 (orange). In Year 1, the maximum achieved fluid power was approximately 6 000 kW. In Year 2, this was improved upon, as the maximum output was approximately 7 500 kW. More fluid power was produced by the compressor with the same, or slightly lower, energy input. This indicates an improvement in the compressor performance in Year 2. If operation can be maintained as in Year 2, less energy will be required to maintain pressure on the plant.

This visualisation was presented to a focus group in the form of a questionnaire using the visualisation effectiveness checklist developed in Section 0. Each participant was asked to complete the checklist and make a conclusion regarding the performance of the system with the use of this visualisation. The outcome of this questionnaire will be discussed in Section 3.6.

3.5 Data visualisation: Case study 4

Introduction

This case study focussed on a fridge plant cluster on a South African gold mine that is referred to as Mine B. The cluster consists of four fridge plants and forms part of a larger refrigeration system.

The data from the fridge plants was used to demonstrate the method developed in Section 2.3. The goal of this method is to create visualisation that will provide insight from available data, thereby elevating the available data from mines. This insight could then be used to achieve energy savings and focus on sustaining long-term savings.

Identify and collect

The goal of the refrigeration system of Mine B is to cool down water coming from the underground levels of the mine. One of the fridge plants is a newer model and was expected to be more efficient than its counterparts.

Each of the four fridge plants in this cluster contains a 2 100 kW compressor. The compressor is responsible for the bulk of the power consumption of the fridge plant. Each plant also features several auxiliary systems, including an evaporator pump, condenser pump, and a condenser fan.

Figure 48 illustrates the layout of the mine refrigeration system used in Case Study 4. Each fridge plant has a power meter, a flow meter (shown in yellow), and two thermometers (green) to determine the temperature of the water entering and exiting the fridge plant. Hot

water from underground is fed to the fridge plants for cooling. The cooled water is then used in the bulk air coolers (BACs), as well as being sent underground.

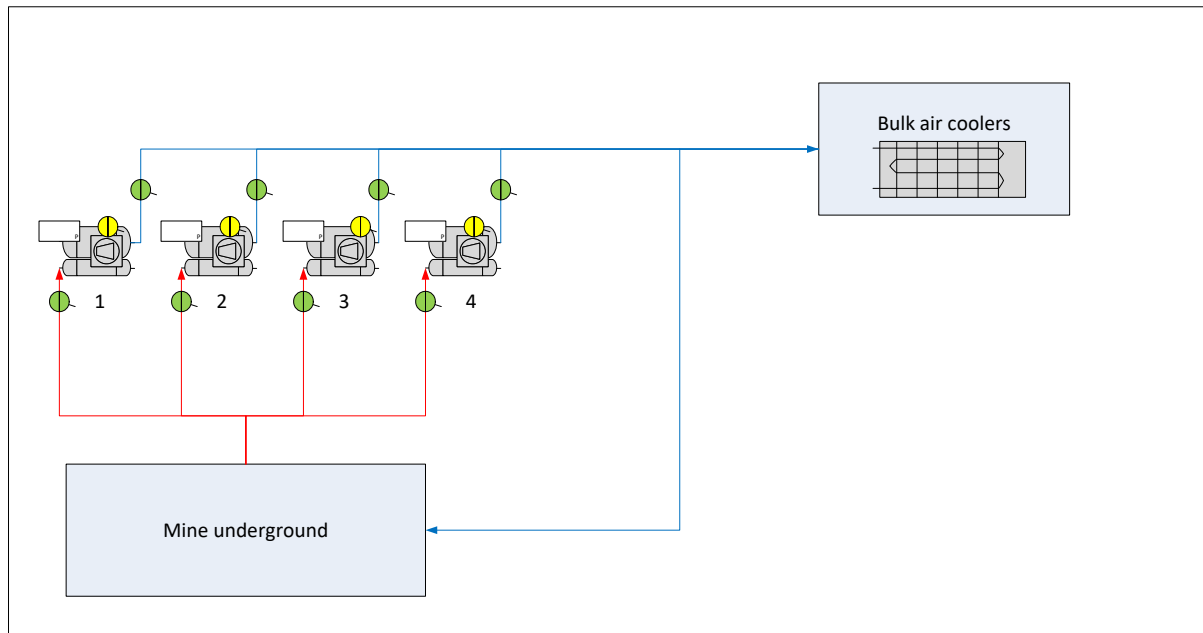


Figure 48: Simplified layout of mine refrigeration system

The performance of the fridge plant is determined by the cooling it produces according to Equation 8 ($Q = mC_p\Delta T$), the value of the water mass flow through the fridge plant, and the change in temperature. Its KPIs are thus mass flow and temperature, as well as power consumed.

The following measurements relating to the refrigeration system are available from the mine:

- main power (compressor);
- auxiliary power;
- evaporator: flow, temperature in, temperature out;
- condenser: flow, temperature in, temperature out;
- status;
- ambient temperature;
- dam temperatures;
- underground water temperature and
- BAC measurements.

Of these measurements, the following were deemed relevant:

- main power (compressor),
- evaporator mass flow, and
- evaporator inlet and outlet temperatures.

The data for these variables is available for two years. The data was obtained from several sources and needed to be assessed before a final dataset could be compiled.

Common data error check

Data is available at daily intervals for a two-year period. Data for most of the identified KPIs is available. The unavailable data will be discussed during the missing data checks.

While most variables were only available from one source, some were available from more than one. The datasets were plotted together, and no discrepancies were found between the sources. The most complete dataset was selected. All the selected datasets were then combined into a single spreadsheet for ease of use.

The following figures show the power consumption in kW over the two-year period for which data was collected for Fridge plant 1. The two plots represent the data before the data analysis phase (Figure 49) and after the data analysis phase (Figure 50). All changes made to the dataset are discussed in the following paragraphs.

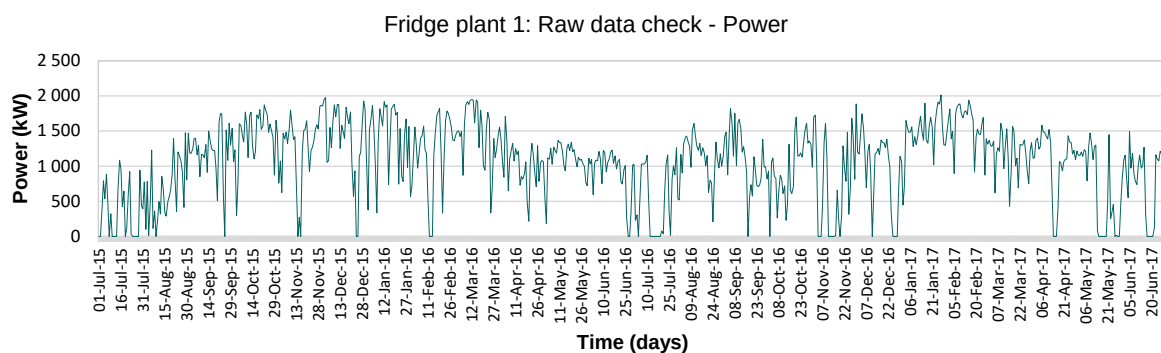


Figure 49: Fridge plant 1 - Raw power data error check

The power data displayed in Figure 49 varies greatly over time. There were several instances where no power was consumed by the fridge plant. This should coincide with periods where its status is 0. The fridge plant was found to be in operation for most of the two-year investigation period.

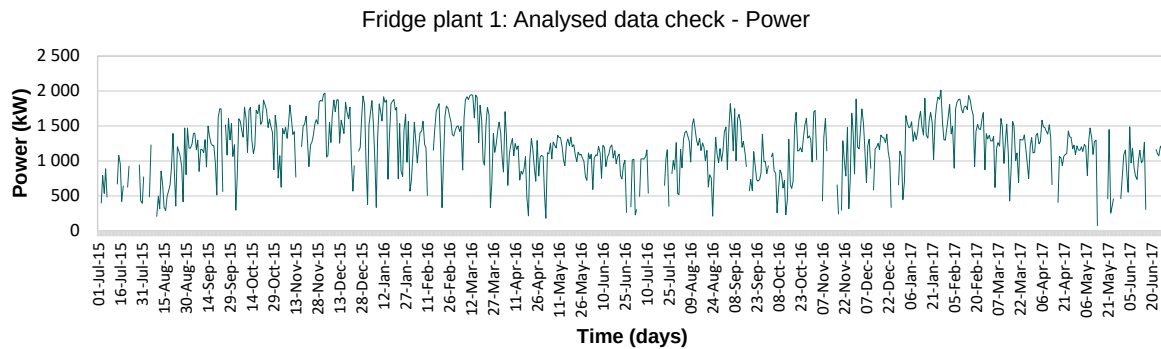


Figure 50: Fridge plant 1 - Analysed power data

After analysis, the data from Figure 50 had changed slightly. The periods of no power had been removed as performance evaluation was not needed while the plant was not operational.

A data quality check was done on single variables as described in Section 2.3 of this document. As in Figure 49 and Figure 50, a single variable quality check was done on all the available variables.

- *Check for missing data*

Data was plotted and manually checked for missing data. All four fridge plants have had three consecutive days of missing data over the same period. No evaporator inlet temperature data was available for Fridge plant 4. Apart from this, no further data was missing.

- *Missing data mitigation*

Ideally, according to the method to mitigate missing data in Section 0, missing data should be discarded. The three days of missing data were, therefore, left out of this investigation. Simple imputation can be used to approximate the value of the evaporator inlet temperature for Fridge plant 4. As can be seen in the layout in Figure 48, the hot water from underground is fed from a single source. The temperature was assumed to be similar between the fridge plants. In Figure 51, the evaporator inlet temperatures to each fridge plant were compared to validate this assumption.

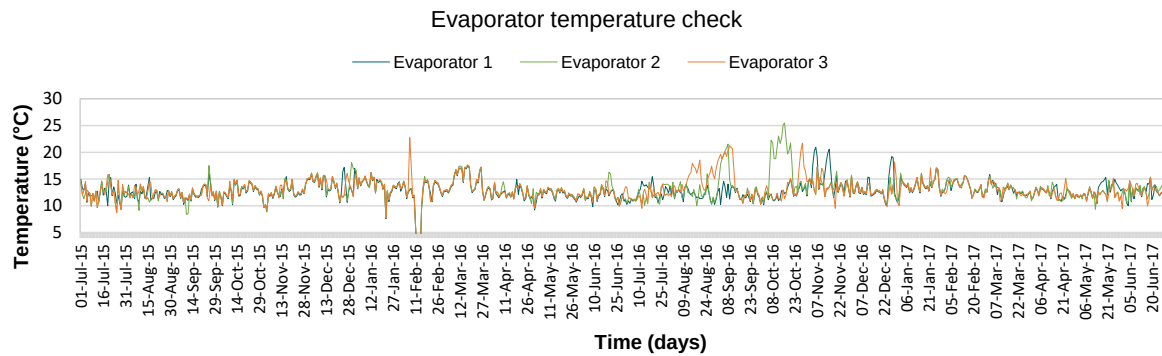


Figure 51: Evaporator temperature check

It is clear from the figure that, for most of the evaluation period, the temperatures were uniform, and their average could be used to approximate the inlet temperature of Evaporator 4. Some discrepancies exist in the data; however, they will be addressed in the abrupt error section.

- *Check for stuck-at errors*

Data was plotted and manually checked for stuck-at errors. The mass flow data remained relatively constant, but showed some variation. This is to be expected during constant operation.

- *Stuck-at error mitigation*

Stuck data can be avoided by not using data from when the plant is non-operational. As the received data for this case study was daily averages, the status value could be anywhere between 0 and 1. From the variance in the power data seen in Figure 50, fridge plants are not operated constantly. Using data only from when the fridge plants were operating twenty-four hours of the day would lead to a severely reduced dataset. Therefore, data for when the status was less than 0.1 was discarded for this investigation. Discarding values while the plant was non-operational did not bias the dataset.

- *Check for out-of-bounds errors*

Data was plotted to identify possible out-of-bounds errors. The easiest of these errors to quantify was the maximum power of the fridge plant. It was expected that the maximum power consumed by a single fridge plant would not exceed 2 100 kW by more than 2%. No power measurements exceeded this boundary.

As the system operates with liquid water, temperatures could also be checked for boundaries. No temperatures below 0°C or above 100°C were expected within this fridge plant as liquid water at atmospheric pressure is used. Aside from the three days of data loss, no out-of-bounds temperatures were found. High temperatures will be addressed in abrupt errors.

- *Check for abrupt errors*

A sanity check was performed to ensure that all data regarding the fridge plants makes sense. Since the fridge plant cools the water, the inlet temperature was expected to be higher than the outlet temperature. Instances where this was not the case were discarded.

After the logic test data was plotted over time, no further outliers were detected. Once data had been plotted to show relationships between data, outliers should become more apparent. Green's method for sample size (Equation 1) was used with power, flow, temperature in, and temperature out chosen as parameters. The minimum sample size for statistical significance according to this was 70 data points. Year 1 of this study was left with 335 data points after analysis, and Year 2 with 317. Both were thus large enough for the study to continue.

The cooling duty was calculated with Equation 2 once all the data mitigations had been made. All data checks were repeated on the calculated values and no further issues were encountered. These checks and their corresponding visualisations are available in Appendix C.

A final dataset was compiled containing the date, power consumption of each fridge plant, and the cooling duty produced. This dataset could now be used to create insightful visualisations that could be used to evaluate plant performance.

Visualise and report

Once analysed for quality, the data could now be visualised. The visualisation must be able to display the cooling duty of the fridge plant, the power consumed by it, and the relationship between the two variables. This would allow individual fridge plants to be compared year on year, and different plants to be compared with each other. According to the properties of visualisations, discussed in Section 0, a scatterplot can be used for this purpose.

This visualisation were displayed digitally or printed in colour. Colour could, therefore, be used to differentiate between datasets. This visualisation was done in MS Excel. Fridge plant 1 continued to be used as an example for these visualisations. It was, thereafter, compared

to the other three fridge plants on the mine so that its performance could be evaluated within context. Results for the other fridge plants are presented in Appendix C.

Figure 52 presents a visualisation intended to display the relationship between the power in kW consumed by the fridge plant on the y-axis, and the cooling duty in kW produced by the fridge plant on the x-axis. Two years of the fridge plant performance are compared to determine whether the performance changed over time.

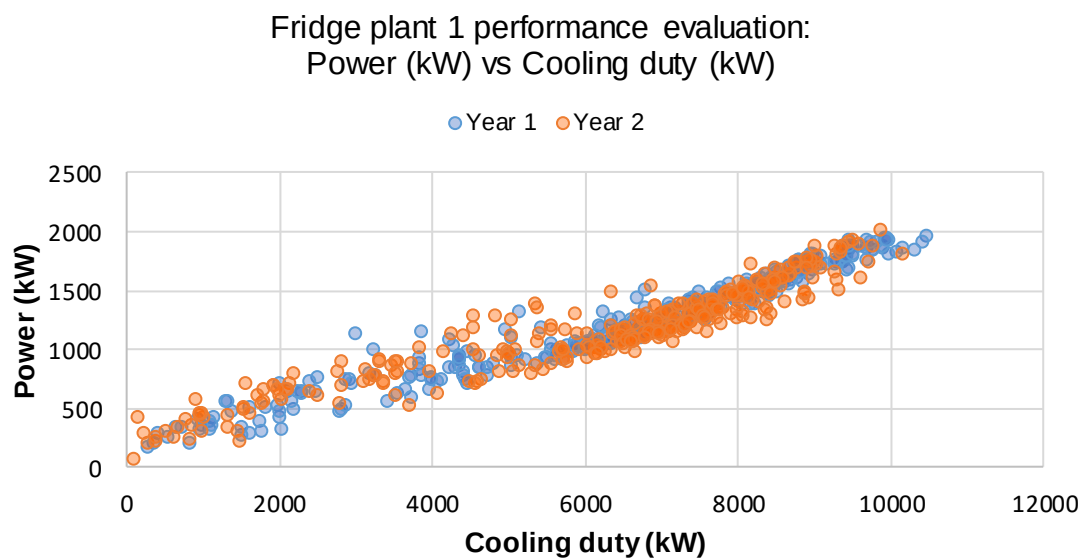


Figure 52: Fridge plant 1 performance evaluation visualisation

Figure 52 indicates that Fridge plant 1 had a slightly lower cooling duty in Year 2 (orange) than in Year 1 (blue). The maximum power usage was fairly constant throughout the two years. The performance of all four fridge plants was also compared to determine whether any one was more efficient.

Figure 53 presents a comparison of Fridge plants 1, 2, 3, and 4 for the second year of the evaluation. This visualisation used the same variables and relationship as in Figure 52 to compare the performance of the different fridge plants.

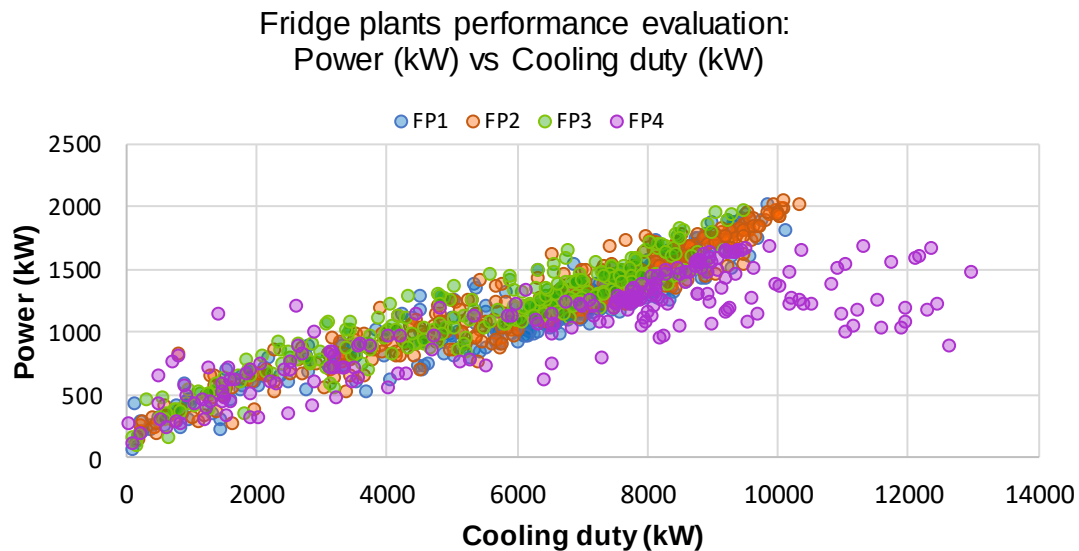


Figure 53: All fridge plants year 2 performance evaluation visualisation

From Figure 53 it can be seen that Fridge plants 1 (blue), 2 (orange), and 3 (green) performed very similarly. The newly installed Fridge plant 4 (purple) was able to produce a much higher cooling duty than any of the other fridge plants, as was expected. The data from Fridge plant 4 might look like outliers, but as the data had been assessed to remove common errors, the result could be trusted.

This fridge plant was thus more efficient than the other three. It would be beneficial for the mine to install additional new fridge plants, as the potential for sustained savings can be significant.

This visualisation was presented to a focus group in the form of a questionnaire using the visualisation effectiveness checklist developed in Section 0 of this study. Each participant was asked to complete the checklist and make a conclusion regarding the performance of the system with the use of this visual. The outcome of this questionnaire will be discussed in Section 3.6.

3.6 Discussion and validation of results

Preamble

This section will present a discussion of each of the case studies presented in Chapter 3. A validation of results will also be presented for the results of the case studies.

The data normalisation case studies were verified through an article, written by the author of this dissertation [59], which explains how the method was successfully applied to multiple mines with significant improvement to budget allocation achieved.

As discussed in the previous sections, a questionnaire was used to evaluate and validate the final results obtained in Case studies 3 and 4. A group of eight engineers took part in this evaluation. Their fields of expertise included measurement and verification, mining operations, energy efficiency projects, operational maintenance, and strategic planning and optimisation.

The group was varied in experience, and held positions in management, daily operations, project implementation, opportunity investigation, and maintenance. The eight completed questionnaires can be found in Appendix D.

Data normalisation: discussion of Case study 1

The first normalisation case study was performed on a small gold mining operation. The mine's largest sub-system is pumping. None of the other sub-systems of the mine run at capacity. This has a negative effect on the measurements available from the mine, as the meters had been made to measure larger quantities.

The mine metering system was investigated, and analysed for quality. All the collected data passed the common data error check. The incomer meter was validated using the Eskom POD data, as none of the mine's meters are calibrated.

The mine sub-systems were compared to the incomer and a 4.4% difference was found. The normalisation calculation was done so that the sub-systems would add up to the mine incomer.

The results obtained from this case study were successful. It was noted that the errors on the underused sub-systems might be larger relative to those on the pumping sub-system, as the installed meters were not equipped to measure such small values. Despite this the method could still mitigate R984 000 of uncertainty per year through improved budgets.

Data normalisation: discussion of Case study 2

The second normalisation case study was performed with data from a medium-sized gold mine that forms part of a cluster of mines. The mine relies on some of the other mines for refrigeration and ventilation, but has a fan sub-system that is used for its own ventilation during summer.

After investigating the metering system and collecting the available data, the data was put through the common data error check that was developed. No errors were detected in the data.

The Eskom POD was used to validate the data of the mine incomer meter. This could be done as there was a difference of only 0.3% between the two measurements.

The sub-systems were then compared to the newly verified incomer meter. A 5.0% discrepancy was found between the two, which should be zero if all data had been accurate.

The normalisation method was applied to the data in order to mitigate the error that was found. The results of this method were evaluated using the rated capacities of the sub-systems. All results were acceptable and within range.

Should this method be applied on a mine, the mine personnel would be able to be aware of the actual energy used by each sub-system on the mine. This allows for realistic usage projections and budgeting.

An adaptation of the data normalisation method developed in this study was applied to a section of a gold mining group and reported in a peer reviewed article [59]. The method reduced the error on budgeting within this mining group by R55 million in one year. This method thus improved the energy data available to the mine and can result in long-term savings.

Data visualisation: discussion of Case study 3

The results obtained from the visualisation effectiveness checklist are summarised in Table 15. The reviewers were presented with the compressor performance evaluation visualisation shown in Figure 47 and the visualisation effectiveness checklist developed in Section 0, and were prompted to evaluate and comment on the performance of the pictured system.

Table 15: Visualisation evaluation questionnaire results - Case study 3

Case study 3: Questionnaire results		
Question	Yes	No
Does the visualisation convey the necessary information?	75%	25%
Is the visual in its simplest form?	75%	25%
Is an appropriate colour scheme used?	100%	0%
Does the visual encourage comparison?	100%	0%
Does the graph choice suit the information to be conveyed?	100%	0%
Is the graph clear?	88%	12%
Are the legends, titles and labels clear and self-explanatory?	75%	25%
Are the legends, titles and labels well-positioned?	100%	0%

The majority of reviewers found that the visualisations met the desired criteria. The reviewers' main concerns with the visualisations resulting from Case Study 3 were that the visual did not convey all the necessary information, that the visual was not in its simplest form, and that the legends and titles were not self-explanatory. One reviewer also felt that the graph was not clear enough. This can be addressed by using lower frequency data. They were also unclear about how the setpoint change contributed to the change and felt that it could have been added to the visualisation. A report could be included with the visualisation explaining how the intervention brought about the observed change in operation.

One reviewer felt a daily efficiency over time graph may have communicated the change in the system better. As stated in Chapter 1, many studies have already interpreted short-term data with observational visualisation. The intention of this study was to visualise long-term performance for evaluation.

The reviewers felt that the graph did communicate the fact that Compressor 6 performed much better in Year 2 than in Year 1. As the main objective of this method was to produce a visualisation that could be used for performance evaluation, this visualisation passed the evaluation.

Data visualisation: discussion of Case study 4

The results obtained from the visualisation effectiveness checklist are summarised in Table 16. The reviewers were presented with visualisation of the fridge plants performance evaluation as shown in Figure 53 and the visualisation effectiveness checklist as developed in Section 0, and were asked to evaluate and comment on the performance of the systems in the provided visualisation.

Table 16: Visualisation evaluation questionnaire results - Case study 2

Case study 4: Questionnaire results		
Question	Yes	No
Does the visualisation convey the necessary information?	88%	12%
Is the visual in its simplest form?	63%	37%
Is an appropriate colour scheme used?	88%	12%
Does the visual encourage comparison?	75%	37%
Does the graph choice suit the information to be conveyed?	50%	50%
Is the graph clear?	63%	37%
Are the legends, titles and labels clear and self-explanatory?	88%	12%
Are the legends, titles and labels well-positioned?	100%	0%

The majority of reviewers found that the visualisations met the desired criteria. The reviewers' main concern with the resulting visualisation from Case Study 4 was the choice of graph. They felt that the graph was crowded, unclear, and not in its simplest form. More than one reviewer felt that the results could be better visualised by displaying the coefficient of performance (COP) of each fridge plant, as opposed to the relationship. This can be obtained by dividing the cooling duty through the power consumed, as illustrated in Equation 9 [96]:

$$COP = \frac{Q}{P}$$

Equation 9: Coefficient of performance equation

Where:

Q = cooling duty in kW, and

P = power in kW.

The COP provides a measure of how much cooling was produced per unit of power, and thus a higher COP indicates better performance. The noted issues with the graph also caused issues in terms of comparing results. This will be addressed by reconstructing the visualisation to meet all the required outcomes.

Taking these opinions and advice into account, the graph in Figure 54 was constructed, which should better visualise the difference in operation from Fridge plant 4 compared to the other three fridge plants. It displays the occurrences of the COP of each of the fridge plants for Year 2 of the investigation.

