Measurement and verification of industrial DSM projects

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ABSTRACT

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Energy cost-reduction projects implemented on complex industrial systems present several challenges. The involvement of multiple project stakeholders associated with programmes such as demand side management (DSM) further increases potential risks. The process of determining project impacts is especially important due to the direct financial impact on stakeholders. A good understanding of the independent measurement and verification (M&V) process is therefore vital to ensure an unbiased process.

A review of existing M&V frameworks and guidelines found that M&V protocols and templates are well developed and widely implemented. Unfortunately, the official literature provides little guidance on the practical M&V of industrial DSM projects. This prompted a detailed literature analysis of numerous publications to ascertain the industry norm. The diverse results obtained are categorised, normalised and graphically presented to highlight shortcomings in present M&V processes.

This thesis develops several practical methodologies and guidelines to address the needs highlighted by the literature analysis. Three chapters are dedicated to the development and verification of these solutions. The first entails the evaluation of data quality with the aim of producing an accurate and error-free dataset. The second develops, evaluates and ultimately selects a baseline model representative of normal system operations. The final chapter presents project performance and uses existing methods to monitor system changes and project performance over the long term.

The new methodologies are designed to simplify the practical implementation of different processes. Results are graphically presented thereby enabling quick and intuitive evaluation whilst adhering to present M&V requirements. This makes the M&V process accessible to all stakeholders and enables the transparent development and improvement of all processes.

The practical application of the new methodologies is verified by using 25 industrial case studies. The results obtained are validated using data obtained from independent third parties. This proves the functionality of the methodologies and highlights trends that can be evaluated in future studies.

The new methodologies improve the accuracy and efficiency of the evaluation process. The potential annual impacts amount to R27 million for DSM stakeholders and R19 million for M&V teams. The extrapolation of these results indicates a massive potential impact on international projects. These results, albeit estimates, confirm the significant contribution of the new methodologies.

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On a personal note, I would like to thank God for making all things possible. Thank you my dearest family, friends and all who had a profound impact on my life. For you I quote Paulo Coelho's Alchemist: "And, when you want something, all the universe conspires in helping you to achieve it.". Thank you for your love, sacrifice, support and being part of my universe. I dedicate this work to you.

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ABBREVIATIONS

AC	Air conditioning
AEE	Association for Energy Engineers
AP	Average profile
APE	Absolute percentage error
ASHRAE	American Society of Heating, Refrigeration and Air-conditioning Engineers
CMVPSA	Council of Measurement and Verification Professionals of South Africa
CUSUM	Cumulative sum
DSM	Demand side management
EE	Energy efficiency
EP	Evening peak
ESCO	Energy services company
FEMP	Federal Energy Management Program
HMI	Human machine interface
HVAC	Heating, ventilation and air conditioning
IPMVP	International performance measurement and verification protocol
LS	Load shifting
M&V	Measurement and verification
MAE	Mean absolute error
MAPE	Mean absolute percentage error
PA	Performance assessment
PLC	Programmable logic controller
PT	Performance tracking
SCADA	Supervisory control and data acquisition
SLA	Service level adjustment
TOU	Time of use

Units of Measure

°C	Degrees Celsius
A	Ampere
kPa	Kilopascal
kV	Kilovolt
kW	Kilowatt
kWh	Kilowatt-hour
mA	Milliampere
MW	Megawatt
V	Volt

Symbols

μ	Mean
$\bar{y}$	Mean of the values of y
$\acute{y}_i$	Predicted value of y_i
θ	Quality variable
σ	Standard deviation
df	Degrees of freedom
R^2	Coefficient of determination
RMSE	Root mean squared error
SSResid	Residual sum of squares
SSTo	Total sum of squares
T	Target value

CHAPTER 1

INTRODUCTION TO MEASUREMENT AND VERIFICATION

1. INTRODUCTION TO MEASUREMENT AND VERIFICATION

1.1. REVIEW OF PRESENT M&V PROCESSES

1.1.1. INTRODUCTION

Energy Services Companies (ESCOs) endeavour to improve energy usage in the commercial, municipal and industrial sectors. There are, however, several challenges associated with energy cost-reduction projects [1]. One of these challenges is calculating the avoided energy usage and costs in an efficient and accurate manner [2]. This information enables project stakeholders to objectively gauge project benefits [3]. The results have direct financial impact on the stakeholders, thus making it a very relevant risk [4]. This risk is mitigated by appointing independent measurement and verification (M&V) teams, thereby increasing confidence in reported results [5], [6]. The M&V teams calculate the environmental, social and economic impact of the project (savings) [7], [8].

Several guidelines have been created to aid and to standardise the M&V process. The International Performance Measurement and Verification Protocol (IPMVP) and the Federal Energy Management Program (FEMP) M&V guides are the most prevalent [2], [7], [9]. Groups such as the American Society of Heating, Refrigeration and Air-Conditioning Engineers (ASHRAE), the Association for Energy Engineers (AEE) and the Council of Measurement and Verification Professionals of South Africa (CMVPSA) use these guidelines as a basis to develop and adhere to standards such as SANS 50010:2010 [2], [10]. The groups' adherence to these strict principles gives specialist M&V teams the ability to objectively report on high-value projects and policies with a high level of trust and credibility [5], [8], [11], [12], [13].

The cost of electricity in South Africa resulted in incentives for energy-related projects only becoming relevant during 2005 [14]. At this stage, the national energy supplier (Eskom) and government launched several programmes to fund energy-related projects [12]. The goal of programmes such as demand side management (DSM) was decoupling industrial growth from power consumption, delaying the need for new power stations and improving national energy efficiency [15], [16], [17].

The South African energy industry has since continued to evolve with additional project-funding models being developed. The latest incentive is the section 12L of the Income Tax Act that came into operation in November 2013 [18], [19]. The M&V process will have a direct impact on the size of the rebate and should be conservative, accurate, independent and auditable to protect all parties involved. It therefore remains a prerequisite that an independent certified M&V professional quantifies and compiles the savings report to ensure that the process can be regulated and results can be trusted [20].

DSM projects can be implemented in various sectors, utilising different technologies and methods to achieve savings without adversely affecting system performance [21], [22]. DSM projects have significant potential, especially for energy efficiency projects in industry [23], [24]. Increased project complexity coupled with stricter funding models is a challenge to all stakeholders. It is therefore imperative that the M&V process should grow with the rest of industry, thus ensuring fair evaluation of all projects. Chapter 1 investigates the present state of M&V in South Africa with specific focus on industrial projects.

1.1.2. Overview of the M&V process

The project lifecycle documentation process for South African M&V teams was developed based on the IPMVP and FEMP guidelines [5]. Figure 1-1 illustrates how a typical DSM project and its M&V process interact [25], [26].

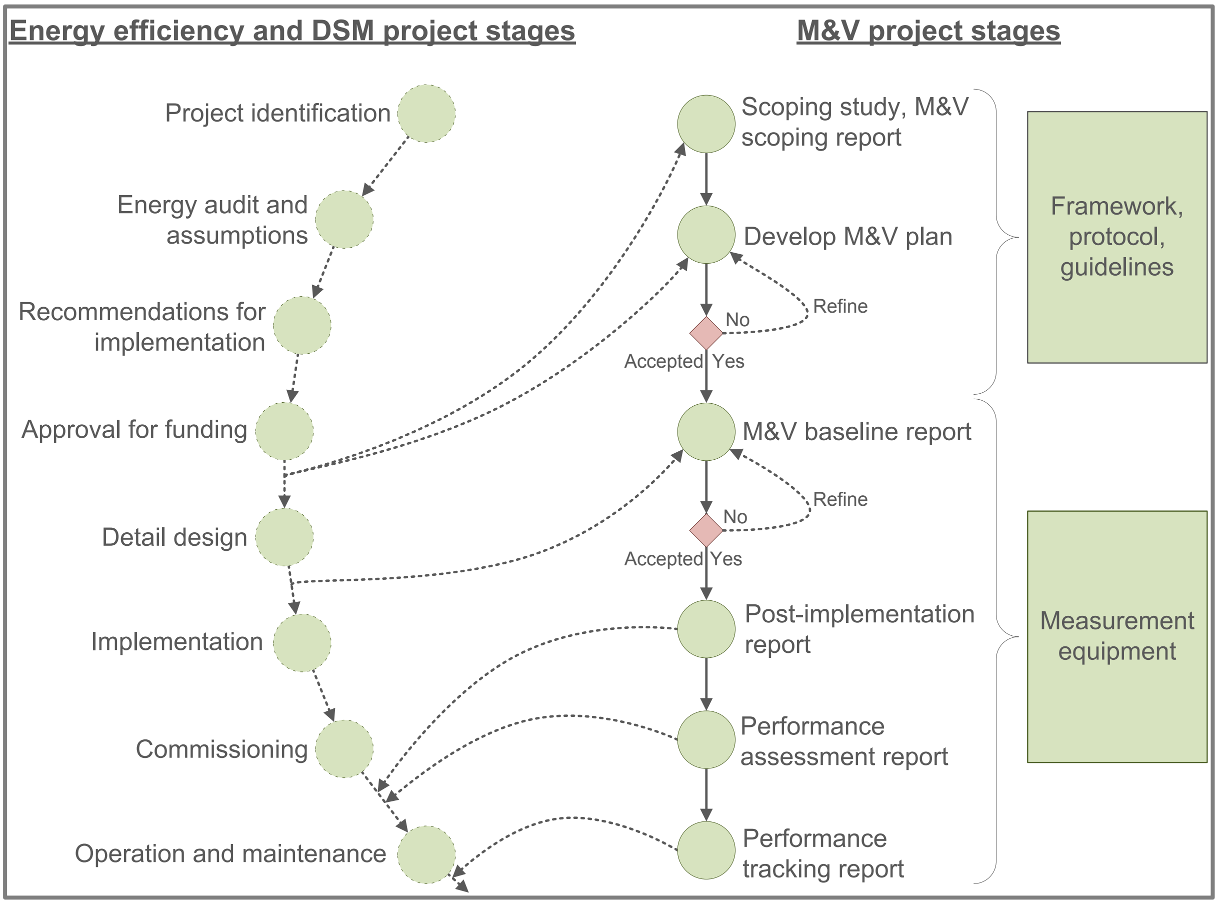

Figure 1-1: The interaction between M&V and typical DSM project stages

The generic M&V project stages in Figure 1-1 are well established and guidelines regarding the layout and function of each document are readily available. However, the content of each document will slightly differ depending on which M&V option is selected.

The M&V team determines the M&V option by firstly establishing a measurement boundary when assessing a new project. The components encapsulated by the boundary define what will be measured and how the impact of the project will be quantified. The different types of measurement boundaries are referred to as M&V Option A, Option B, Option C and Option D. Figure 1-2 illustrates the process of determining the appropriate M&V option [7], [27], [28].

The options are [7], [9]:

- Option A: Retrofit isolation with key parameter measurement;
- Option B: Retrofit isolation with all parameter measurement;
- Option C: Utility data analysis; and
- Option D: Calibrated computed simulation.

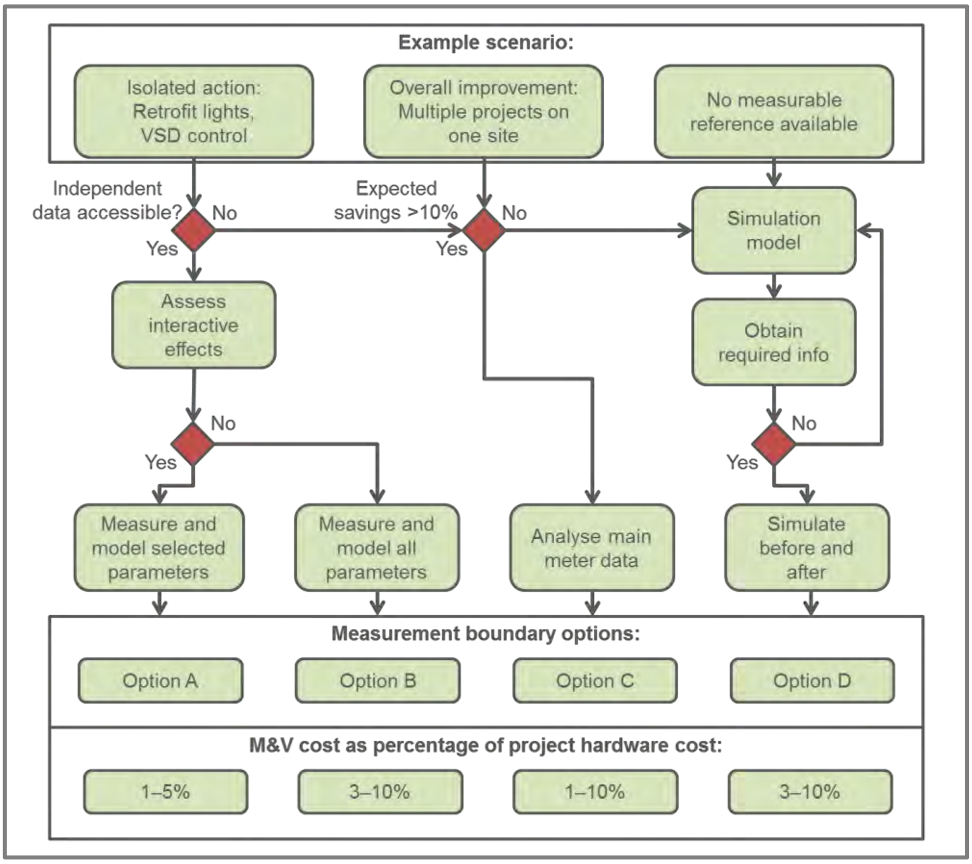

FIGURE 1-2: SELECTING AN APPROPRIATE MEASUREMENT BOUNDARY

The primary factors affecting the selection process are the type of project (retrofit, control or behaviour change) and the availability of data (installed meter, utility bills, no data). The different options will incur different M&V costs, which may also affect the selection process [24]. The selected M&V option, together with the site and project details, is incorporated into the M&V plan (Figure 1-1) and submitted to all parties.

1.1.3. GUIDELINES FOR DATA COLLECTION

Once the relevant M&V option has been selected, the required data must be captured. M&V Option A and Option B utilises measured system data. The M&V guideline for energy efficiency projects states that a dataset consisting of three consecutive months is an acceptable sample period [26]. It is, however, important to include any cyclic operational variance in this sample [22]. If the cyclic operational variance does not occur during the three months the period should be expanded to include the cyclic operational variance [11]. For example, a dataset of twelve months can be used to capture seasonal effects.

Industrial sites often log the required data to use it for their own energy management programmes, performance monitoring and billing purposes [29]. The Eskom M&V guideline allows the use of existing data and metering infrastructure [30]. If the required data is unavailable, loggers should be installed. The logged data must be stored safely on restricted systems to prevent tampering[7]. The relevant equipment details (make, model, location, accuracy and calibration) must be thoroughly documented [31].

In the event of M&V Option C being selected, monthly billing invoices can be used, supplemented by periodic readings captured using portable metering equipment [29]. The baseline dataset can be further enhanced by linking the billing data with other system variables [32]. Matching the system operation with that of other similar systems, using techniques such as benchmarking and clustering, can give a good prediction of the system operation [33], [34], [35]. Option D utilises calculations and simulations to determine project impact.

Before the acquired data can be used it has to be verified and validated thus ensuring a true representation of the system [31]. A dataset free from any erroneous data will result in a reliable baseline [26], [36]. The collected data is ultimately used to develop a baseline model.

1.1.4. Developing the baseline model

The project baseline represents system energy consumption prior to the project or intervention. The project impact cannot be measured but only estimated by comparing the baseline to the actual (post-implementation) power consumption as illustrated with the basic equation [37]:

$$\textit{Project impact} = \textit{Baseline} - \textit{Actual} \tag{1}$$

It is, however, not always possible to accurately determine project impact using a fixed baseline. The baseline must be normalised to compensate for changes to the system. This is achieved by using a baseline model to determine what the system operation would have been for different scenarios.

Figure 1-3 shows a simplified power consumption profile illustrating the concept of using a baseline model to indicate what the system operation "would have been" without the intervention [9], [38]. The baseline model is developed using data collected before the start of project implementation. The model is then used to determine what the system operation would have been under the present circumstances. The calculated baseline is compared to the new system operation to determine the impact of the project.

Baseline normalisation can be split into two scenarios; namely, routine and non-routine adjustments [37]. Routine adjustments will be implemented regularly to compensate for changes in production output, occupancy, environmental conditions, and so forth. Non-routine adjustments will be for once-off changes that occur irregularly. Physical changes to the facility, equipment type and number and operational changes will all result in non-routine adjustments [37]. The impact of the project can therefore be estimated using the following equation [37]:

$$\boldsymbol{Project\ impact} = (\boldsymbol{Baseline} - \boldsymbol{Actual}\,) \pm \boldsymbol{Adjustments} \tag{2}$$

The routine adjustments can be incorporated into the baseline by developing a routinely adjustable baseline model [39]. The resulting data requirements, accuracy and development costs will depend on the model and specific scenario. A highly accurate model will increase the confidence in reported savings, but will also increase M&V cost. There will, however, always be a balancing point as illustrated in Figure 1-4 [37].

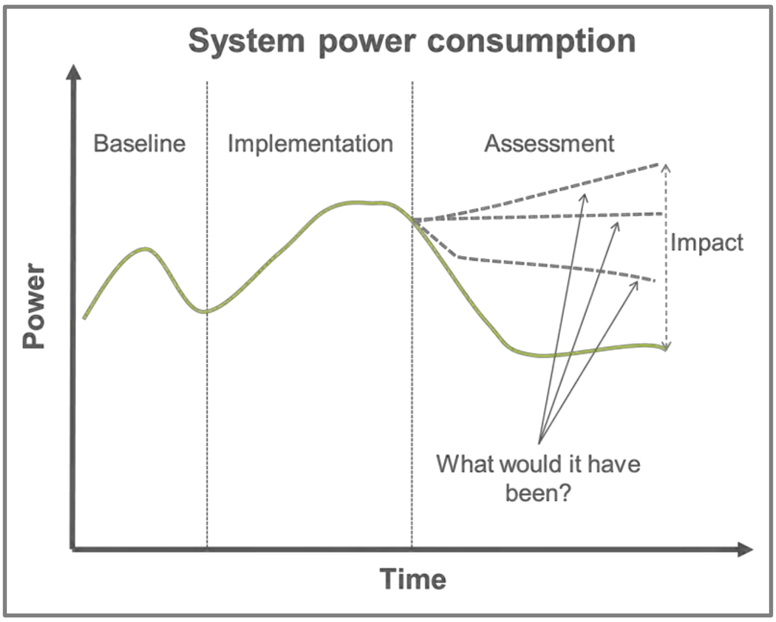

Figure 1-3: System power consumption and the need for baseline adjustments

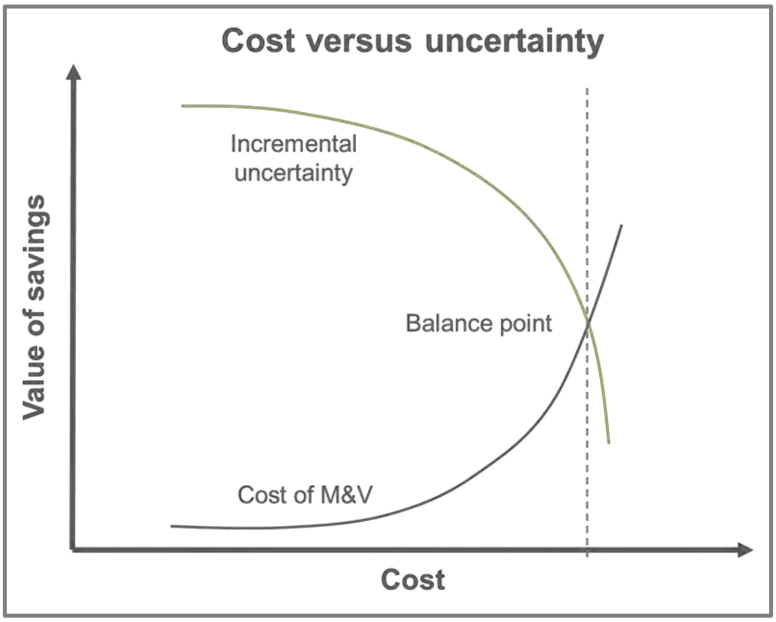

FIGURE 1-4: COST OF M&V VERSUS UNCERTAINTY

The costs and uncertainty can be reduced further by using the same model for various projects [40]. Regression models are regularly used because they can estimate system power consumption based on independent system variables [7]. Figure 1-5 illustrates how a basic regression model for an air-conditioning system is developed.

In Figure 1-5 the system baseline dataset is used to find a correlation between daily air-conditioning power and ambient temperature. Ambient temperature is a good example of an independent variable as it influences air-conditioning power consumption, but not vice versa.

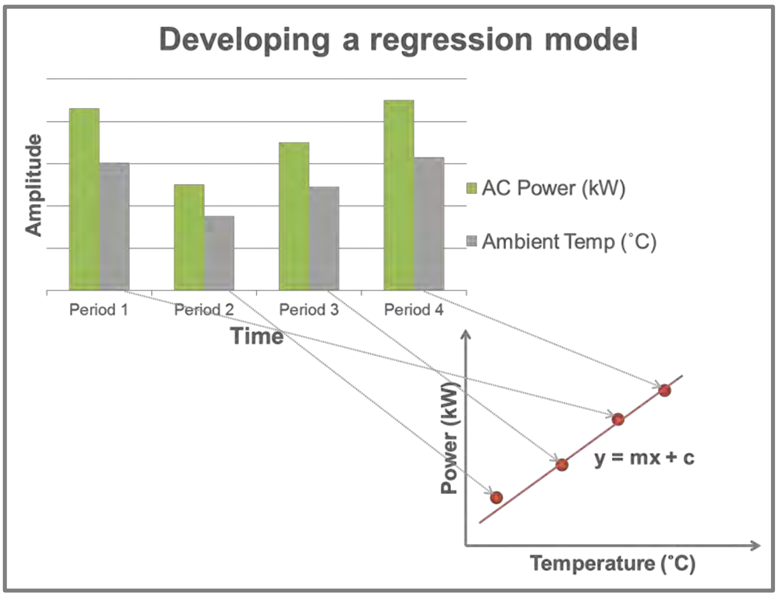

FIGURE 1-5: DEVELOPMENT OF A BASIC REGRESSION MODEL

The result is the linear regression line in Figure 1-5 which is represented by the equation:

$$y_{Power} = (m_{angle\ of\ line} * x_{Ambient\ Temp}) + Constant \tag{3}$$

The constant value and the angle of the line are determined by the system characteristics. Equation 2 can therefore be used as the baseline model representing what the system power would have been based on the ambient temperature.

Determining which variables to use in a baseline model remains a challenge. It requires selecting only the variables that have a significant impact, thus avoiding overfitting the model by using too many irrelevant variables [41]. Some of the available variables may also be linked to one another or other unknown factors. This may result in inexplicable behaviour further complicating the process of selecting the best set of variables [31]. It is therefore extremely important to evaluate the baseline model thoroughly.

1.1.5. Evaluating the baseline model

The results calculated by the baseline model will never be 100% accurate. Instead, it will produce a value that falls within a specific range (for example ±10% of the true value) at a certain level of confidence (for example 80%) [8]. Some level of uncertainty will always remain [7], [42]. It is therefore important to evaluate the various model options to ensure the selected model represents the system as accurately as possible.

Numerous statistical evaluation methods exist. Several published articles were reviewed to determine which statistical methods were generally used by the international M&V community. The list that follows gives the most common methods as well referencing literature relating to its application:

- Absolute percentage error (*APE*) [43];
- Average error [44];
- Coefficient of determination (R^2) [31], [41], [45], [46];
- Degrees of freedom (*df*) [45];
- F-Statistic [45] and T-statistic [31];
- Mean absolute error (*MAE or MAPE*) [43];
- Mean bias error [31], [47];
- Net determination bias [48]; and
- Root mean squared error (*RMSE*) [43], [46], [47].

Although the above-mentioned methods are noted in M&V guidelines and published case studies only two methods seemed to use consistent criteria throughout the literature reviewed. The first method is the coefficient of determination (R^2) that must be above 0.75. The second method is the root mean squared error (*RMSE*) that must be below 15%.