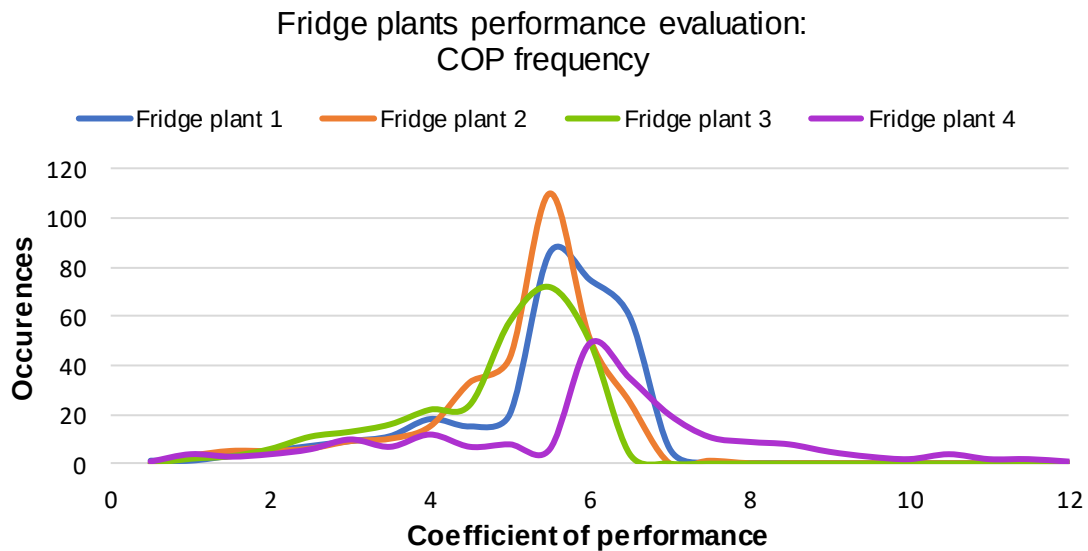


Figure 54: Fridge plants performance evaluation using COP

In Figure 54, the COP for four fridge plants is displayed. Fridge plant 1 (blue) had a relatively high COP and was performing efficiently. Fridge plants 2 (orange) and 3 (green) had the same COP, but Fridge plant 2 was being operated more frequently. Fridge plant 4 (purple) had the highest coefficient of performance, and thus produced the most cooling per unit of power consumed. Additionally, it can be seen that Fridge plant 4 is underused as its total occurrences were much lower than that of the other fridge plants.

From this visualisation, plant personnel will be able to evaluate the performance of each fridge plant and make a decision regarding the operation of these systems. This may lead to the system being more energy efficient.

3.7 Conclusion

Four case studies were presented in this chapter. They were used to test the two sections of the method developed in Chapter 2.

Case studies 1 and 2 were used to test the method developed in Section 2.2. The goal of this method is to improve the energy-related data available from South African mines. This improved data can then be used to evaluate the performance of systems. This can lead to energy efficiency and can be maintained in the long term.

The method section started with a metering system investigation that collected information on the system for which the data was being improved. This was followed by a common data

error check. Common error types on mines were identified from literature and were identified and mitigated. Very few errors were found for the first two case studies.

The final step of the first section of the method was to check whether the data adds up to the check meter, and to normalise it when it does not. In both Case study 1 and Case study 2, the data did not add up. The normalisation calculations were done on both systems, and the data was evaluated.

The evaluation of Case study 1 found that some of the meters on Mine α might be faultier than others. This is due to them having meters that are rated for usages beyond what is observed on the mine. Regardless of this, the accuracy of the data on the mine was still improved significantly.

The evaluation of Case study 2 found all resulting data to be within the expected range, as determined by the ratings of the equipment on the mine. Validation for this method section was presented in the form of a peer reviewed conference paper by the author [59]. This method succeeded in improving energy data that is available from mines and resulted in a cost avoidance of R55 million.

Case studies 3 and 4 applied the method developed in Section 2.3. Case study 3 was done on a compressor cluster of a South African platinum mine, and Case study 4 on a group of fridge plants on a South African gold mine.

The three phases of the second section of the method were applied to each of these case studies. Relevant data was identified using the questions set out in Phase 1, and subsequently collected. The selected data was then analysed for errors commonly found on mines. Errors were mitigated, resulting in high-quality datasets. This data was then visualised using the steps outlined in Phase 3 of the method section.

The visualisation effectiveness questionnaire developed in Section 0 was used as part of a survey to validate the obtained results. Case study 3 obtained at least 75% “yes” answers for each question, and the performance of the system it represented was correctly evaluated by all participants. Some participants felt that the results from the visualisation did not correlate with the intervention in the system and felt that it warranted further investigation.

Case Study 4 was not received as well, according to the questionnaire, with one category only receiving 50% “yes” answers. The participants’ main concern was the choice of graph, followed by the clarity and simplicity of the visual. In response to this, an additional graph (Figure 54) was added as a supplementary visualisation for Case Study 4. This visual used a

frequency plot to display the coefficient of performance (COP) of each fridge plant. From this, it became clear that the more efficient fridge plants were underused.

Both resulting visualisations could be used to evaluate the performance of the mine systems they represented. Case Study 3 could be directly used to motivate an energy efficiency initiative, and Case Study 4 could lead to an investigation of the effects of operational changes on the efficiency of the system.

4 CONCLUSION AND RECOMMENDATIONS

4.1 Summary of work done

The goal of this study was to improve the quality of the data that is available from South African mines and implement visualisations which can then be used to assess the performance of systems and identify potential for energy efficiency initiatives. This can then be used to achieve long-term energy efficiency.

A need for improved energy-related data to be used for energy efficiency exists within the mining industry of South Africa. This industry collects large amounts of data but does not use the data effectively. The available data contains valuable information that could be used for performance evaluation. Performance evaluation can, in turn, be used to establish and maintain long-term energy savings in the mining industry.

It was found that data available on mines is often not of usable quality. Since high quality data must be used to achieve high quality results, the quality of the available data should be assessed and improved before it is put to use.

Visualisation was selected as the method to gain insights and information from data so that the performance of systems can be evaluated. The visualisations resulting from this study are intended to be used to evaluate the performance of systems on mines. This performance evaluation could lead to the identification of opportunities for future energy efficiency projects.

The methodology that was developed for this study has two sections. One focusses on improving the quality of data available from mines, and one focuses on improving how the data is presented.

The first section is broken up into a metering system investigation, a data error check and a data normalisation step. The first phase serves to inform a user of the systems that the investigation will be performed on. This provides important context for the remainder of the study.

The second phase presents common errors found in data from mining environments. Identification and mitigation strategies are given to ensure that the data is of high quality. The third phase presents a seven-step method to improve the accuracy of the data available from mines. This results in data that is accurate and of high quality, and can thus be used to achieve accurate high-quality results.

The second section was developed to provide a step-by-step guide to turn data into information. The method is also presented in three phases. Firstly, the identification and collection of relevant data, then the common data error check as seen in the first method, and finally a phase to visualise and report the collected data.

In the first phase, relevant data is identified through a series of investigative questions, and then subsequently collected. The data should be compiled into a single datasheet to facilitate further phases.

The second phase of the method considers the available data intervals to choose a relevant span for the investigation. The data is thereafter analysed to determine and improve its quality. Several quality indicators were chosen to evaluate the quality of the dataset.

Once the quality of the dataset is confirmed, Phase three can commence. This phase focusses on the visualisation and reporting of the data. Several considerations are provided to guide the user towards the most relevant visualisation. A checklist was provided to evaluate the resulting visualisations for effectiveness.

These three phases combined will turn data into usable information for performance evaluation. These phases were applied to case studies to determine the validity of the steps. The results were circulated in questionnaires to confirm the effectiveness of the resulting visualisations and their ability to communicate system performance.

Two case studies were used to test each section of the methodology. Both method sections delivered satisfactory results, and provided insights into the data of the systems they were applied to. The first method successfully improved the data accuracy of both the mines used as case studies. One study was found to have data that might be less accurate due to the operation of the sub-systems.

For the second section, questionnaires were used to validate the results of the case studies. This was done by proving that the resulting visualisations can be used to evaluate system performance. Suggestions made by the reviewers led to more effective visualisations which can be used to optimise system operation for energy efficiency.

4.2 Conclusion

The objective of this study was to create a method to improve the quality of available data from mines, and to improve the presentation of that data so that more information can be gained from it. The expected results were high-quality and visualisations that can be used for performance assessment and the identification of potential energy efficiency initiatives.

The results from this study, if successful, should be usable to achieve and maintain long-term energy efficiency on South African mines.

The objectives of this study were thus met since a methodology that can improve both the quality and presentation of energy data was created. The combination of the two methods developed in this study was also found to improve energy-related data from mines. This improved data can be applied to achieve long-term energy savings.

4.3 Recommendations for further work

Automate the data normalisation method

Once all the boundaries of the system have been established and the accuracy of the data confirmed, little input is needed in the normalisation process.

The data normalisation and evaluation steps can be automated as long as the check meter remains accurate.

Automate method for continuous performance evaluation:

Frequent performance evaluation is required for a process to operate optimally. This can be ensured by automating the process outlined in this study. Relevant data can be automatically collected by a system and analysed for quality with specialty software. Once visualisation considerations have been made, results can be repeated automatically, and regular performance evaluation reports can be generated. This will allow inefficiencies to be monitored regularly.

If this method is automated, advanced analysis can be used to create a predictive model. This model will be able to identify inefficiencies before they occur [65].

Mitigate metering errors in data:

During this study, some “impossible data” was encountered. This data could be due to faulty meters, poorly specified meters, or a lack of calibration. As mines have multiple financial constraints, the likelihood of these meters being fixed or replaced is low. There is an opportunity to use meters known to be correct to estimate more accurate values for such faulty meters if these cannot be calibrated due to financial constraints [59].

Use specialised visualisation packages:

The visualisations within this study were done on easily-available and widely-used software. While these visualisations are adequate and deliver interpretable results, specialised visualisation software exists that has the ability to create more intricate graphs. These

graphs will lead to better and more professional reports which are better able to convey information.

Expand method to energy-intensive systems beyond the mining industry:

This study focussed on the mining industry, as this industry is energy-intensive and constantly looking for energy efficiency opportunities. This study can also be applied to other industries. Several industries have energy-intensive systems, and similar steps to those outlined in this study can be applied to any such system to evaluate its performance.

Adapt method for other types of energy:

This study focussed solely on the performance evaluation of systems intensive in electrical energy. Mines, however, also consume chemical energy. If chemical energy carriers can be quantified and suitably monitored, this method can be applied to evaluate the performance of systems relying on chemical energy.

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APPENDIX A : DATA VISUALISATION

A.1 Introduction

The role of visualisation in communicating data was discussed in Section 1.4. This section will provide background on available visualisations and their most common applications. This can then be used as a reference point to select visualisations for certain goals.

A.2 Available visualisations

Visualisation, in any form, is intended to convey information to a user [74], [84]. Visualisation is a powerful tool, allowing users to “see the unseen” in data [75]. The type of visualisation used depends on the type of data to be communicated and the intent of the visualisation^{3 4}.

Of the four levels of visualisation identified by Chen and Golan [86], only the first three are typically used for data communication. Disseminative visualisation is used to display data directly. Observational visualisation is more complex, allowing for data exploration. Analytical visualisations are used to identify patterns in data. Beyond these three, there is model-development visualisation, used to create and improve models and algorithms, not to communicate existing data.

Disseminative visualisation is used only to inform. This is usually done by displaying a value, or several values. These visualisations are often accompanied by simple figures to highlight the meaning of the value. Figure 55 provides an example of commonly used disseminative visualisations, used to inform users about data.

³ M. Bediger, “How to Choose the Best Charts for Your Infographic - Venngage.” [Online]. Available: <https://venngage.com/blog/how-to-choose-the-best-charts-for-your-infographic/>. [Accessed: 12-Nov-2018].

⁴ “How to Choose the Right Chart - A Complete Chart Comparison.” [Online]. Available: <https://www.edrawsoft.com/chart/choose-right-chart.php>. [Accessed: 14-Nov-2018].

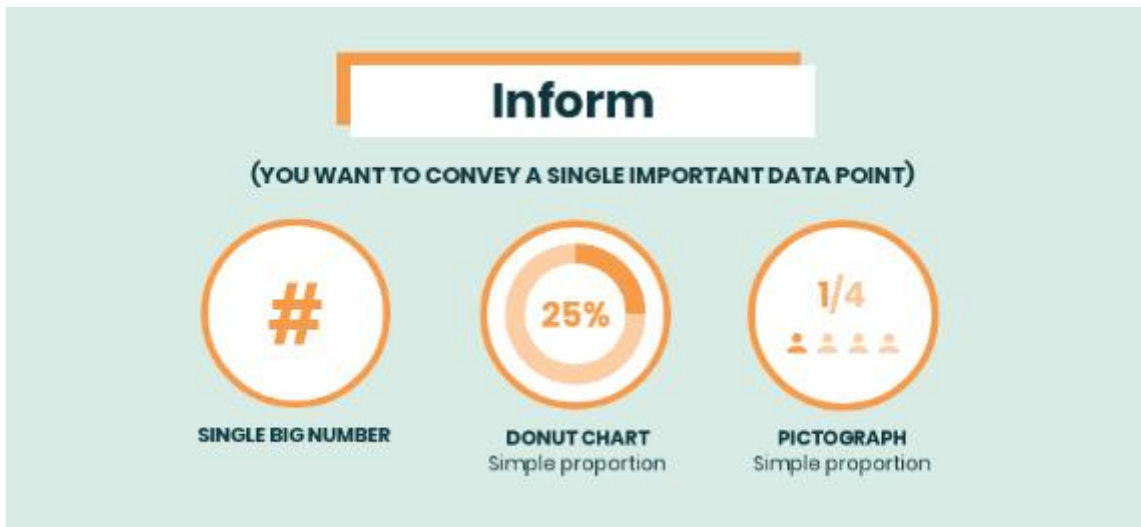


Figure 55: Examples of visualisations used to inform

Observational visualisations can be used for two functions: to compare data, or to show change in data. Bar charts, pie graphs and word clouds are commonly used comparative visualisations. These visualisations may allow a user to investigate the composition of a dataset, and to explore groups within the data. Figure 56 shows several possible visualisations to use when comparing data. It also suggests which data types to use certain visualisations for. A pie chart, for instance, is best used to communicate composition. Bar charts can be used to compare many categories, and bubble charts can be used to compare fewer categories.



Figure 56: Examples of visualisations used to compare

To show change in data, a second variable is added to the visualisation. Change is mostly displayed over time, but can be shown using other variables. Timelines and line graphs are some of the most common visualisations used to communicate change. Figure 57 shows these visualisations, and more, that can be used to show change in data.



Figure 57: Examples of visualisations used to show change

Analytical visualisations are used to allow users to identify patterns and trends in data. This can be done in two ways: by organising data, or by determining the relationship between datasets. Visualisations used to organise, as in Figure 58, are used to show processes or groups present within data. Examples of this are pyramids or flow charts. Figure 58 provides several possibilities, each with the data it is best suited to visualise.

Relationships in visualisation can be used to find correlation between two or more variables, or to show the distribution of a single variable. These visualisations can even be combined with visualisations to show change and to observe how relationships behave over a period of time. Figure 59 provides examples of the most commonly used visualisations to display relationships in data.



Figure 58: Examples of visualisations used to organise data

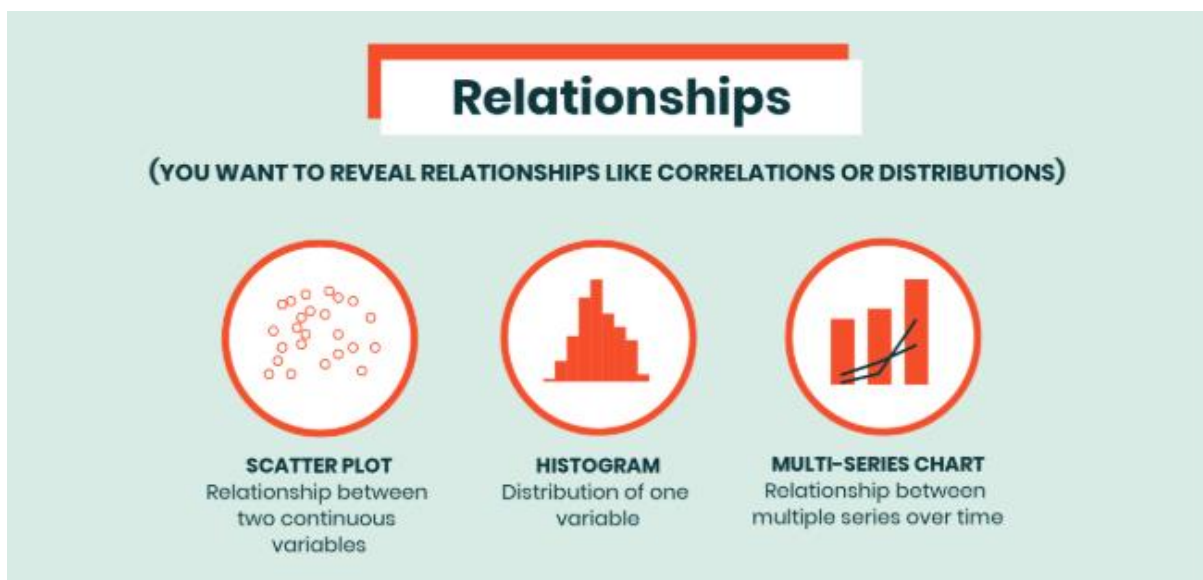


Figure 59: Examples of visualisations used to show relationships between datasets

A.3 Conclusion

Information from data in the form of visualisations can achieve several different goals. Visualisations can be used to inform, to compare, to show change, to organise, and to find relationships within data. This section presented several possible visualisations to be used to reach each of these goals. A visualisation chosen for a specific goal will effectively communicate data to a user.

APPENDIX B : MINE LAYOUTS

Obtaining electrical layouts is a required step of the data quality improvement method as put forth in Section 0. The layout obtained for Mine α is presented in Figure 60. This layout was studied and simplified to create Figure 23 in Section 0.

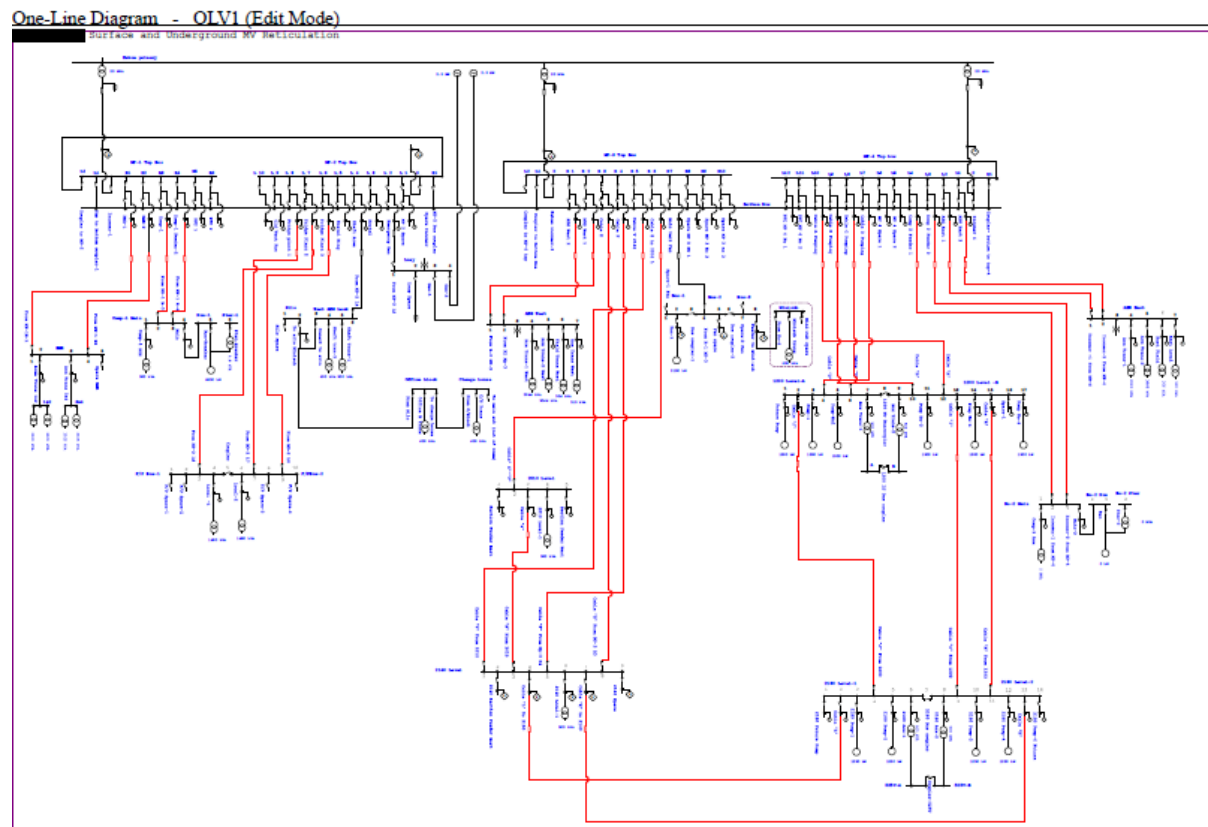


Figure 60: Mine α full electrical layout

The layout obtained for Mine β is presented in Figure 61. This layout was studied and simplified to create Figure 34 in Section 0.

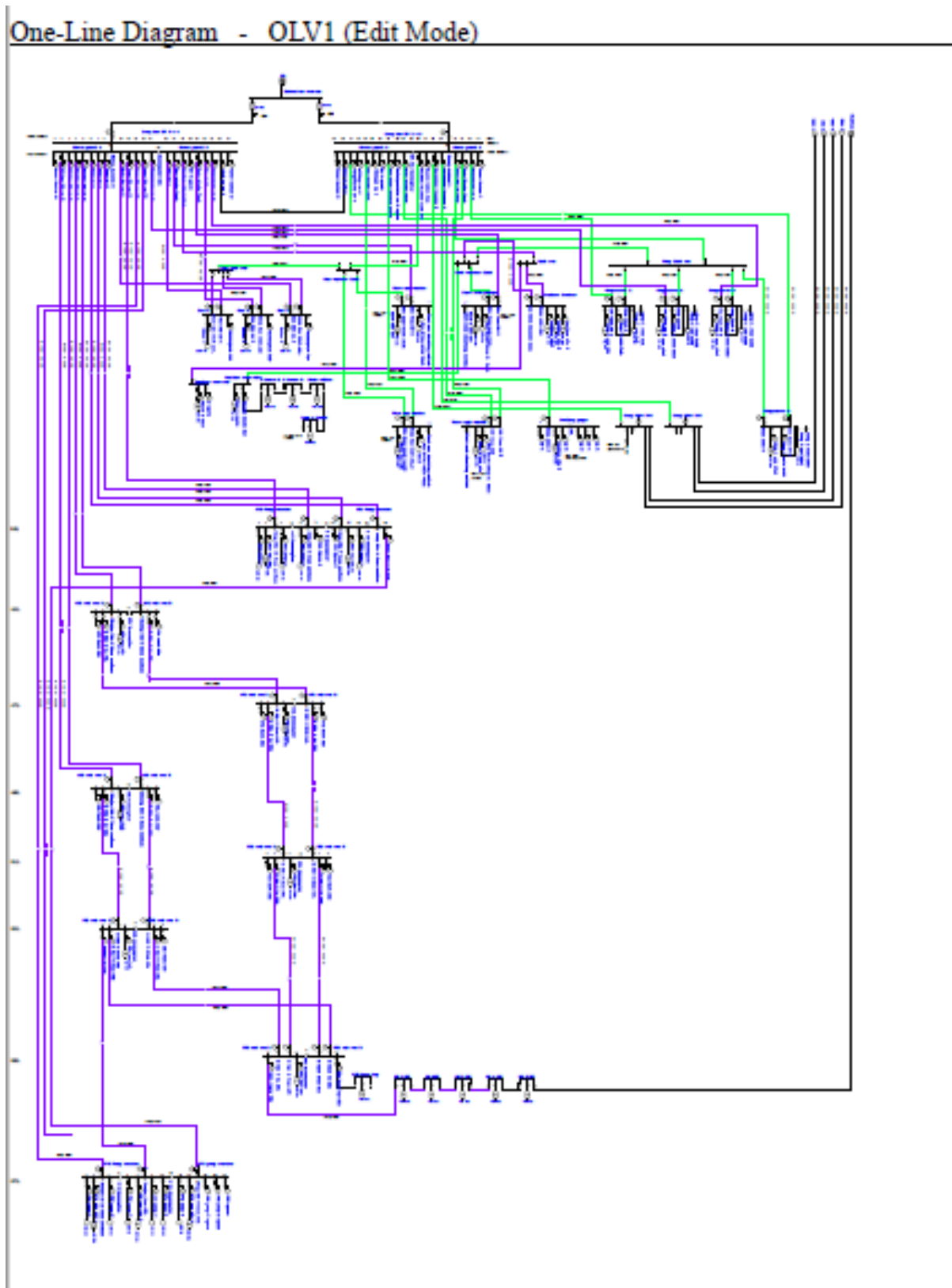


Figure 61: Mine β full electrical layout

APPENDIX C : CASE STUDIES

C.1 Introduction

This appendix contains all case study work not shown in Chapter 3. The bulk of this is from the common data error check sections, where only one variable from each study was used to demonstrate the method.

C.2 Case study 1

Common data error check

The following figures were used to check the data of the incomer and sub-systems of Mine α. Conclusions made from these figures are given in Section 0.

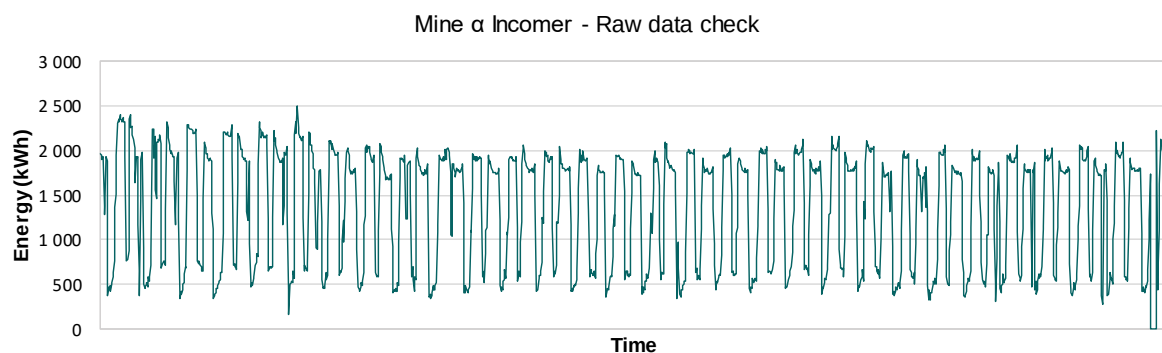


Figure 62: Mine α incomer raw data check month profile

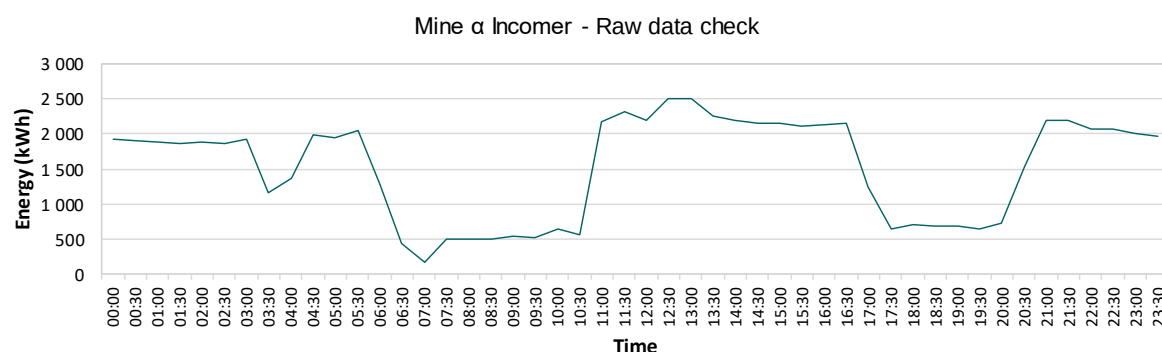


Figure 63: Mine α incomer raw data check day profile

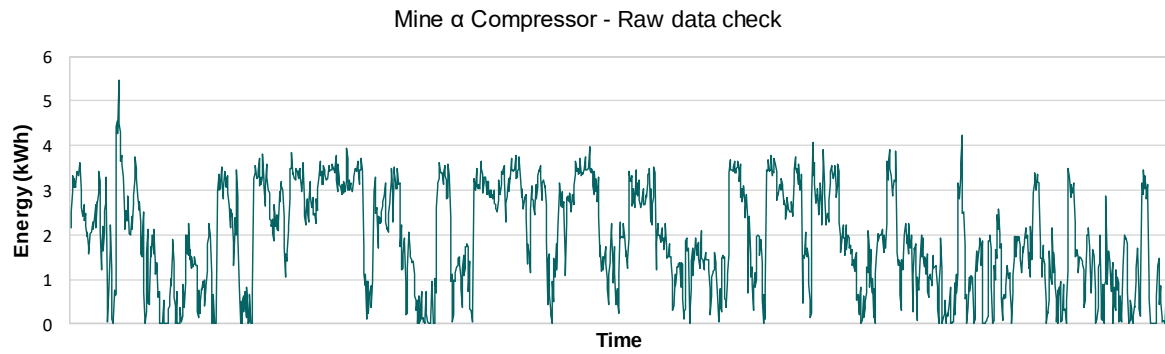


Figure 64: Mine α compressor raw data check month profile

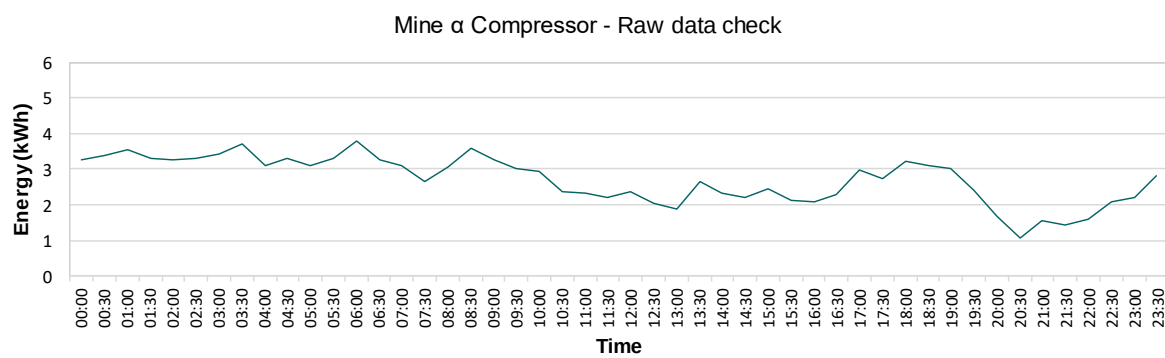


Figure 65: Mine α compressor raw data check day profile

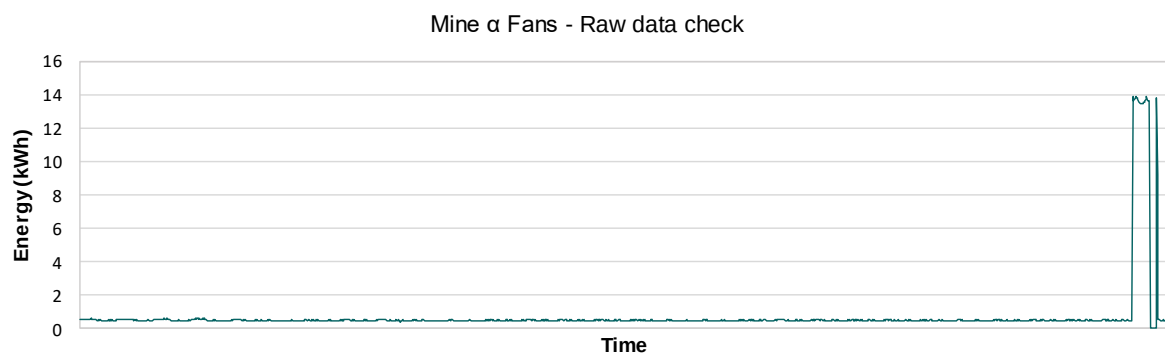


Figure 66: Mine α fans raw data check month profile

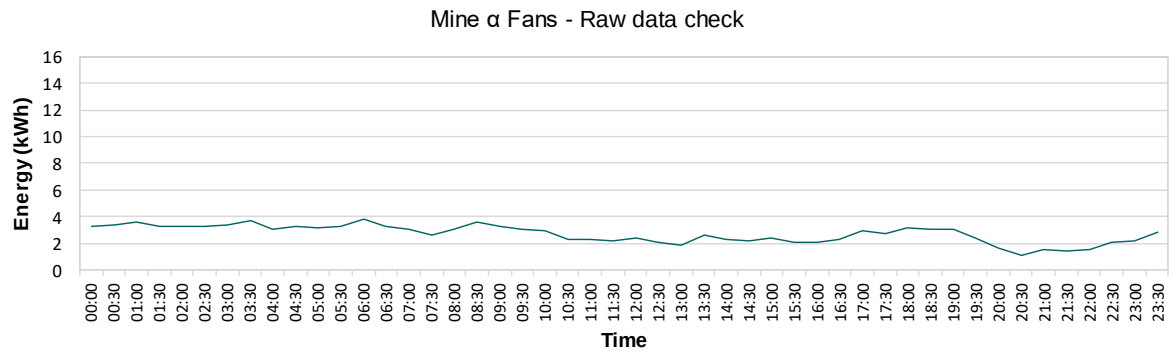


Figure 67: Mine α fans raw data check day profile

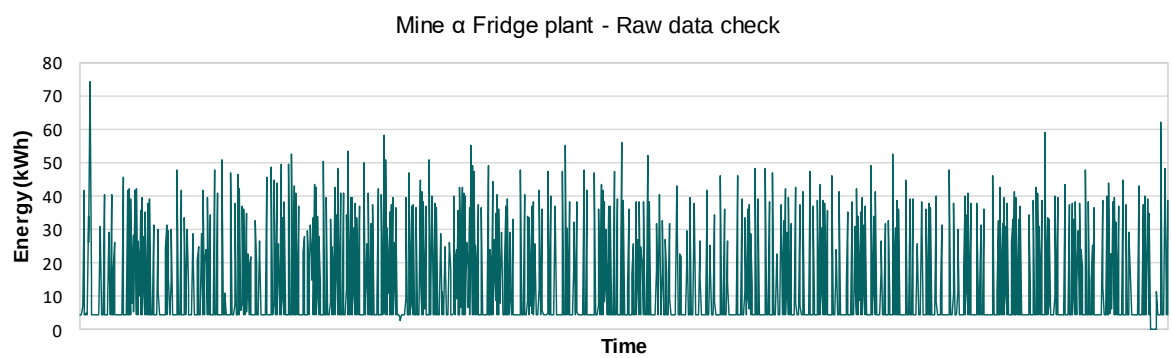


Figure 68: Mine α fridge plant raw data check month profile

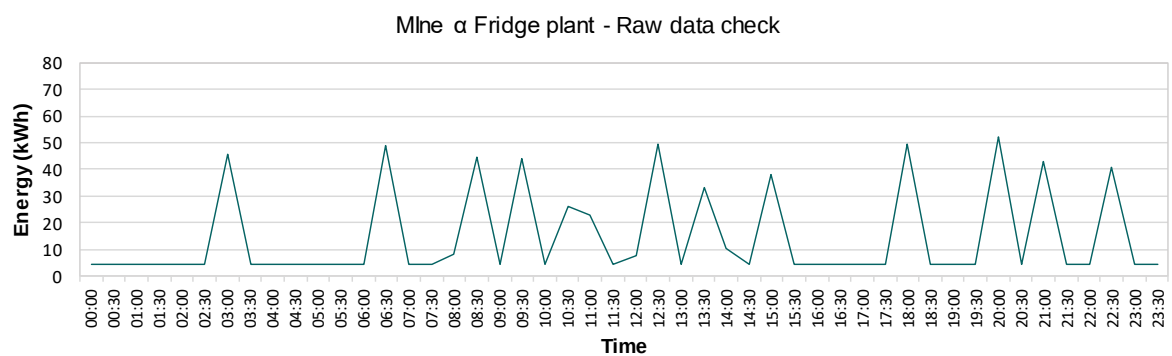


Figure 69: Mine α fridge plant raw data check day profile

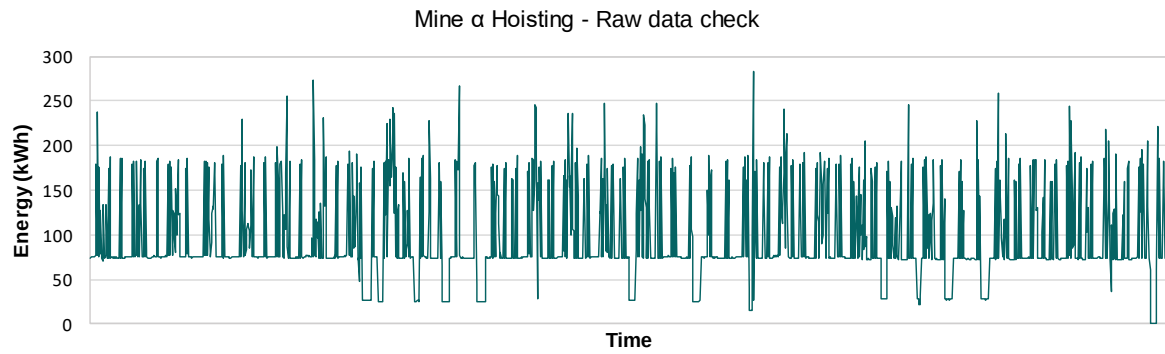


Figure 70: Mine α hoisting raw data check month profile

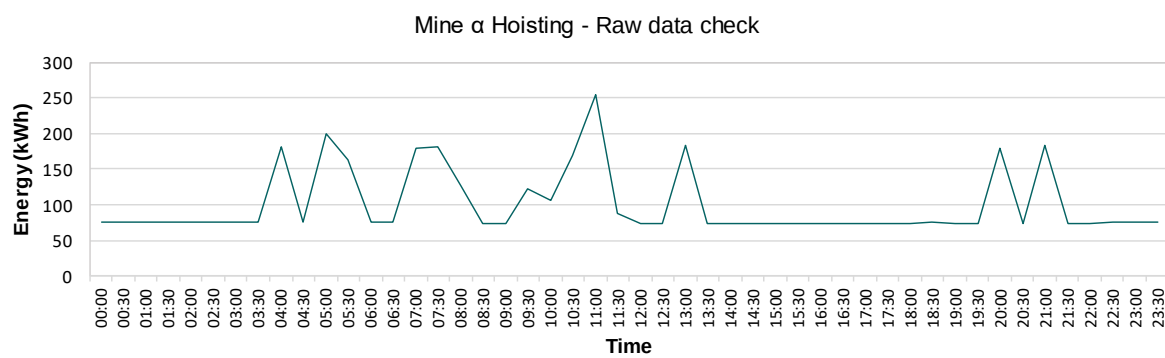


Figure 71: Mine α hoisting raw data check day profile

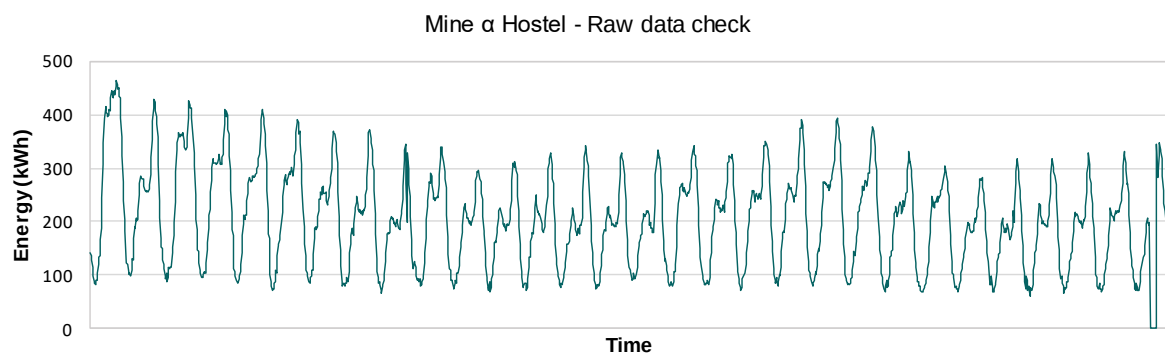


Figure 72: Mine α hostel raw data check month profile

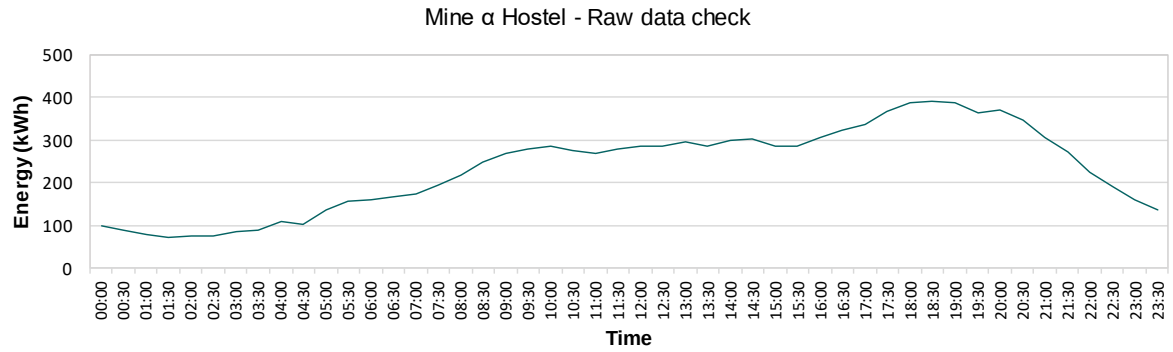


Figure 73: Mine α hostel raw data check day profile

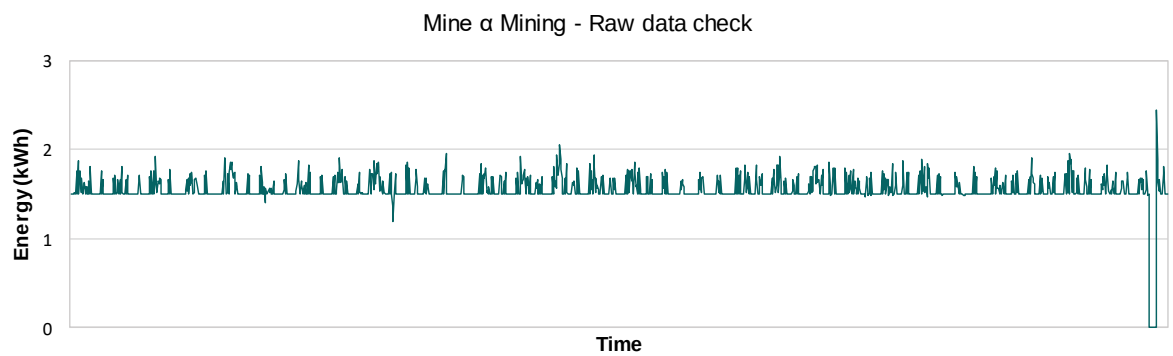


Figure 74: Mine α mining raw data check month profile

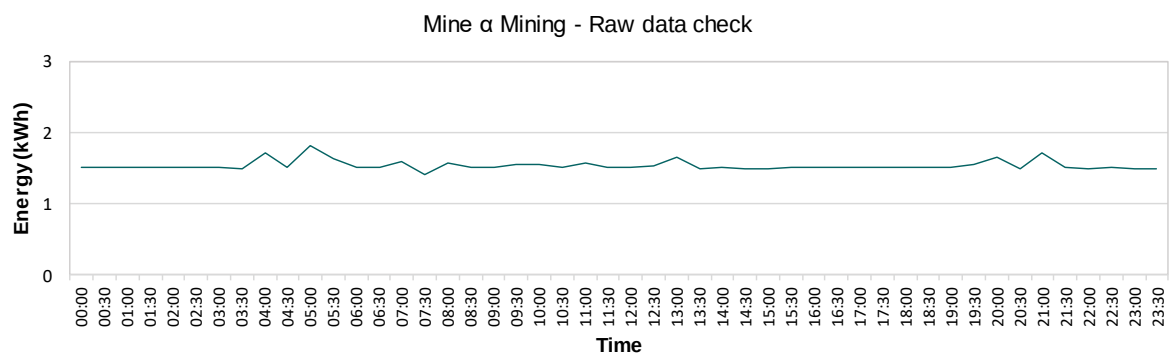


Figure 75: Mine α mining raw data check day profile

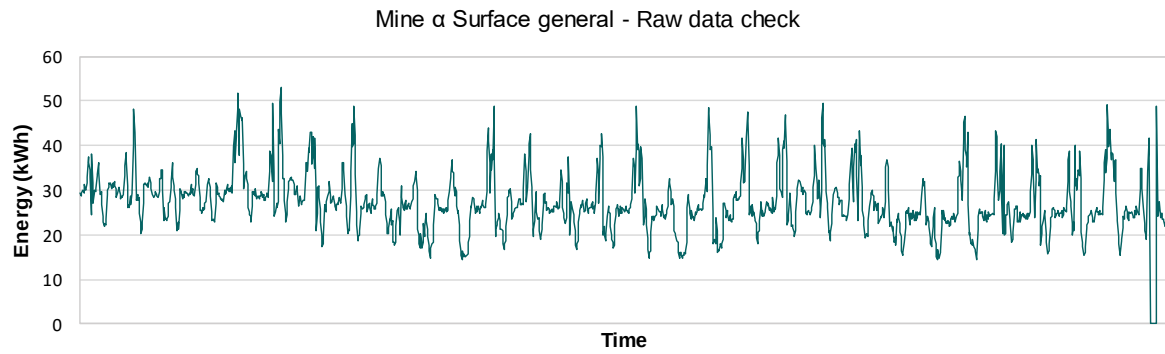


Figure 76: Mine α surface raw data check month profile

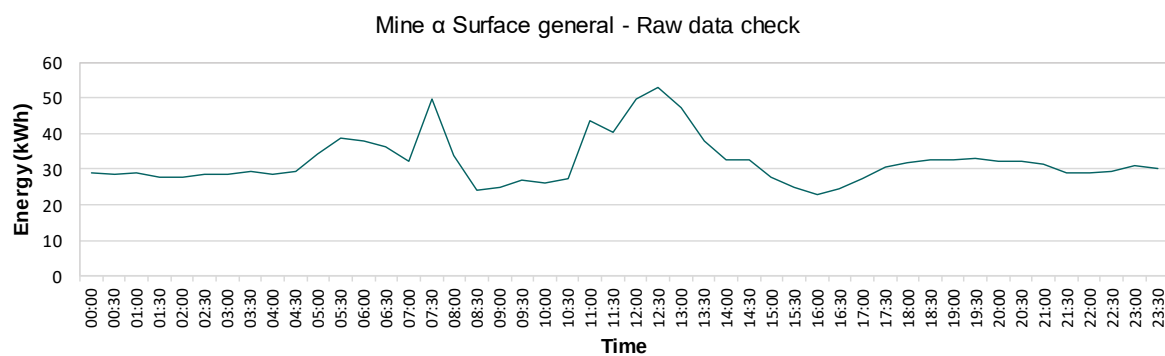


Figure 77: Mine α surface raw data check day profile

Normalised data evaluation

The results of the normalised pumping data from Mine α was presented in Section 0. The following figures present the results of all the other sub-systems.

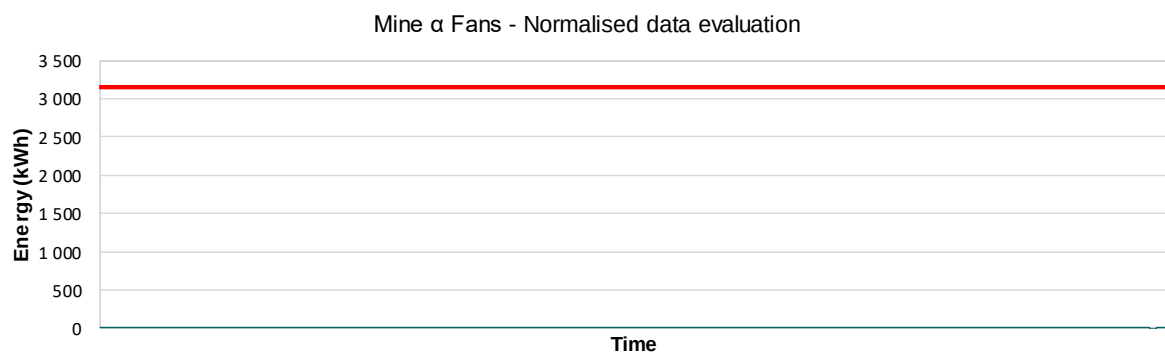


Figure 78: Mine α fans normalised data evaluation

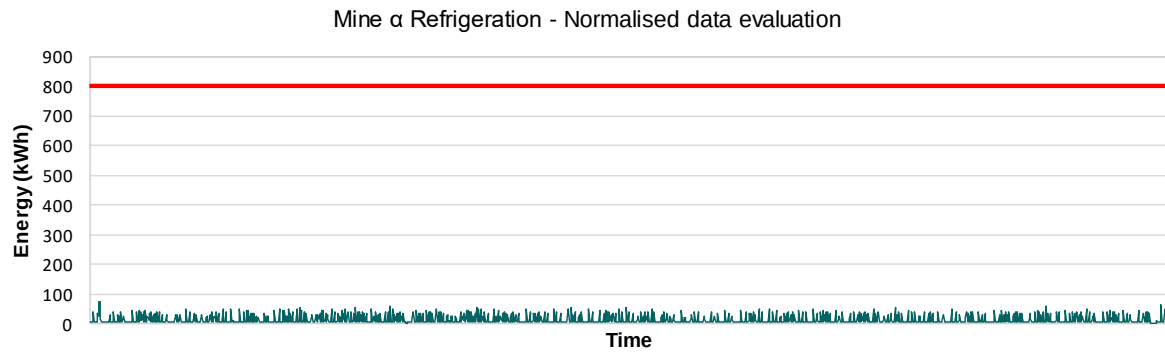


Figure 79: Mine α refrigeration normalised data evaluation

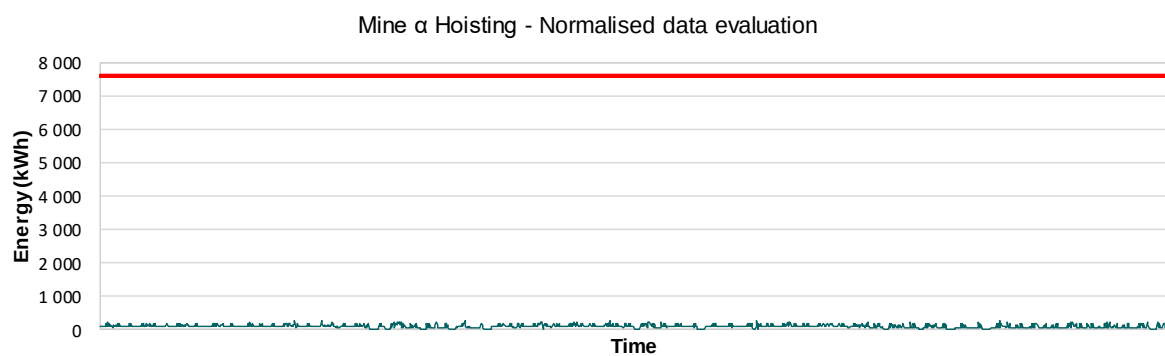


Figure 80: Mine α hoisting normalised data evaluation

From these figures, it can be seen that the normalisation did not push any data outside of its expected boundaries.

C.3 Case study 2

Common data error check

The following figures were used to check the data of the incomer and sub-systems of Mine β . Conclusions made from these figures are given in Section 0.