R^2 is used to illustrate how well the regression model fits the data points. When evaluating the regression model developed in Figure 1-5, R^2 will give the proportion of variance in the y-value that can be attributed to changes in the x-value [49]. R^2 can be calculated using the following equation [49]:

$$R^2 = 1 - \frac{SSResid}{SSTo} \tag{4}$$

The residual sum of squares (*SSResid*) can be calculated by [49]:

$$SSResid = \sum_{i=1}^{n} (y_i - \dot{y}_i)^2 \tag{5}$$

Where y_i is the i^{th} value to be predicted, $\acute{y}_i$ the predicted value of y_i and n the number of values. The total sum of squares can be calculated as [49]:

$$SSTo = \sum_{i=1}^{n} (y_i - \overline{y})^2 \tag{6}$$

Where y_i is the i^{th} value to be predicted and $\bar{y}$ is the mean. The mean can be calculated by [49]:

$$\overline{y} = \frac{y_1 + y_2 + \cdots + y_n}{n} \tag{7}$$

RMSE measures the difference between the predicated value and the actual value. It can be calculated using the equation [49]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \dot{y}_i)^2}{n}} \tag{8}$$

Where y_i is the i^{th} value to be predicted, $\acute{y}_i$ the predicted value of y_i and n the number of values.

Analysing the developed baseline model based on its R^2 and *RMSE* characteristics provides valuable input into the model selection process. The process of developing and evaluating the baseline model will be repeated several times before a suitable model is found. During the process, the following steps can be taken to improve the model [7], [9]:

- Properly select, install, calibrate and maintain measurement equipment;
- Ensure that all interactive components are incorporated into the measurement boundary;
- Review system variables and prevent overfitting by excluding the irrelevant ones; and

- Change the sampling rates of specific system components.

Implementing these steps can improve the baseline model, but will potentially increase the duration and cost of the M&V process. This will again affect the cost versus uncertainty balance illustrated in Figure 1-4.

The ideal outcome is a baseline model that adheres to cost, statistical and user constraints. The model, together with the necessary details, is published in the baseline report (see Figure 1-1). Once project implementation has started it is no longer possible to measure a new baseline as the old system no longer exists [9]. The baseline model will now be used to determine the project impact after commissioning is completed.

1.1.6. Estimating project impact

The Eskom M&V guideline for energy efficiency projects refers to the evaluation period as "performance assessment". The general duration of performance assessment is three months; systems with large operational cycles such as seasonal-dependent systems can be assessed over longer periods [26]. Referring back to Section 1.1.4, and specifically to Figure 1-3, it is important to note that the baseline can be adjusted to give an accurate representation of what the system operation would have been during performance assessment [37].

Figure 1-6 illustrates two linear regression models that depict system operation before and after intervention [5], [19], [25]. The "before linear model" is developed using the baseline dataset and the "after linear model" is developed using the performance assessment dataset. The models must be constructed using data points collected from the same source.

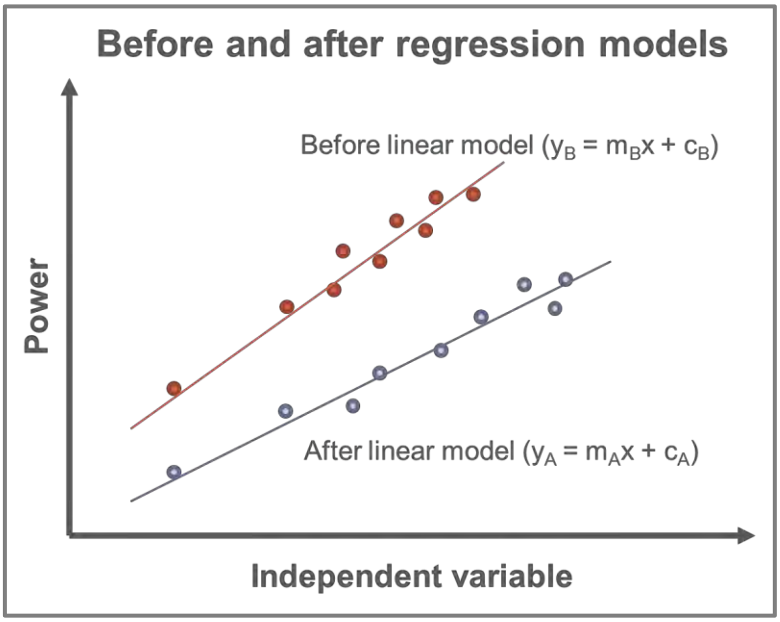

FIGURE 1-6: LINEAR REGRESSION MODELS DEPICTING SYSTEM OPERATION

Figure 1-7 shows an example of how the impact for a specific scenario is calculated. The figure can, for example, represent the air-conditioning unit in Section 1.1.4. The specific impact calculated will then indicate the average daily power reduction for a specific temperature. Figure 1-7 also illustrates the process of calculating project impact for a specific scenario. It is also possible to evaluate project performance over a wider period by using the model as reference point.

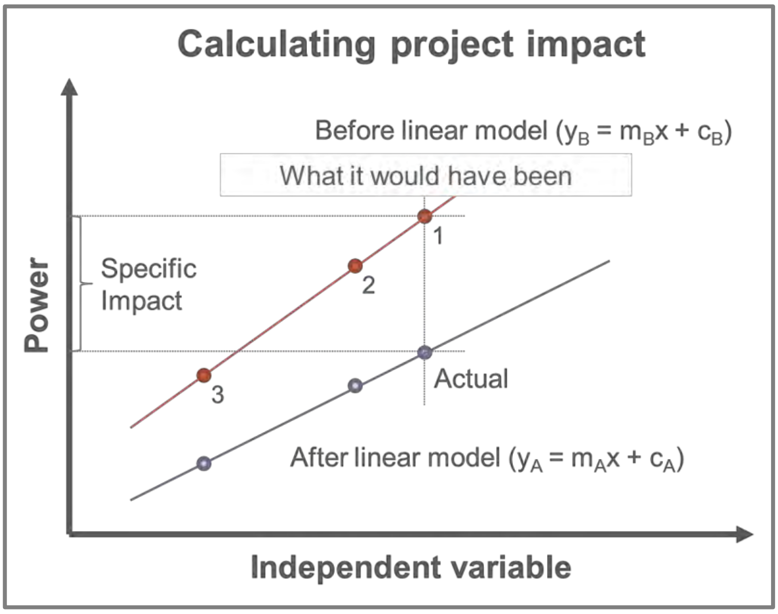

FIGURE 1-7: CALCULATING PROJECT IMPACT FOR A SPECIFIC SCENARIO

Figure 1-8 shows two 24-hour profiles labelled "Original Baseline" and "Actual Profile". The profiles were constructed using the baseline and performance assessment datasets. The baseline profile must be adjusted to represent performance assessment conditions before it can be compared to the actual profile. The baseline is adjusted using a scaling ratio (also referred to as the service level adjustment) that can be calculated using values from the baseline model:

$$\textit{Service Level Adjustment}\ (SLA) = \frac{\textit{Calculated BL value}}{\textit{Original BL value}} \tag{9}$$

The baseline profile can then be adjusted using the *SLA* scaling ratio:

$$\textit{Adjusted Baseline} = \textit{Original Baseline} * SLA \tag{10}$$

If the original baseline conditions are represented by Point 2 and the performance assessment conditions are represented by Point 1 in Figure 1-7, then the baseline will be scaled upward to match the conditions. If the performance assessment conditions were represented by Point 3, the baseline has to be scaled down. The result is the "Adjusted Baseline" profile in Figure 1-8.

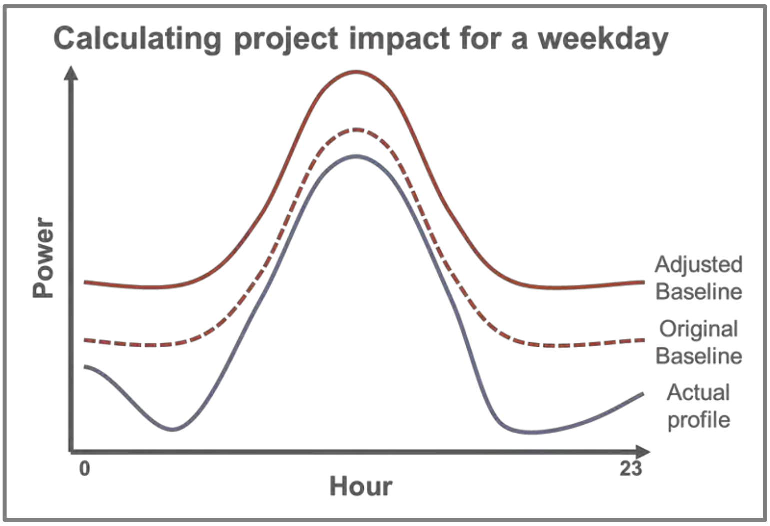

FIGURE 1-8: CALCULATING PROJECT IMPACT FOR AN AVERAGE WEEKDAY

The results of the performance assessment period are published in the Performance Assessment report (see Figure 1-1). The performance assessment results will ultimately indicate the success or failure of the project. The performance of the project is tracked for the remainder of the agreed period. During the performance tracking period the baseline will be routinely and non-routinely adjusted to ensure it remains relevant. It is possible that other interventions will be implemented on the system during the performance tracking period. This creates additional challenges to account for the interactive effects of different interventions [26].

An interactive effect between two systems will be where performance tracking of the primary system is affected by an independent intervention on another system. An example is an intervention targeting building lighting that also affects the building air-conditioning system by removing heat sources (incandescent globes) from the building. The additional impact on the air-conditioning system should therefore be attributed to the second intervention. The interactive effects can be included by expanding the project measurement boundary [9].

An interactive effect on the same system is where performance tracking of the system is affected by an additional intervention on the same system. An example is a retrofit intervention (replacing inefficient lighting) followed by a control intervention (controlling lighting according to occupation). Assessment of these interventions must be staggered to avoid double-counting [26].

The complexity of performance tracking can increase as more factors come into play. It is therefore important to evaluate the baseline model and performance tracking strategy regularly. Any changes to the model and any non-routine adjustments have to be noted in the Performance Tracking report (see Figure 1-1).

1.2. Critical analysis of published literature

1.2.1. Overview of the literature

Section 1.1 gave a condensed overview of present M&V processes. The review found that the frameworks used to manage and document the M&V process are well established. However, it indicated a lack of methodologies and guidelines on how to implement M&V practically.

A wide literature survey was therefore conducted to better understand the practical application of M&V processes, such as the selection of baseline models and the calculation of project performance. The survey endeavoured to find guidelines and methodologies specifically focusing on the M&V of industrial DSM projects. Unfortunately, the survey found no official or otherwise published documents relating to this issue.

As a result the survey approach was changed to include any published literature that could give an indication of how to practically approach M&V. The research included M&V and non-M&V publications addressing topics such as load modelling, forecasting, energy reporting, as well as management plans, policies and strategies. Numerous publications were considered and ultimately a final set of 62 publications (consisting of 42 book excerpts, seventeen journal articles and three conference papers) was selected for further review. The publications are listed in Appendix A.

The publications spanned a wide range of contexts and as a result produced a large quantity of facts and details. This alone did not give a clear indication of the industry norm and required further analysis to objectively indicate how industry practically approached M&V. The results were therefore categorised and normalised to enable analysis. The analysis was further simplified by graphically displaying results thereby indicating the general characteristics of the specific scenario.

Figure 1-9 gives an overview of the selected publications based on sector and technology, indicating that the majority of selected publications entailed industrial process control. Publications from other sectors and technologies are retained, as their methods can potentially be adapted for implementation in the industrial sector.

The M&V frameworks presented in Section 1.1 can be condensed to three practical steps. Results from the critical analysis will be grouped according to three core steps:

- Baseline dataset quality evaluation;
- Baseline model development and evaluation; and
- Performance assessment and tracking.

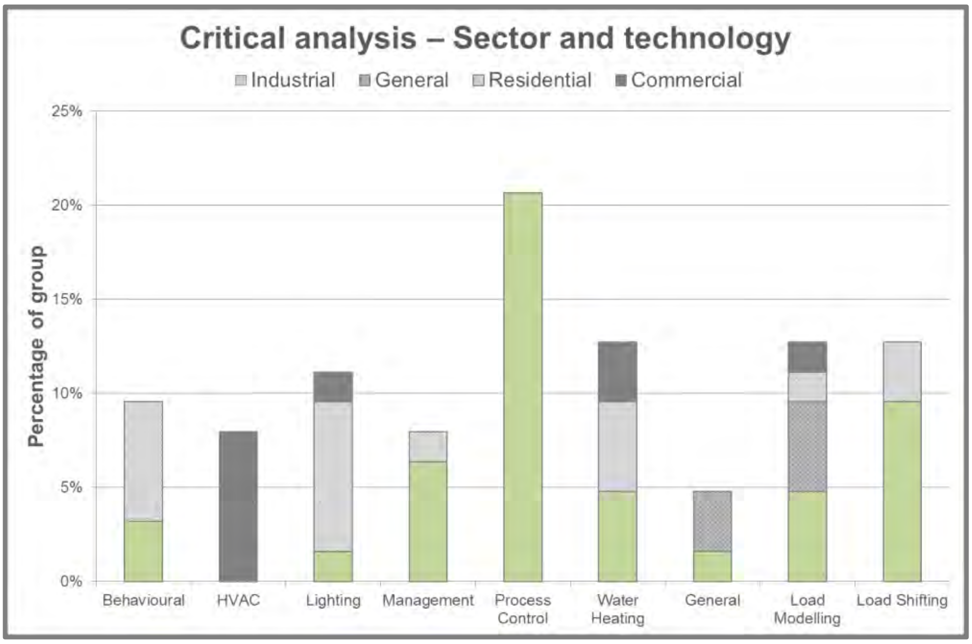

FIGURE 1-9: CRITICAL ANALYSIS – SECTOR AND TECHNOLOGY

1.2.2. ANALYSIS OF BASELINE DATASET QUALITY

The guidelines in Section 1.1.3 state that a baseline dataset has to represent a full system operation cycle. It further states that the data should be verified and validated to ensure that it is error-free. This analysis focuses on identifying the period of data selected to represent the system. The analysis further investigates the evaluation process used to verify and validate the dataset. If the process of baseline dataset selection is well documented, the lessons learnt can be applied to other industrial projects. The results are graphically grouped based on the following questions:

- What period of data is used?
- Is the dataset evaluated?

From the results in Figure 1-10 it is apparent that the majority of the publications do not use measured system data; or do not divulge what was used. The available details indicate a wide range of periods being used. The majority of datasets spanning more than six months consist of low-resolution data (typically monthly measurements). The studies with high-resolution data generally have less than a year's data available.

An apparent issue is the low availability of usable data. Small datasets prevent proper evaluation of system characteristics. It also limits the amount of data that can be discarded before voiding M&V guidelines on sample size. The result is that all available data have to be used instead of being able to select the best dataset.

An additional issue is the quality of the data. Only 22% of the publications implemented some form of data verification or validation. The majority of these studies used measurements to verify simulation models. This implies that the quality of the data source remains unchecked. However, it is probable that some form of data evaluation is performed and that the details are unfortunately omitted from the published literature.

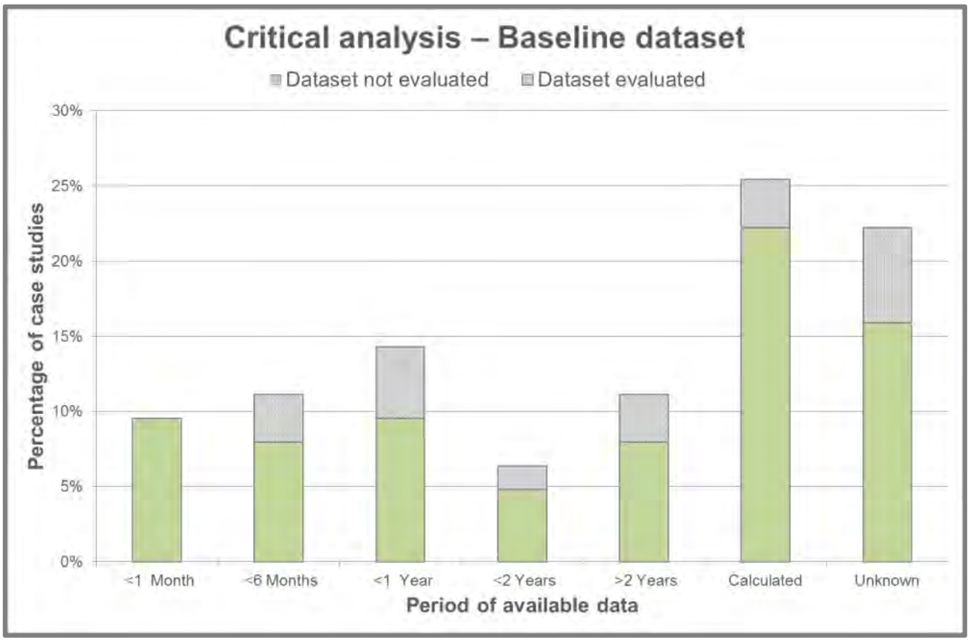

FIGURE 1-10: CRITICAL ANALYSIS – BASELINE DATASET EVALUATION

The analysis of baseline dataset selection processes and methods highlighted two major issues: low data availability and data quality. Limited data together with a lack of evaluation guidelines will affect the confidence in the selected baseline dataset. If the selected baseline dataset does not represent normal system operation the entire M&V process can be compromised.

1.2.3. ANALYSIS OF BASELINE MODEL DEVELOPMENT AND EVALUATION

The next core step is the process of developing and evaluating the baseline model. The analysis evaluates the selected publications to determine how the various baseline models are developed. The analysis first determines the modelling method used. It is critical that the developed baseline model accurately represents the system as it was during the baseline period. The analysis then determines how the accuracy of the model is evaluated. The graphical presentation groups results based on the questions:

- What type of baseline model is used?
- Is the accuracy of the model evaluated?

A significant portion of the publications in Figure 1-11 does not disclose all the required details. The use of regression models is the best documented process and is also the process that is predominantly implemented on industrial projects. The use of proportional relationships is mentioned but no usable details are provided.

Linear regression seems to be the most popular method for developing baseline models. There are, however, no clear guidelines on what (or how many) variables are required to develop an acceptable model. The publications give the impression that power consumption is linked to all available variables.

The lack of a consistent development process can result in inadequate models being used. This not only complicates the process by increasing the number of variables, but can also have a significant financial impact due to the cost of additional hardware requirements.

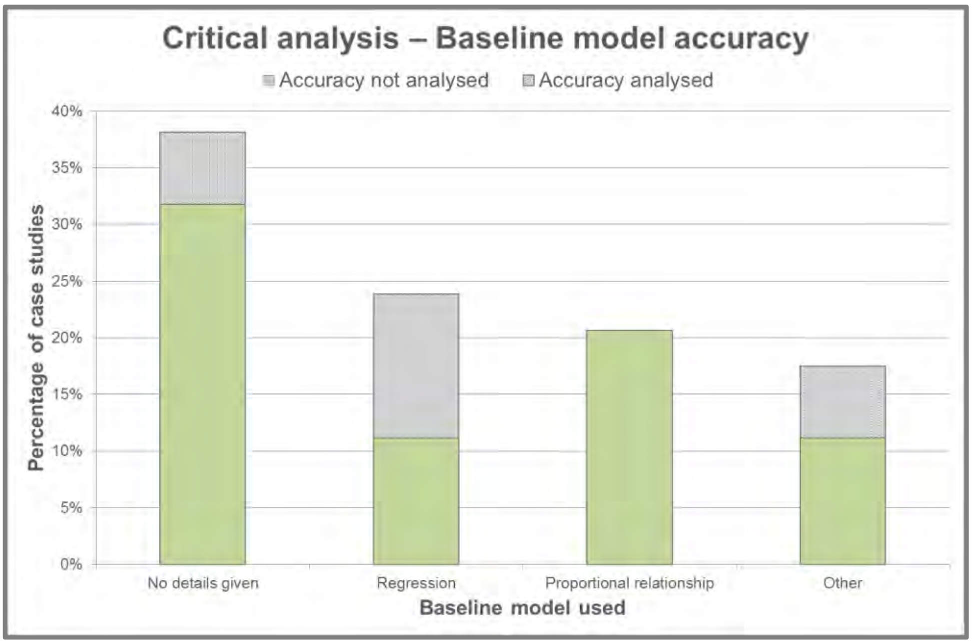

FIGURE 1-11: CRITICAL ANALYSIS – BASELINE MODEL ACCURACY

The analysis found that regression models are generally evaluated using the statistical methods discussed in Section 1.1.5. Unfortunately, the evaluation process is inconsistent and the various evaluation methods make model comparison difficult. Some of the model statistics do not adhere to the guidelines in Section 1.1.5 indicating that the models should have been discarded. A few of the publications report accuracy in terms of percentage, for example 90% accurate. No details are, however, given as to how the accuracy is determined and how it should be interpreted.

The analysis indicates that the general evaluation of baseline models does not follow a clear and concise procedure. Baseline model development should be an iterative process where a model is selected, evaluated and adjusted until it renders satisfactory results. Details on how M&V teams approach this process are omitted from literature. This omission prevents outside parties from understanding, and even improving, the process.

The statistical guidelines used to evaluate baseline models are abstract. The relevance of the model is therefore not clearly understood and results are not correctly represented. Other methods are needed to simplify the evaluation process giving a clear indication of the model impact without requiring an advanced understanding of statistical methods.

1.2.4. Analysis of performance assessment and tracking

Project success is established during the performance assessment period. It is therefore an extremely important period for the stakeholder responsible for implementing the project. The results of performance assessment are calculated by comparing the electricity consumption of the new system operation to the adjusted baseline. External factors can influence performance assessment thereby preventing the project from consistently performing under ideal conditions. It is therefore important to understand how the performance assessment process is conducted and how results are interpreted in order to understand the true nature of project performance.

After performance assessment is completed project performance monitoring continues. This is referred to as performance tracking and it will continue for the rest of the project lifecycle. Industrial systems, however, do not operate in isolation. It is very likely that some external factors will change and impact project performance. Evaluating long-term performance tracking results will give significant insight by identifying components affecting project performance.

The analysis focuses on performance assessment and performance tracking. To understand the factors affecting these core processes better, the analysis results are grouped based on the questions:

- What is the duration of evaluation?
- Are the results discussed in detail?

The analysis finds that the majority of publications do not indicate the performance assessment or performance tracking period. The duration of evaluation for the remaining studies is generally less than six months. The typical duration for DSM project performance assessment is three months. This relative short-term evaluation limits the perspective on other influences potentially affecting results. The absence of published reviews on long-term data makes it impossible to evaluate the continued relevance of specific baseline models.

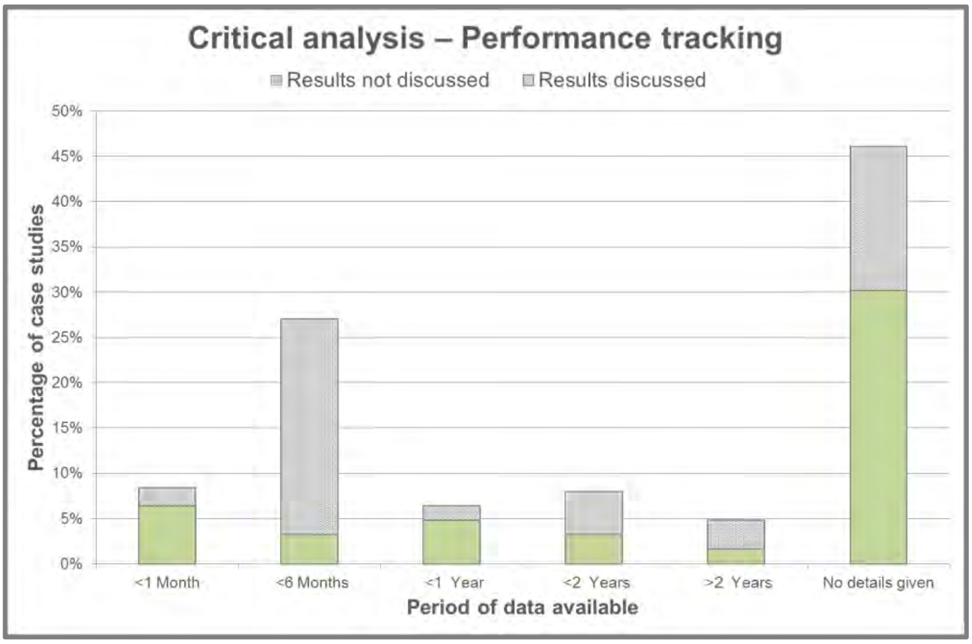

FIGURE 1-12: CRITICAL ANALYSIS – PERFORMANCE TRACKING EVALUATION

The discussion of the majority of publication results is limited to a summary of the project target and the achieved performance assessment values. The publications do not elaborate on methods of calculation or give analyses of results. It is, however, interesting to note that the majority of results are reported at a high level of accuracy (often up to 0.1% of target value). These results are presented without indicating the statistical relevance of the result. The inherent variance in model accuracy and system operation will make it impossible for the project to achieve the exact result every day of the assessment period. It is therefore necessary to give some form of indication representing the range in which the result will vary.