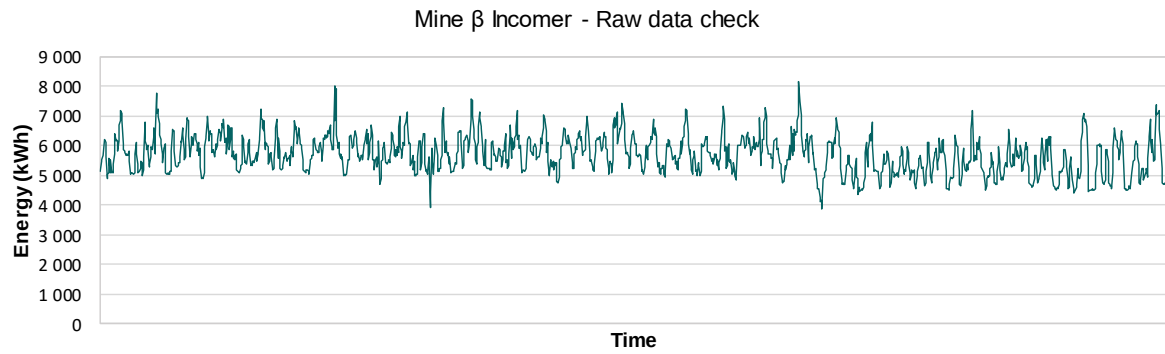


Figure 81: Mine β incomer raw data check month profile

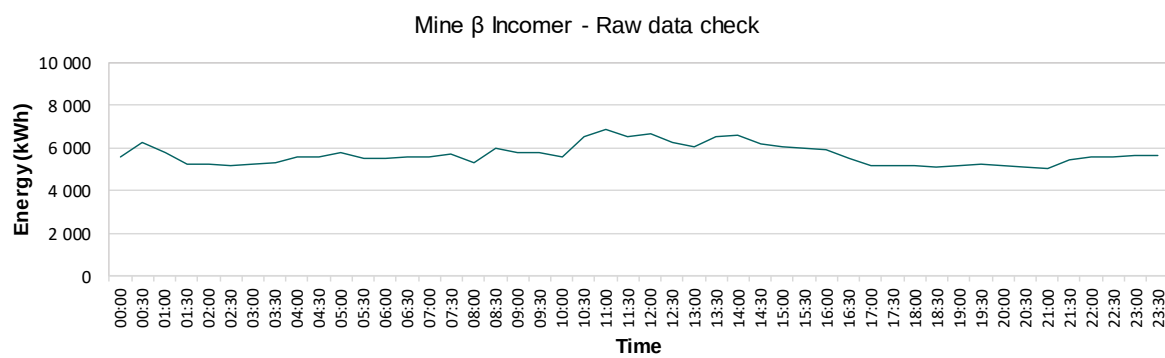


Figure 82: Mine β incomer raw data check day profile

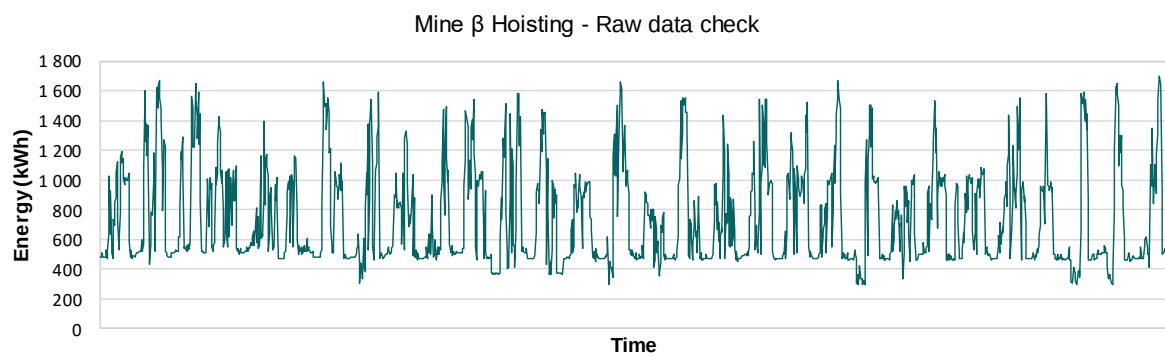


Figure 83: Mine β hoisting raw data check month profile

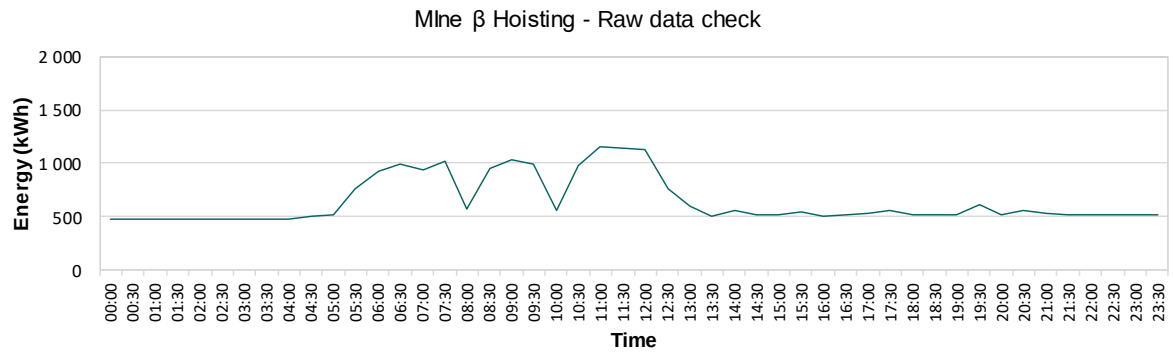


Figure 84: Mine β hoisting raw data check day profile



Figure 85: Mine β hostel raw data check month profile

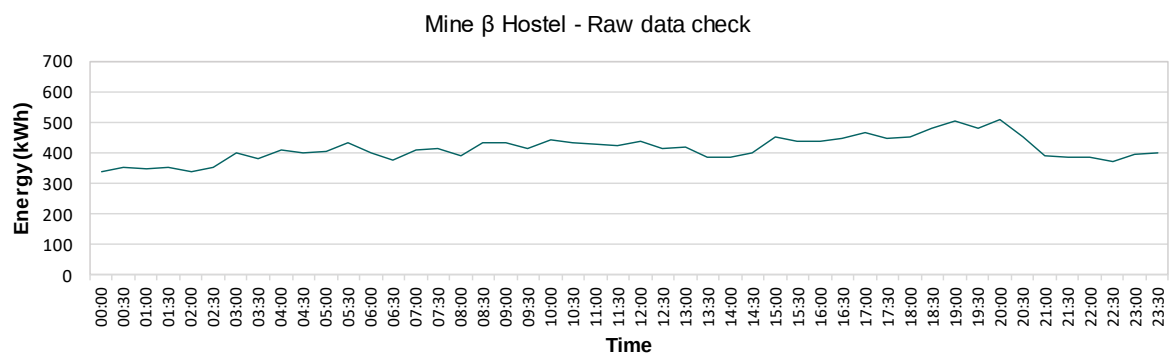


Figure 86: Mine β hostel raw data check day profile

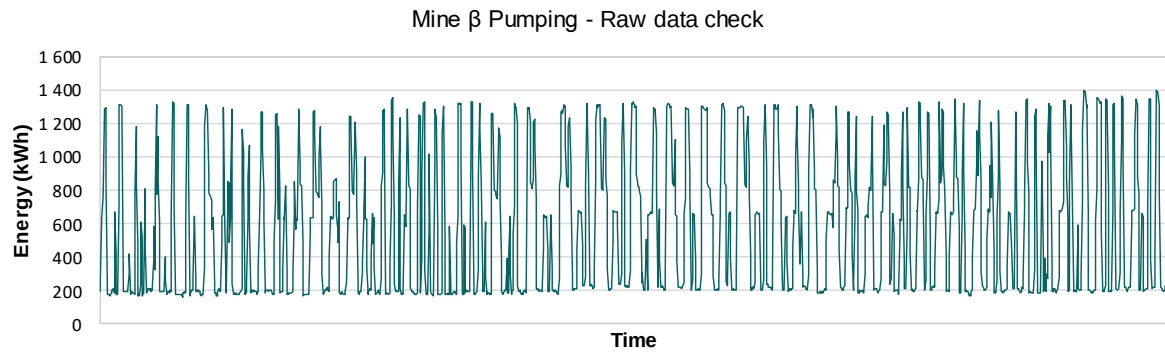


Figure 87: Mine β pumping raw data check month profile

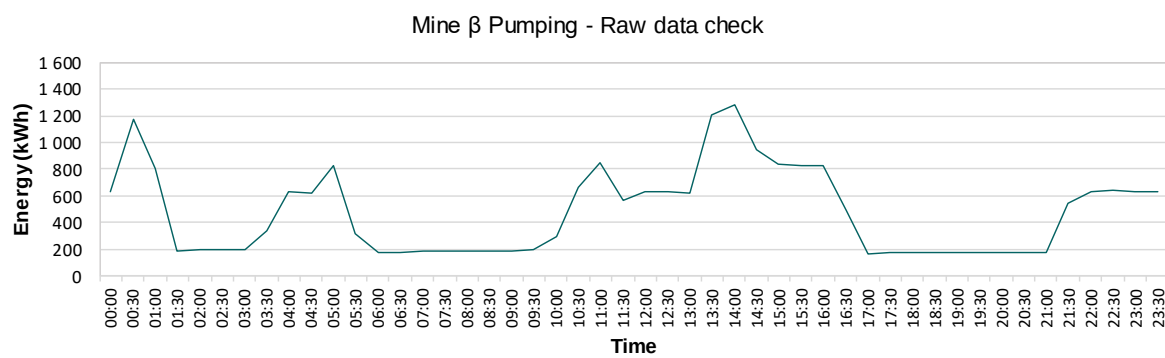


Figure 88: Mine β pumping raw data check day profile

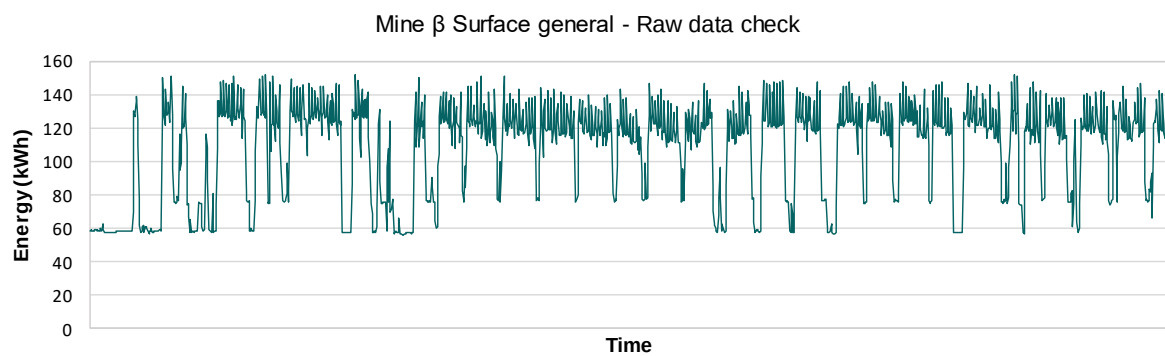


Figure 89: Mine β surface raw data check month profile

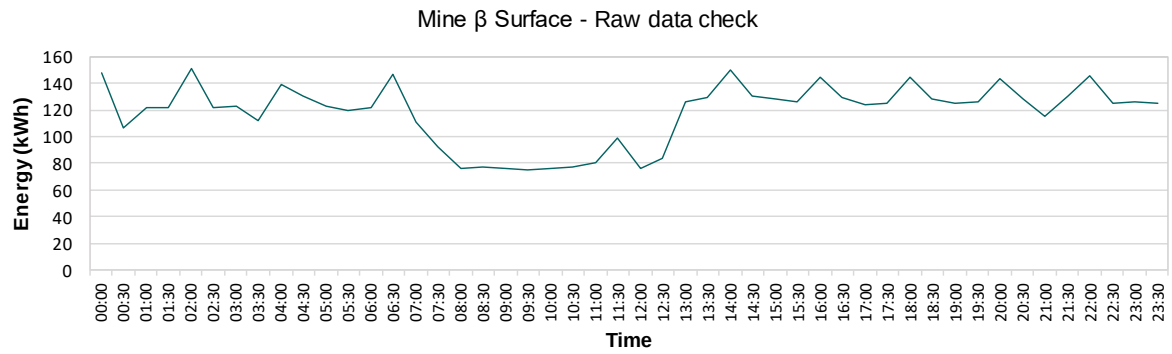


Figure 90: Mine β surface raw data check day profile

Normalised data evaluation

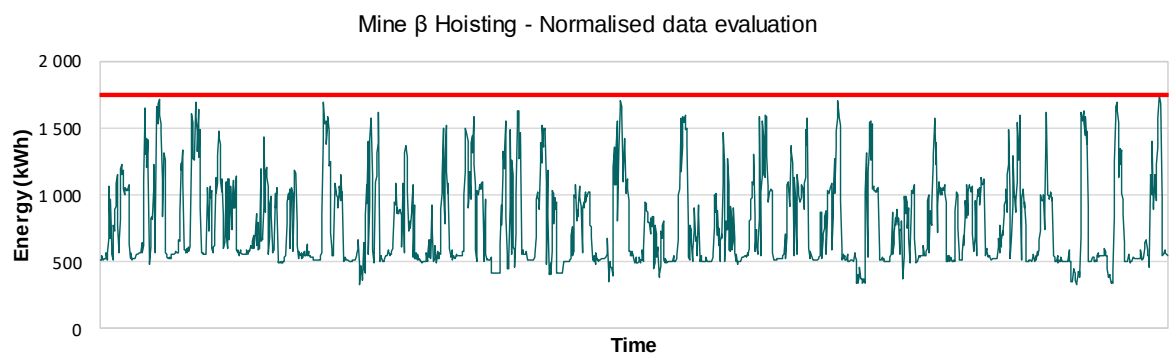


Figure 91: Mine β hoisting normalised data evaluation

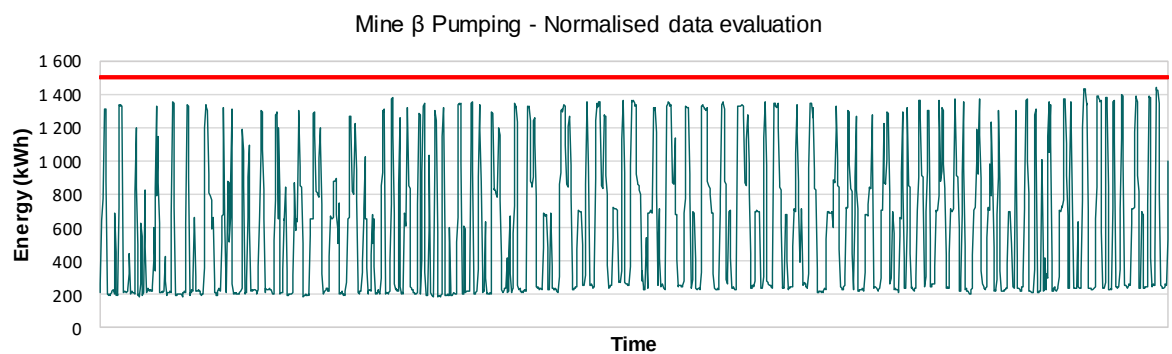


Figure 92: Mine β pumping normalised data evaluation

C.4 Case study 3

Common data error check

The data analysis methods discussed in Chapter 2 were applied to all the compressors studied in Case study 3. The following figures were obtained through this method.

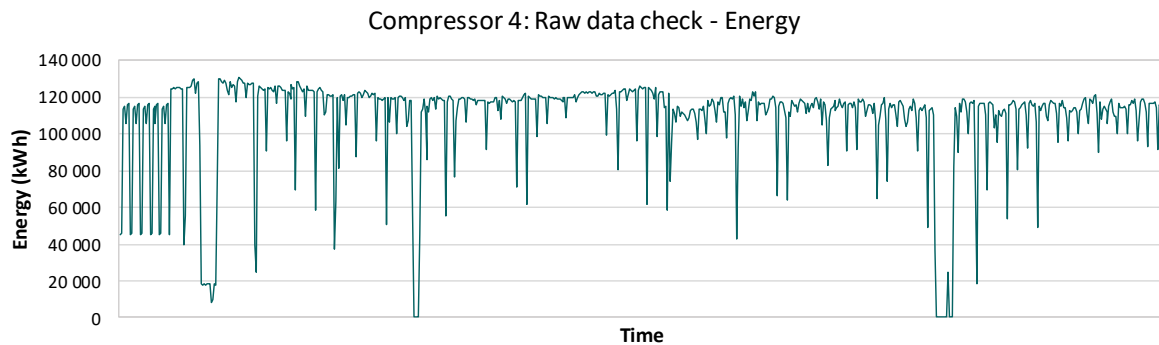


Figure 93: Compressor 4 - Raw energy data error check

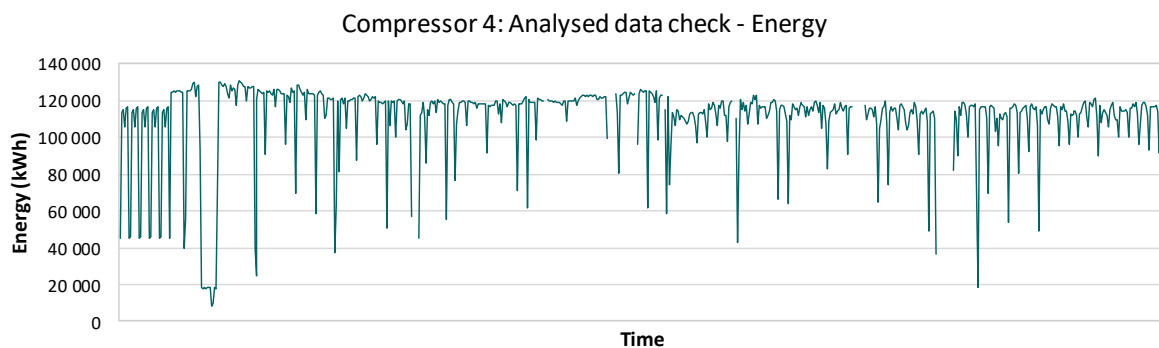


Figure 94: Compressor 4 - Analysed energy data

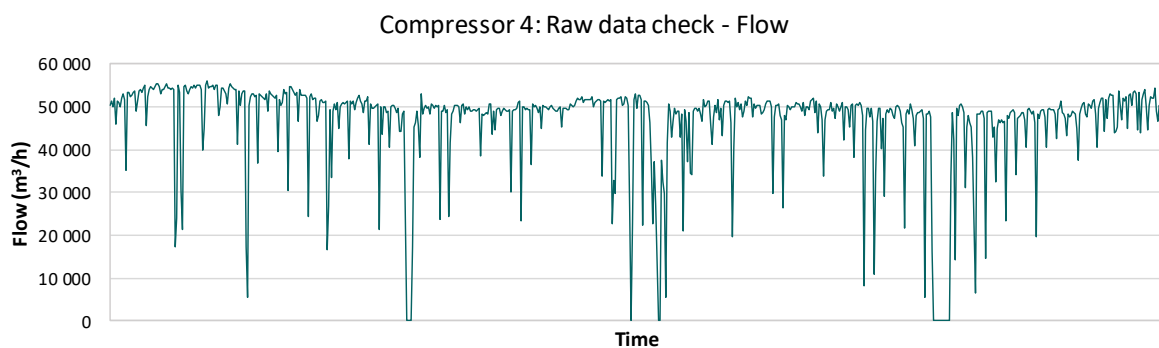


Figure 95: Compressor 4 - Raw flow data error check

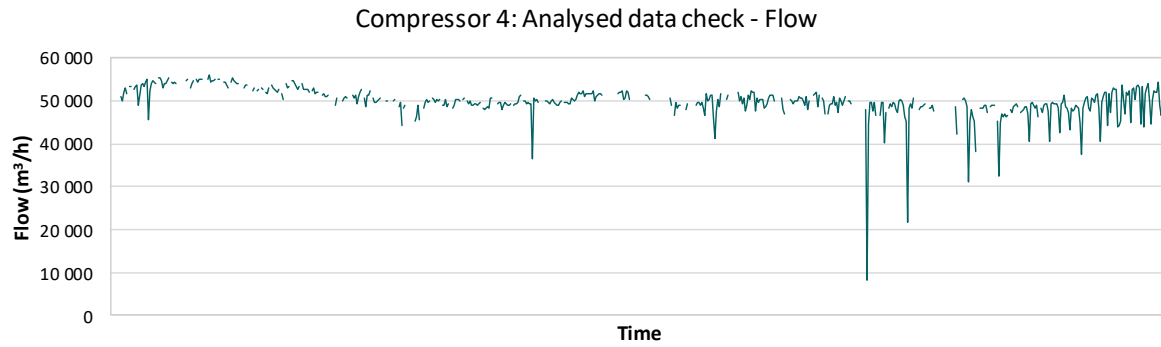


Figure 96: Compressor 4 - Analysed flow data

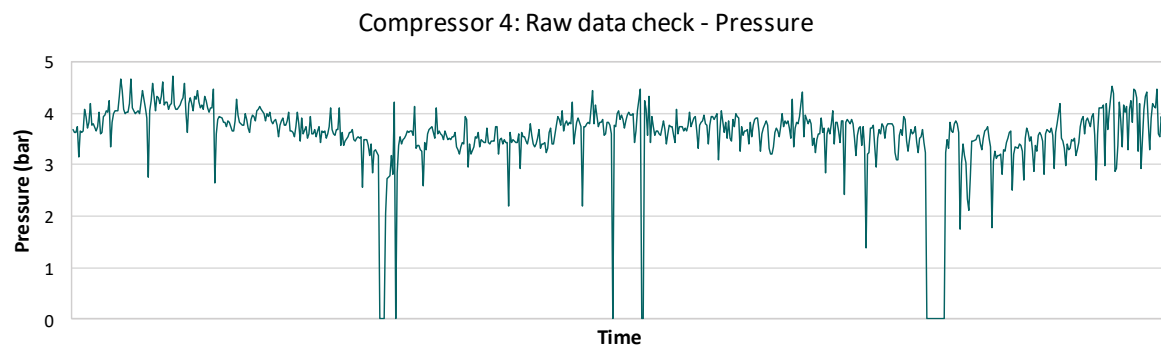


Figure 97: Compressor 4 - Raw pressure data error check

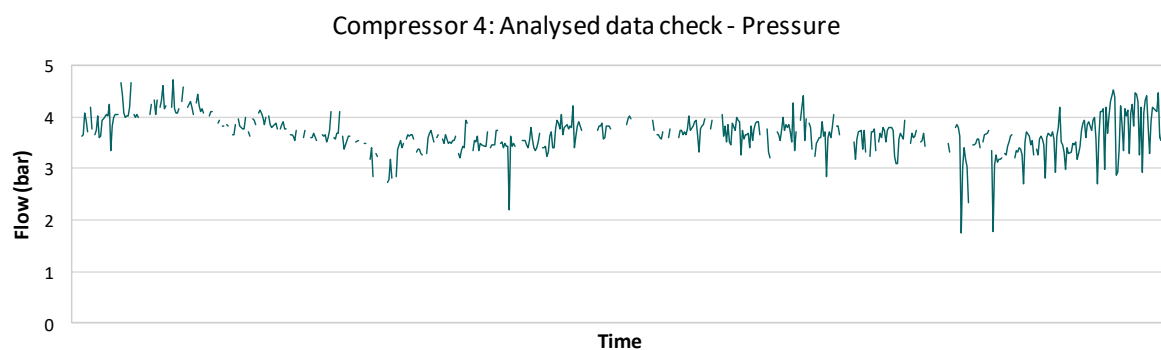


Figure 98: Compressor 4 - Analysed pressure data

Periods of inactivity, as well as data errors, were removed from the dataset. The final dataset for Year 1 contained 271 data points, and that for Year 2 contained 284 points.

Compressor 5: Raw data check - Energy

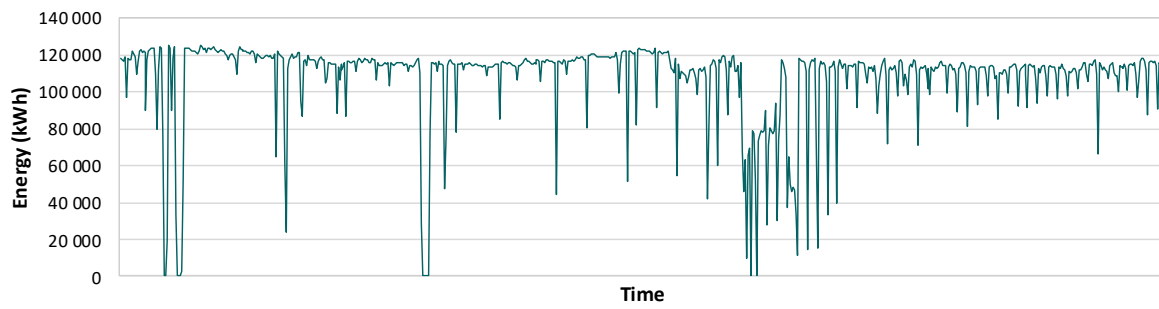


Figure 99: Compressor 5 - Raw energy data error check

Compressor 5: Analysed data check - Energy

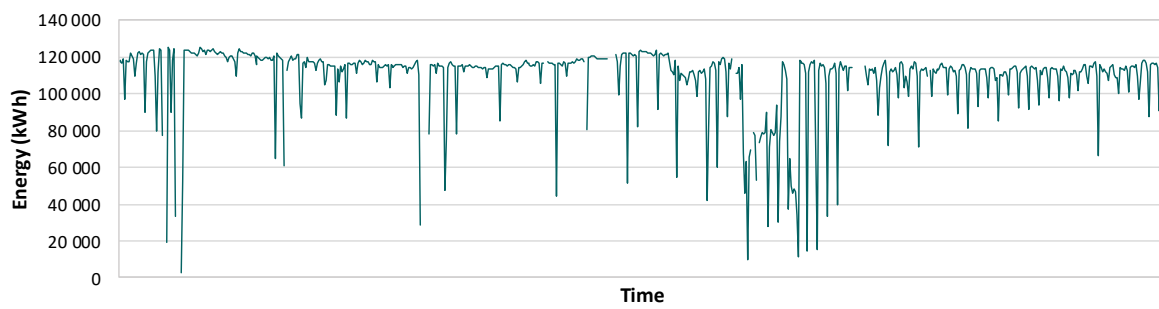


Figure 100: Compressor 5 - Analysed energy data

Compressor 5: Raw data check - Flow

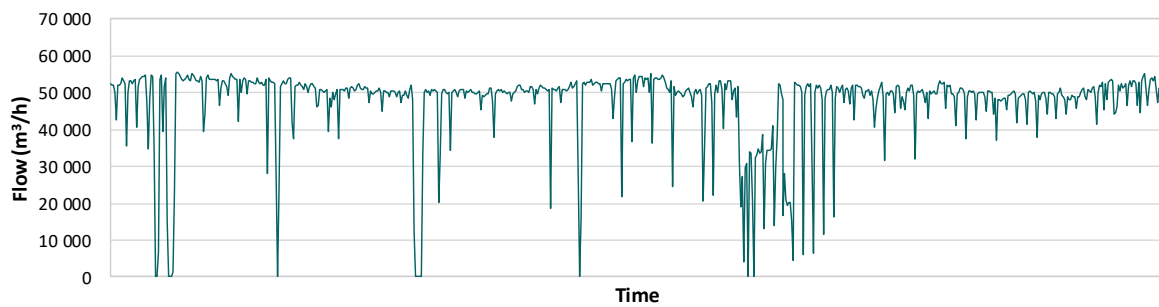


Figure 101: Compressor 5 - Raw flow data error check

Compressor 5: Analysed data check - Flow

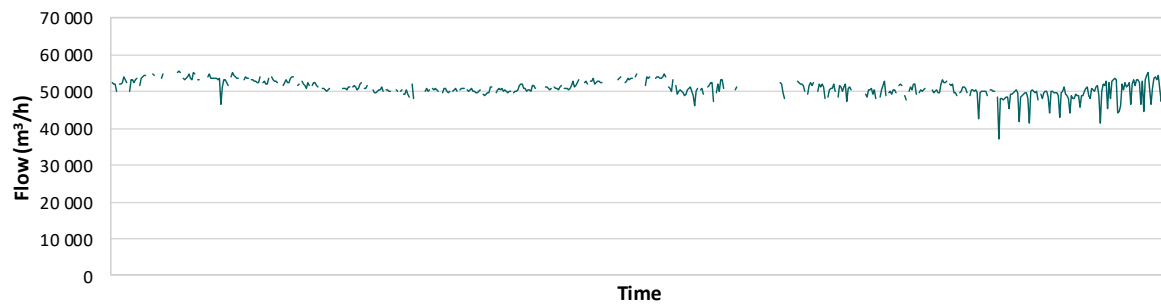


Figure 102: Compressor 5 - Analysed flow data

Compressor 5: Raw data check - Pressure

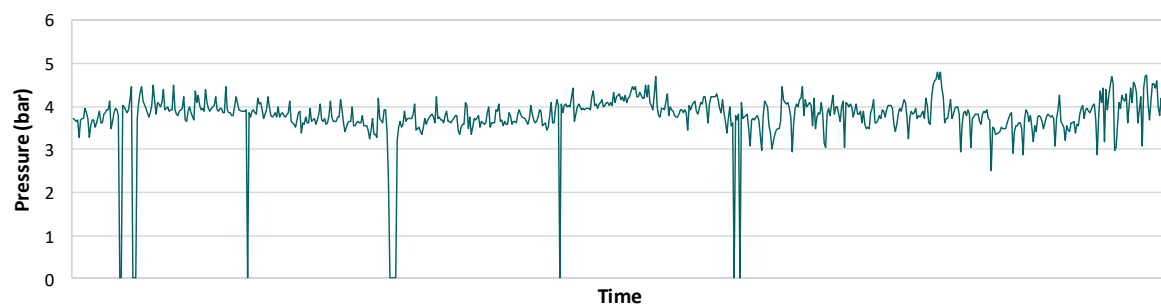


Figure 103: Compressor 5 - Raw pressure data error check

Compressor 5: Analysed data check - Pressure

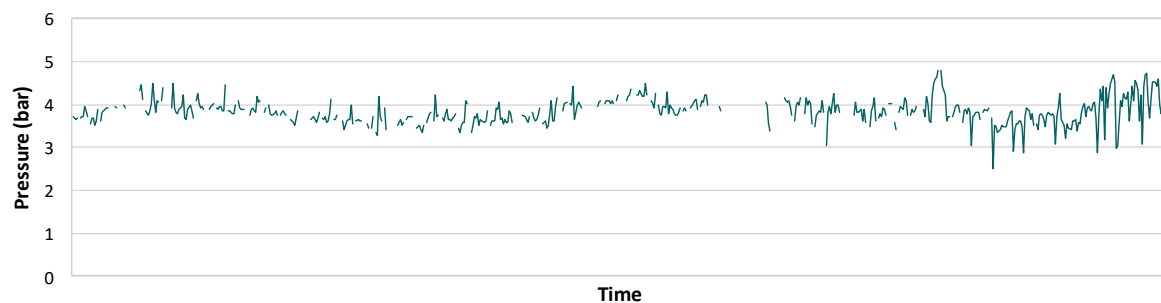


Figure 104: Compressor 5 - Analysed pressure data

Periods of inactivity, as well as data errors, were removed from the dataset. The final dataset for Year 1 contained 268 data points, and that for Year 2 contained 281 data points.

Compressor 6: Raw data check - Energy

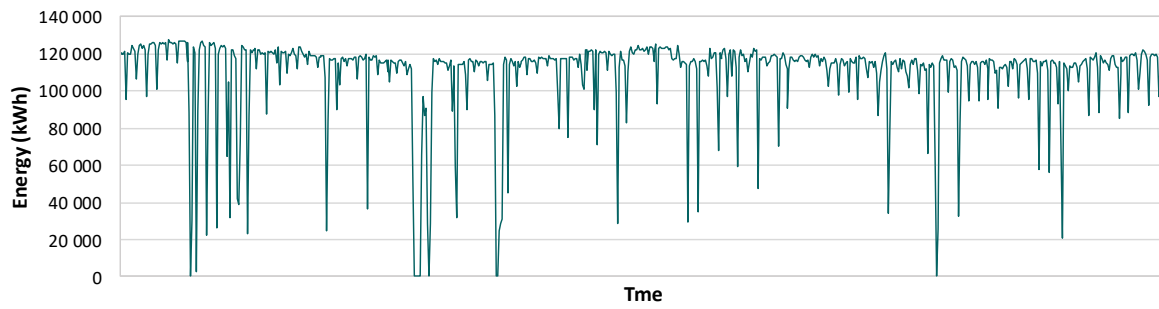


Figure 105: Compressor 6- Raw energy data error check

Compressor 6: Analysed data check - Energy

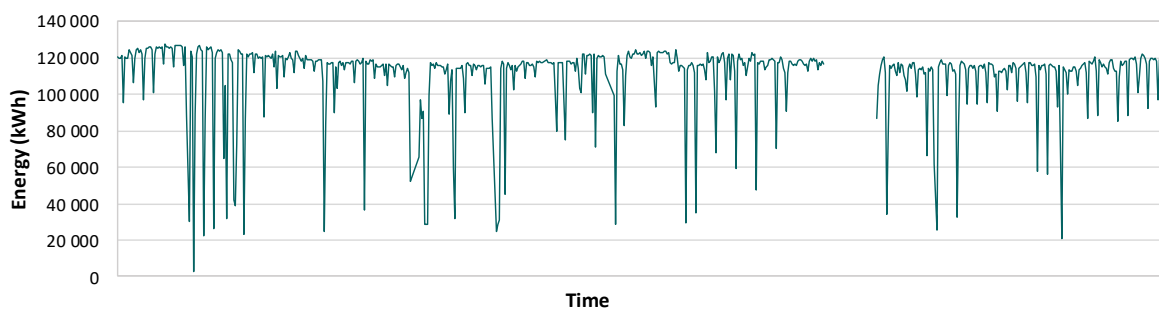


Figure 106: Compressor 6 - Analysed energy data

Compressor 6: Raw data check - Pressure

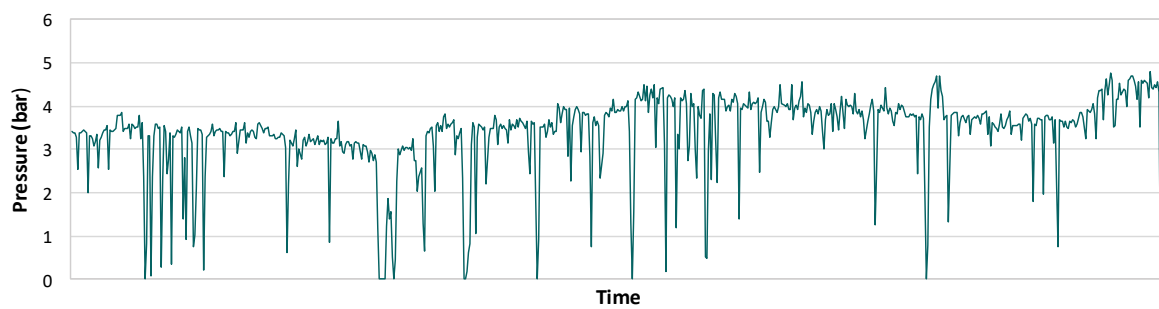


Figure 107: Compressor 6 - Raw pressure data error check

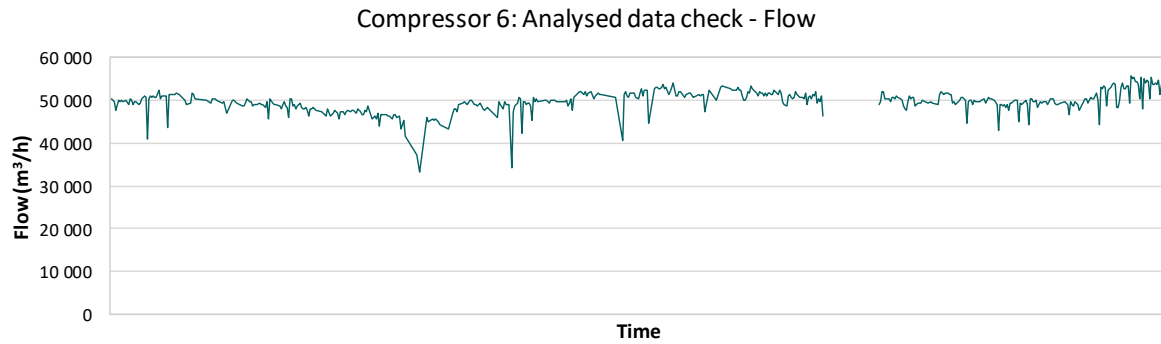


Figure 108: Compressor 6 - Analysed pressure data

Periods of inactivity, as well as data errors, were removed from the dataset. The final dataset for Years 1 and 2 contained 251 and 268 data points, respectively.

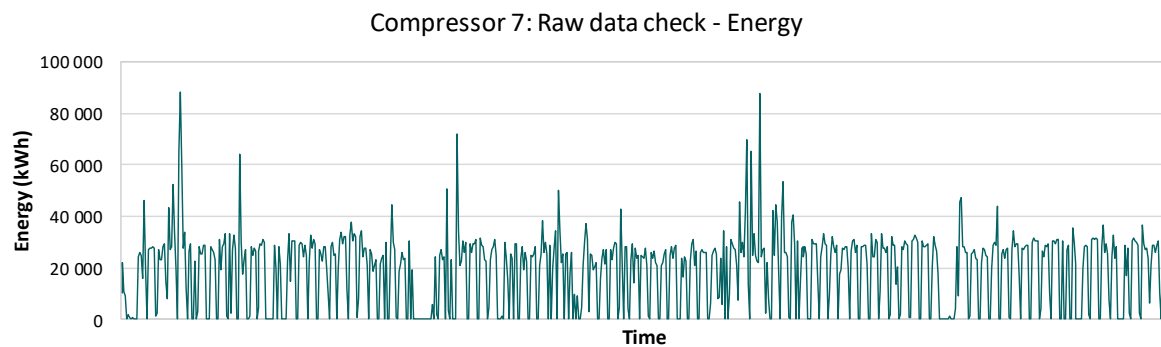


Figure 109: Compressor 7 - Raw energy data error check

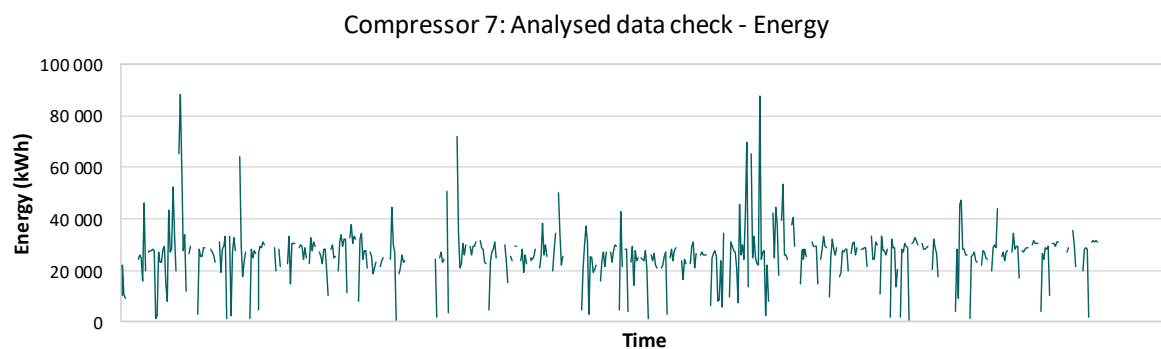


Figure 110: Compressor 7 - Analysed energy data

Compressor 7: Raw data check - Flow

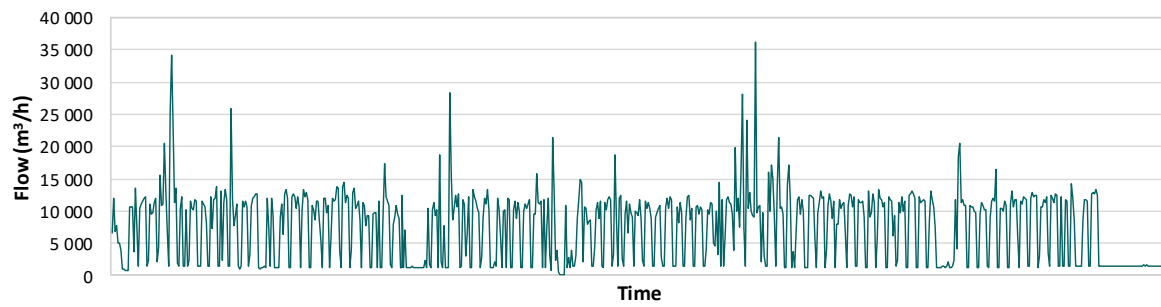


Figure 111: Compressor 7 - Raw flow data error check

Compressor 7: Analysed data check - Flow

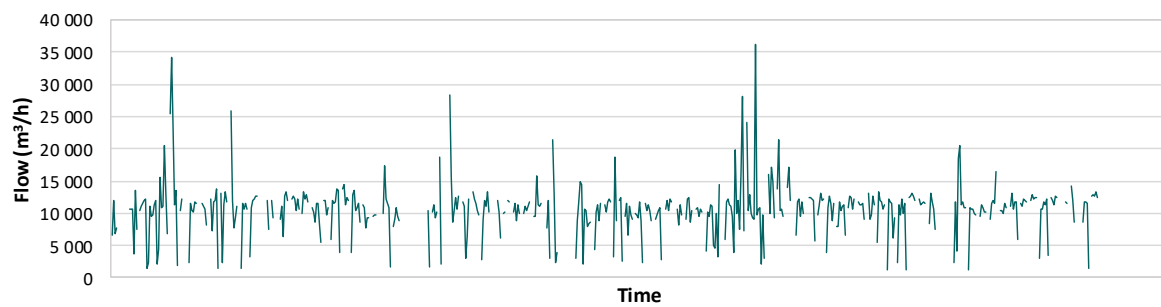


Figure 112: Compressor 7 - Analysed flow data

Compressor 7: Raw data check - Pressure

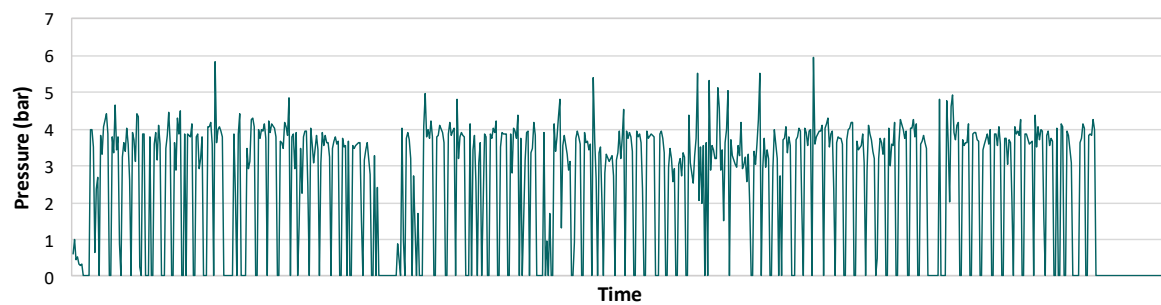


Figure 113: Compressor 7 - Raw pressure data error check

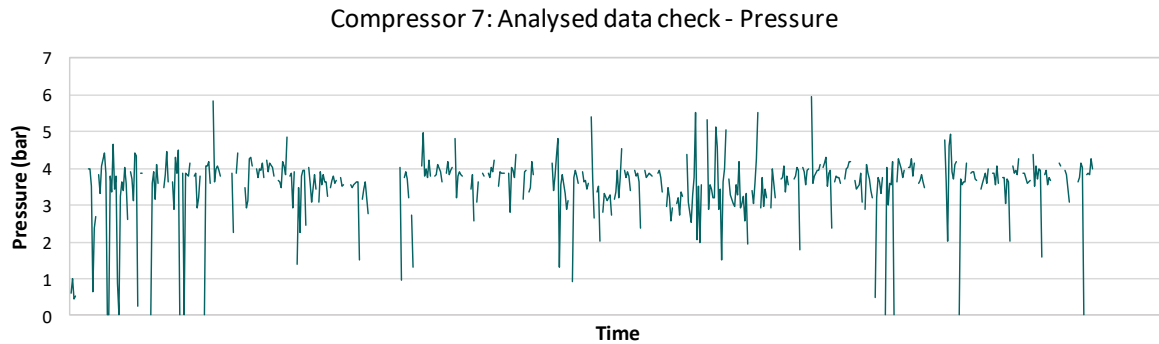


Figure 114: Compressor 7 - Analysed pressure data

Compressor 7 is not operated as frequently as Compressors 4, 5 and 6. Throughout the 2-year investigation, the compressor did not once run for 24 hours on a single day. The compressor is used as a standby. This can be observed in the low use of energy by the compressor. This compressor was not studied further as performance evaluation is futile on a system that is not used to its full capacity for a significant amount of time.

Data visualisation

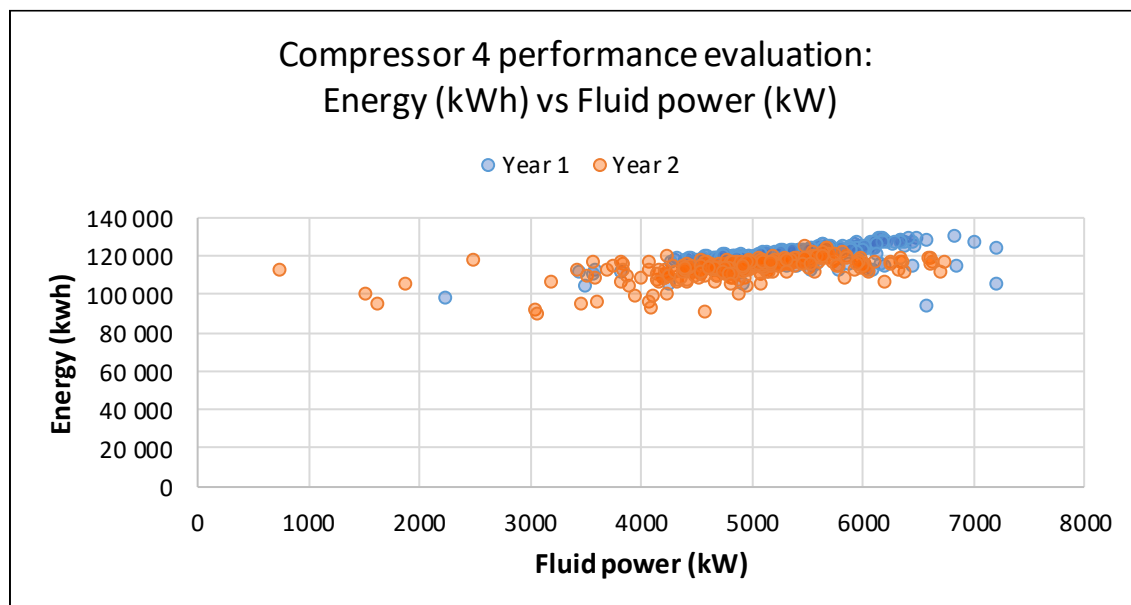


Figure 115: Compressor 4 performance evaluation visualisation

In Compressor 4, the energy used by the compressor in Year 2 is marginally lower than in Year 1. This is especially noticeable where a higher fluid power was achieved. This visualisation allows a user to evaluate the change in performance between the two years of operation.

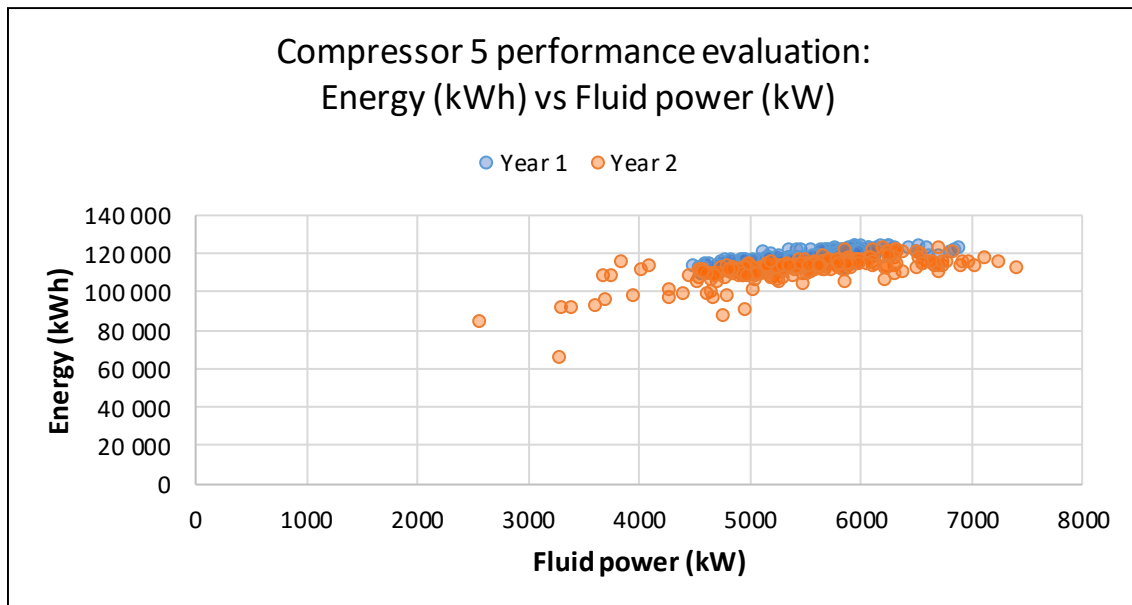


Figure 116: Compressor 5 performance evaluation visualisation

In year 2 of this study, Compressor 5 produced higher fluid power while consuming a constant amount of energy. The compressor did, however, have a less constant performance, with some scattered data to the left of the plot.

C.5 Case study 2

Data analysis

The data analysis methods discussed in Chapter 2 were applied to all the fridge plants studied in Case study 2. The following figures were obtained through this method.

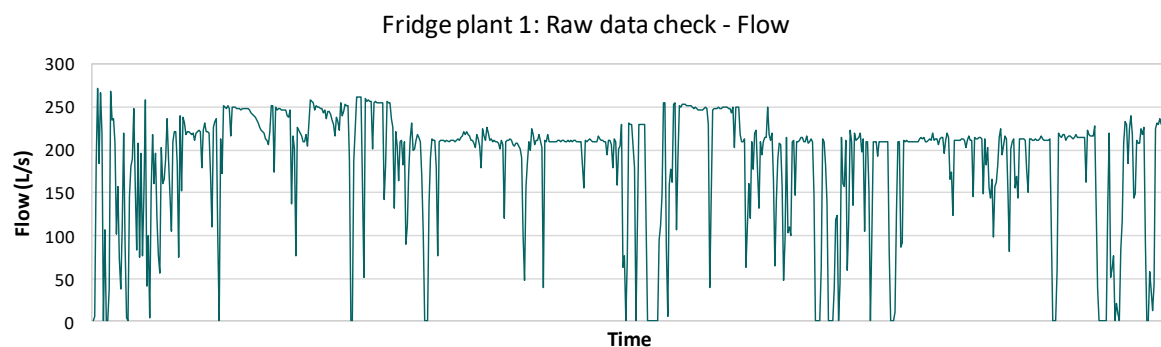


Figure 117: Fridge plant 1 - Raw flow data error check

Fridge plant 1: Analysed data check - Flow

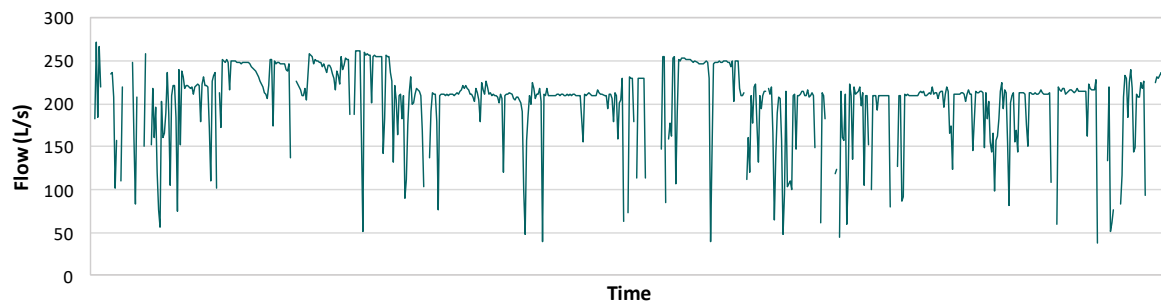


Figure 118: Fridge plant 1 – Analysed flow data

Fridge plant 1: Raw data check - Temperature

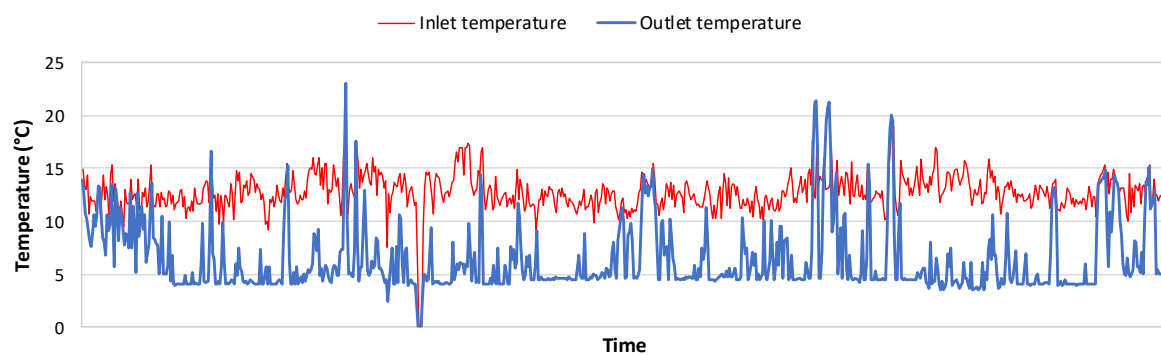


Figure 119: Fridge plant 1 - Raw temperature data error check

Fridge plant 1: Analysed data check - Temperature

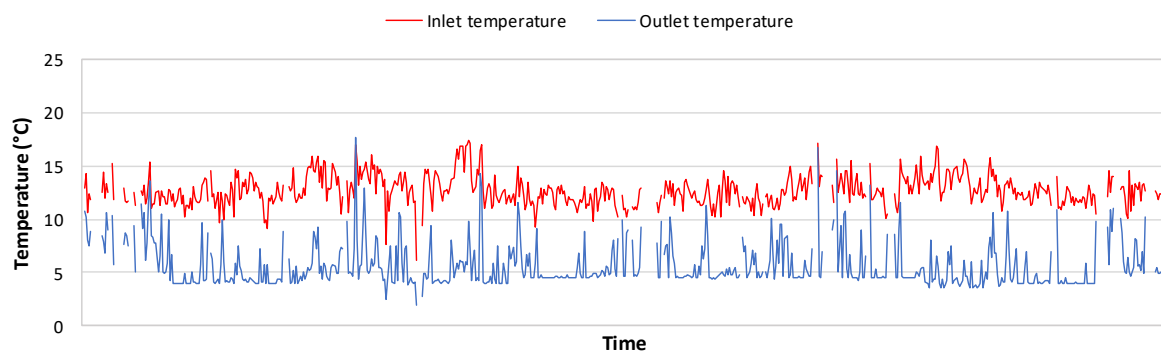


Figure 120: Fridge plant 1 – Analysed temperature data

Periods of inactivity, as well as data errors, were removed from the dataset. The final dataset for Year 1 contained 335 data points, that for Year 2 contained 317. Instances where the outlet temperature exceeded the inlet temperature were removed from the final dataset.