The guidelines in Section 1.1 states that the reported results should always be on the lowest, and therefore the most conservative end of the margin. This guideline can be used to avoid detailed statistical results by reporting a conservative value. This approach may be acceptable for projects where the evaluation simply indicates success or failure. Projects where remuneration is linked to results cannot be assessed in this manner without at least indicating what the savings margin is.

Finally, there is a possibility to implement additional interventions on the same system. If multiple projects with interactive effects do occur it will affect the validity of the baseline model and subsequently performance tracking. The calculation of these results is further complicated when multiple stakeholders are involved. Unfortunately, none of the publications discusses this scenario.

1.3. Contributions of this study

Section 1.1 gave a brief overview of existing M&V processes. The review found the generalised M&V process to be well developed and widely implemented. However, official M&V literature lacks detail regarding the practical steps and processes required to evaluate industrial DSM processes. The critical analysis of published literature in Section 1.2 again highlighted the lack of details. Publishing detail methodologies and results will enable outside review, critique and stimulate further development.

The core M&V steps of evaluating data quality, developing a good baseline model and objectively assessing performance are critically important. Failure to conduct any of these steps properly will ultimately affect the confidence in the M&V process and the subsequent results. This thesis will therefore endeavour to deliver several contributions to aid the M&V of industrial DSM projects. The main contributions of this study are discussed in the sub-sections that follow:

Identification of an M&V need for industrial DSM projects:

A wide literature survey was narrowed down to a set of 62 publications (books, articles and conference papers) relevant to the practical M&V of industrial projects. A critical analysis evaluated how industry approached the three core M&V steps. The results were summarised and normalised to enable an objective comparison between the different sectors and categories. A graphical representation of the results was devised to further simplify the comparison process. This thorough collection, summary and representation of information identified M&V areas in need of further development.

Data evaluation methodology:

The quality of a project dataset is a critical component of the M&V process. However, no official M&V methodologies exist to evaluate data quality. The newly developed methodology evaluates data quality using a two-pronged approach. Data source evaluation ensures that the dataset accurately represents the measurements in the field. Evaluation of the dataset identifies and removes abnormalities thus producing a dataset representative of system operation. The data evaluation methodology produces a high quality dataset that can be confidently used in subsequent M&V processes.

Guideline for baseline dataset selection:

The system characteristics and events included in the baseline dataset will have a significant impact on the baseline model. The critical analysis identified some generic guidelines, but determined that the majority of practical studies did not divulge the dataset selection or quality evaluation process used to develop a baseline model. A simplified guideline is therefore developed to highlight important characteristics indicative of a good baseline dataset. The guideline touches on data availability and identifying a full operational cycle. A simple process of evaluating different modes of operation further aids the process of selecting a representative baseline dataset.

Guideline for modelling industrial systems:

There are only a few clear guidelines to aid the baseline model development process. This results in the process becoming time-consuming and expensive. Using models that have already been developed and approved will reduce inherent costs and risks. The new guideline presents three widely used models focusing on their application in modelling industrial systems. Special attention is given to the use of regression models. The guideline presents a unique approach utilising dependent variables to model system operation. Major factors affecting model accuracy are also illustrated and discussed.

Baseline model evaluation methodology:

Baseline model accuracy will have a significant effect on the calculated project impact. It is therefore imperative that all parties understand the potential repercussions of the selected baseline model. The statistical methods currently used to determine baseline model accuracy often render results that are too abstract. The academic background required to interpret and compare results can potentially exclude some stakeholders from the development process.

This thesis develops a new methodology to objectively evaluate and compare various baseline models. The use of complex statistical evaluation methods is avoided by graphically presenting results. This novel approach simplifies the evaluation process and enables stakeholders with no background in statistics to partake in the process; including site personnel who form part of project teams.

Methodology for graphically presenting project performance:

The literature review highlighted a general tendency to present project results as a single value. This single value alone cannot objectively convey project performance. The monetary remuneration and risks linked to project performance justify a more detailed presentation of project performance.

The developed methodology implements the same concepts used to present baseline model accuracy. However, it adds additional information to portray the occurrence and variance of results. The graphical presentation of results conveys the true nature of project performance without overwhelming the reader with information. The thorough, yet simplified, indication of performance enables an objective and generally accessible evaluation of results.

A long-term evaluation methodology:

Most projects will reach a point where changes in system operation or project performance necessitate a revision of the baseline model, project target or project configuration. There are, however, no specific rules governing when the revision has to occur. The burden therefore rests on the stakeholders to prompt a revision.

The new methodology adapts an existing concept to be used in the long-term evaluation of project results. The methodology uses a control chart to indicate significant changes in system operation or project performance. This structured approach can be used to indicate when a more detailed investigation is required thereby reducing reliance on stakeholders to identify issues.

Guideline for evaluating interactive projects:

It is possible that different projects will eventually be implemented on the same system. There is, however, no practical approach or documented publications showing how to handle such a situation. The newly developed guideline presents a structured approach to evaluating interactive projects implemented on the same system. The occurrence of interactive projects is evaluated for two scenarios: chronological and concurrent implementation. The guideline discusses the use of multiple baselines to evaluate chronological projects. A single baseline is used for concurrent projects; two different models of savings allocation are presented.

Implementation of practical case studies:

Project results are generally published without describing how they were obtained. This lack of transparency makes it difficult for results to be objectively reproduced. It prevents future projects from building on existing knowledge, thereby allowing the same mistakes to be repeated.

The new methodologies and guidelines developed in this thesis are applied to real industrial DSM projects. The projects are selected to illustrate various different scenarios and systems. The implementation serves to verify the practical application of the new methodologies. The results also double as case studies illustrating the practical application of the methodologies. The transparent presentation of the process will allow future studies to build on the findings of these case studies.

Comparison of methodology results and published M&V results:

The review of the 62 cases is the only published comparison of M&V results and processes. Utilising the newly developed methodologies and guidelines to compare results from different models, processes and projects stands to add significant value to our understanding of present M&V practices. The results from the verification case studies are also compared with official M&V results. This comparison not only validates the methodology results, but also opens the door for future studies investigating the effects of present M&V practices.

1.4. DOCUMENT OUTLINE

Chapter 1 gives an overview of the present M&V process with specific focus on components relating to the M&V of industrial DSM projects. A critical analysis of published literature highlights several issues and subsequent needs. Chapter 2, Chapter 3 and Chapter 4 will each address a specific need. Each of these chapters will develop a methodology supplemented with the required theory and guidelines. The practical application of the methodology is verified at the end of each chapter.

Chapter 2 is the first methodology chapter and focuses on developing a practical approach to data evaluation and baseline dataset selection. The chapter begins with the development of methodologies to evaluate project data quality. A guideline on selecting an appropriate baseline dataset is also discussed. The developed methodologies and guideline are implemented on fifteen industrial case studies. Results from the case studies are presented and discussed.

Chapter 3 focuses on the development and evaluation of baseline models. The chapter guidelines discuss the development and selection of three baseline models. A methodology is developed to evaluate the new baseline models. The methodology is verified by applying it to evaluate 31 baseline models.

Chapter 4 investigates the process of evaluating and presenting project performance and subsequently develops a methodology to represent calculated results objectively. The methodology utilises a simplified approach to clearly convey project performance without requiring abstract statistical analysis. The chapter also presents a methodology enabling long-term project evaluation focusing on identifying when a detailed investigation is required. Finally, a guideline for the assessment of multiple interactive projects is discussed. The developed methodologies and guideline are verified with the application of five industrial case studies.

Chapters 2, 3 and 4 developed guidelines and methodologies to address the needs identified in Chapter 1. The practical application of these solutions was verified using several industrial projects as case studies.

Chapter 5 validates each chapter's results using results obtained from independent third parties. The validated results are used to estimate the potential impact the new methodologies may have on the national and international communities.

Chapter 6 concludes the thesis and gives recommendations for additional work.

MEASUREMENT AND VERIFICATION OF INDUSTRIAL DSM PROJECTS

CHAPTER 2

DATA EVALUATION AND DATASET SELECTION

2. DATA EVALUATION AND DATASET SELECTION

2.1. INTRODUCTION

A vital part of the M&V process is the quality of the baseline dataset. Any abnormalities included in the baseline dataset can have a significant impact on subsequent processes thereby tainting all calculated results. It is therefore critical to ensure that a high quality dataset, representative of system operation, is used as the baseline dataset.

The review in Chapter 1 gave an overview of different measurement boundary options, data sources and baseline data requirements. The critical literature analysis highlighted the lack of detailed published methods facilitating data evaluation and guidelines supporting baseline dataset selection. This indicated the need for new developments to aid these processes.

This chapter will develop two new methodologies to evaluate the data used in the M&V process. The first methodology will evaluate data source quality ensuring that data samples accurately reflect field measurements. The second methodology will evaluate the content of the dataset ensuring that no measurement or operational abnormalities are included in the set. Finally, a guideline for identifying and selecting an appropriate baseline dataset is developed.

The impact of the new methodologies and guideline is verified by using several industrial DSM projects as case studies. The results of the verification process are evaluated to verify the relevance of the new methodologies and guideline.

2.2. DATA EVALUATION METHODOLOGY

2.2.1. FACTORS AFFECTING MEASUREMENT QUALITY

The data samples used in the M&V process often reach the user in the form of a spreadsheet. The spreadsheet entries are, however, only a representation of measurements taken by field instruments. Any issues experienced during the process of converting a signal to a measurement, and then transferring the measurement to a spreadsheet can produce significant errors. It is therefore necessary to confirm that the data source used to develop the spreadsheet accurately represents the actual measurements.

The process of checking and confirming whether the data points were accurately transferred is generally referred to as data verification. The term "verification" is, however, used in a different context throughout this document. This section will therefore refer to the process as the evaluation of data source quality.

Figure 2-1 shows the path a measurement takes to ultimately form part of the spreadsheet data sample. The path on the right of the figure illustrates some possible conversions that may occur. The method of converting measurements from one scale (or medium) to another is dependent on the relevant equipment. Variables, such as power, are the product of several other measurements (voltage, amps, and power factor). Any error induced during either conversion or calculation will be carried forward through the entire process.

Data source quality can be assured by checking and calibrating every component in the system. This will, however, require system access, time, money and expertise, any of which may not be readily available. An alternative method to evaluate the data source quality is comparing measurements from different sources representing the same variable. The checkpoints on the left of Figure 2-1 indicates several data sources that can be used. It is therefore possible to evaluate data source quality by comparing the readings from a portable power meter to data samples collected from the supervisory control and data acquisition (SCADA) system.

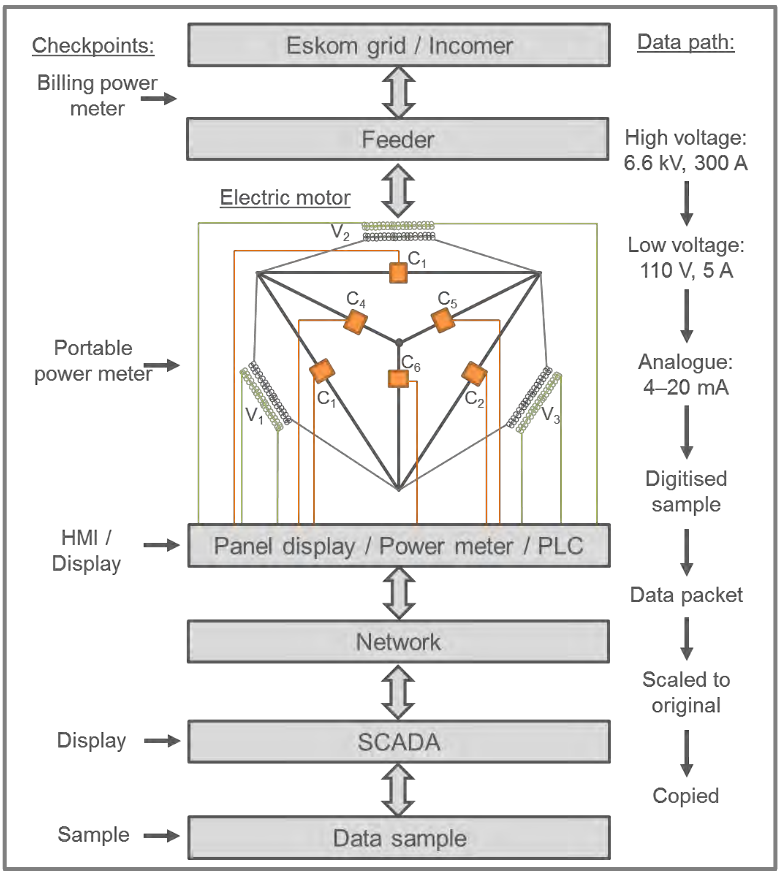

FIGURE 2-1: THE DATA PATH OF ELECTRICAL READINGS

2.2.2. DATA SOURCE EVALUATION – METHODOLOGY

Figure 2-2 gives a flow diagram that formalises the methodology that evaluates data source quality. Any abnormalities identified during the evaluation process will bring the quality of the specific data source into question. The overall dataset quality can be improved by removing any abnormal data samples. The process needs to be structured to ensure consistency and to avoid discarding too many samples that may render a viable source useless. Each phase of the evaluation methodology will now be discussed in more detail.

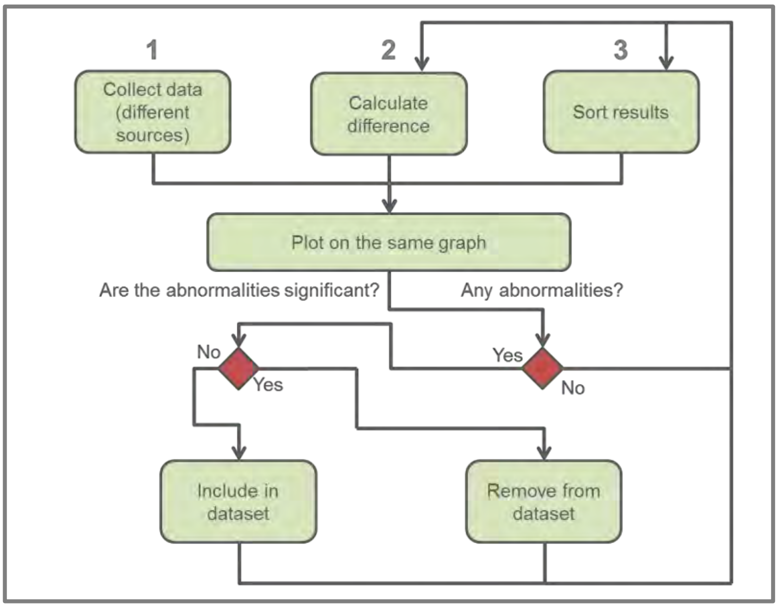

FIGURE 2-2: DATA SOURCE EVALUATION – METHODOLOGY

Phase 1 of the methodology consists of collecting and comparing measurements from different sources. Plotting the measurements on the same graph will immediately highlight major abnormalities. An example of three data sources measuring the same variable is illustrated in Figure 2-3.

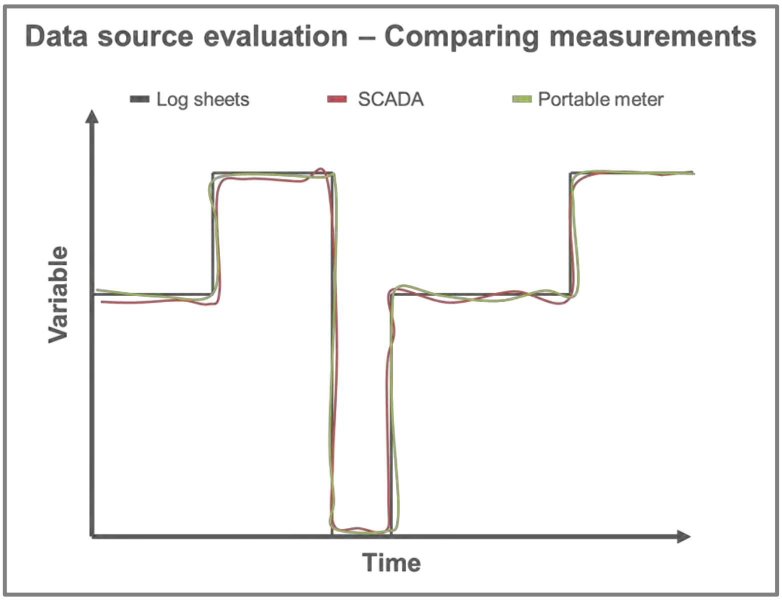

FIGURE 2-3: DATA SOURCE EVALUATION – COMPARING MEASUREMENTS FROM DIFFERENT SOURCES

The different measurements in Figure 2-3 all follow the same trend thereby confirming the data source quality. It is, however, not always possible to evaluate measurements by visual comparison only. Phase 2 of the methodology therefore evaluates two sources by calculating the difference between their measurements. Figure 2-4 shows an example of the results obtained.

The results indicate the amplitude and frequency of the differences between the compared sources. High amplitude results will indicate a significant difference, while results that remain around zero will indicate similar measurements. A constant difference will confirm data source quality.

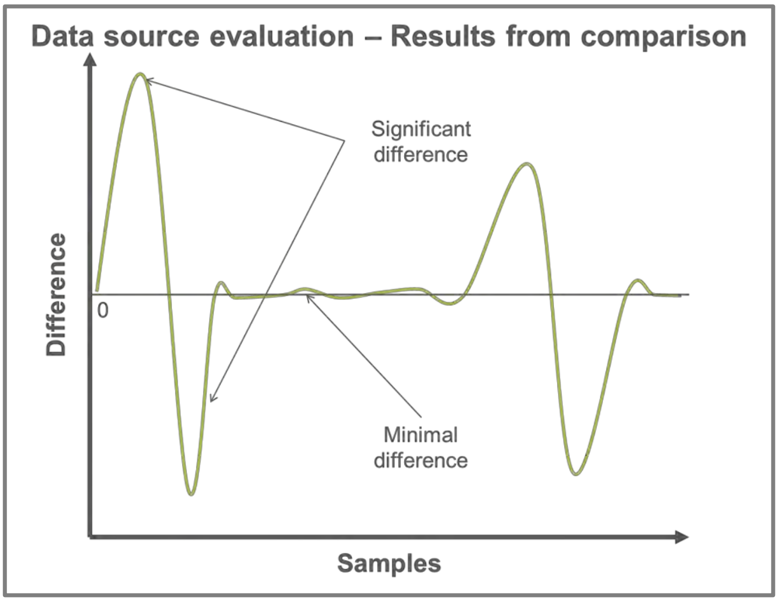

FIGURE 2-4: DATA SOURCE EVALUATION – CALCULATED DIFFERENCE BETWEEN SOURCES

Multiple discrepancies between the data sources and the calculated results will render a graph with many peaks and dips. It may be difficult to make assumptions based on the random results. In this case, Phase 3 of the methodology can be applied. Phase 3 entails sorting the results from the lowest value to the highest value. Figure 2-5 illustrates an example of results that have been sorted.

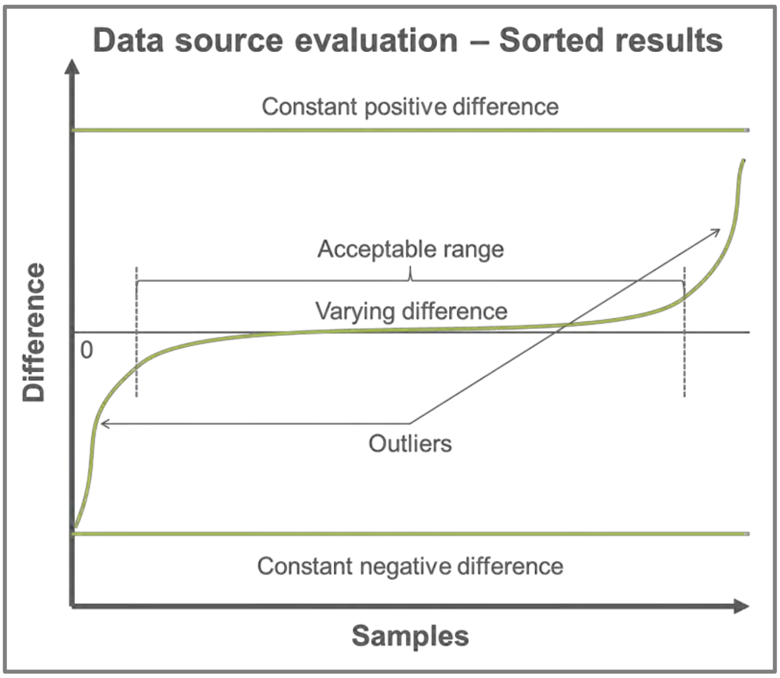

FIGURE 2-5: DATA SOURCE EVALUATION – SORTED RESULTS

Sorting calculated results will render a line similar to the example in Figure 2-5. The line will indicate the occurrence of outliers as well as the general difference between the data sources. Presenting the methodology results in this format enables an objective review. A consistent or constant difference will confirm the source quality. By identifying occasional outliers, faulty data can be identified and removed. If outliers occur regularly it may indicate issues in data source quality.

The outcome of the methodology is a dataset where the quality of the data source has been evaluated. It is ultimately up to the stakeholders to select an acceptable range of varying difference. The next step will be to determine the quality of the contents of the dataset.

2.2.3. DATASET EVALUATION – METHODOLOGY

Evaluating the data source confirms that measurements are correctly transferred from the source. However, it is still possible that field instrumentation logged or created errors. The dataset quality evaluation methodology will therefore evaluate the collected dataset to identify any potential errors and abnormalities. Erroneous or abnormal data points will be removed, thereby improving the quality of the dataset. The process of evaluating dataset content is also referred to as validation. This document will, however, use the term “validation” in a different context. References to data validation will therefore be avoided in this section.

The dataset quality evaluation methodology can be broken up into four steps: Step 1, Step 2 and Step 3 aim to identify abnormal measurements; Step 4 identifies abnormal operation. The methodology is summarised in Figure 2-6. Details of the methodology will be discussed in terms of abnormal measurements and abnormal operation.

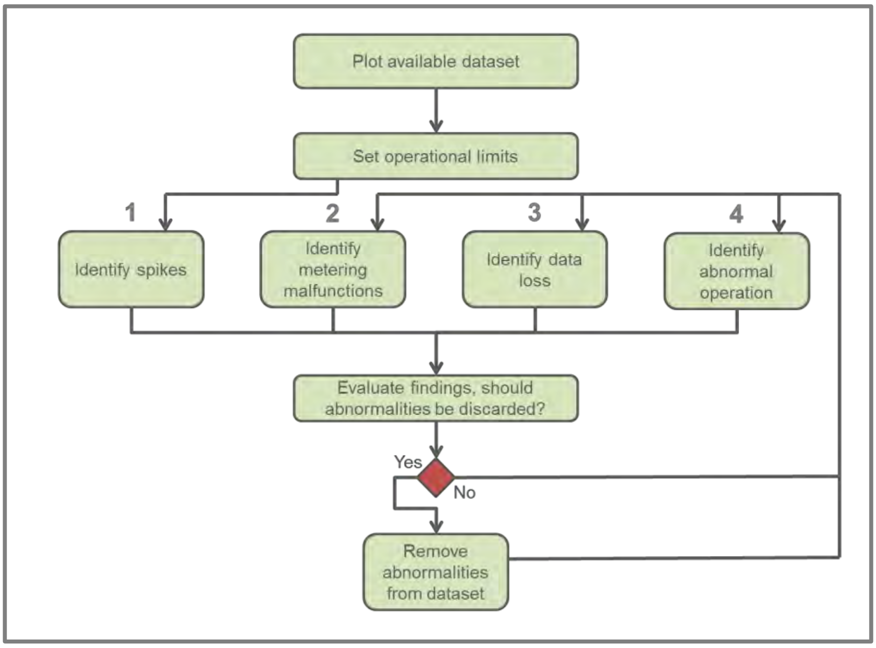

FIGURE 2-6: DATASET EVALUATION – METHODOLOGY

Figure 2-7 illustrates a simplified example of a dataset containing typical measurement abnormalities. The minimum and maximum operational limits are selected based on the variable being evaluated. For electric motor power consumption the minimum limit can be set as zero; the maximum limit can be set as the installed capacity.