Fridge plant 2: Raw data check - Power

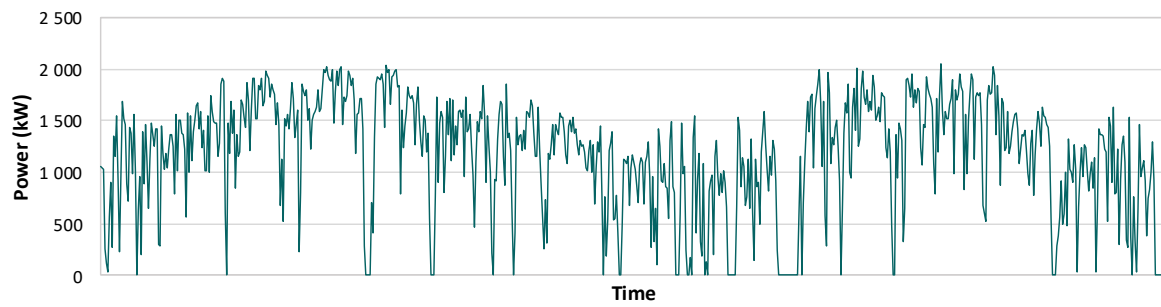


Figure 121: Fridge plant 2 - Raw power data error check

Fridge plant 2: Analysed data check - Power

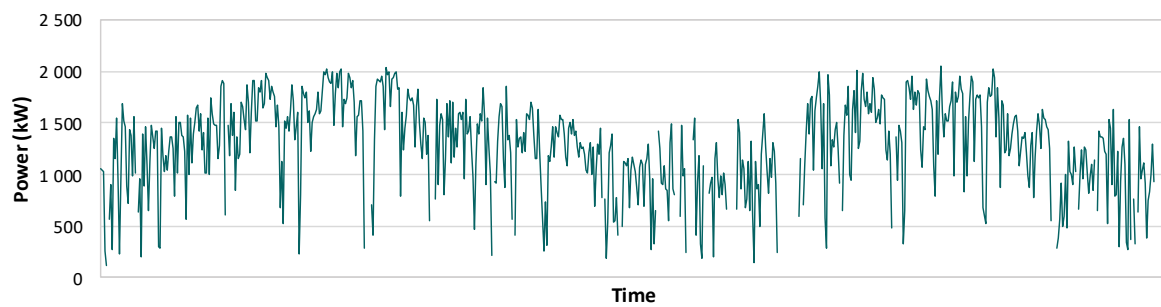


Figure 122: Fridge plant 2 – Analysed power data

Fridge plant 2: Raw data check - Flow

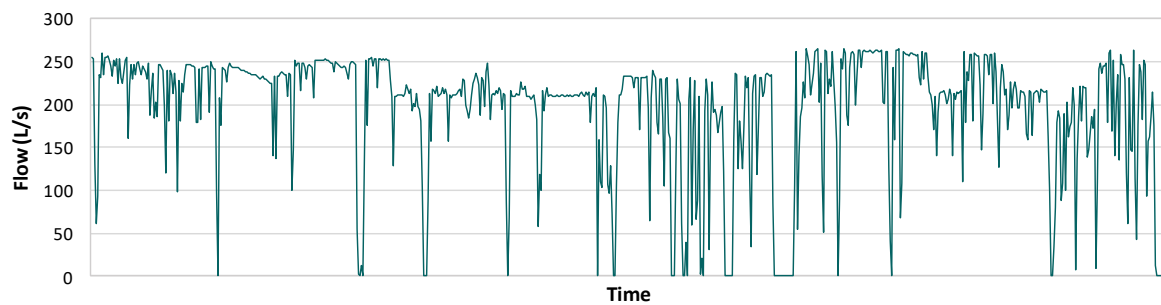


Figure 123: Fridge plant 2 - Raw flow data error check

Fridge plant 2: Analysed data check - Flow

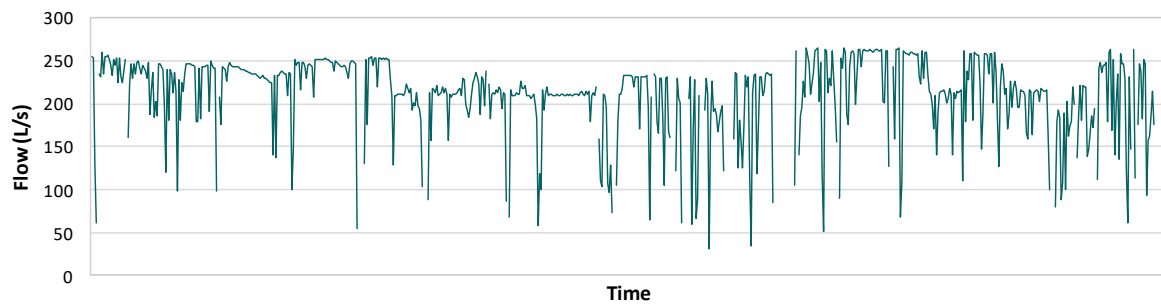


Figure 124: Fridge plant 2 – Analysed flow data

Fridge plant 2: Raw data check - Temperature

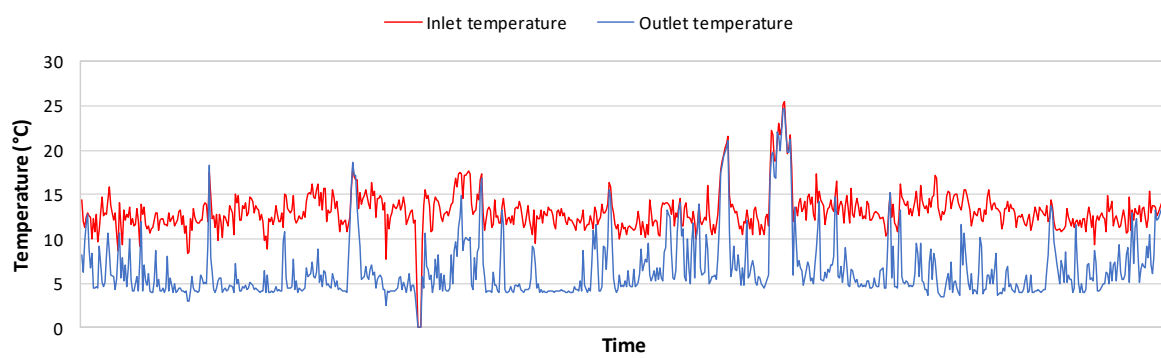


Figure 125: Fridge plant 2 - Raw temperature data error check

Fridge plant 2: Analysed data check - Temperature

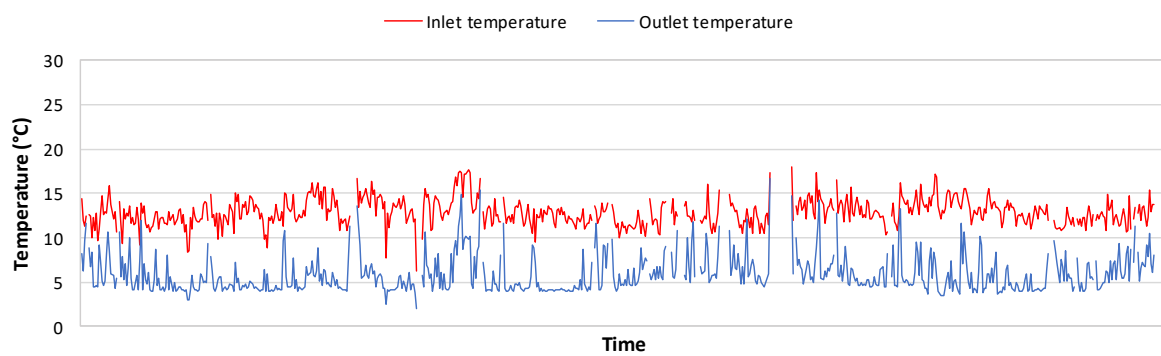


Figure 126: Fridge plant 2– Analysed temperature data

Periods of inactivity, as well as data errors, were removed from the dataset. The final dataset for Years 1 and 2 contained 350 and 316 data points, respectively.

Fridge plant 3: Raw data check - Power

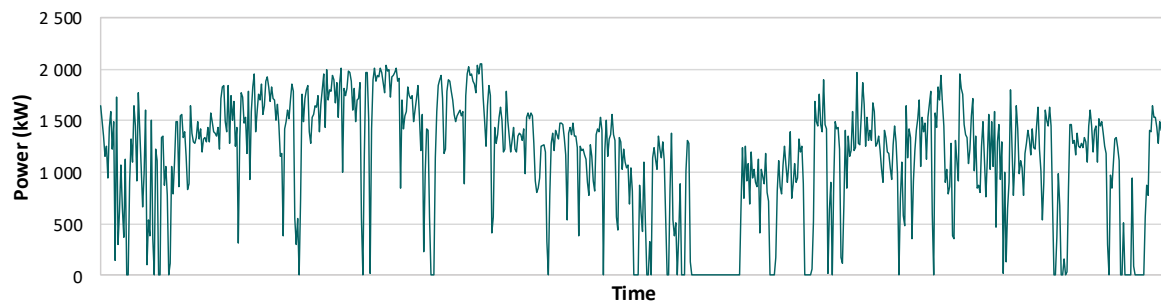


Figure 127: Fridge plant 3 - Raw power data error check

Fridge plant 3: Analysed data check - Power

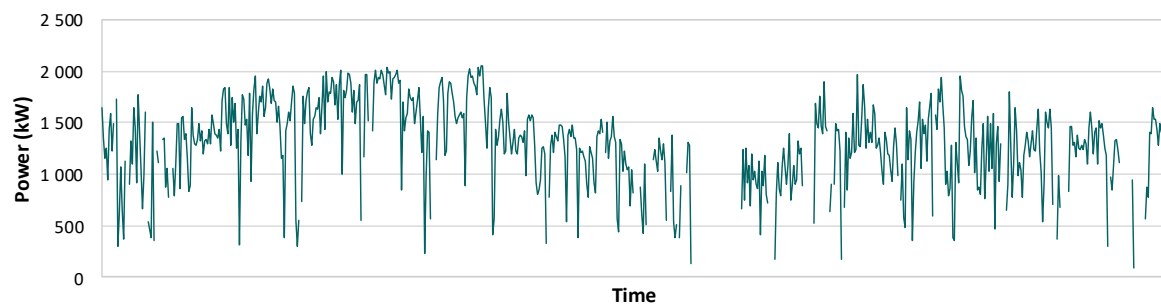


Figure 128: Fridge plant 3 – Analysed power data

Fridge plant 3: Raw data check - Flow

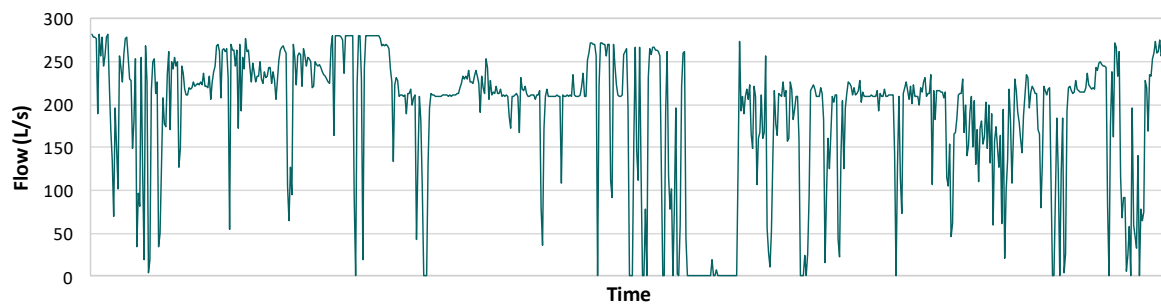


Figure 129: Fridge plant 3 - Raw flow data error check

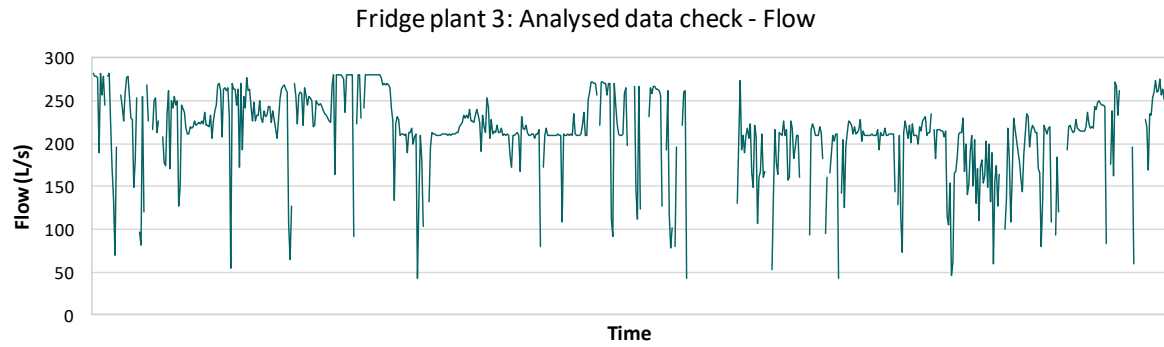


Figure 130: Fridge plant 3 – Analysed flow data

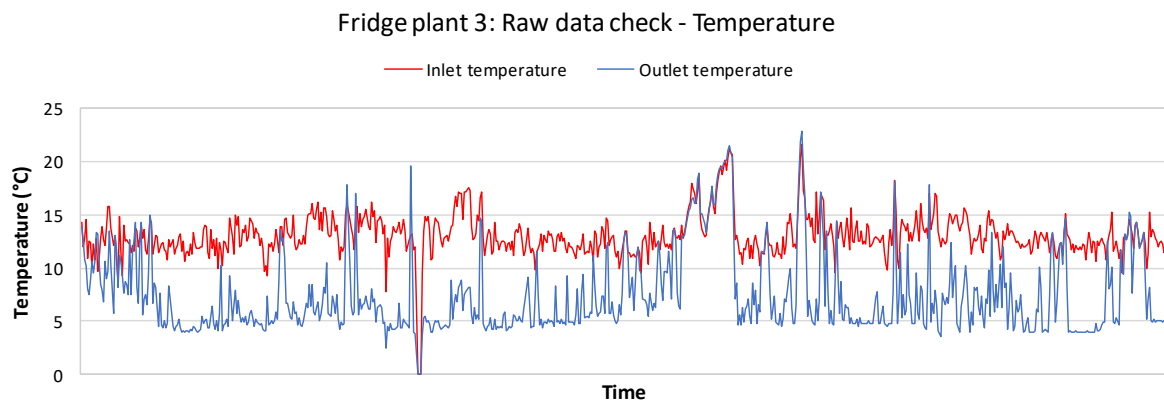


Figure 131: Fridge plant 3 - Raw temperature data error check

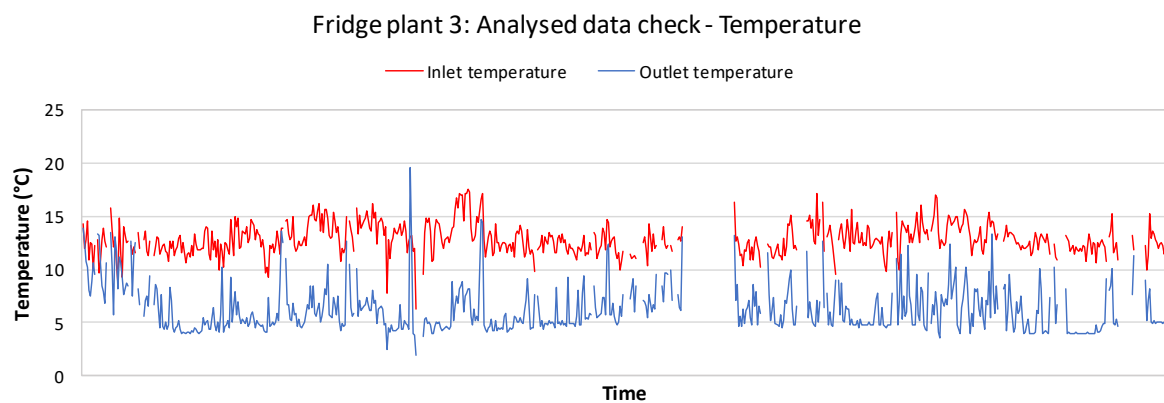


Figure 132: Fridge plant 3 – Analysed temperature data

Periods of inactivity, as well as data errors, were removed from the dataset. The final dataset for Year 1 contained 338 data points, and the dataset for Year 2 281. Instances where the outlet temperature exceeded the inlet temperature were removed from the final dataset.

Fridge plant 4: Raw data check - Power

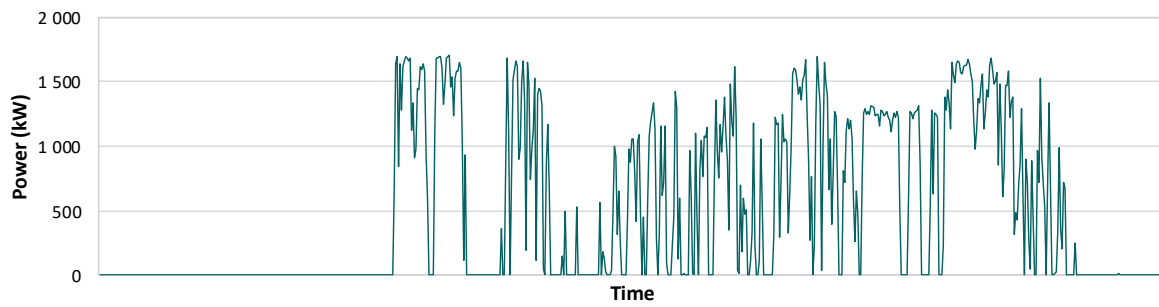


Figure 133: Fridge plant 4 - Raw power data check

Fridge plant 4: Analysed data check - Power

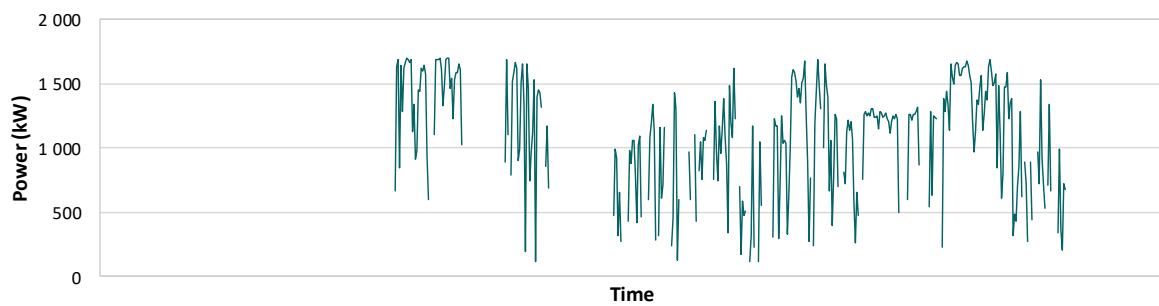


Figure 134: Fridge plant 4 - Analysed power data

Fridge plant 4: Raw data check - Flow

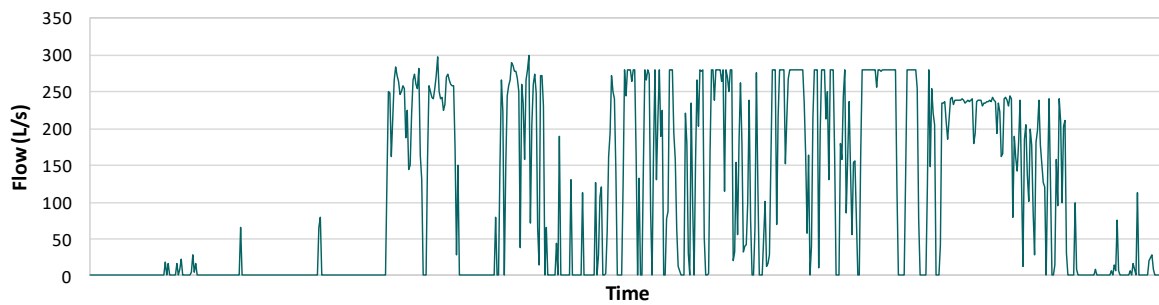


Figure 135: Fridge plant 4 - Raw flow data error check

Fridge plant 4: Analysed data check - Flow

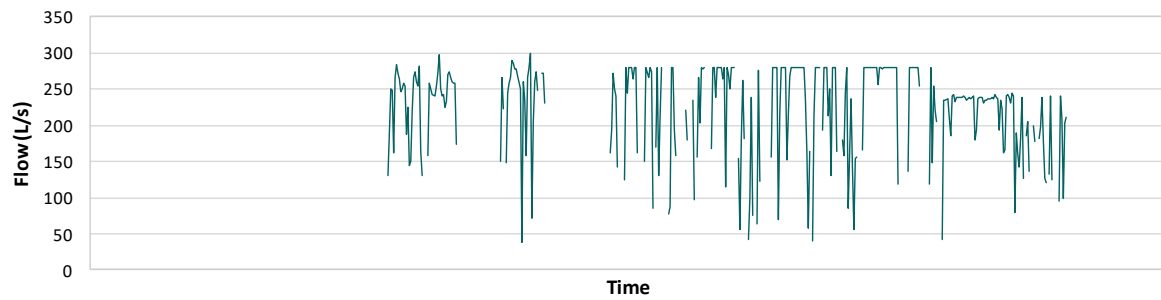


Figure 136: Fridge plant 4 – Analysed flow data

Fridge plant 4: Raw data check - Temperature

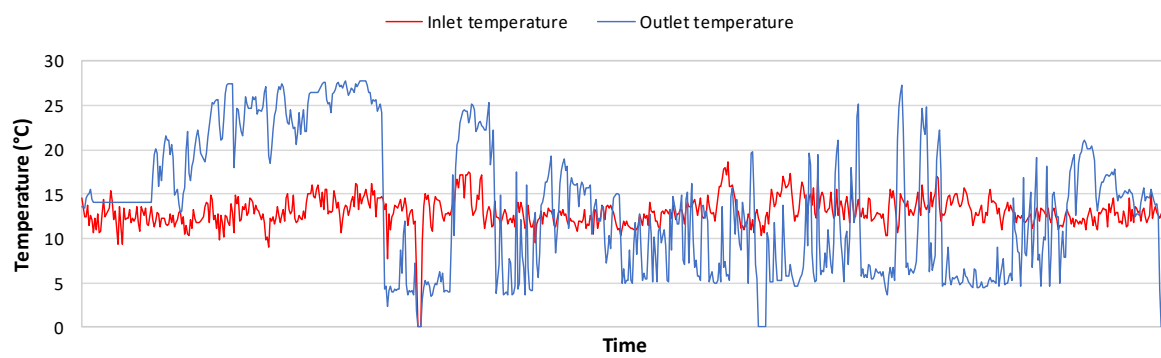


Figure 137: Fridge plant 4 - Raw temperature data error check

Fridge plant 4: Analysed data check - Flow

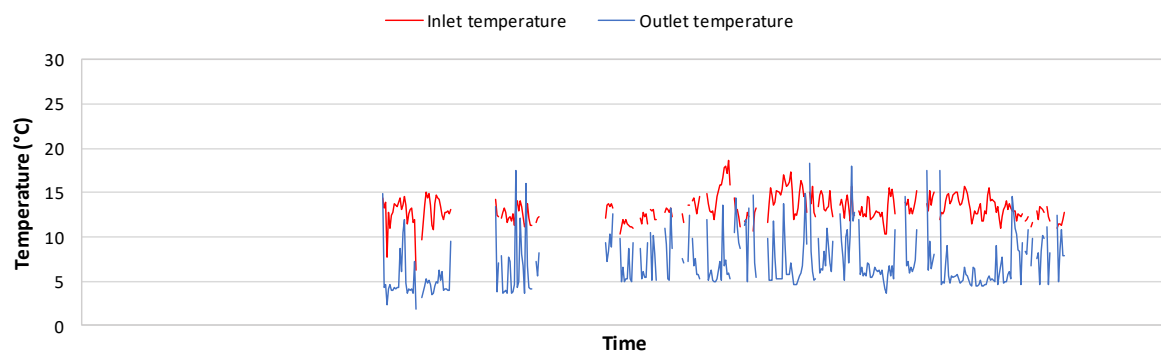


Figure 138: Fridge plant 4 – Analysed temperature data

Periods of inactivity, as well as data errors, were removed from the dataset. The final dataset for Year 1 contained 81 data points, as the fridge plant did not operate for the full year, and the dataset for Year 2 contained 220. Instances where the outlet temperature exceeded the inlet temperature were removed from the final dataset.