Data spikes are the first data abnormalities illustrated during Step 1 of the data evaluation methodology. Data spikes occur when metering equipment malfunction or when communication is temporarily lost. Although these events tend to occur over short time periods, their amplitude can still affect the accuracy of calculations.

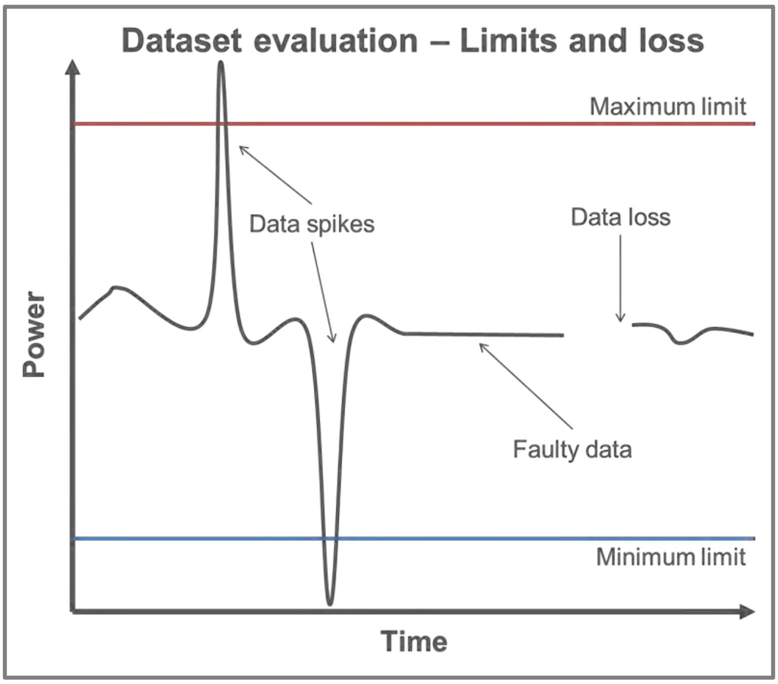

FIGURE 2-7: DATASET EVALUATION – IDENTIFYING ABNORMAL MEASUREMENTS

Step 2 aims to identify metering malfunctions. When equipment malfunctions, it can also result in faulty data being logged. Figure 2-7 illustrates this abnormality as a constant value depicting the last reading received from the power meter. If the faulty data value falls within the normal operational limits, results from subsequent calculations will remain within normal bounds. Calculated results will therefore "look right", but in reality the results will be biased due to the constant value. This makes detecting the abnormality difficult, especially after the raw dataset has been processed. Some data-logging systems will check the "health" of each measurement instrument and log its status. These health checks can be helpful when identifying faulty data.

During Step 3 data loss is identified. Identifying the final measurement abnormality requires distinguishing between what constitutes data loss, and what indicates that the system is not running. To do this it is necessary to understand how the specific system (SCADA, power meter) indicates data loss. Figure 2-7 illustrates data loss as the absence of logged values while other systems will log a "flag value" (for example "-1", "null" or "bad"). If the flag value falls outside the set boundaries it will automatically be excluded during the previous evaluation phases. If the data loss is logged as a blank or zero value, care should be taken to ensure that these values are also excluded from the dataset.

Step 4, the last step in the methodology, identifies abnormal system operation. Evaluating the raw data (with all the abnormal measurements removed) does not guaranteed the identification of abnormal operation. The dataset therefore needs to be processed to enable an objective evaluation of the system operation. Figure 2-8 shows several profiles depicting workday operation.

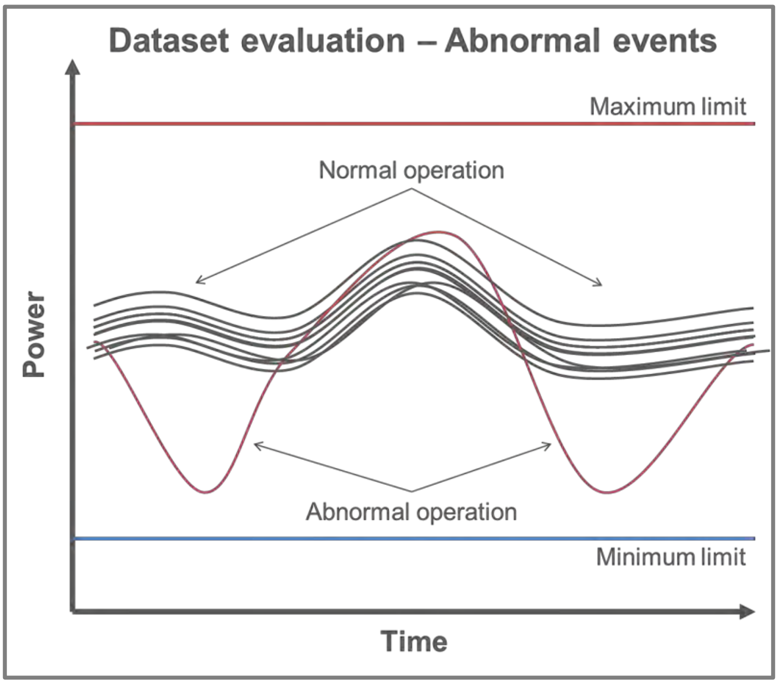

FIGURE 2-8: DATASET EVALUATION – IDENTIFYING ABNORMAL OPERATION

In Figure 2-8 several profiles follow the same trend, indicating normal operation. A single profile differs from the trend and is identified as abnormal. There is no fixed rule as to what constitutes abnormal operation and great care must be taken in analysing these results. Profiles that differ significantly (for example workday, Saturday and Sunday operations) can still indicate normal operations and should therefore not be excluded from the dataset without consultation. This final step of the methodology requires a good understanding of system operation. Results should be discussed with all stakeholders before any measurements are removed.

The dataset quality methodology evaluated the dataset with the goal of removing any measurement abnormalities and identifying operational abnormalities. Any decisions and subsequent results should be approved by all stakeholders. The outcome of the data evaluation methodology is a high quality dataset collected from an evaluated source. The next step will be to select a subset from this dataset to represent the system baseline operation.

2.3. GUIDELINE FOR BASELINE DATASET SELECTION

The baseline dataset should represent a full cycle of normal system operation. It is therefore important that the correct dataset is selected from the pool of available data. This section will discuss guidelines to simplify the selection of a representative baseline dataset. The guidelines will elaborate on:

- Reviewing data availability and identifying a full cycle of operation;
- Identifying different modes of operation.

Great care is usually taken when collecting and evaluating electrical data. The baseline model may, however, also require data from other variables. The absence of a single variable can potentially render an entire dataset useless. It is therefore important to ensure that all other variables (for example pressure, flow, production and temperature) are also collected and evaluated. Figure 2-9 illustrates system operation and the data availability of three different datasets.

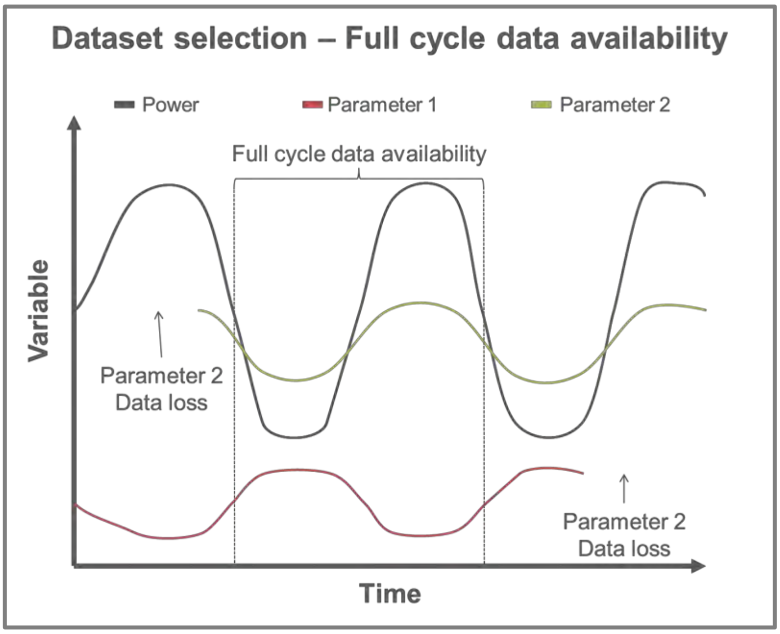

FIGURE 2-9: DATASET SELECTION – ILLUSTRATION OF GUIDELINES

The example in Figure 2-9 has only one cycle of operation that includes all the required variables. Anything less than one cycle will affect the baseline model's ability to represent the system accurately. It is also possible for the system to have several different cycles or modes of operation. The ideal dataset should therefore contain as much data as possible to ensure that the relevant cycles can be identified.

When confronted with different modes of operation it is important to discuss the scenario with all stakeholders. This is to ensure that a baseline dataset representative of the relevant system operation is selected. If several different operations have to be represented, different baselines (each based on a unique dataset) should be developed.

Step 4 of the data quality methodology (identifying abnormal operation) will already have indicated the presence of different operational modes. Additional analysis is often required to understand the relevance of different modes of operation. Figure 2-10 illustrates a system in two different modes of operation.

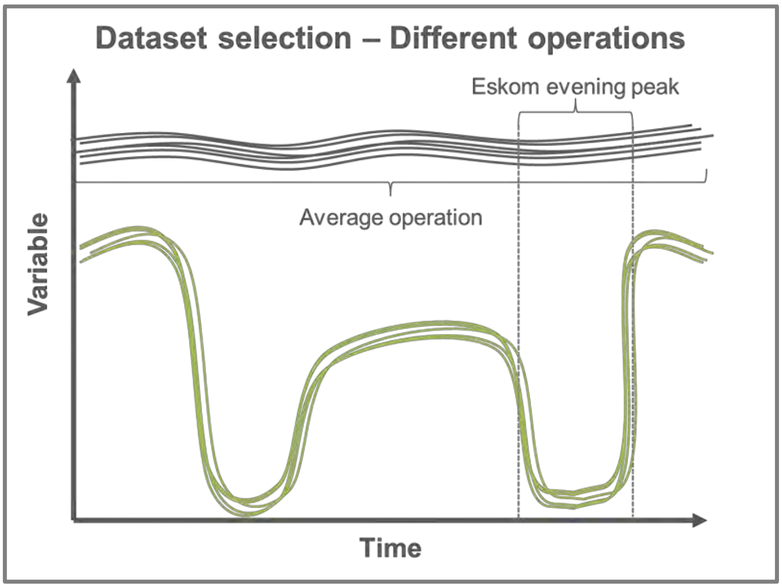

FIGURE 2-10: DATASET SELECTION – COMPARING DIFFERENT SYSTEM OPERATIONS

The two modes of operation shown in Figure 2-10 represent high-production output (grey) and cost-savings operation (green). In high-production mode the system runs at full capacity, while in cost-saving mode the capacity varies to avoid Eskom's peak rates. These operations differ clearly and are therefore easily distinguishable. This is often not the case as actual system operation will probably fluctuate between different combinations of the operational modes.

Different modes of operation can be identified by separating the dataset into subsets based on profile shape. This can be accomplished by visually inspecting each profile. An alternative approach is to present profile shape as a calculated value. The profiles in Figure 2-10 can be evaluated based on the relation between the evening peak (EP) value and the average of the profile (AP). The ratio can be calculated by dividing the average EP value by the AP value (EP divided by AP). The results can then be grouped into subsets based on ratio value.

Calculating the ratio between the Eskom EP value and the average operation for each profile in Figure 2-10 will render the results shown in Figure 2-11. A high ratio (close to one) indicates high-production output and a low ratio (close to zero) indicates cost-savings operation. The use of a calculated ratio normalises all profiles, thereby only representing the shape of the profile. The results can now be used to identify when the system operated under a specific condition.

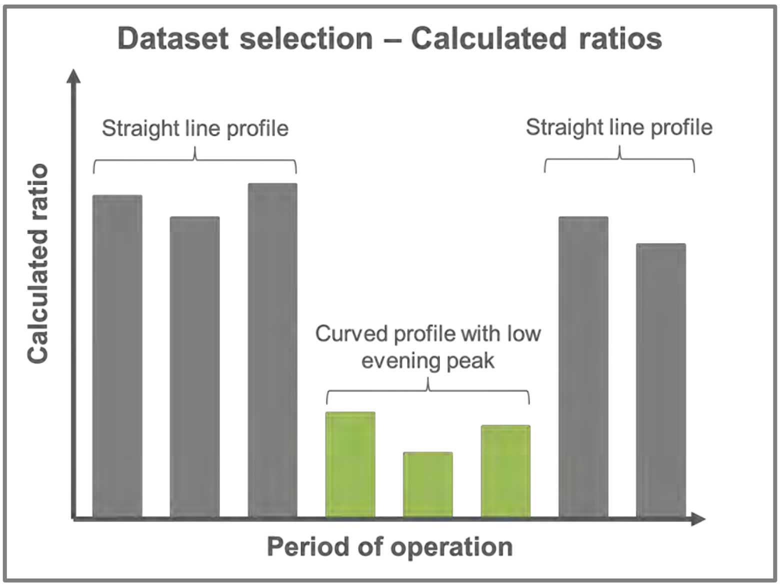

FIGURE 2-11: DATASET SELECTION – COMPARING CALCULATED RATIOS

The guidelines presented in this section will aid the selection of a baseline dataset. Although it gives no fixed rules, it aims to formalise and simplify the selection process. This is achieved by presenting data in a manner that is easy to understand and to discuss with the relevant stakeholders.

2.4. VERIFICATION OF METHODOLOGIES

2.4.1. OVERVIEW OF CASE STUDIES

The methodologies and guideline developed in the previous section were implemented on several case studies. Only the relevant results of each case study will be presented in this section. All the case studies with the complete set of methodology results are available in Appendix B.

2.4.2. CASE STUDY 1 TO 5 – DATA SOURCE QUALITY

CASE STUDY 1 – EVALUATING SCADA DATA USING LOG SHEETS

Case Study 1 evaluates a SCADA system as data source. The source is evaluated by comparing SCADA data with log sheet readings. The high number of recorded samples made it difficult to detect any differences visually when plotting the entire dataset. A subset was therefore selected for visual inspection.

Visual inspection of the subset identified a small continued offset combined with larger sporadic discrepancies. The measurements were subsequently used to calculate the difference between the sources. The results of the calculation were sorted and are displayed in Figure 2-12.

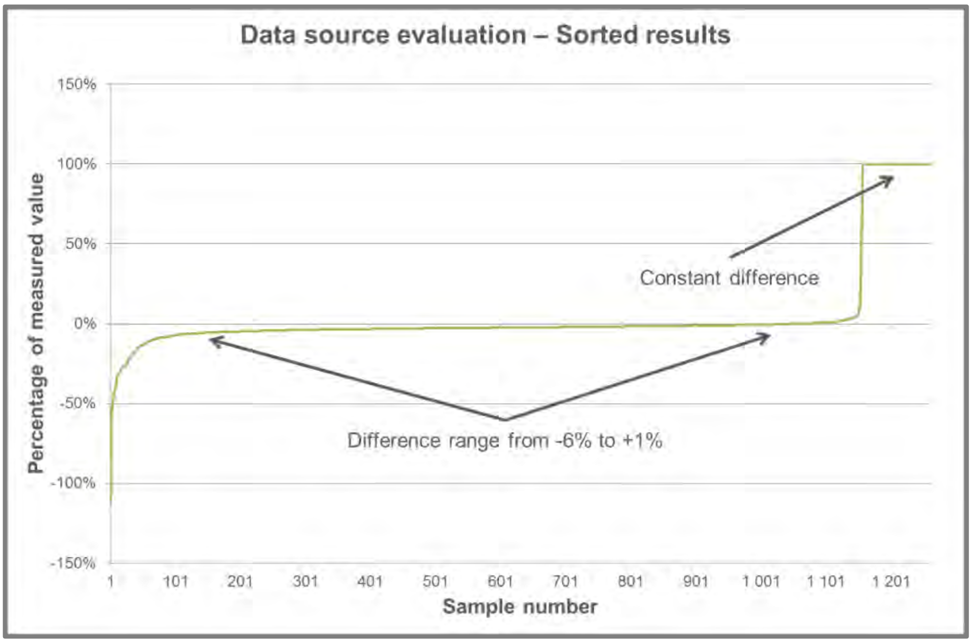

FIGURE 2-12: DATA SOURCE EVALUATION – SCADA VERSUS LOG SHEETS (SORTED RESULTS)

The constant difference in Figure 2-12 confirms the presence of zero value data. The positive offset indicates that the zero values were present in the log sheet dataset. In addition to this, the outliers on each end of the line indicate several other scenarios where the two datasets did not match.

The sorted results indicate that the majority of the data did, however, match differences ranging from -6% to +1%. In this case study SCADA source quality is evaluated and confirmed using log sheets taken at the same point of measurement.

CASE STUDY 2 – EVALUATING PORTABLE POWER METER DATA USING LOG SHEETS

Case Study 2 evaluates a portable power logger as data source by comparing its measurement to log sheet data taken at the same point of measurement. Figure 2-13 shows a subset of the available data. Initial evaluation of the figure seems to indicate that the two datasets do not match at all. Closer inspection reveals the presence of a time-offset discrepancy. The offset is a result of the datasets using different timestamps. This time offset can be rectified by shifting one of the profiles so it matches the other. Removing the time offset enables the profiles to be objectively compared.

Figure 2-14 illustrates the calculated difference between the datasets, sorted from low to high. The results illustrate the major impact a time offset can have on the evaluation of different data sources. The adjusted results, albeit better than the original dataset, still indicate a significant and varied difference between the datasets. Further investigation into why the sets differ will be required before the quality of the source can be confirmed.

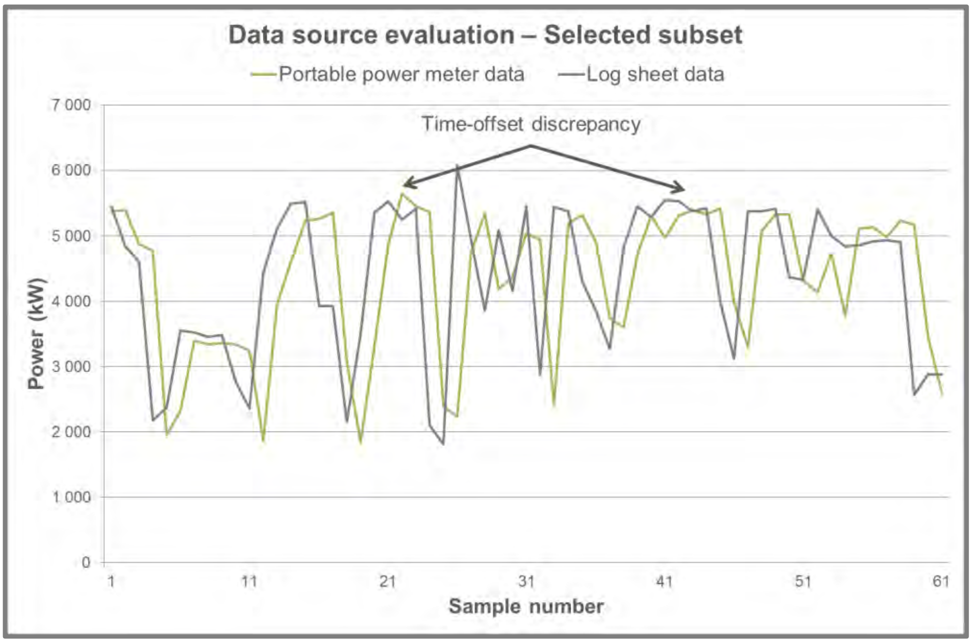

FIGURE 2-13: DATA SOURCE EVALUATION – PORTABLE POWER METER VERSUS LOG SHEETS (DATA SUBSET)

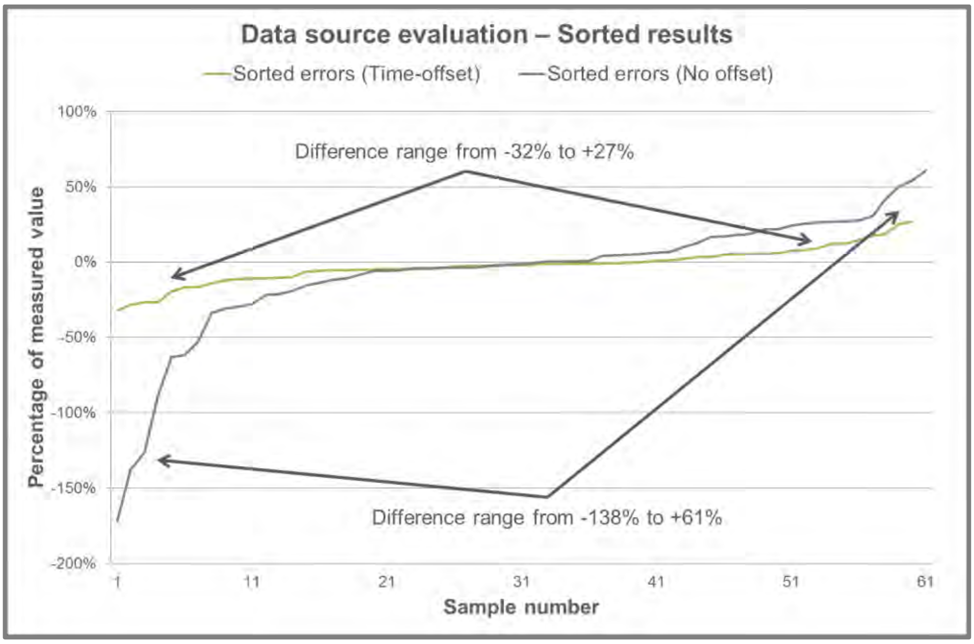

FIGURE 2-14: DATA SOURCE EVALUATION – PORTABLE POWER METER VERSUS LOG SHEETS (RESULTS)

CASE STUDY 3 – EVALUATING LOCAL METER USING FEEDER METER

Case Study 3 evaluates a local power meter as data source by comparing its measurements with the measurements from a feeder power meter. The power meter measures the power consumption of an electric motor while the second power meter measures the feeder supplying power to the motor. The two readings should be almost identical assuming that the feeder line does not supply other users.

As with the previous studies the two datasets are compared with each other. No significant difference between the two is visible so the difference is calculated and the results sorted. Figure 2-15 illustrates the results.

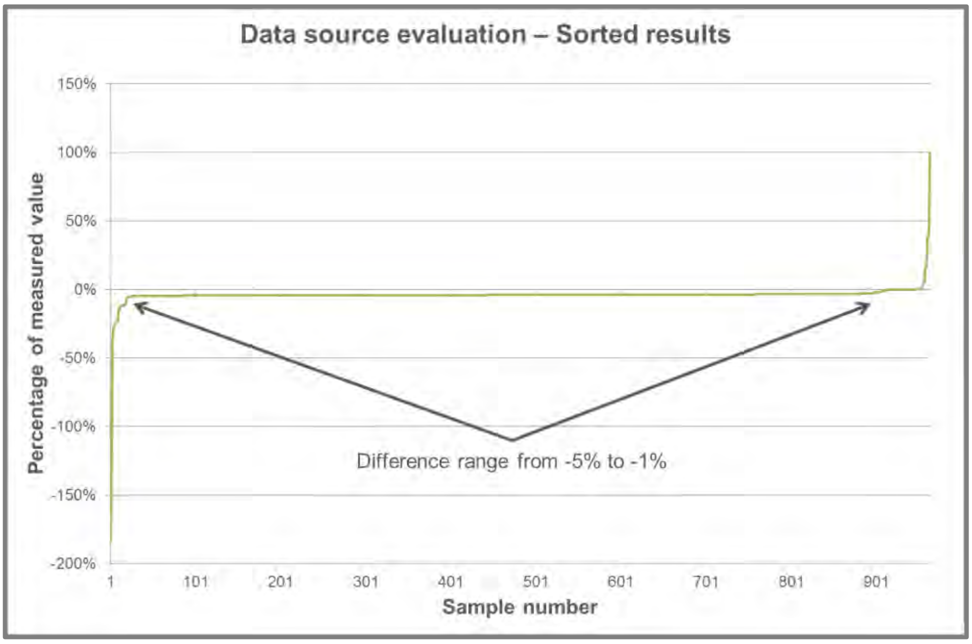

FIGURE 2-15: DATA SOURCE EVALUATION – LOCAL POWER METER VERSUS FEEDER METER (SORTED)

From the results in Figure 2-15 it is apparent that the data source quality can be confirmed. The calculated difference between the two power meters rendered a minimal amount of outliers with the general difference being between -5% and -1%. The difference can be attributed to small unidentified consumers connected to the feeder. This case study presents an excellent example of data source evaluation.

CASE STUDY 4 – EVALUATING POWER METER USING BILLING METER

Case Study 4 evaluates a power meter as data source by comparing its data with data from a billing meter. The power meter measures the total power consumption of a compressor house while the billing meter is situated on the supplying feeder. A year's data was collected, but due to the monthly resolution of the billing readings only a few data points exist. The local power meter data was processed to indicate monthly consumption, allowing the two sets to be compared. Figure 2-16 illustrates the results.

The negative results in Figure 2-16 indicate that the billing meter value is generally higher than that of the power meter. The low resolution of the data makes it difficult to determine a general trend, especially when compared with the other high-resolution case studies. The low resolution of the data does not justify the large dataset and the period required to collect it.

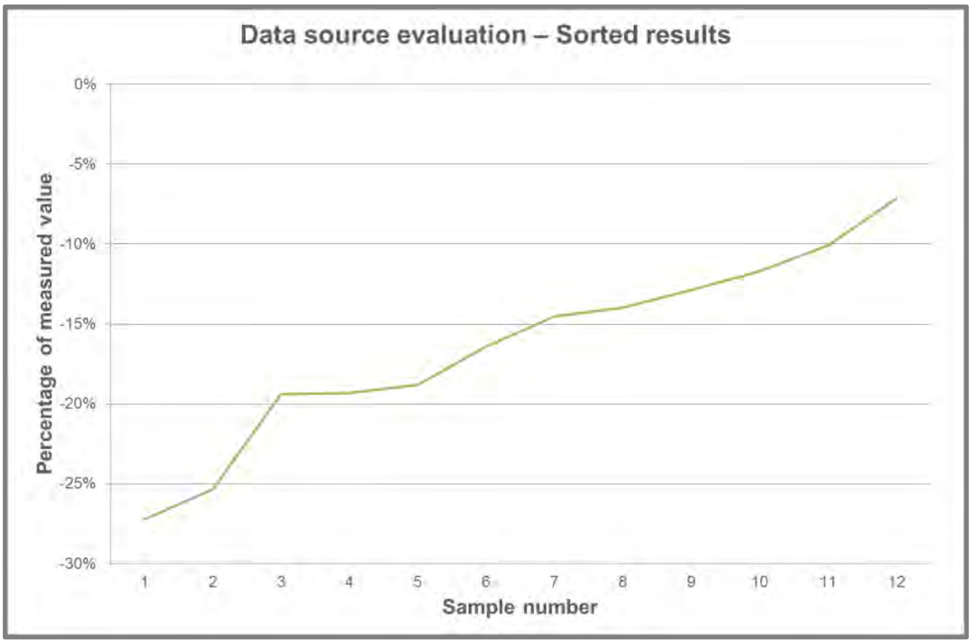

FIGURE 2-16: DATA SOURCE EVALUATION – POWER METER VERSUS BILLING METER (SORTED)

CASE STUDY 5 – EVALUATING TOTALISED FEEDERS USING INCOMER

Case Study 5, the final data evaluation case study, evaluates a set of feeder power meters as data source by comparing the totalised measurement with the consumption measured on the Eskom incomer. The datasets were compared and the difference calculated. The sorted results are displayed in Figure 2-17. The comparison shows several significant outliers, generally more than the rest of the case studies. The outliers can be attributed to other unidentified users not supplied by the selected feeders. The evaluation therefore identified the presence of unknown users that must be further investigated before the source quality can be evaluated any further.

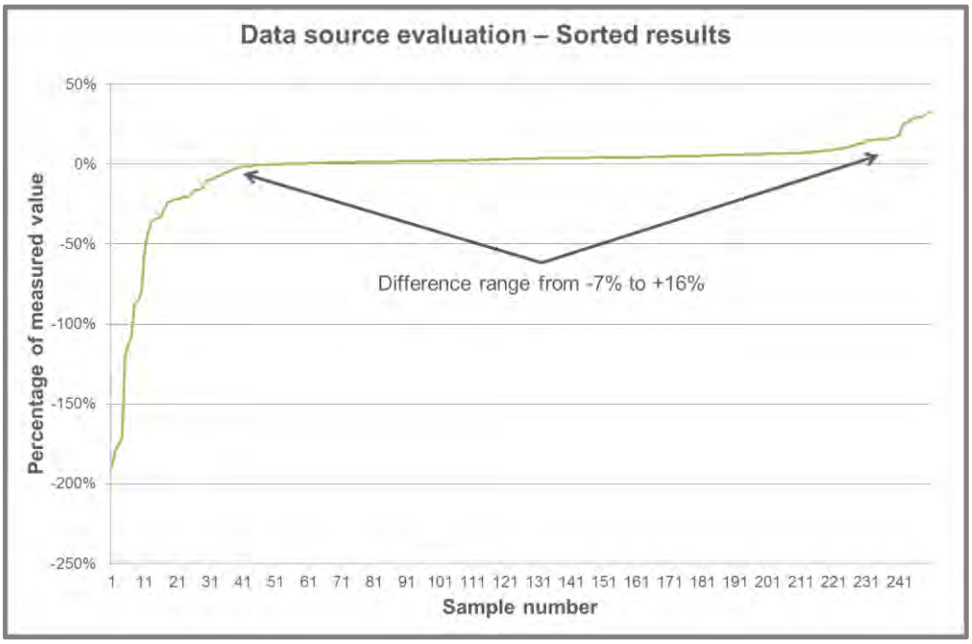

FIGURE 2-17: DATA SOURCE EVALUATION – TOTALISED FEEDERS VERSUS INCOMER (SORTED)

2.4.3. Case Study 6 to 10 – Dataset quality

Case Study 6 – Dataset evaluation: Identifying voltage dip

The dataset quality evaluation methodology was used to evaluate a dataset collected from a power logger. The power and current profiles were evaluated and deemed normal. The voltage evaluation, however, indicated that one of the voltage measurements fell outside the allocated band. The voltage profiles are shown in Figure 2-18.

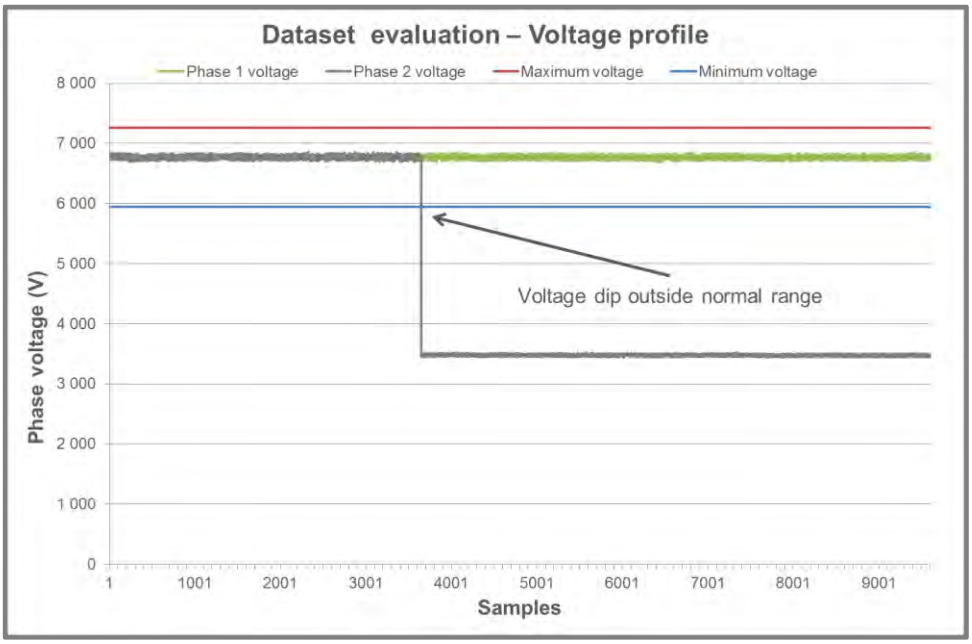

Figure 2-18: Dataset evaluation – Voltage profile evaluation (voltage dip)

If the voltage of both phases dipped, it may have indicated a power supply issue. The single-phase dip probably points to a metering malfunction such as a disconnected voltage clip. The result of the dip is small enough to go unnoticed when evaluating the calculated power results. This case study is a good example of how the malfunction of a single measurement can result in an error propagating through the M&V process unnoticed.

Case Study 7 – Dataset evaluation: Identifying multiple abnormalities

Case Study 7 evaluates data recorded by a portable power meter. The power and voltage logs were evaluated and deemed to be normal except for the occurrence of a few minor discrepancies. Figure 2-19 depicts the phase current profiles illustrating data loss, constant values and spikes.

This case study presents another illustration of a single measurement affecting calculated results. The occurrence of spikes in the dataset may point to potential measurement issues. It is only when the current profiles are evaluated that the full set of errors become apparent. The constant value measured complicates error detection when evaluating only power consumption, because the results will still fall within the correct range. The example illustrates three potential errors and confirms the importance of evaluating the quality of all measured variables and not only power.

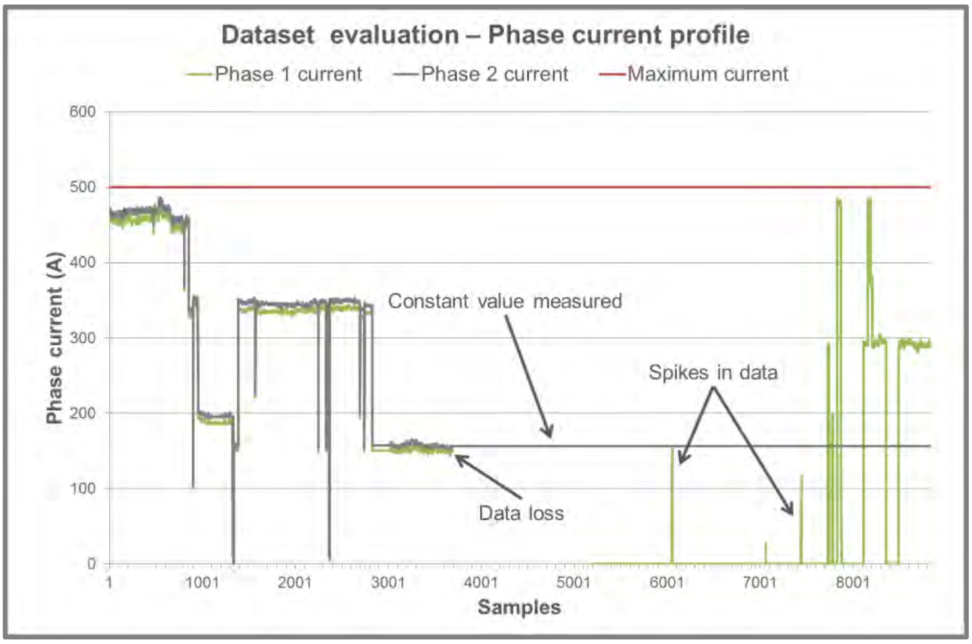

FIGURE 2-19: DATASET EVALUATION – CURRENT PROFILE EVALUATION (MULTIPLE ABNORMALITIES)

CASE STUDY 8 – DATASET EVALUATION: IDENTIFYING CONSTANT VALUES

No current and voltage measurements were available thereby presenting only the power measurements for evaluation. Figure 2-20 illustrates a power profile with data spikes and a section logging a constant value. The spikes measured before and after the constant value indicate that the measurement abnormality was probably caused by a meter malfunction. The previous two case studies highlighted the potential impact of a single measurement error. It is therefore very important to scrutinise power data closely if the voltage and current measurements are not available.

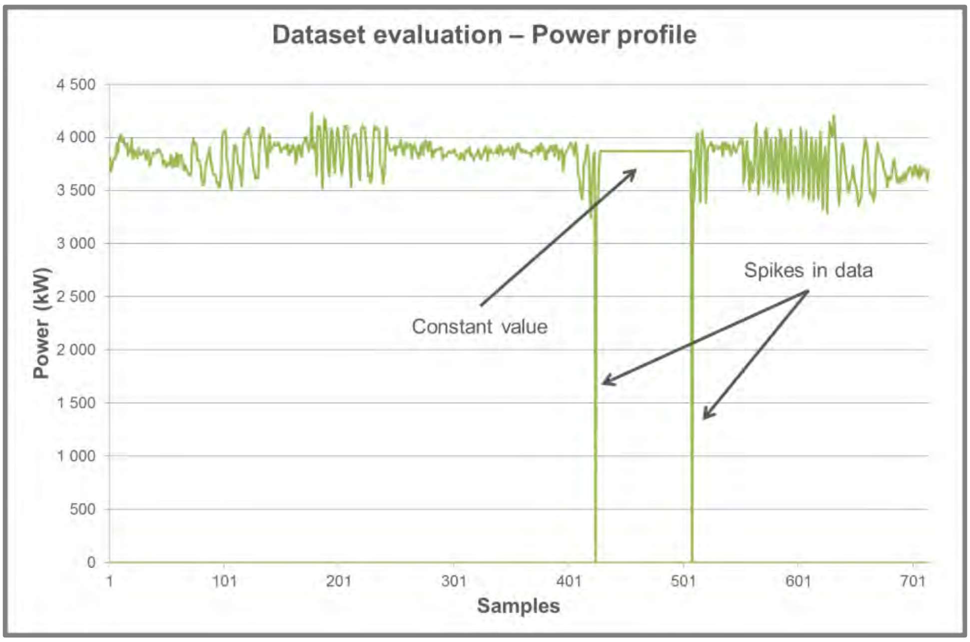

FIGURE 2-20: DATASET EVALUATION – POWER PROFILE EVALUATION (CONSTANT MEASUREMENT)

Case Study 9 – Dataset evaluation: Identifying a data spike

Figure 2-21 shows a power profile with a massive data spike (almost 5000 kW). The duration of the data spike is relatively short, but due to the amplitude it can have a significant impact on subsequent calculations. The occurrence of the spike also casts doubt on the validity of the rest of the dataset.

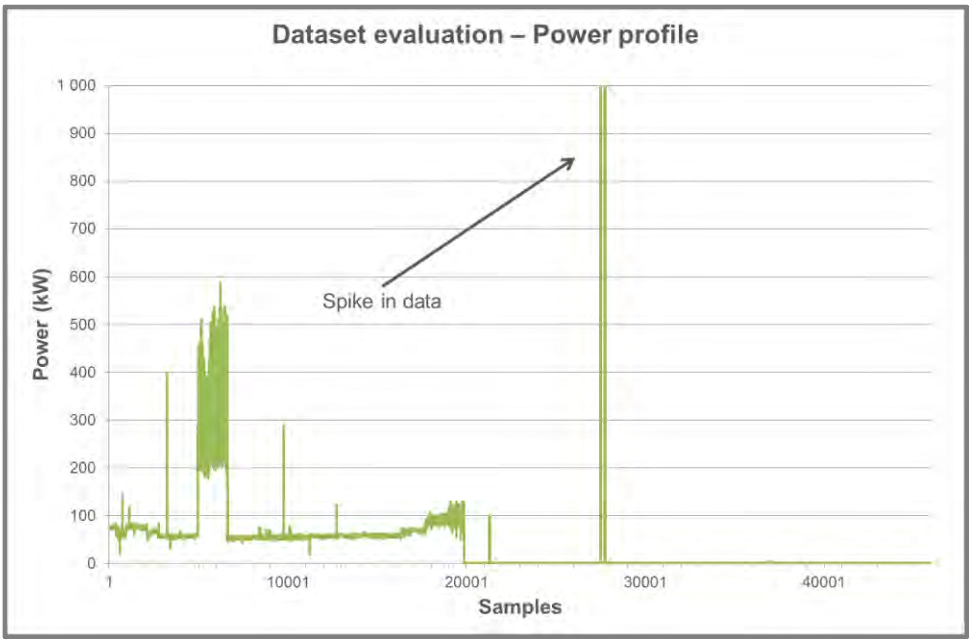

Figure 2-21: Dataset evaluation – Power profile evaluation (data spike)

Case Study 10 – Dataset evaluation: Identifying abnormal operation

Evaluation of the logged data did not indicate any abnormal measurements. The data was subsequently processed to present average weekday profiles (per month). Figure 2-22 illustrates the results and identifies an operational abnormality that requires additional investigation.

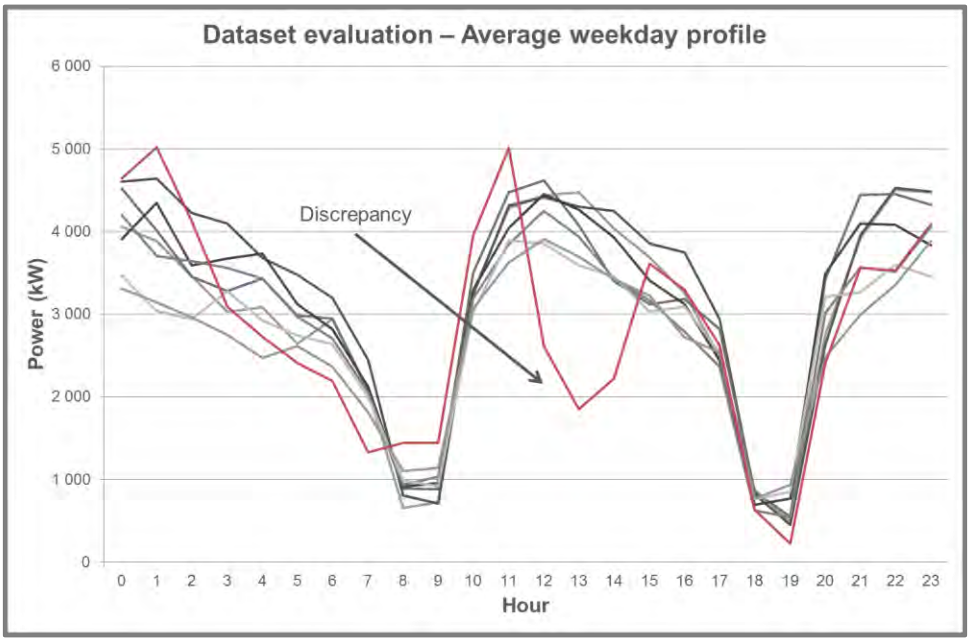

Figure 2-22: Dataset evaluation – Monthly profile evaluation (abnormal operation)

2.4.4. Case Study 11 to 15 – Dataset selection

Case Study 11 – Dataset selection: Identifying a complete dataset

Figure 2-23 illustrates the complete dataset collected for a project. The collected power data spans almost two years. The inclusion of flow and pressure data reduces the usable power data to almost 20% of the original dataset.

This case study illustrates the importance of collecting the full spectrum of required data. The presented set will severely limit dataset options if a regression model requiring flow is used to model the system. The limited availability of a complete dataset will force the model development to compromise the process. It can opt to reduce the number of variables used thereby excluding flow. Alternatively, it can use the available flow data without being able to confirm whether it is representative of normal system operation.

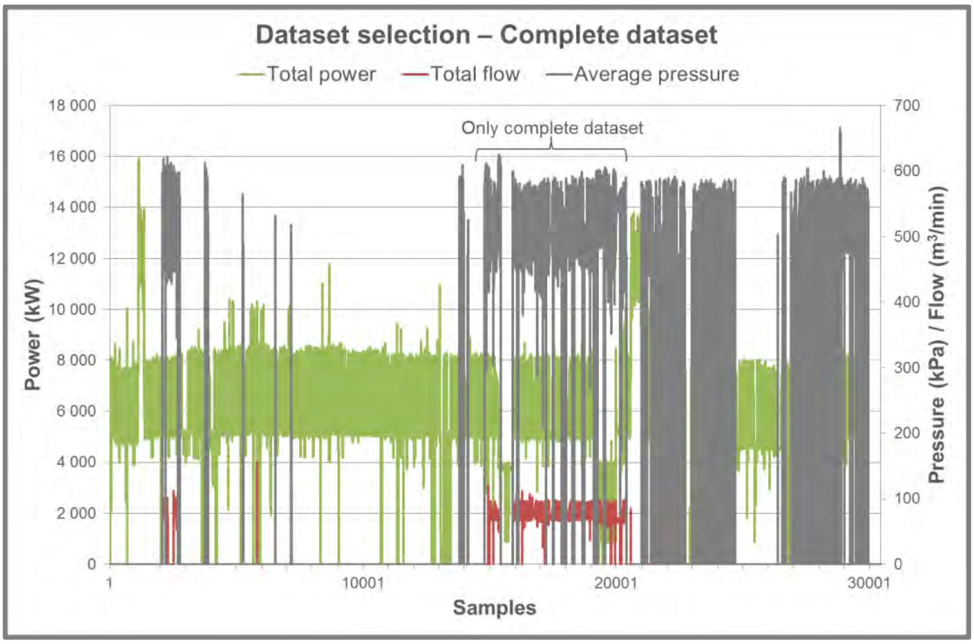

Figure 2-23: Dataset selection – Data availability evaluation

Case Study 12 – Dataset selection: Identifying seasonal cycle

Figure 2-24 illustrates the total power consumption of components presenting a mine cooling system. A review of the total power consumption identified the presence of a seasonal variance. A detailed analysis found that only the surface cooling component is seasonally dependent.

The dataset analysis identified the possibility of developing a separate baseline for each different component. The lack of any significant variance indicates that any dataset can be selected to represent the underground cooling and the dewatering pumps. Specific datasets will, however, be required to represent the different operational modes of the surface cooling component.

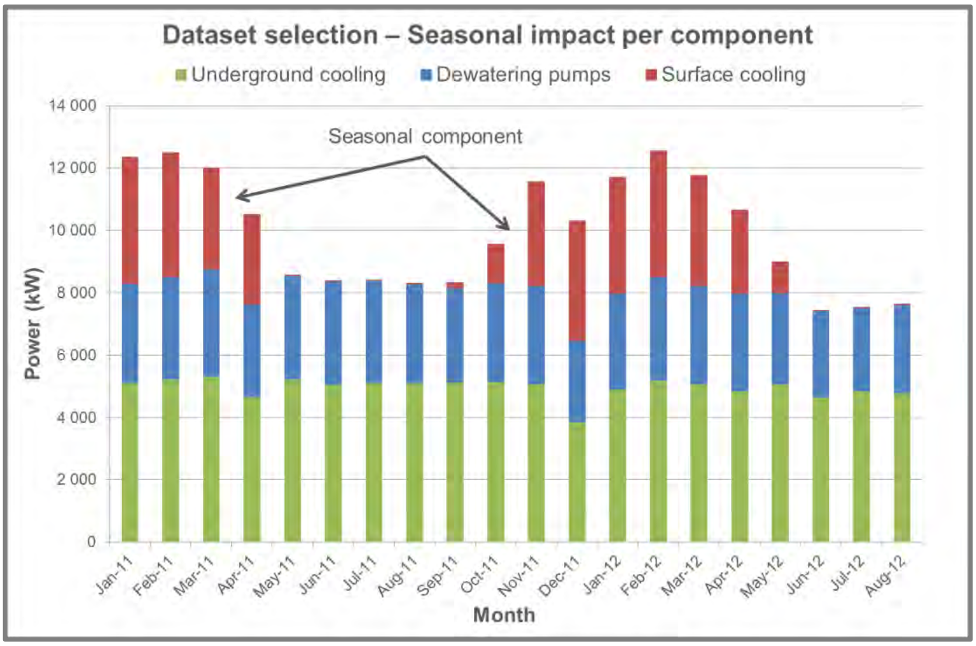

FIGURE 2-24: DATASET SELECTION – AVERAGE COMPONENT CONSUMPTION (SEASONAL IMPACT)

CASE STUDY 13 – DATASET SELECTION: IDENTIFYING OPERATIONAL PROFILES

Case Study 13 evaluates the operational characteristics of a pumping system. The available data is processed to present the average weekday profiles (per month). The profiles are normalised to simplify the evaluation process. The results in Figure 2-25 show that all the months present the same operation. It is therefore possible to use any selection of the set as the baseline dataset as long as the slight variance in amplitude can be accounted for by the model.