Data visualisation

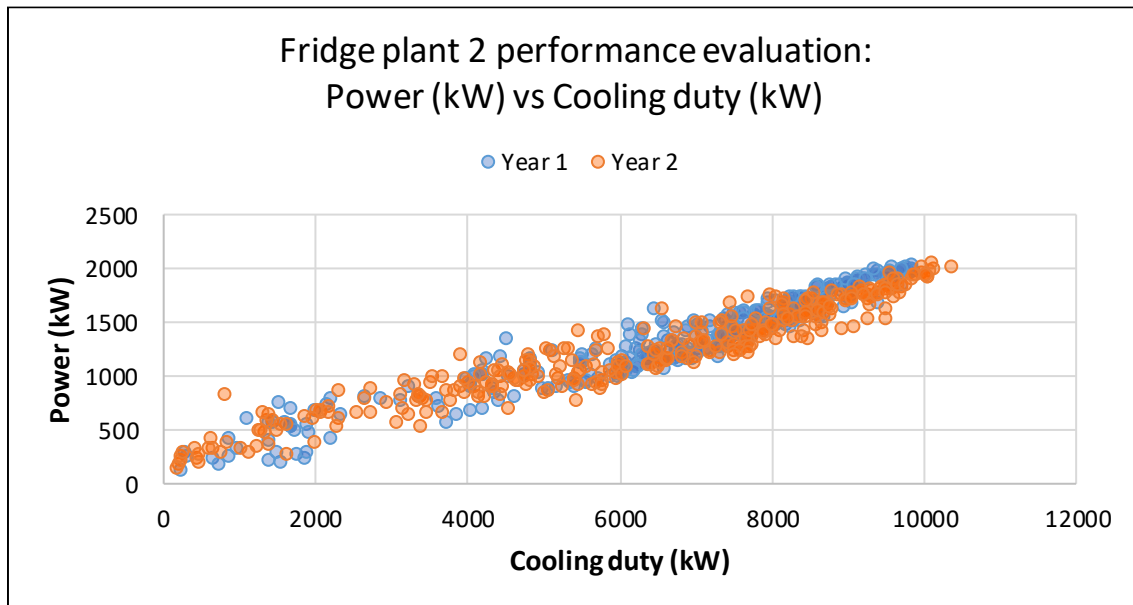


Figure 139: Fridge plant 2 performance evaluation visualisation

Fridge plant 2 displays a clear correlation between the power consumed by the fridge plant and the cooling duty produced. Its performance was satisfactory as no changes were made to its operation.

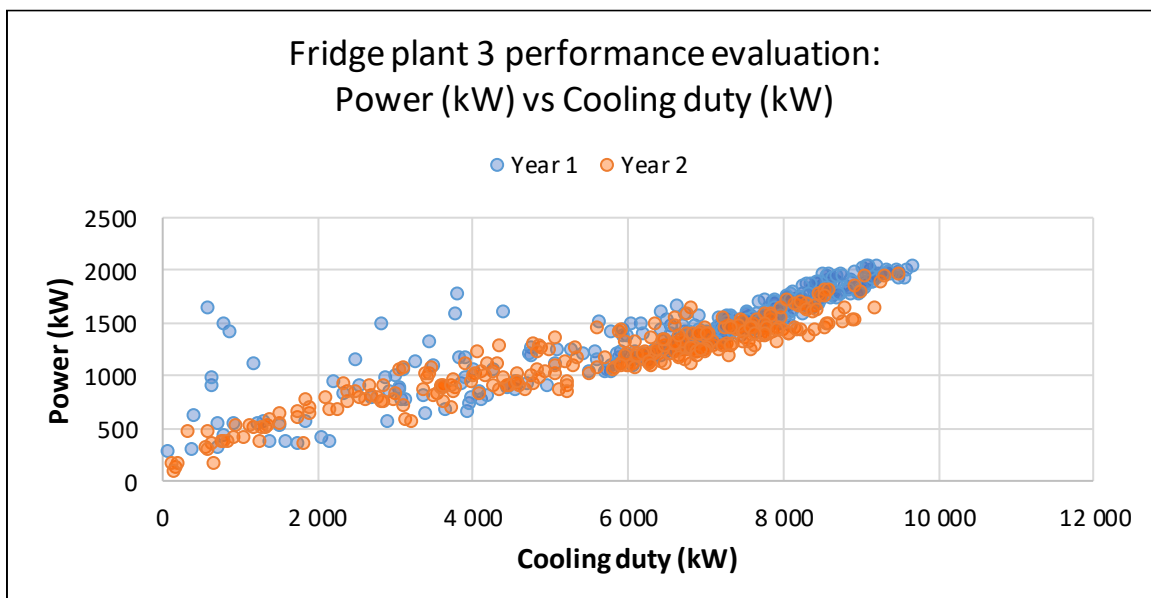


Figure 140: Fridge plant 3 performance evaluation visualisation

Fridge plant 3 experienced more unstable operation during Year 1 than during Year 2. In Year 1, the fridge plant produced a higher cooling duty than in Year 2. The performance of this fridge plant should be monitored further to ensure that no further reductions occur.

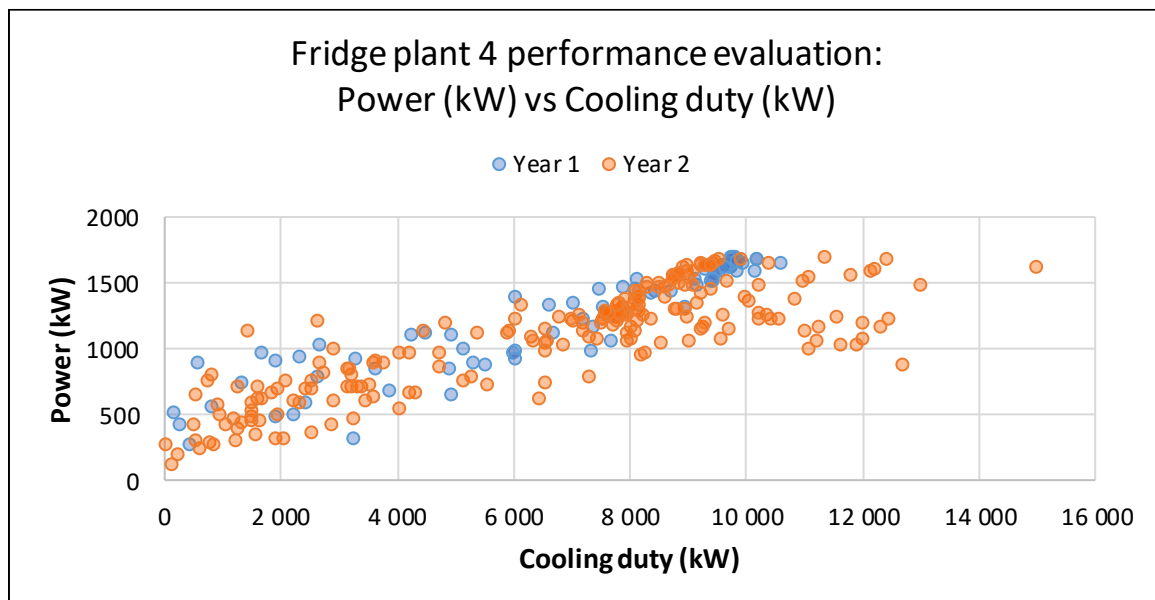


Figure 141: Fridge plant 4 performance evaluation visualisation

Fridge plant 4 is not yet operating as stable as the other plants in this study. It performed much better in Year 2, but its fluctuations in power usage should be addressed.

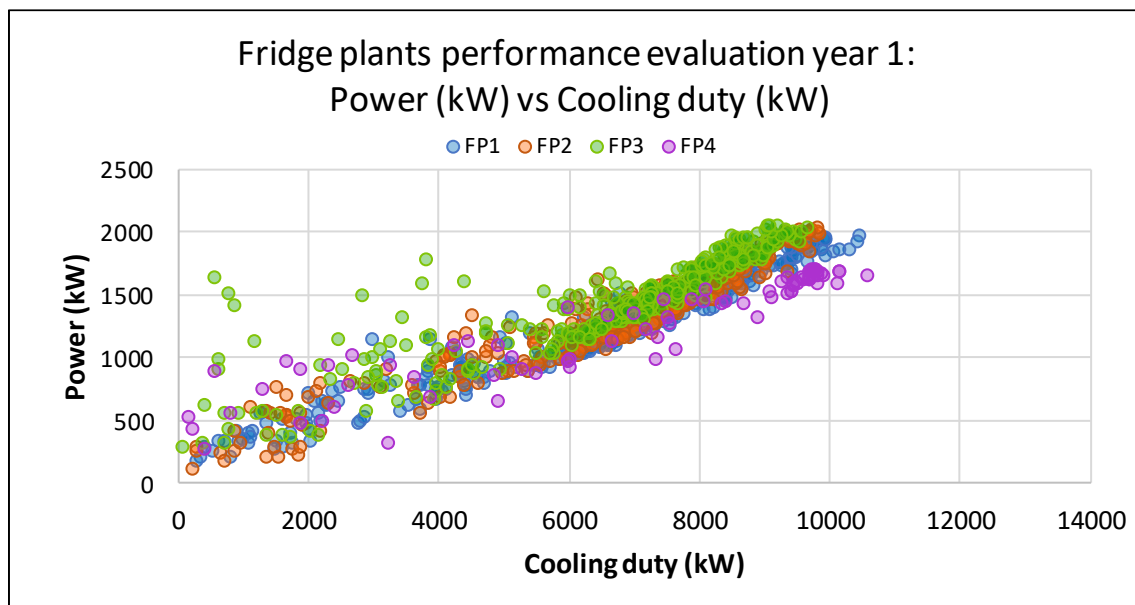


Figure 142: All fridge plants year 1 performance evaluation visualisation

In Year 1, all fridge plants performed on a very similar level. Fridge plant 4, although not operated for the full year, uses less power than the other fridge plants to produce the same cooling duty.

APPENDIX D : QUESTIONNAIRES

D.1 Introduction

This appendix contains the 8 completed visualisation effectiveness questionnaires. These were used to validate the results of the case studies done in Chapter 3.

D.2 Questionnaire 1

Reviewer details: _____

Field of expertise:

☒ Measurement & Verification	☐ Support systems (IT, information networks)
☒ Mining operations	☐ Operational maintenance
☒ Energy efficiency projects	☒ Strategic planning and optimisation

Years of experience:

☒ 1 – 2	☐ 6 – 10
☐ 3 – 5	☐ 10 +

Role within field:

☐ Manager/Strategic decision making	☒ Opportunity investigations
☒ Project implementation	☒ Maintenance
☒ Daily operation	

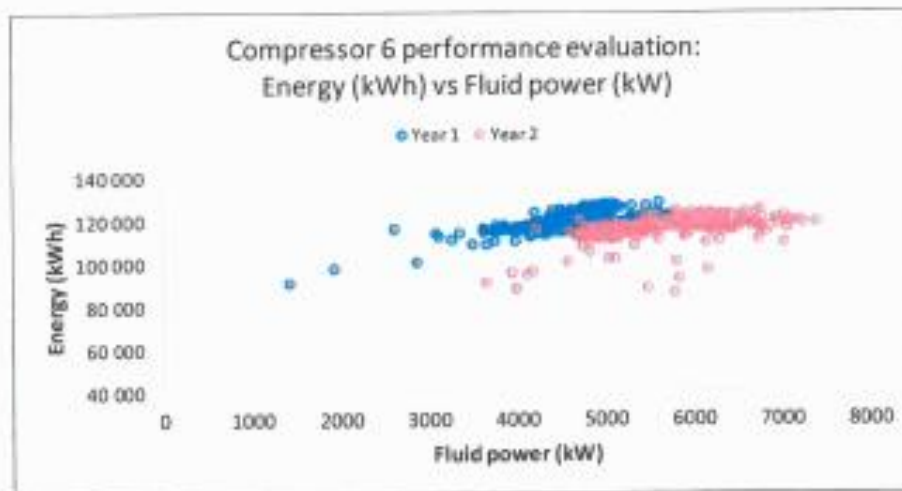
Thank you for taking the time to participate in this questionnaire. Your feedback will be used to validate the results obtained in my master's study: *Developing a methodology for evaluation of mine system performance*.

The study found that mines collect large amounts of data that could potentially be used for performance evaluation, but that the data is largely unutilised. Information can be extracted from this data through analysis and effective visualisation. This information may then be used to identify opportunities for energy efficiency initiatives.

You will review the visualisation results from three different case studies. Each case study will be briefly explained, and a visualisation will be presented. Please fill out the checklist provided for every visualisation and answer the accompanying question.

A study was done on a compressor cluster that forms a part of the compressed air system of a South African platinum mine. The goal of the compressed air system is to provide 5 mine shafts with compressed air. The pressure setpoint on the compressors was changed during this investigation, and an increased energy efficiency is expected.

The following graph uses daily average data from full days of operation to compare the performance compressor 6 over two years. Energy consumption is compared to fluid power, a function of the flow and pressure provided by the compressor.



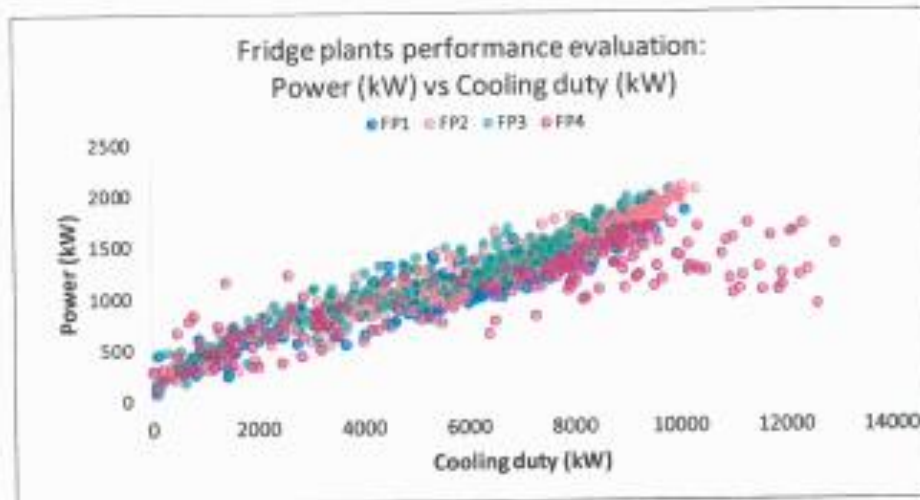
Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✗	✗
Is the visual in its simplest form?	✓	
Is an appropriate colour scheme used?	✗	
Does the visual encourage comparison?	✗	
Does the graph choice suit the information to be conveyed?	✗	
Is the graph clear?	✗	
Are the legends, titles and labels clear and self-explanatory?	✗	
Are the legends, titles and labels well-positioned?	✗	

Please comment on the performance of this system using the information provided in the visualisation.

How does this relate to the set-point. There is a performance increase based on the data but I don't understand how this relates to set-point changes?

A study was done on a fridge plant cluster on a South African gold mine. The cluster consists of four fridge plants that are part of a larger refrigeration system on the mine. The goal of the fridge plants is to cool water coming from the underground levels of the mine. One of the fridge plants were replaced during this investigation and the new fridge plant is expected to be more energy efficient.

The following graph uses daily average data from the mine to compare the four fridge plants. Power consumed by each fridge plant is compared to cooling duty, a factor of the water flow through the fridge plant and the change of temperature in the water.



Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	×	
Is the visual in its simplest form?	×	
Is an appropriate colour scheme used?	×	
Does the visual encourage comparison?	×	
Does the graph choice suit the information to be conveyed?	×	
Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?	×	
Are the legends, titles and labels well-positioned?	×	

Please comment on the performance of this system using the information provided in the visualisation.

FP4's performance increased but I would've expected a ^{smaller} ~~more~~ spread of data points. The duty improved substantially across a wide range of energy consumptions. It seems like there may be another factor influencing the duty.

D.3 Questionnaire 2

Reviewer details:

Field of expertise:

- | | |
|--|---|
| ☒ Measurement & Verification | ☐ Support systems (IT, information networks) |
| ☒ Mining operations | ☐ Operational maintenance |
| ☐ Energy efficiency projects | ☒ Strategic planning and optimisation |

Years of experience:

- | | |
|---|---------------------------------|
| ☐ 1 – 2 | ☐ 6 – 10 |
| ☒ 3 – 5 | ☐ 10 + |

Role within field:

- | | |
|---|--|
| ☒ Manager/Strategic decision making | ☒ Opportunity investigations |
| ☐ Project implementation | ☐ Maintenance |
| ☐ Daily operation | |

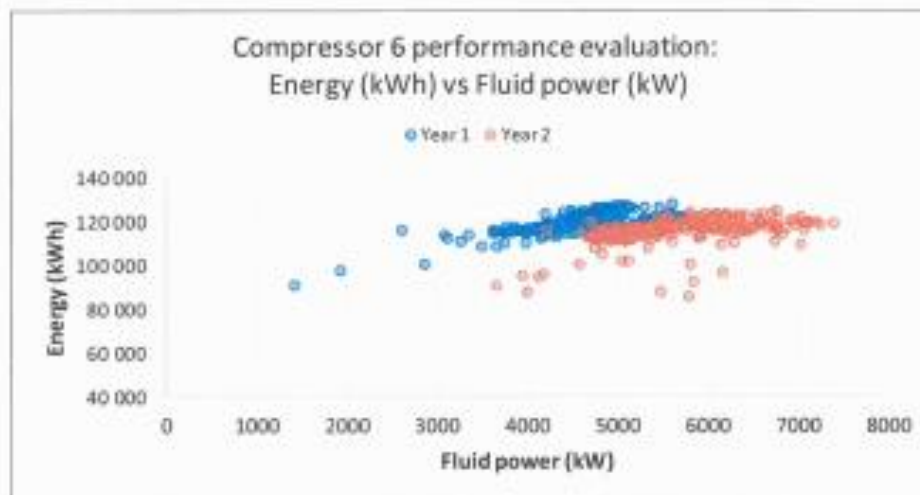
Thank you for taking the time to participate in this questionnaire. Your feedback will be used to validate the results obtained in my master's study: *Developing a methodology for evaluation of mine system performance*.

The study found that mines collect large amounts of data that could potentially be used for performance evaluation, but that the data is largely unutilised. Information can be extracted from this data through analysis and effective visualisation. This information may then be used to identify opportunities for energy efficiency initiatives.

You will review the visualisation results from three different case studies. Each case study will be briefly explained, and a visualisation will be presented. Please **fill out the checklist** provided for every visualisation and **answer the accompanying question**.

A study was done on a compressor cluster that forms a part of the compressed air system of a South African platinum mine. The goal of the compressed air system is to provide 5 mine shafts with compressed air. The pressure setpoint on the compressors was changed during this investigation, and an increased energy efficiency is expected.

The following graph uses daily average data from full days of operation to compare the performance compressor 6 over two years. Energy consumption is compared to fluid power, a function of the flow and pressure provided by the compressor.

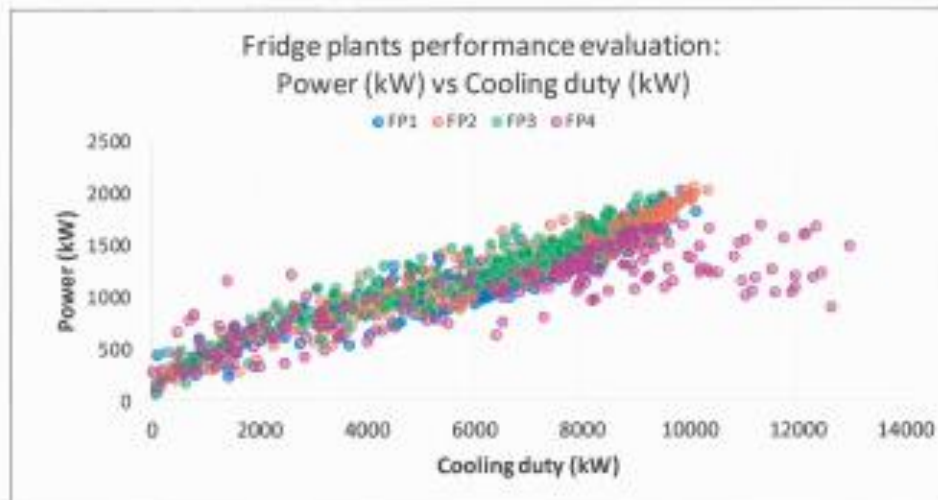


Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✓	
Is the visual in its simplest form?	✓	
Is an appropriate colour scheme used?	✓	
Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?	✓	
Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

A study was done on a fridge plant cluster on a South African gold mine. The cluster consists of four fridge plants that are part of a larger refrigeration system on the mine. The goal of the fridge plants is to cool water coming from the underground levels of the mine. One of the fridge plants were replaced during this investigation and the new fridge plant is expected to be more energy efficient.

The following graph uses daily average data from the mine to compare the four fridge plants. Power consumed by each fridge plant is compared to cooling duty, a factor of the water flow through the fridge plant and the change of temperature in the water.



Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✓	
Is the visual in its simplest form?		✓
Is an appropriate colour scheme used?		✓
Does the visual encourage comparison?		✓
Does the graph choice suit the information to be conveyed?		✓
Is the graph clear?		✓
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

It is difficult to distinguish between normal operation and ~~edge~~ outliers. Maybe a timeline should be added.

D.4 Questionnaire 3

Reviewer details:

Field of expertise:

- | | |
|--|---|
| ☒ Measurement & Verification | ☐ Support systems (IT, information networks) |
| ☒ Mining operations | ☐ Operational maintenance |
| ☐ Energy efficiency projects | ☒ Strategic planning and optimisation |

Years of experience:

- | | |
|--------------------------------|--|
| ☐ 1 – 2 | ☐ 6 – 10 |
| ☐ 3 – 5 | ☒ 10 + |

Role within field:

- | | |
|---|---|
| ☒ Manager/Strategic decision making | ☐ Opportunity investigations |
| ☐ Project implementation | ☐ Maintenance |
| ☒ Daily operation | |

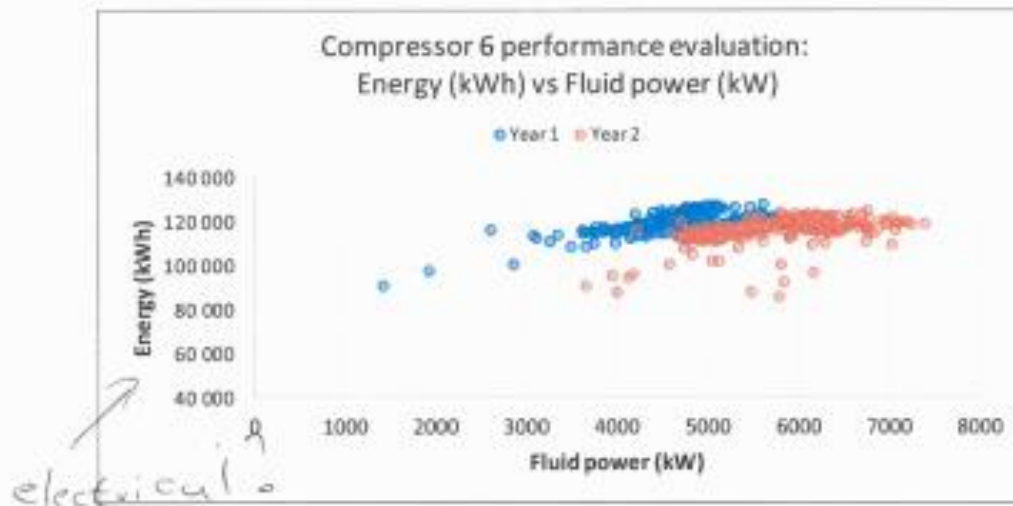
Thank you for taking the time to participate in this questionnaire. Your feedback will be used to validate the results obtained in my master's study: *Developing a methodology for evaluation of mine system performance*.

The study found that mines collect large amounts of data that could potentially be used for performance evaluation, but that the data is largely unutilised. Information can be extracted from this data through analysis and effective visualisation. This information may then be used to identify opportunities for energy efficiency initiatives.

You will review the visualisation results from three different case studies. Each case study will be briefly explained, and a visualisation will be presented. Please **fill out the checklist** provided for every visualisation and **answer the accompanying question**.

A study was done on a compressor cluster that forms a part of the compressed air system of a South African platinum mine. The goal of the compressed air system is to provide 5 mine shafts with compressed air. The pressure setpoint on the compressors was changed during this investigation, and an increased energy efficiency is expected.

The following graph uses daily average data from full days of operation to compare the performance compressor 6 over two years. Energy consumption is compared to fluid power, a function of the flow and pressure provided by the compressor.



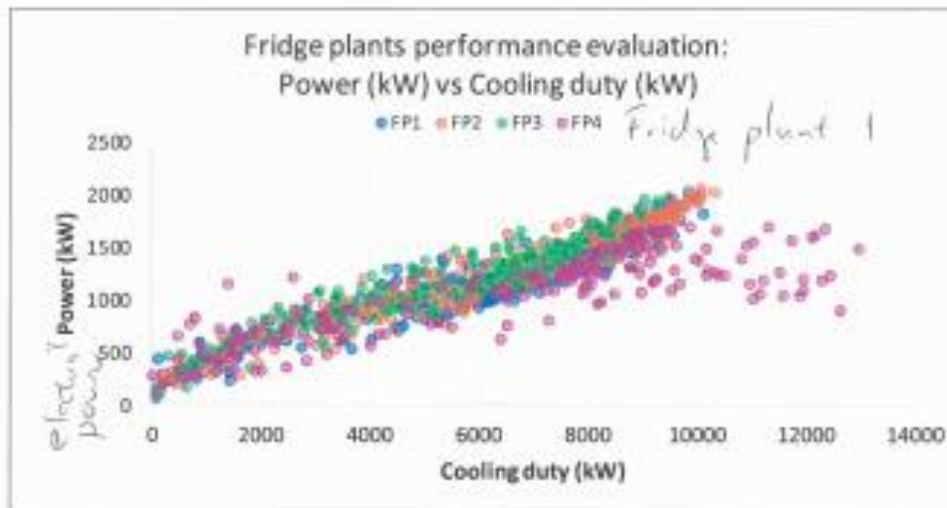
Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	X	
Is the visual in its simplest form?		X
Is an appropriate colour scheme used?	X	
Does the visual encourage comparison?	X	
Does the graph choice suit the information to be conveyed?	X	
Is the graph clear?		X
Are the legends, titles and labels clear and self-explanatory?	X	X
Are the legends, titles and labels well-positioned?	X	

Please comment on the performance of this system using the information provided in the visualisation.