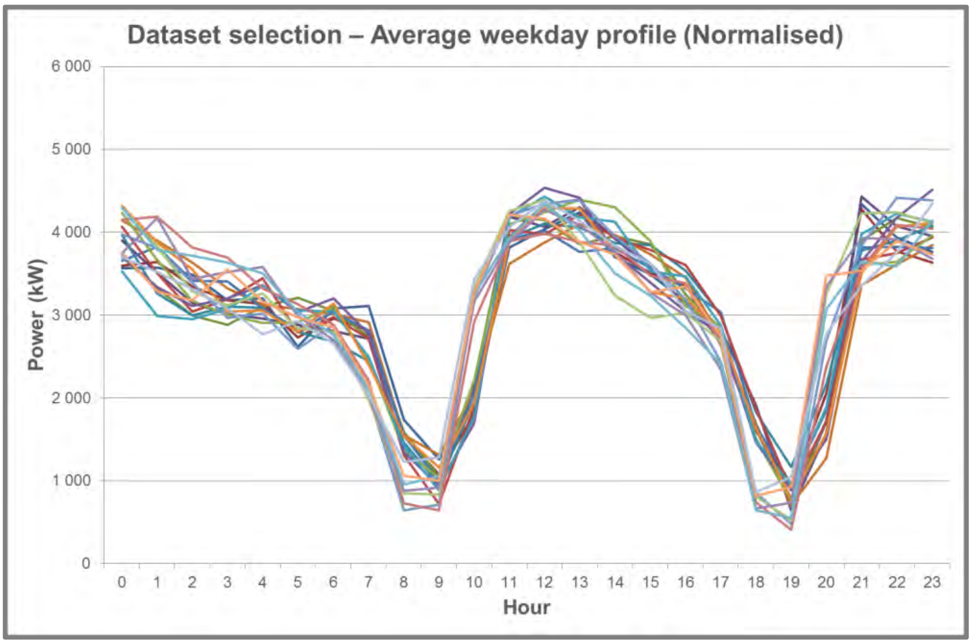

FIGURE 2-25: DATASET SELECTION – AVERAGE MONTHLY PROFILE EVALUATION (NORMALISED)

Case Study 14 – Dataset selection: Identifying operational profiles

Case Study 14 applies the dataset evaluation methodology to evaluate a compressed air system. The average monthly power consumption showed some variance, but no seasonal dependency could be identified. The average weekday profiles (per month) were subsequently developed and normalised. The results are shown in Figure 2-26.

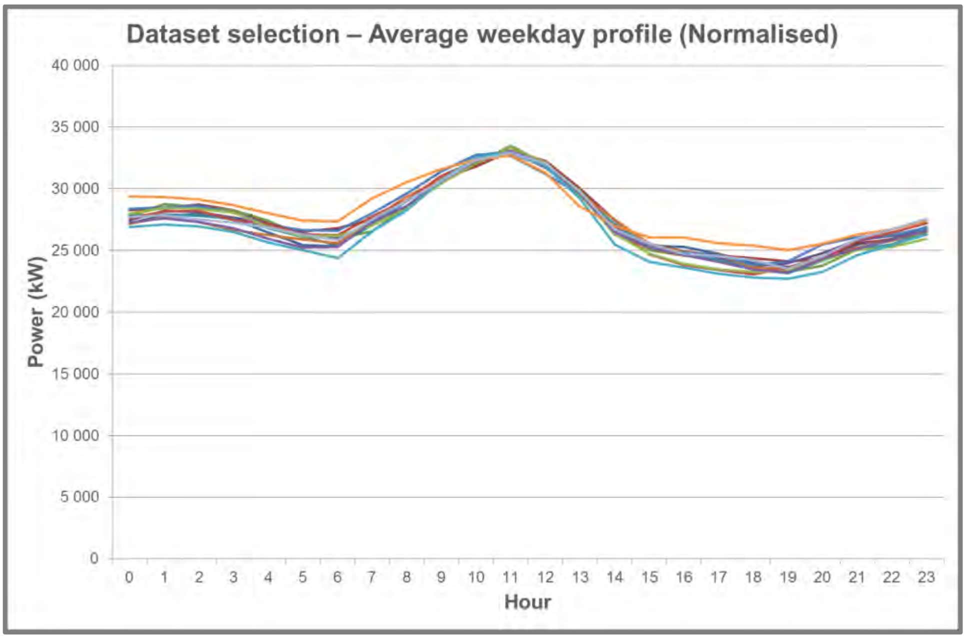

Figure 2-26: Dataset selection – Average weekday profiles (normalised)

From the results it is apparent that the compressed air system (just like the pumping systems) follows the same operational pattern throughout the year. It is therefore possible to use any of the months as part of the baseline dataset. The baseline model should include a method of scaling which will accurately compensate for the variance in amplitude.

Case Study 15 – Dataset selection: Identifying operational profiles

The average monthly power consumption of a cement plant was evaluated and no seasonal or cyclic pattern could be identified. The evaluation did, however, confirm that the plant indicated significant variance in monthly consumption. The variance was further analysed by calculating the relation between the Eskom evening peak and the average daily power consumption.

Inspection of the results identified different modes of operation throughout the year. The calculated ratios are used to identify datasets depicting the different operational scenarios of the plant. Figure 2-27 illustrates the two profiles presenting the most common modes of operation. The identified datasets can now be used to develop two baselines, each representing a different mode of plant operation.

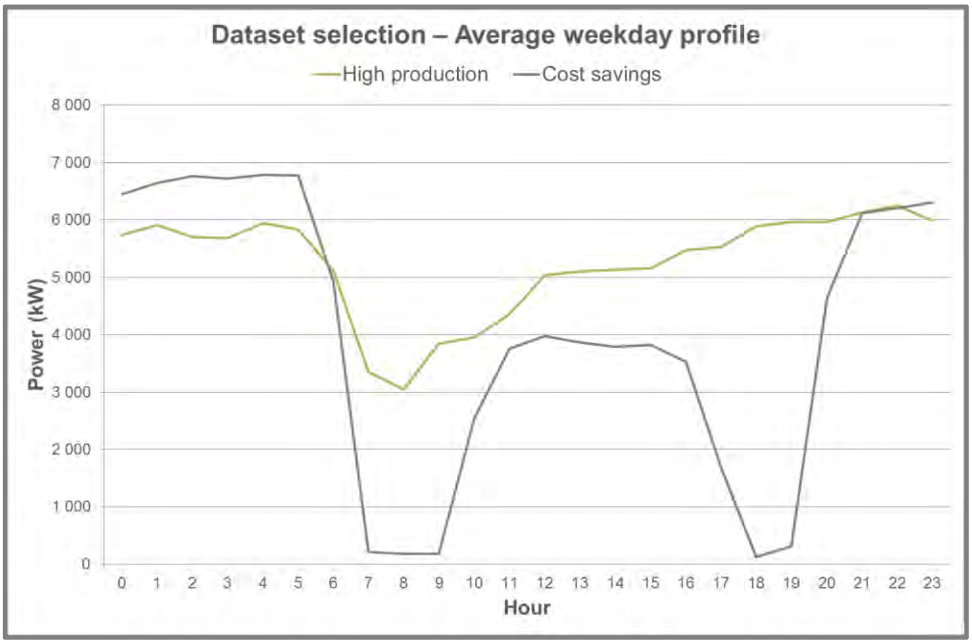

FIGURE 2-27: DATASET SELECTION – AVERAGE WEEKDAY PROFILES (DIFFERENT MODES)

2.5. CONCLUSION

This chapter developed methodologies to evaluate dataset and data source quality. The guideline highlights important criteria to consider when selecting a baseline dataset. The new methodologies and guideline address the need for a structured process to ensure that a high quality dataset representative of the relevant system operation is selected for baseline model development.

The first methodology evaluates the data source by comparing its measurements with that of other sources. The comparison alone does not clearly confirm the source accuracy. The methodology's simplified process of sorting and graphically presenting the results significantly enhances the evaluation process. The resulting graph clearly indicates the prevalence of outliers as well as the general difference between the two sources.

The dataset collected from the evaluated source is further inspected to ensure that the dataset is error-free. The second methodology evaluates the dataset by identifying abnormal measurements and behaviour. The methodology identifies common data errors by comparing measurements to user specified boundaries. The visual evaluation of results enables the user to identify errors promptly.

The removal of the major data errors enables the raw data to be processed without compromising data quality. The methodology compares the processed results to identify any abnormal system operation. Data presenting abnormal operation can be removed from the dataset, thus ensuring that the baseline model is developed with data representing normal system operation.

The practical implementation of the methodologies is illustrated with the use of fifteen specifically selected case studies. The results clearly illustrate the functionality of the new methodologies. The dataset produced can now be used to develop a baseline model representing system operation.

Chapter 3

CHAPTER 3

BASELINE MODEL DEVELOPMENT AND EVALUATION

3. Baseline model development and evaluation

3.1. Introduction

Applying the methodologies and guideline developed in Chapter 2 will produce a high quality baseline dataset. The next step is to develop a baseline model representing system operation. The development process should strike a balance between minimising development costs and maximising model accuracy. This will only be achieved if the model can be objectively evaluated and compared with other models.

The review and literature analysis of Chapter 1 noted the existence of several evaluation methods. Unfortunately, these evaluation methods all require a good understanding of statistics to use the models effectively. It is, however, unlikely that all parties involved in industrial DSM projects will possess the required statistical background. This chapter will therefore develop several simplified solutions to improve the process baseline model development and evaluation.

The chapter begins with a basic baseline model development guideline. The guideline focuses on three widely used models and their application to industrial projects. The models are matched to system-specific characteristics to simplify the selection process for future projects. The models discussed are also applied to several industrial case studies as part of the methodology verification process.

The guideline is followed by a review of basic statistical methods that can be used to present a baseline model's accuracy graphically. The methods are utilised to develop a new baseline model evaluation methodology. The methodology presents a simplified and structured approach to evaluate and compare the accuracies of several baseline models. The graphical presentation of the different models enables stakeholders to visually compare models and intuitively select the best option. The methodology is finally verified by implementing it on several industrial case studies.

3.2. Guideline for modelling industrial systems

3.2.1. Constant baseline model

The constant baseline model is a very basic model used to represent systems with consistent operation. The model is developed by calculating an average profile for each operational model included in the baseline dataset. These profiles are never adjusted to compensate for system changes.

Figure 3-1 illustrates three profiles representing different operational modes. Profile 1 represents the average system operation for a normal workday. The normal workday dataset will include all weekdays, but can also include "working" Saturdays, Sundays and public holidays. The Saturday and Sunday profiles represent the respective days for non-working weekends. Public holidays are classified as either Saturdays or Sundays.

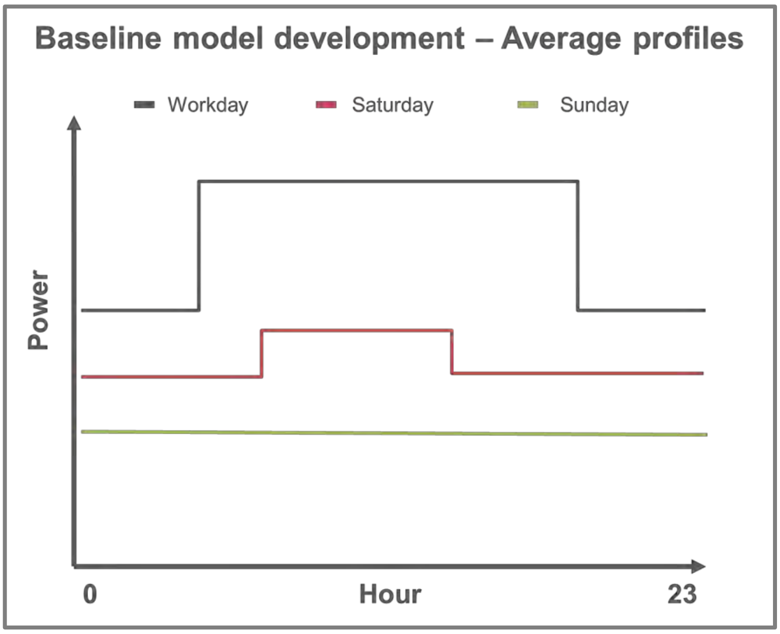

FIGURE 3-1: BASELINE MODEL DEVELOPMENT – CONSTANT BASELINE (AVERAGE PROFILES)

A timer-controlled lighting system is an example of consistent system operation. The system will follow the same profile of operation and as a result consume the same amount of energy per day. A constant baseline profile can therefore be used to represent system operation.

The average power consumption of the baseline profile can also be used as a reference when evaluating project impact. Figure 3-2 gives a comparison between the average baseline power and the average system power that over time reflects the project impact.

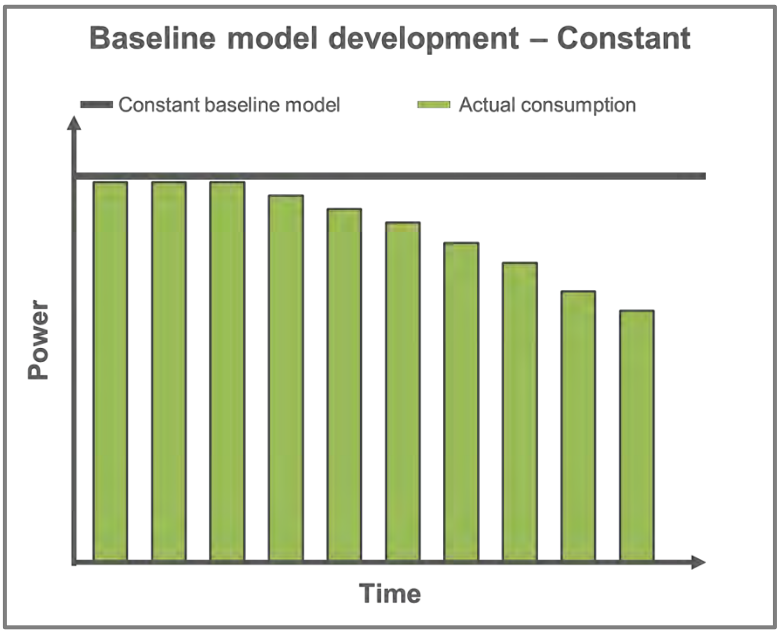

FIGURE 3-2: BASELINE MODEL DEVELOPMENT – CONSTANT BASELINE (MONTHLY CONSUMPTION)

The comparison in Figure 3-2 clearly illustrates the project impact. Comparing the hourly baseline and post-implementation profiles will give a detailed indication of how the project affected system operation. It will also allow for an accurate calculation of the monetary impact for systems billed on a "time of use" (TOU) structure. Figure 3-3 compares a workday (post-implementation) and constant baseline profile.

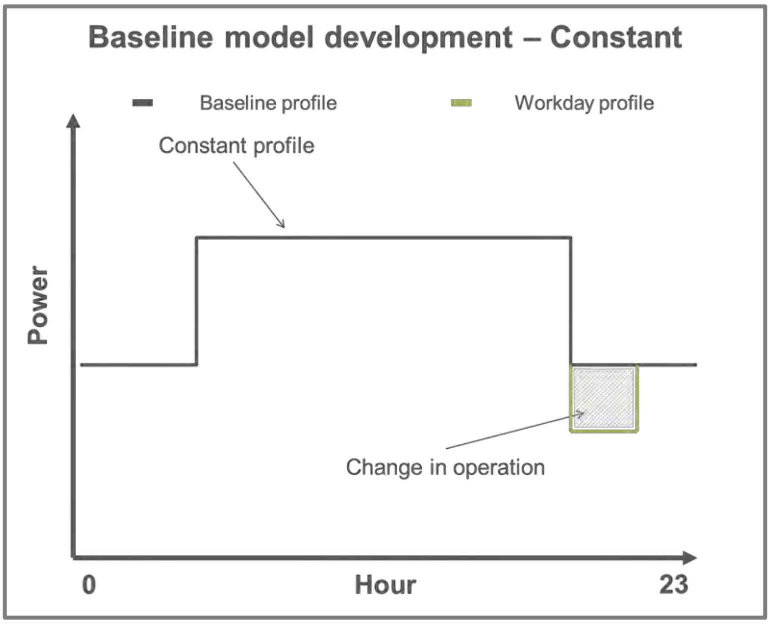

FIGURE 3-3: BASELINE MODEL DEVELOPMENT – CONSTANT BASELINE (WORKDAY PROFILE)

The constant baseline model has been used by industries (such as mines) to evaluate system power consumption. Changes in consumption are calculated by comparing system operation on a year-on-year basis (for example March 2011 versus March 2012). This approach compensates for system changes that are linked to a specific time of the year. These changes can include seasonal effects as well as variance in production due to public and school holidays.

The constant baseline approach is simple to develop and implement, but lacks the ability to accurately represent systems with fluctuating operation. The next section will discuss a baseline model that uses measured energy as a reference point for model adjustment.

3.2.2. ENERGY-NEUTRAL BASELINE MODEL

The energy-neutral baseline model develops baseline profiles in the exact same manner as the constant baseline model. This model, however, differs from the constant model by using energy usage as reference for model adjustment. The model retains the baseline profile shape, but adjusts its amplitude to represent system operation for a specific scenario. Figure 3-4 illustrates the basic concept.

In Figure 3-4 a specific area under the average profile is selected as reference point. The selected area, which can range from one hour to the entire day, depends on the system and project characteristics. The energy consumption for this reference point is calculated for the baseline (A) and the assessed profile (B). The results are used to calculate a scaling ratio (B divided by A). The baseline profile is then adjusted (up or down) according to the scaling ratio. The end result is a scaled baseline profile with the exact same reference energy as the assessed profile.

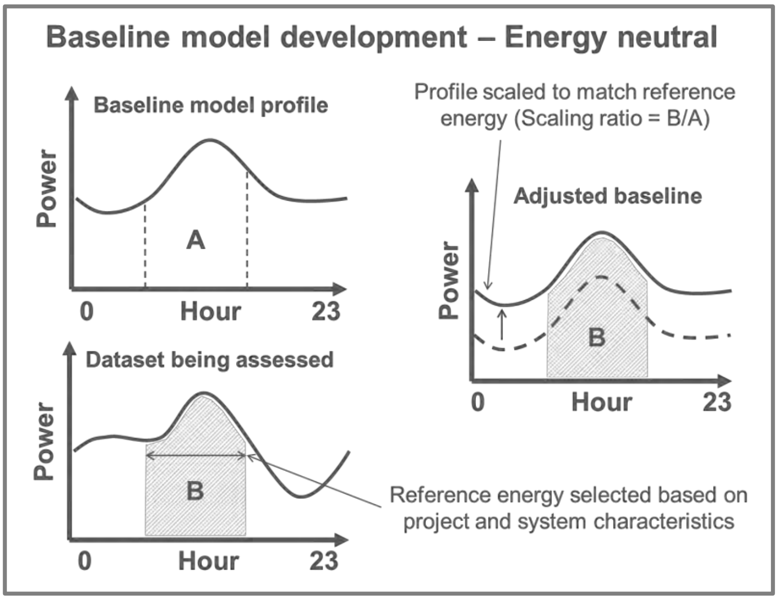

FIGURE 3-4: BASELINE MODEL DEVELOPMENT – ENERGY-NEUTRAL BASELINE (AVERAGE PROFILES)

Figure 3-5 compares the scaled baseline and actual power consumption. In this example the entire area under the curve is used as a reference point. The result is an adjusted baseline that will always be energy neutral when compared to the actual system consumption.

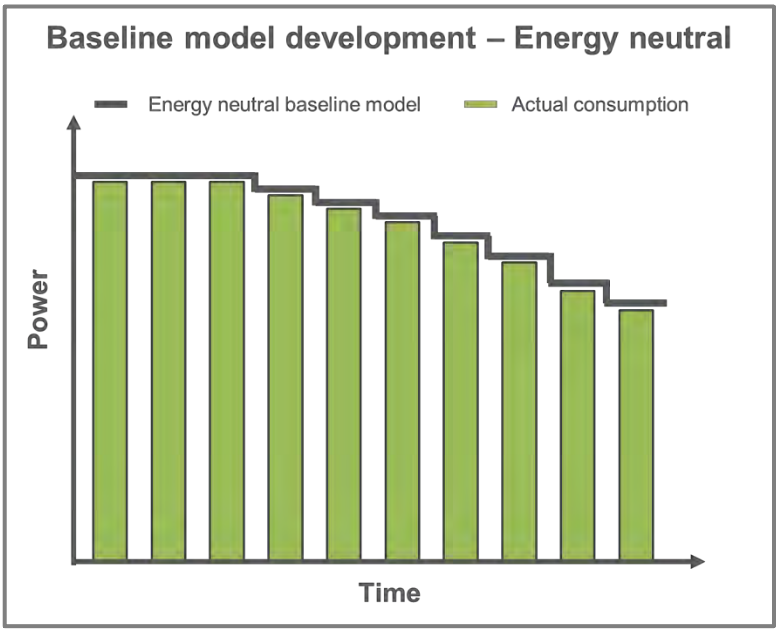

FIGURE 3-5: BASELINE MODEL DEVELOPMENT – ENERGY-NEUTRAL BASELINE (MONTHLY CONSUMPTION)

The energy-neutral baseline model can be used to represent systems where the operational profile is fixed, but the amplitude varies due to external influences. A good example is load shifting projects where operational load is moved from one period to another. Figure 3-6 illustrates an example.

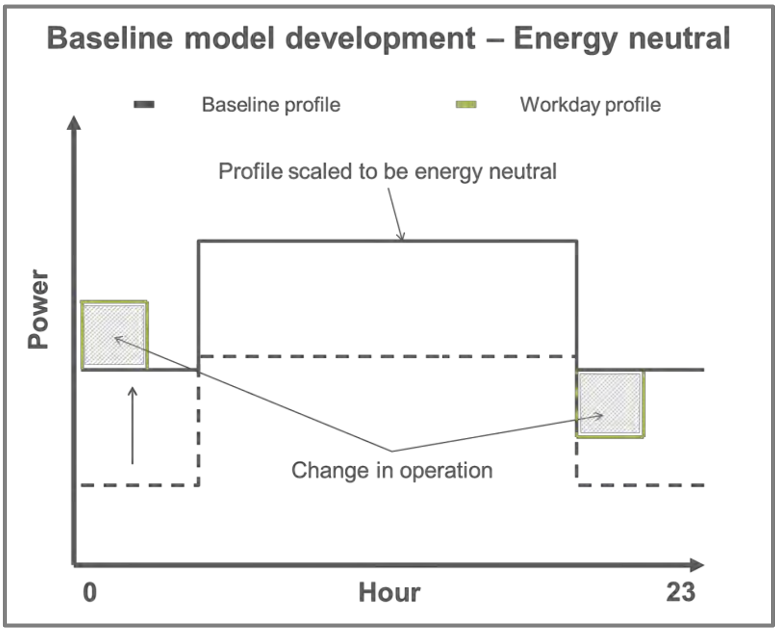

FIGURE 3-6: BASELINE MODEL DEVELOPMENT – ENERGY-NEUTRAL BASELINE (WORKDAY PROFILE)

In Figure 3-6 the energy in the evening is moved to the early morning. If the baseline model is scaled according to the entire day's energy consumption, the profiles will be completely energy neutral. The project will then result in zero energy reduction, but will affect operational costs due to the cheaper TOU tariffs.

The energy-neutral baseline model can be used for projects where the operational profile is changed without affecting total energy consumption. It can also be used for projects where an energy efficiency component is introduced for a specific (and limited) period of the day. The model does not work well for systems where a general efficiency is introduced. If energy cannot be used as reference other system variables should be incorporated. This is done by developing a baseline regression model.

3.2.3. REGRESSION BASELINE MODEL

Energy-neutral baseline models use energy consumption as an indication of changes in system operation. Baseline regression models link changes in system variables to changes in system power consumption. The basic regression model has already been discussed in Section 1.1, but will be discussed further in this section.

Figure 3-7 (a repeat of Figure 1-5 placed here for quick access) illustrates how independent variables are matched to system power consumption. The results are used to develop a linear regression line that can be represented using a mathematical formula ($y = mx + c$).

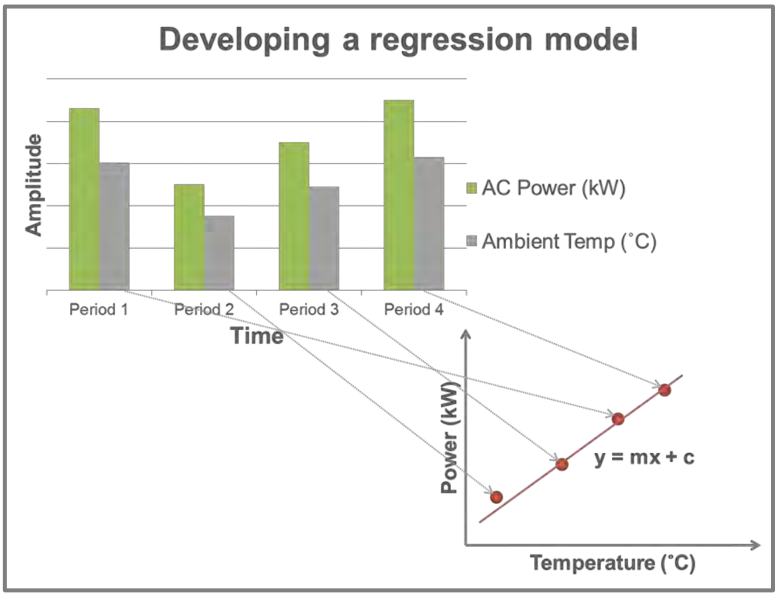

FIGURE 3-7: BASELINE MODEL DEVELOPMENT – REGRESSION MODEL (INDEPENDENT VARIABLES)

The evaluation of industrial projects found that suitable variables were not always readily available. Production figures were often deemed confidential while ambient conditions did not always have a significant effect on the relevant systems. System-specific variables such as temperature, pressure and flow are often available and produce good regression models. These variables are, however, affected by the project making them dependent variables. The use of a dependent variable regression model will result in the project influencing baseline scaling and therefore the project savings. Figure 3-8 illustrates this effect.

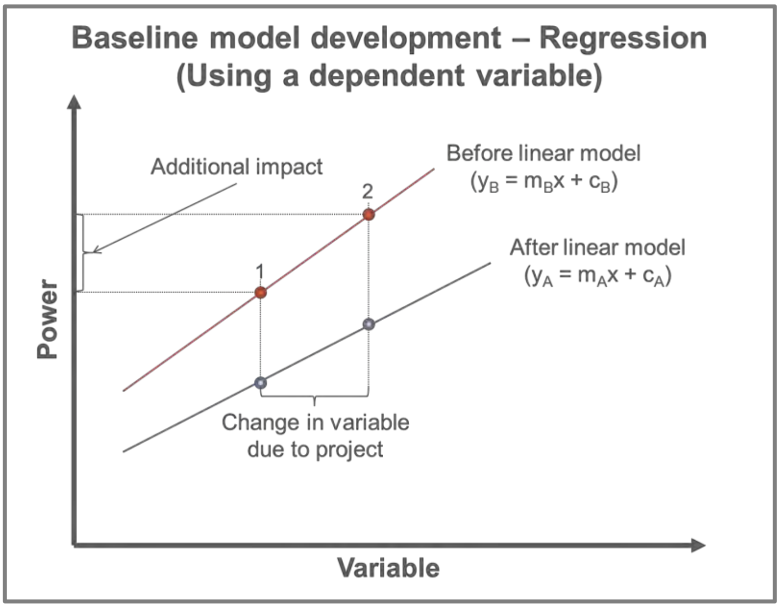

FIGURE 3-8: BASELINE MODEL DEVELOPMENT – REGRESSION MODEL (DEPENDENT VARIABLES)

Figure 3-8 shows how changes in the variable value significantly affect the calculated power. The variable can therefore only be used if the project's influence on the variable can be quantified. It is, however, not always practical or possible to isolate project-induced changes from other changes.

An alternative approach is to select a reference section where the project has no impact on the dependent variable. Changes in the variable during this period will therefore represent system changes independently from the project changes. A new regression model can now be developed to represent this point of system operation. Figure 3-9 illustrates an example:

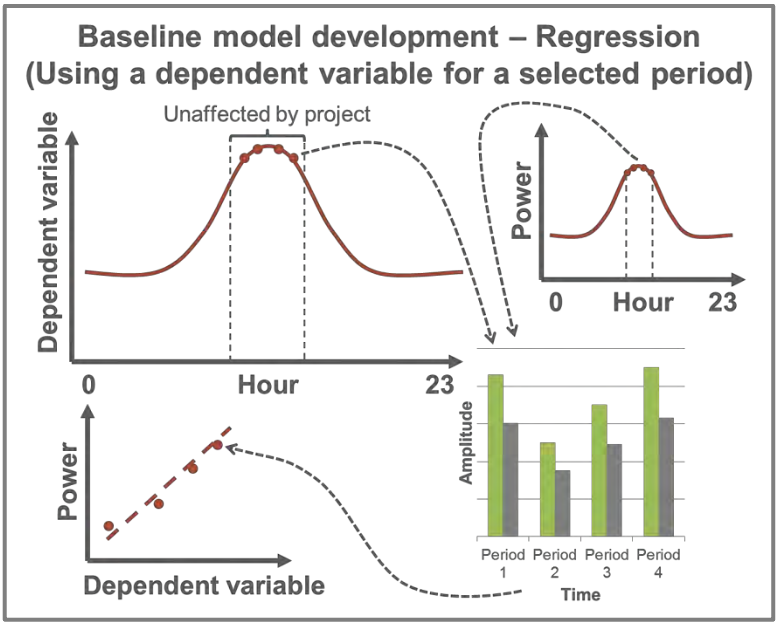

FIGURE 3-9: BASELINE MODEL DEVELOPMENT – REGRESSION MODEL (SELECTED PERIOD)

The process illustrated in Figure 3-9 only uses data that is unaffected by the project (in this case the peak in the middle of the day). The new regression model will therefore indicate power consumption of this specific section only. The result is a reference point that can be used to scale the baseline profile as shown in Figure 3-10.

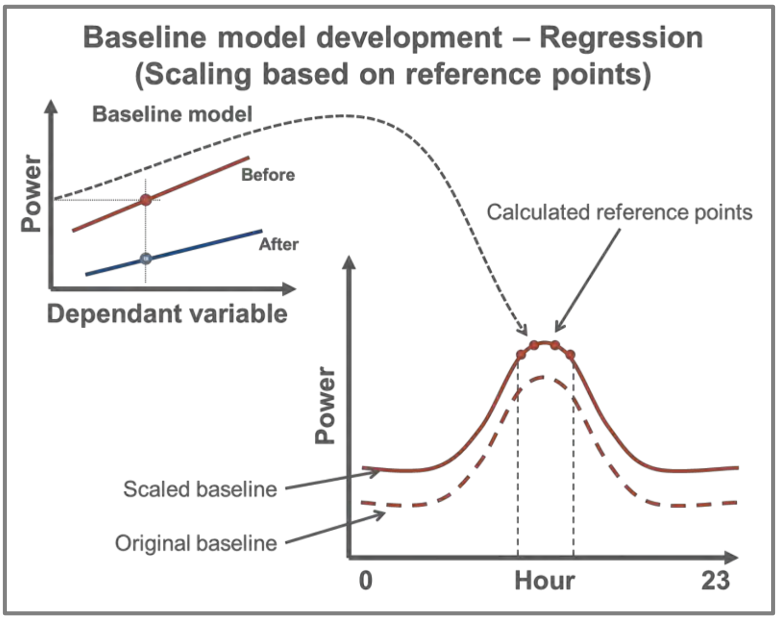

FIGURE 3-10: BASELINE MODEL DEVELOPMENT – REGRESSION MODEL (SCALING ON REFERENCE POINTS)

Figure 3-10 shows how the regression model is used to determine what the reference point power consumption "would have been" based on post-implementation variable data. The baseline profile is then scaled to match the calculated points. Figure 3-11 gives an example of the result.

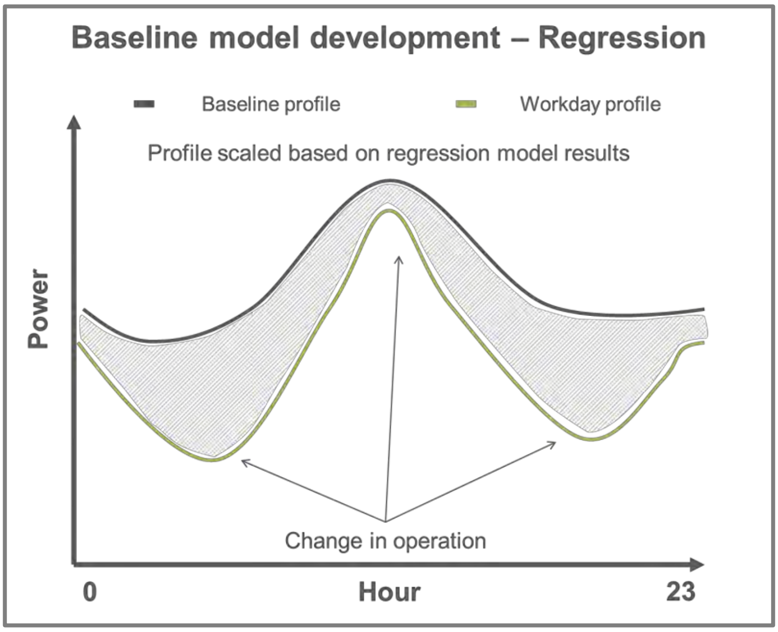

FIGURE 3-11: BASELINE MODEL DEVELOPMENT – REGRESSION MODEL (WORKDAY PROFILE)

The workday profile illustrating the post-implementation system operation differs from the baseline in several aspects. This illustrates why it is not possible to use any period's energy as reference point. The scaled baseline profile can now be used to determine the average power consumption as illustrated in Figure 3-12.

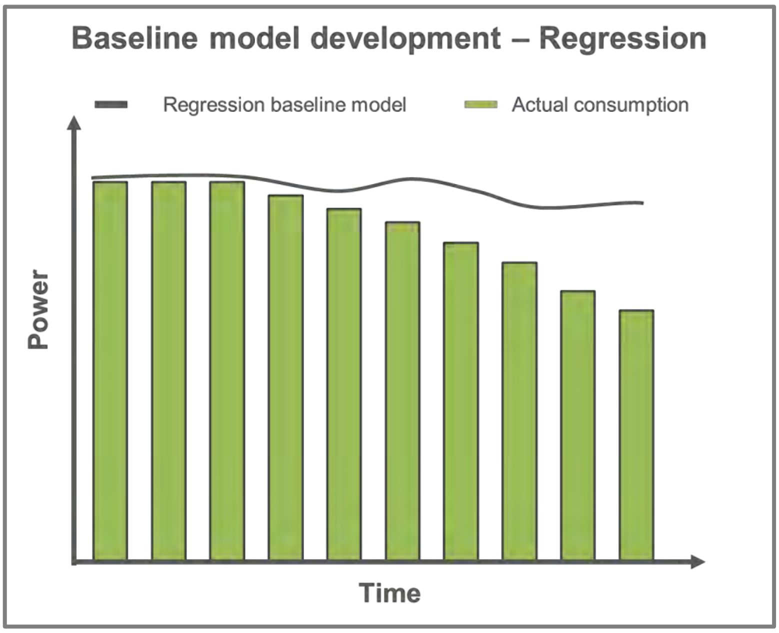

FIGURE 3-12: BASELINE MODEL DEVELOPMENT – REGRESSION MODEL (MONTHLY CONSUMPTION)

3.2.4. Factors affecting regression model accuracy

Constant and energy-neutral baseline models work well for relatively simple projects. It is, however, inevitable that some industrial projects will have to make use of regression baseline models. It is therefore important to note that various factors can affect regression model accuracy. The following section will briefly discuss some relevant factors.

The first factor is the selection of variables used to develop the model. Using too few variables can produce a model that is not sensitive enough. Using too many variables can overfit the model making it sensitive to random noise. It is also a risk that a random combination of variables and data can produce a regression model that seems to represent the system well. Figure 3-13 illustrates two different variable combinations.

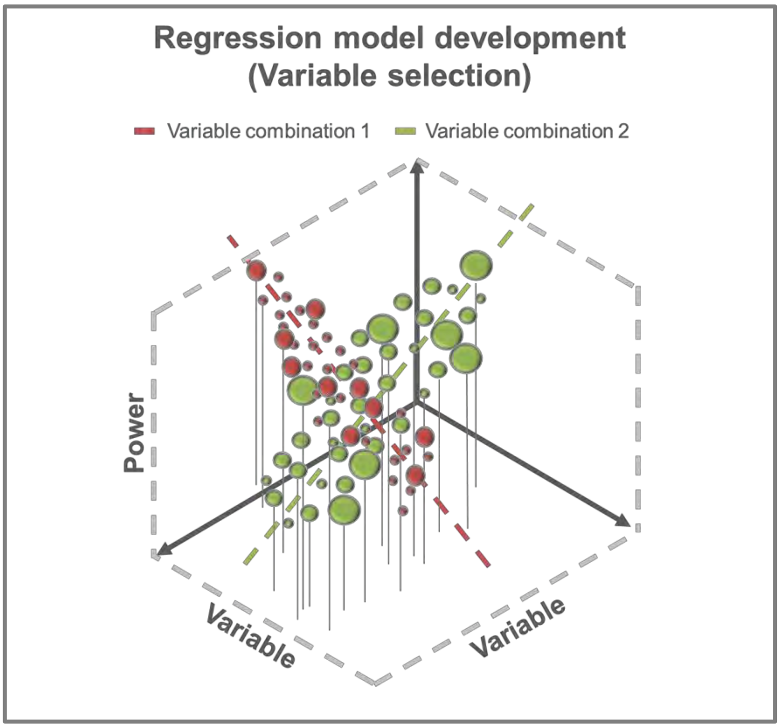

Figure 3-13: Baseline model development – Regression model (variable selection)

The first combination (red) represents system operation while the second (green) represents a random variable linked to system power consumption. The two combinations will render completely different regression models with only one being correct. It is therefore important to properly evaluate and compare different variable combinations when developing a model.

Another factor influencing model accuracy is the period of data each data point represents. It is not necessarily ideal to select the smallest available period to develop a regression model. For example, hourly data can be used to model the operation of a pump because power is immediately affected by changes in pressure and flow. Daily averages may work better for air-conditioning systems where changing ambient temperature and humidity will have a gradual effect on the system. Weekly averages can give a better fit for production-related outputs where several components and processes have to occur before the output can be measured.

Figure 3-14 illustrates the developed regression lines for a model fitting power to a single variable over different data periods. Evaluating the raw data has the benefit of highlighting potential outliers and abnormal data points. Fitting the model to weekly data will make it less sensitive for potential outliers. It is therefore important to evaluate the different options in order to select the best model.

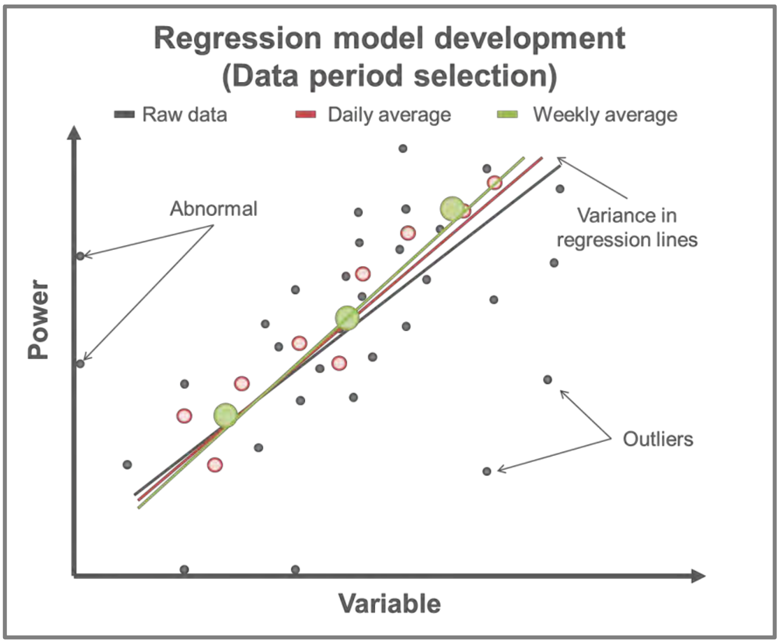

FIGURE 3-14: BASELINE MODEL DEVELOPMENT – REGRESSION MODEL (DATA PERIOD SELECTION)

This section gave a brief guideline on the application of three different baseline models. These models are widely used and can be quickly applied to model similar systems. Several other models exist and can be used to represent system operation although this may increase costs.

In addition to the different models there are also different variables, different combinations of variables and different variable characteristics that can affect model accuracy. Considering these factors it becomes apparent that there are many potential baseline models that can be used to represent a system. The next section will develop a methodology to evaluate and compare the accuracy of these models thereby enabling the best model to be selected.

3.3. BASELINE MODEL EVALUATION METHODOLOGY

3.3.1. MISCONCEPTIONS OF STATISTICAL CHARACTERISTICS

Section 1.1.5 reviewed existing methods used to evaluate baseline model accuracy. The review found that the coefficient of determination ($R^2 > 0.75$) and the root mean squared error ($RMSE < 15\%$) were the most widely used criteria. The author's interaction with industrial sector clients as well as various M&V teams highlighted the fact that the relevance of these criteria was not always fully understood.

Take the coefficient of determination for example. The misconception exists that a high R^2 value indicates a good model while a low R^2 indicates that there are no meaningful relationships in the data [6], [41]. This is not always the case. An excellent example of selected statistical characteristics can result in a misconception as illustrated by Anscombe's quartet shown in Figure 3-15 [50].

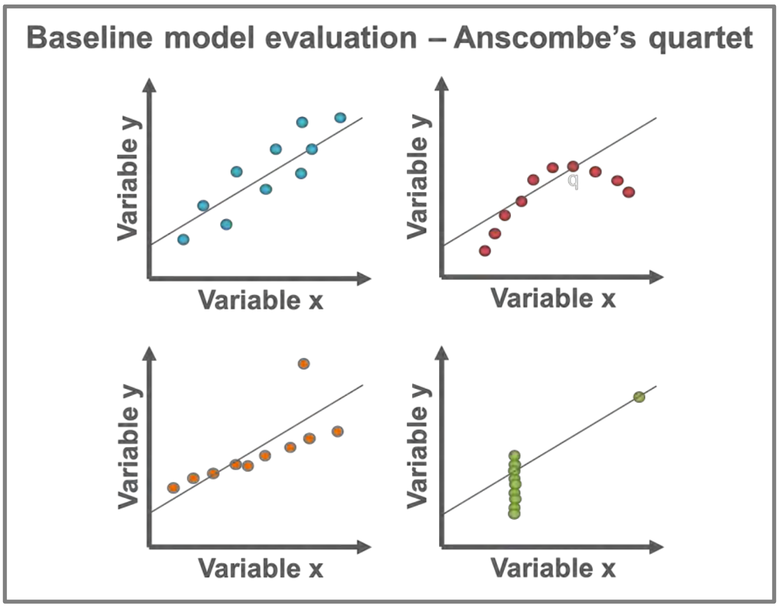

FIGURE 3-15: ANSCOMBE'S QUARTET – DIFFERENT DATASETS WITH THE SAME CHARACTERISTICS

The four datasets shown in Figure 3-15 have the exact same statistical characteristics (mean, variance, coefficient of determination and linear regression formula) [50]. It is, however, obvious that the datasets present completely different scenarios. Evaluating and selecting a baseline model based solely on the statistical characteristics will therefore be misleading.

Figure 3-15 also illustrates how visual inspection can be used as a quick and intuitive method to evaluate the relevance of a developed model. The next section will build on the concept of visual inspection by using some basic statistical methods to display baseline model accuracy.

3.3.2. GRAPHICALLY DISPLAYING MODEL ACCURACY

In Figure 3-16 the calculated results of a regression baseline model are compared to the actual system data. The calculated results follow the trend of the actual data, but there is a definite difference. It is, however, difficult to ascertain the exact accuracy of the model by inspecting this figure alone.

To evaluate the model further the percentage error is calculated for every point in Figure 3-16.

$$Percentage\ error = \frac{Actual\ value - Calculated\ result}{Actual\ value} \tag{11}$$

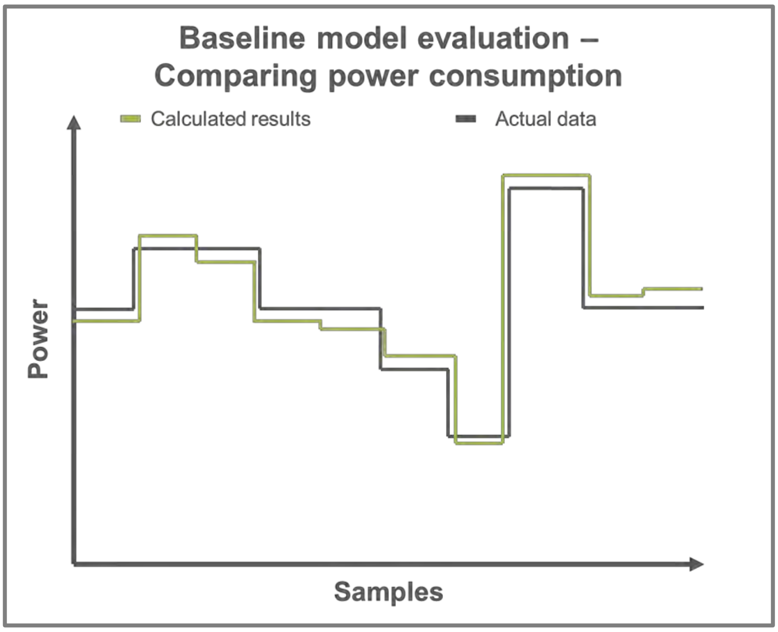

FIGURE 3-16: BASELINE MODEL EVALUATION – COMPARING ACTUAL VALUES TO CALCULATED RESULTS

Plotting the results will only present a scatter of data with no clear indication of model accuracy. To evaluate model accuracy the results can be presented in terms of their value and rate of occurrence. This is achieved by grouping the results into different classes.

A single class is used to represent all data points that fall within a specified range. Combining all the available classes will cover the entire range of possible results. The width of the classes can be constant or varied depending on the dataset characteristics. A general indication of the amount of classes required to group a dataset effectively can be estimated with the formula [49]:

$$\textit{Number of classes} \approx \sqrt{\textit{Total number of data points}} \tag{12}$$

The number and width of available classes can be changed to reflect different characteristics of the dataset. The process of grouping the calculated results into different classes is illustrated in Figure 3-17. The classes in the figure are based on the calculated percentage error.

Once the classes have been populated the relative frequency of each class can be determined using the formula [49]:

$$\textit{Relative frequency} = \frac{\textit{Number of data points in relevant class}}{\textit{Total number of data points}} \tag{13}$$

The ultimate result of this process is a graphical representation of the results (shown in Figure 3-18). This graph is generally referred to as a histogram. Inspection of the histogram clearly illustrates the accuracy of the baseline model in terms of the magnitude and frequency of errors.