I would have liked to see on the efficiency of the compressor for the day
fluid kWh
energy kWh

A study was done on a fridge plant cluster on a South African gold mine. The cluster consists of four fridge plants that are part of a larger refrigeration system on the mine. The goal of the fridge plants is to cool water coming from the underground levels of the mine. One of the fridge plants were replaced during this investigation and the new fridge plant is expected to be more energy efficient.

The following graph uses daily average data from the mine to compare the four fridge plants. Power consumed by each fridge plant is compared to cooling duty, a factor of the water flow through the fridge plant and the change of temperature in the water.



Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?		X
Is the visual in its simplest form?		X
Is an appropriate colour scheme used?	X	
Does the visual encourage comparison?		X
Does the graph choice suit the information to be conveyed?		X
Is the graph clear?		X
Are the legends, titles and labels clear and self-explanatory?		X
Are the legends, titles and labels well-positioned?	X	

Please comment on the performance of this system using the information provided in the visualisation.

D.5 Questionnaire 4

Reviewer details:

Field of expertise:

- | | |
|--|---|
| ☒ Measurement & Verification | ☐ Support systems (IT, information networks) |
| ☒ Mining operations | ☐ Operational maintenance |
| ☒ Energy efficiency projects | ☐ Strategic planning and optimisation |

Years of experience:

- | | |
|---|---------------------------------|
| ☒ 1 – 2 | ☐ 6 – 10 |
| ☐ 3 – 5 | ☐ 10 + |

Role within field:

- | | |
|--|--|
| ☐ Manager/Strategic decision making | ☒ Opportunity investigations |
| ☒ Project implementation | ☐ Maintenance |
| ☐ Daily operation | |

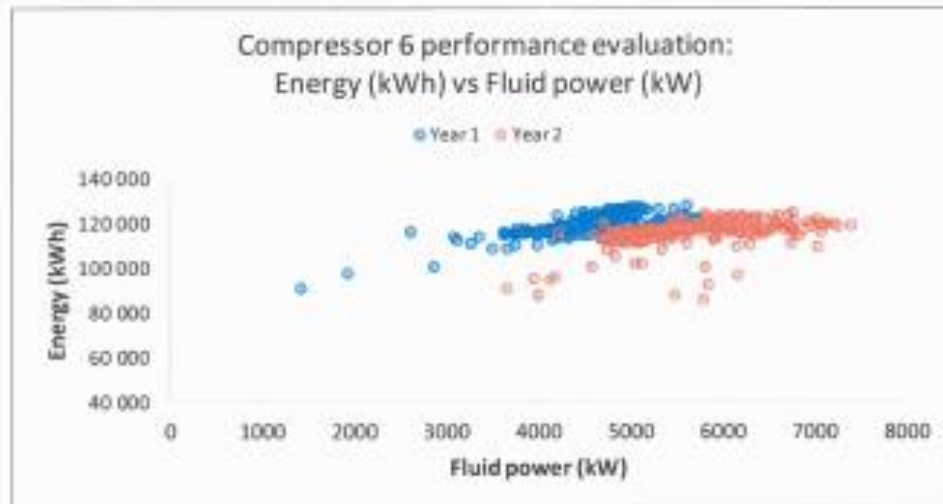
Thank you for taking the time to participate in this questionnaire. Your feedback will be used to validate the results obtained in my master's study: *Developing a methodology for evaluation of mine system performance*.

The study found that mines collect large amounts of data that could potentially be used for performance evaluation, but that the data is largely unutilised. Information can be extracted from this data through analysis and effective visualisation. This information may then be used to identify opportunities for energy efficiency initiatives.

You will review the visualisation results from three different case studies. Each case study will be briefly explained, and a visualisation will be presented. Please **fill out the checklist** provided for every visualisation and **answer the accompanying question**.

A study was done on a compressor cluster that forms a part of the compressed air system of a South African platinum mine. The goal of the compressed air system is to provide 5 mine shafts with compressed air. The pressure setpoint on the compressors was changed during this investigation, and an increased energy efficiency is expected.

The following graph uses daily average data from full days of operation to compare the performance compressor 6 over two years. Energy consumption is compared to fluid power, a function of the flow and pressure provided by the compressor.



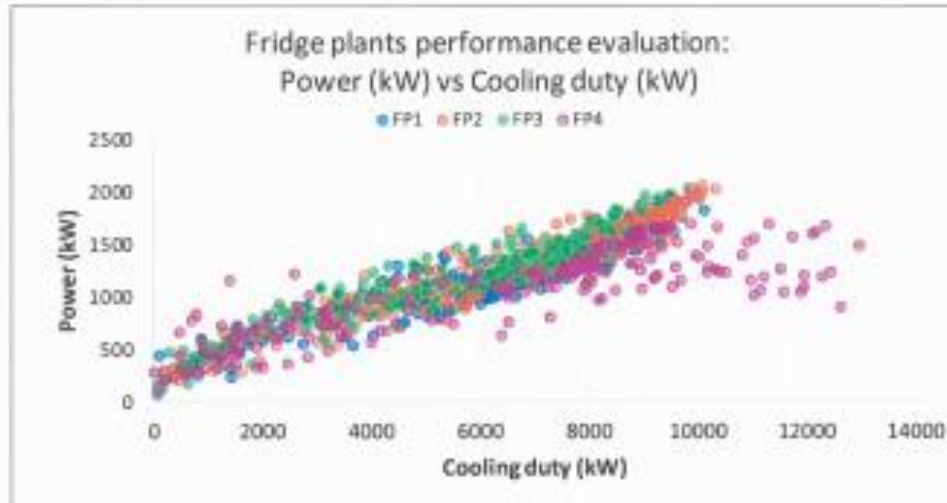
Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✓	
Is the visual in its simplest form?	✓	
Is an appropriate colour scheme used?	✓	
Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?	✓	
Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

Year 2 showed an improved performance of compressor 6, because more fluid power was achieved for the energy input.

A study was done on a fridge plant cluster on a South African gold mine. The cluster consists of four fridge plants that are part of a larger refrigeration system on the mine. The goal of the fridge plants is to cool water coming from the underground levels of the mine. One of the fridge plants were replaced during this investigation and the new fridge plant is expected to be more energy efficient.

The following graph uses daily average data from the mine to compare the four fridge plants. Power consumed by each fridge plant is compared to cooling duty, a factor of the water flow through the fridge plant and the change of temperature in the water.



Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✓	
Is the visual in its simplest form?	✓	
Is an appropriate colour scheme used?	✓	
Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?	✓	
Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

~~The~~ FP 4 seems to have a better performance sector, but a contrasting improvement of performance. This leads me to suspect this fridge plant to have been replaced.

D.6 Questionnaire 5

Reviewer details:

Field of expertise:

- | | |
|--|---|
| ☐ Measurement & Verification | ☐ Support systems (IT, information networks) |
| ☒ Mining operations | ☒ Operational maintenance |
| ☒ Energy efficiency projects | ☒ Strategic planning and optimisation |

Years of experience:

- | | |
|---|---------------------------------|
| ☐ 1 – 2 | ☐ 6 – 10 |
| ☒ 3 – 5 | ☐ 10 + |

Role within field:

- | | |
|---|--|
| ☒ Manager/Strategic decision making | ☒ Opportunity investigations |
| ☐ Project implementation | ☒ Maintenance |
| ☐ Daily operation | |

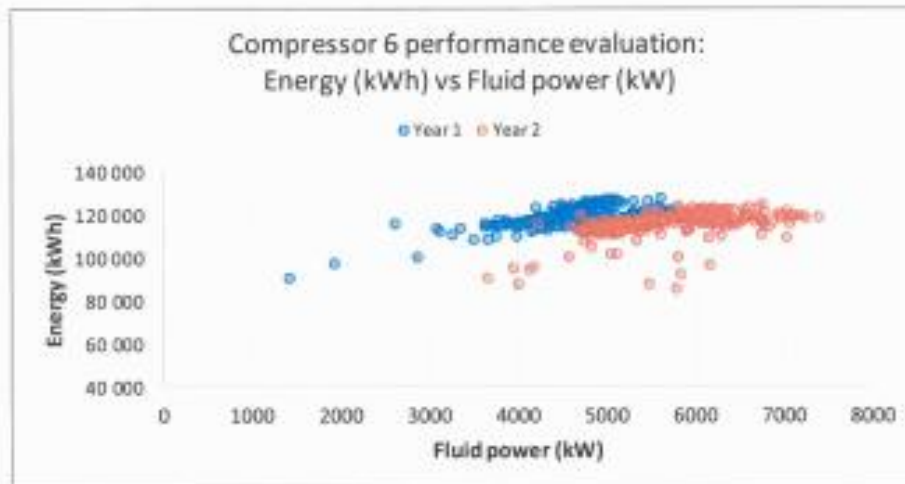
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A study was done on a compressor cluster that forms a part of the compressed air system of a South African platinum mine. The goal of the compressed air system is to provide 5 mine shafts with compressed air. The pressure setpoint on the compressors was changed during this investigation, and an increased energy efficiency is expected.

The following graph uses daily average data from full days of operation to compare the performance compressor 6 over two years. Energy consumption is compared to fluid power, a function of the flow and pressure provided by the compressor.



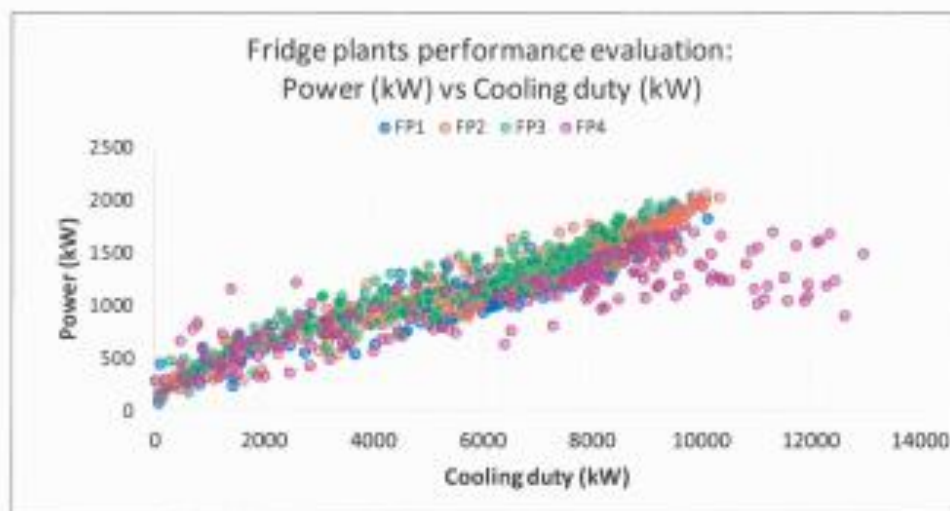
Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✓	
Is the visual in its simplest form?	✓	
Is an appropriate colour scheme used?	✓	
Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?	✓	
Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

Compressor efficiency clearly increased. The information in the graph, however, is not enough to link the improvement to only the change in set-points. The graph, however, clearly displays the improvements on the system, which is the main objective.

A study was done on a fridge plant cluster on a South African gold mine. The cluster consists of four fridge plants that are part of a larger refrigeration system on the mine. The goal of the fridge plants is to cool water coming from the underground levels of the mine. One of the fridge plants were replaced during this investigation and the new fridge plant is expected to be more energy efficient.

The following graph uses daily average data from the mine to compare the four fridge plants. Power consumed by each fridge plant is compared to cooling duty, a factor of the water flow through the fridge plant and the change of temperature in the water.



Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✓	
Is the visual in its simplest form?		✓
Is an appropriate colour scheme used?	✓	
Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?		✓
Is the graph clear?		✓
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

Too much information on graph, difficult to distinguish each FP's data. FP 4 is likely the replaced machine as it has greater efficiency at the top end of its power (full load) usage. It is also clear that FP 4 uses less power, indicating a smaller electric motor than FP 1-3.

D.7 Questionnaire 6

Reviewer details:

Field of expertise:

- ☒ Measurement & Verification
☒ Mining operations
☐ Energy efficiency projects

- ☐ Support systems (IT, information networks)
☐ Operational maintenance
☐ Strategic planning and optimisation

Years of experience:

- ☐ 1 – 2
☒ 3 – 5

- ☐ 6 – 10
☐ 10 +

Role within field:

- ☐ Manager/Strategic decision making
☒ Project implementation
☐ Daily operation

- ☒ Opportunity investigations
☐ Maintenance

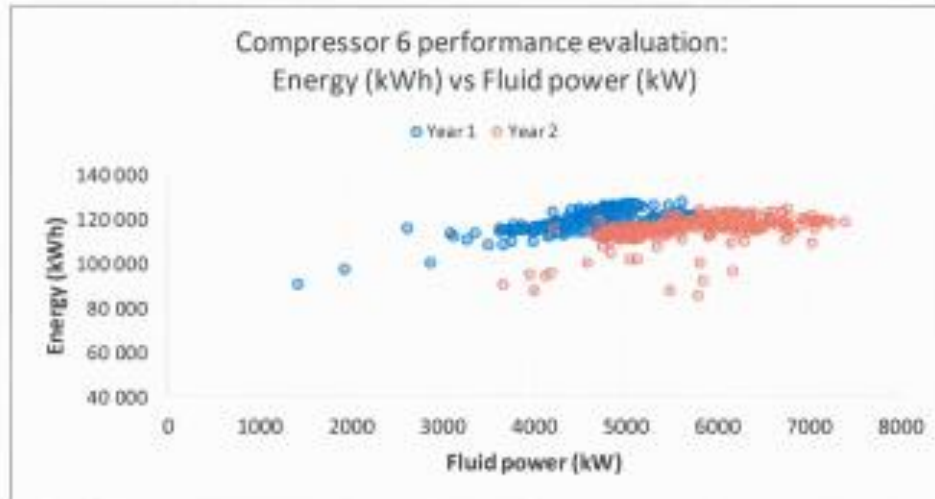
Thank you for taking the time to participate in this questionnaire. Your feedback will be used to validate the results obtained in my master's study: *Developing a methodology for evaluation of mine system performance*.

The study found that mines collect large amounts of data that could potentially be used for performance evaluation, but that the data is largely unutilised. Information can be extracted from this data through analysis and effective visualisation. This information may then be used to identify opportunities for energy efficiency initiatives.

You will review the visualisation results from three different case studies. Each case study will be briefly explained, and a visualisation will be presented. Please fill out the checklist provided for every visualisation and answer the accompanying question.

A study was done on a compressor cluster that forms a part of the compressed air system of a South African platinum mine. The goal of the compressed air system is to provide 5 mine shafts with compressed air. The pressure setpoint on the compressors was changed during this investigation, and an increased energy efficiency is expected.

The following graph uses daily average data from full days of operation to compare the performance compressor 6 over two years. Energy consumption is compared to fluid power, a function of the flow and pressure provided by the compressor.



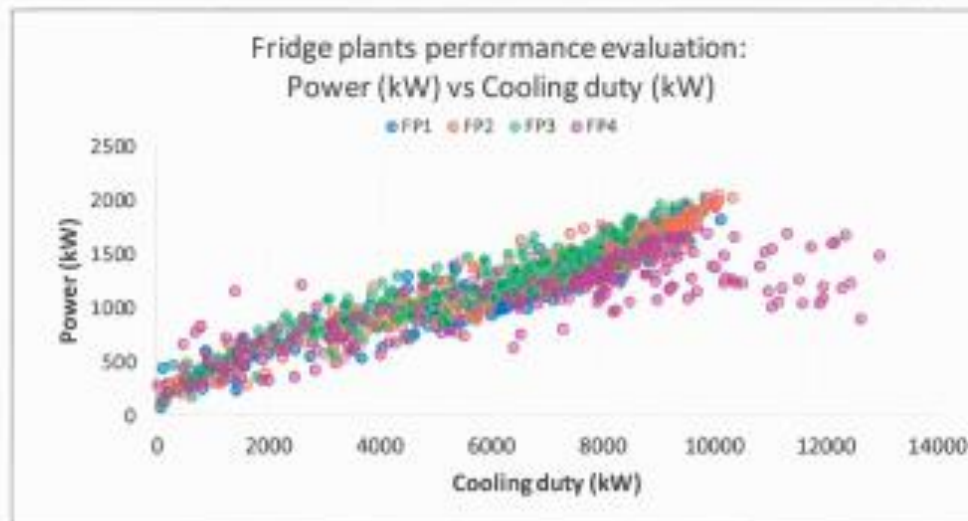
Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✓	
Is the visual in its simplest form?	✓	
Is an appropriate colour scheme used?	✓	
Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?	✓	
Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

It seems as if compressor 6 became more efficient in year 2
(after set-point change)

A study was done on a fridge plant cluster on a South African gold mine. The cluster consists of four fridge plants that are part of a larger refrigeration system on the mine. The goal of the fridge plants is to cool water coming from the underground levels of the mine. One of the fridge plants were replaced during this investigation and the new fridge plant is expected to be more energy efficient.

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Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✓	
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Is an appropriate colour scheme used?	✓	
Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?	✓	
Is the graph clear?	✓	
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Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

FP4 seems as if it can 'produce' more cooling at lower energy consumption. Thus, it is more energy efficient.

FP1 - 3 can be considered to be replaced by the same 'type' of fridge plant as FP4.

D.8 Questionnaire 7

Reviewer details:

Field of expertise:

- | | |
|--|---|
| ☒ Measurement & Verification | ☐ Support systems (IT, information networks) |
| ☐ Mining operations | ☐ Operational maintenance |
| ☒ Energy efficiency projects | ☐ Strategic planning and optimisation |

Years of experience:

- | | |
|--------------------------------|--|
| ☐ 1 – 2 | ☒ 6 – 10 |
| ☐ 3 – 5 | ☐ 10 + |

Role within field:

- | | |
|--|--|
| ☐ Manager/Strategic decision making | ☒ Opportunity investigations |
| ☒ Project implementation | ☐ Maintenance |
| ☐ Daily operation | |

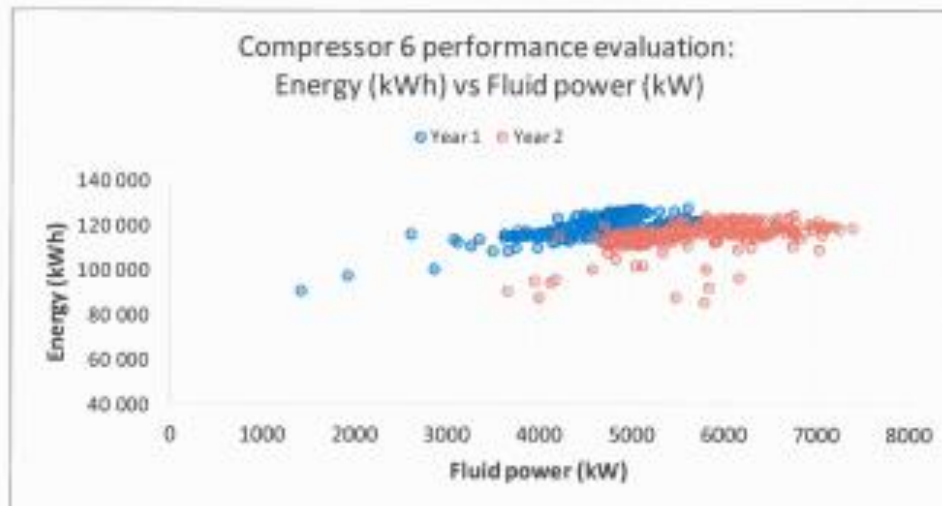
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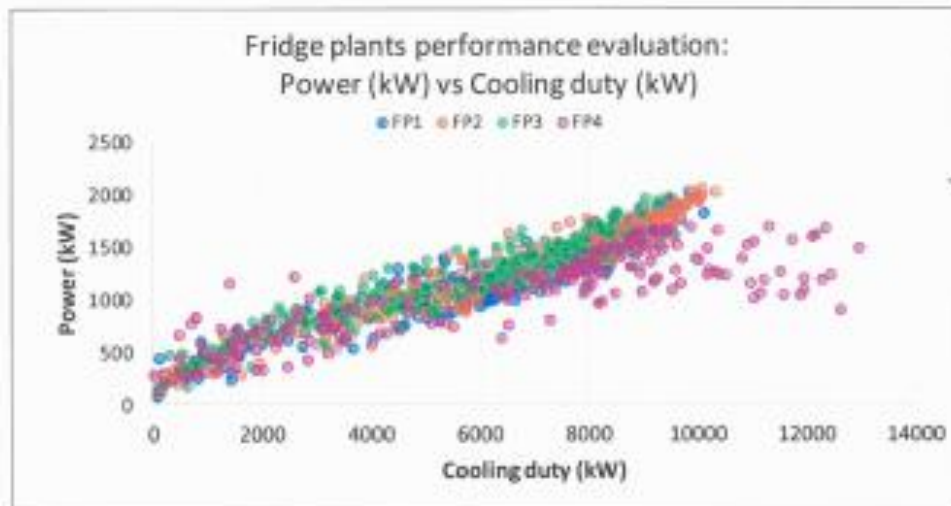
Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?	✓	
Is the visual in its simplest form?	✓	
Is an appropriate colour scheme used?	✓	
Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?	✓	
Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

It is clear from the shift of the data in year 2 that something changed. It cannot be confirmed what caused the shift from the figure. But an efficiency improvement is clearly visible from the figure.

A study was done on a fridge plant cluster on a South African gold mine. The cluster consists of four fridge plants that are part of a larger refrigeration system on the mine. The goal of the fridge plants is to cool water coming from the underground levels of the mine. One of the fridge plants were replaced during this investigation and the new fridge plant is expected to be more energy efficient.

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Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?		✓
Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

The performance of the 4 x Fridge plants seem fairly similar with FP4 having some periods with better performance. FP4 seems to do marginally better at > 6000 kW but not excessively compared to FP1. The biggest area for efficiency is at > 10 000 kW for FP4.

D.9 Questionnaire 8

Reviewer details:

Field of expertise:

☒ Measurement & Verification

☐ Support systems (IT, information networks)

☒ Mining operations

☒ Operational maintenance

☒ Energy efficiency projects

☒ Strategic planning and optimisation

Years of experience:

☐ 1 – 2

☒ 6 – 10

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☒ Opportunity investigations

☐ Project implementation

☐ Maintenance

☐ Daily operation

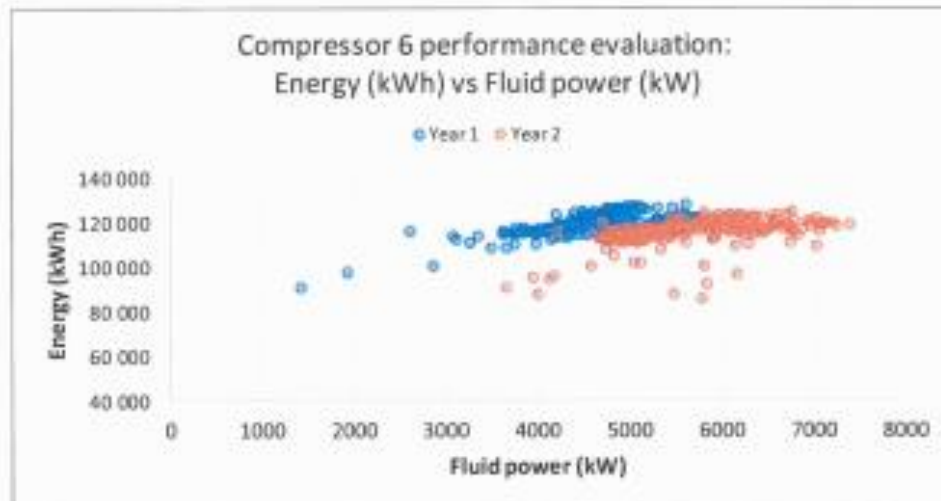
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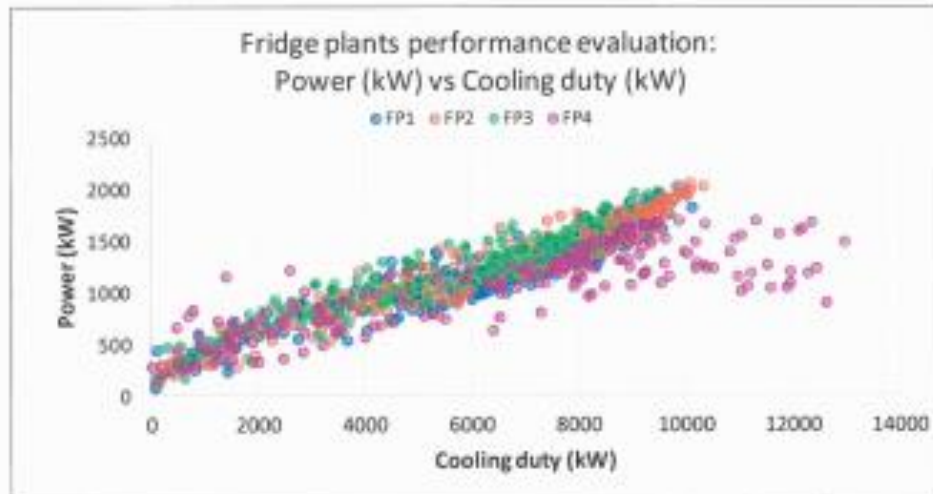
Data visualisation effectiveness checklist		
Question	Yes	No
Does the visualisation convey the necessary information?		✓
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Is an appropriate colour scheme used?	✓	
Does the visual encourage comparison?	✓	
Does the graph choice suit the information to be conveyed?	✓	
Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?		✓
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

From the graph the compressor showed an improved fluid power in Year 2. To me this means they increased the pressure set point in Year 2. However, do not know how the energy consumption decreased with a decrease in pressure set point.

A study was done on a fridge plant cluster on a South African gold mine. The cluster consists of four fridge plants that are part of a larger refrigeration system on the mine. The goal of the fridge plants is to cool water coming from the underground levels of the mine. One of the fridge plants were replaced during this investigation and the new fridge plant is expected to be more energy efficient.

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Is the graph clear?	✓	
Are the legends, titles and labels clear and self-explanatory?	✓	
Are the legends, titles and labels well-positioned?	✓	

Please comment on the performance of this system using the information provided in the visualisation.

Fridge plant 4 performed showed an increased performance in terms of cooling duty while consuming the same (or slightly) lower electrical energy.