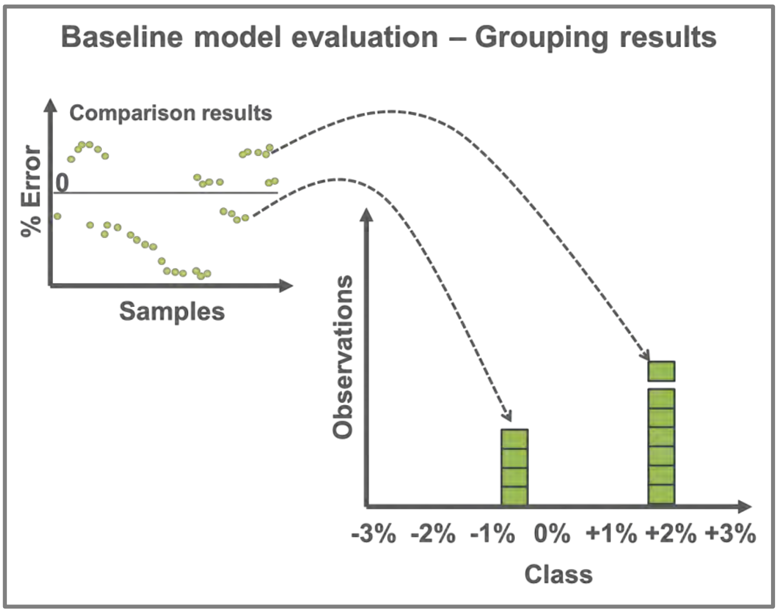

FIGURE 3-17: BASELINE MODEL EVALUATION – GROUPING RESULTS INTO DIFFERENT CLASSES

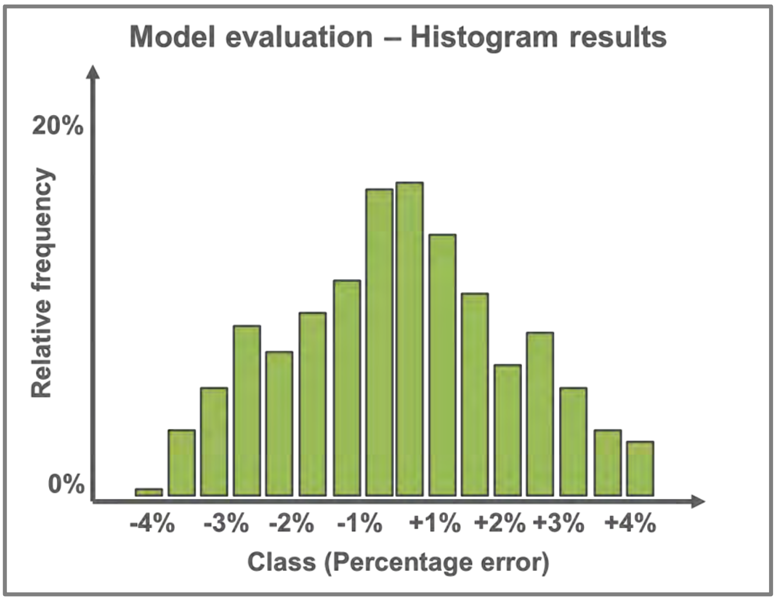

FIGURE 3-18: BASELINE MODEL EVALUATION – HISTOGRAM RESULTS

3.3.3. USING A HISTOGRAM TO EVALUATE BASELINE MODELS

The previous section described the process of developing a histogram. Many data processing software suites such as Microsoft® Excel already have data analysis tools that can be used to develop a histogram. The focus will therefore shift from developing histograms to using them as a means to evaluate various baseline models. Figure 3-19 illustrates the evaluation methodology.

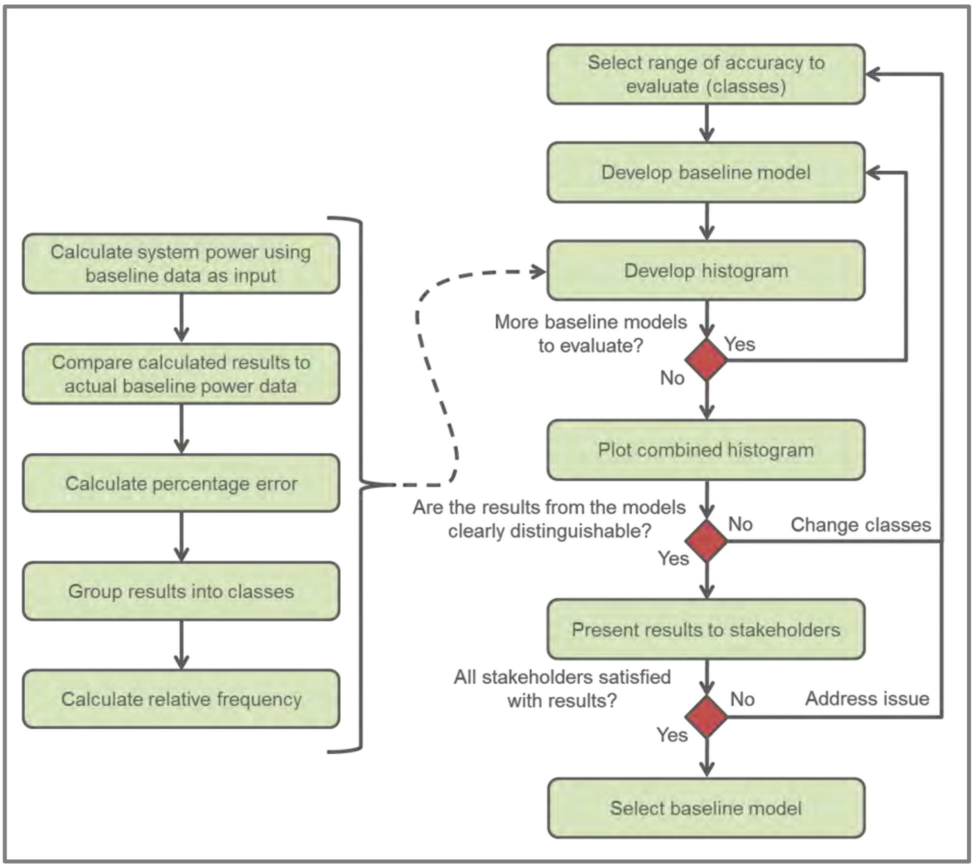

FIGURE 3-19: THE BASELINE MODEL EVALUATION METHODOLOGY

The first step in the evaluation process is to select a suitable set of classes. If a single baseline model is being evaluated the process described in Section 3.3.2 can be followed. When evaluating multiple baseline models the set of classes should be selected with careful consideration as the same set will be used for all models.

The next step will be to develop a baseline model and determine the values used to populate its histogram. This process will be repeated for all the available baseline models. The resulting histograms should all be plotted on the same graph. The results should be inspected to determine whether the results from the various models all fit into the selected classes. If the results do not fit, the process will have to be repeated using a different selection of classes. If the classes were selected correctly, the results should look similar to results presented in Figure 3-20.

Inspection of the example results shown in Figure 3-20 renders the following feedback. Model 1 has a spike in occurrence in the last class. This means that the majority of the baseline model's results were in excess of +4%. Model 2 has a narrow grouping of occurrence around the +2% class. The narrow range indicates high levels of accuracy while the group's centre at +2% indicates that the model is generally biased with +2%. Model 3's results are not as narrow as Models 2's, but the results are centred at 0%. This means that the model is less consistent than Model 2, but it is generally not biased to any side.

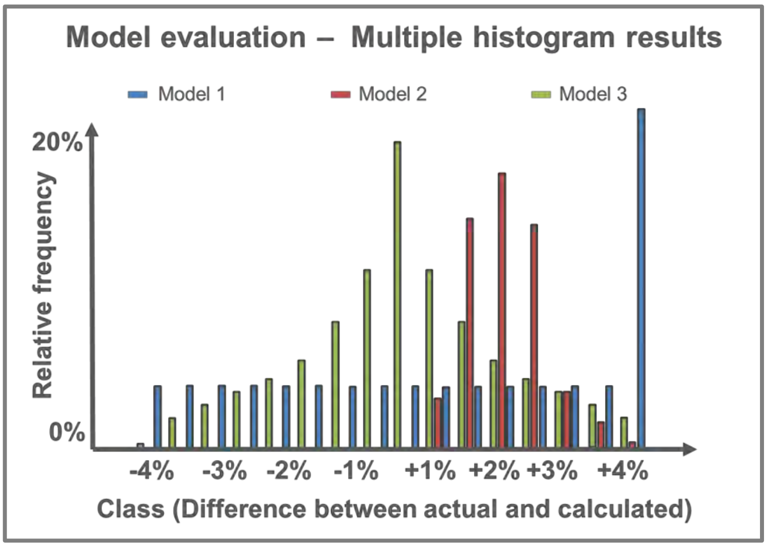

FIGURE 3-20: BASELINE MODEL EVALUATION – MULTIPLE HISTOGRAM RESULTS

The graphic representation of the different models' accuracy can now be presented to the relevant stakeholders. It is now up to the stakeholders to decide whether they prefer a model that is more accurate (Model 2) or less biased (Model 1).

This section discussed several basic statistical concepts and used it to develop a methodology for presenting baseline model accuracy. The result of this methodology is a graphical representation of each model's accuracy. The use of histograms also enables the comparison of various baseline models. This simplified representation can now be presented to all relevant stakeholders for evaluation. The relevance of the developed methodology will now be verified by implementing it on several industrial case studies.

3.4. VERIFICATION OF METHODOLOGY

3.4.1. CASE STUDY 16 – EVALUATING A CONSTANT BASELINE MODEL

In Case Study 16 the power consumption of two mining fridge plants were investigated. The first plant is situated on surface while the second plant is located underground. No system variables were available except for the power consumption of the plants.

A fixed baseline model was selected to present the operation of the underground plant. The profile was based on the average power consumption for January and February 2011. Figure 3-21 compares the average monthly power consumption of the underground plant to the baseline model average.

A long-term analysis of the surface plant's power consumption indicated a significant seasonal effect. Data from January and February 2011 was used to construct a baseline model. The baseline model was used to estimate the average consumption for every month. The results are displayed in Figure 3-22.

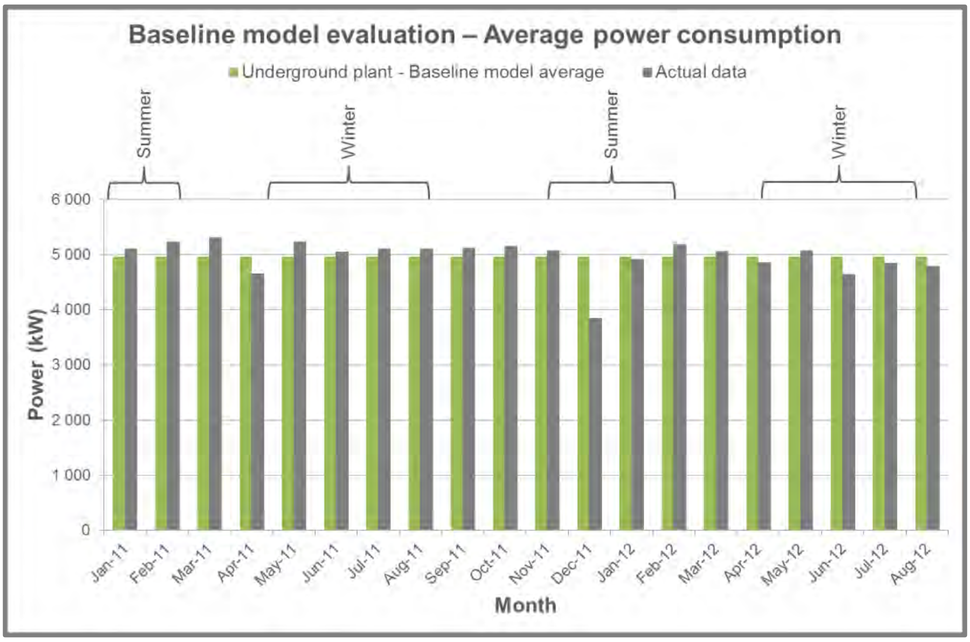

FIGURE 3-21: METHODOLOGY VERIFICATION – CONSTANT BASELINE MODEL (UNDERGROUND PLANT)

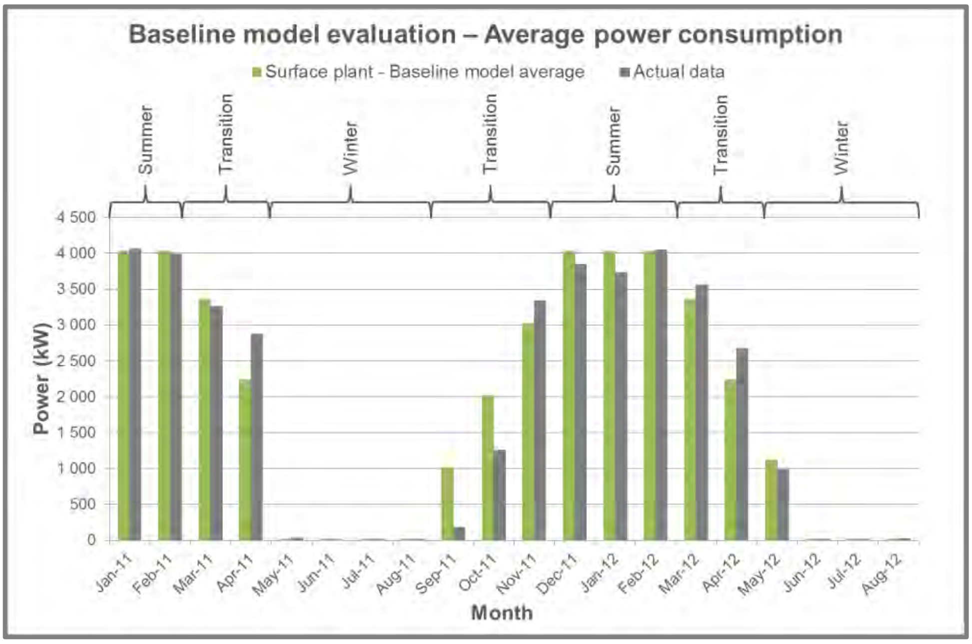

FIGURE 3-22: METHODOLOGY VERIFICATION – CONSTANT BASELINE MODEL (SURFACE PLANT)

Case Study 16 presents two fridge plants with very different power consumption patterns. The constant baseline model was used to predict the operation of both plants. The baseline model evaluation methodology was implemented to evaluate and compare the two different models. The results are shown in Figure 3-23.

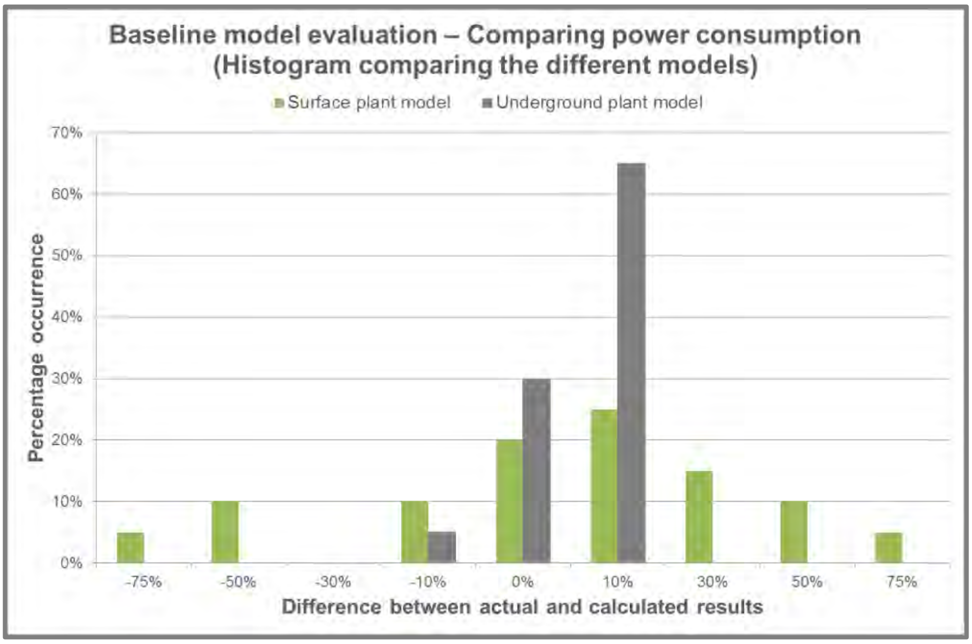

FIGURE 3-23: METHODOLOGY VERIFICATION – CONSTANT BASELINE MODEL (RESULTS)

Inspection of the results immediately identifies the “underground model” as the more accurate baseline model. The magnitude of difference between the actual and calculated results shows that the “surface plant model” has a level of accuracy that will probably not be acceptable to all stakeholders. A closer inspection of the results reveals that both models are biased towards the +10% range. This is probably due to the fact that two summer months were used as the baseline dataset.

3.4.2. CASE STUDY 17 – EVALUATING AN ENERGY-NEUTRAL BASELINE MODEL

Case Study 17 involves a large water-pumping scheme. An analysis of system operation indicated that the amplitude of the power consumption varied according to demand. Normalising the operational profiles, however, indicated that the system followed the same operational profile throughout the year. The energy-neutral baseline model was therefore selected to model the system operation.

The developed baseline model was scaled to be energy neutral with the average power consumption of every evaluated month. As a result the actual average power cannot be compared to the calculated average power (scaling will result in the answer always being zero). The measured and calculated results for the evening peak period (18:00–20:00) were therefore compared instead. Figure 3-24 illustrates the results.

The baseline model evaluation methodology was applied and the results are given in Figure 3-25. The evaluation results indicate that the model managed to calculate the results at an accuracy of at most ±4% with the average bias being closer to 0%.

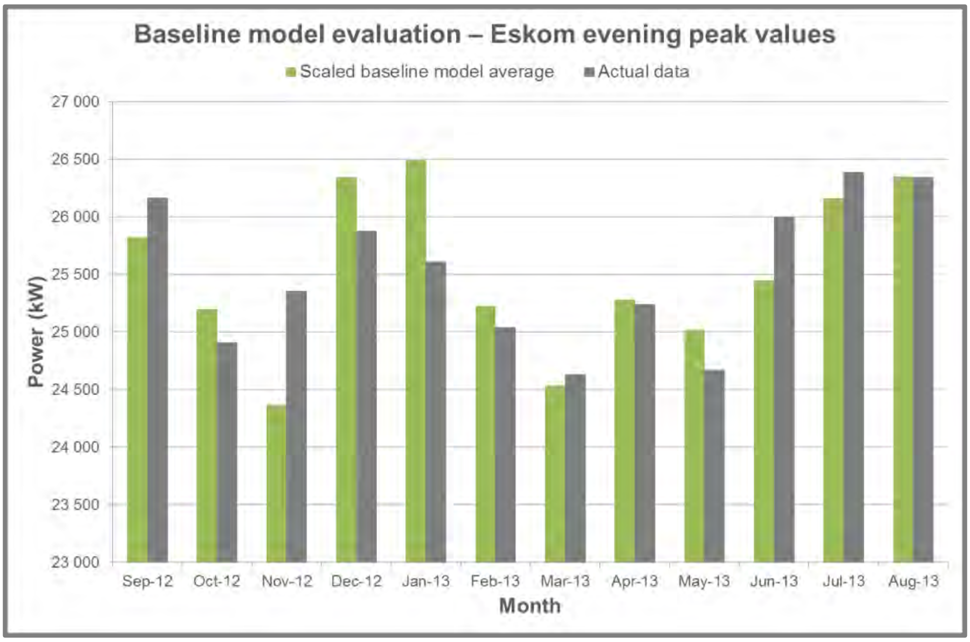

FIGURE 3-24: METHODOLOGY VERIFICATION – ENERGY-NEUTRAL BASELINE MODEL (EVENING PEAK)

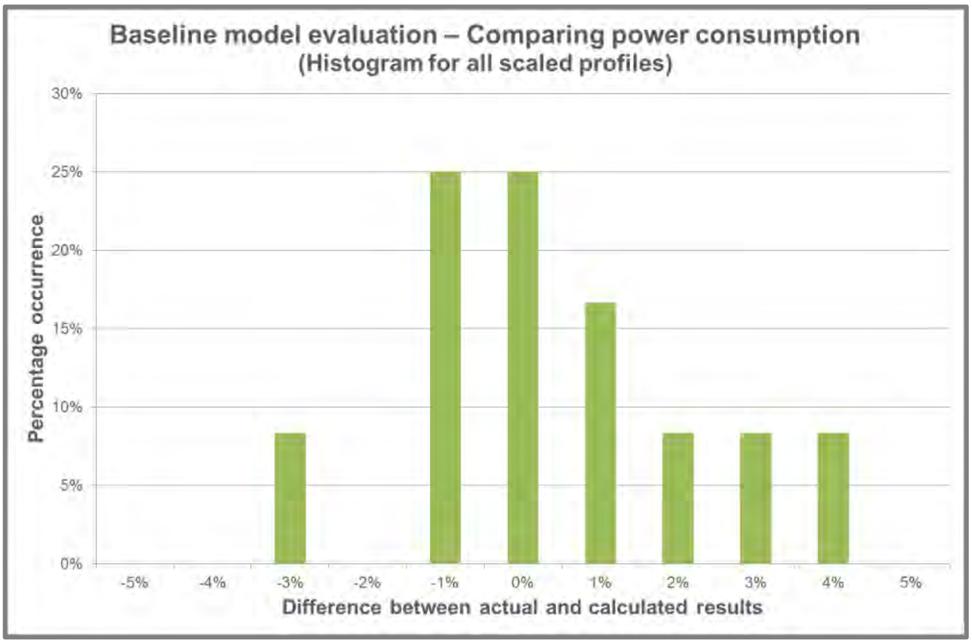

FIGURE 3-25: METHODOLOGY VERIFICATION – ENERGY-NEUTRAL BASELINE MODEL (RESULTS)

3.4.3. CASE STUDY 18 – EVALUATING A SINGLE VARIABLE REGRESSION MODEL

Case Study 18 entails the compressed air system of a large mining complex. A regression baseline model using production data as variable was selected to describe system operation. The mine operation was severely affected by a mass labour strike shortly after the completion of the baseline model. An evaluation of post-strike system operation indicated a significant change in operation – resulting in the redevelopment of the baseline model.

Two potential regression models were developed for each dataset. The first model used the highest resolution of available data (daily) and the second model used weekly averages as input. The various data points are plotted in Figure 3-26.

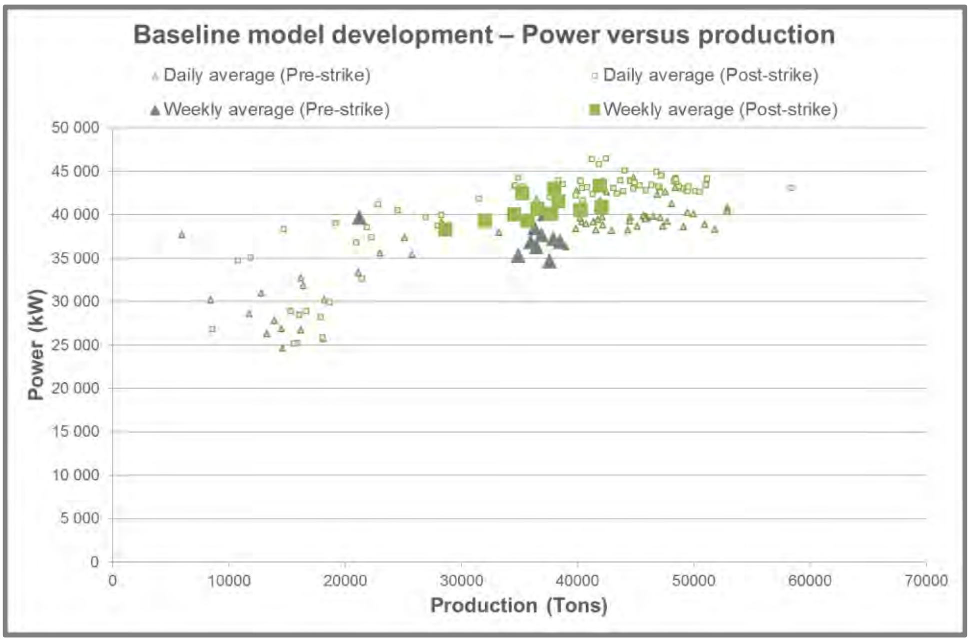

FIGURE 3-26: METHODOLOGY VERIFICATION – SINGLE VARIABLE REGRESSION MODEL (DATA POINTS)

The two different datasets together with the different data point periods resulted in four potential baseline models. The evaluation methodology was implemented to enable a comparison of the different models. Figure 3-27 illustrates the results of the pre-strike models. From the results it seems that the model based on weekly data points is slightly more accurate, although it is biased around +5%. Figure 3-28 illustrates the post-strike models' results. An evaluation of these results also identifies the model using weekly data points as being the more accurate model.

Inspection of Figure 3-27 and Figure 3-28 identifies the regression model using weekly data as more accurate. Figure 3-29 compares pre- and post-strike models (using weekly data). The comparison shows that the post-strike model is the more accurate. Both models are biased towards +5%.

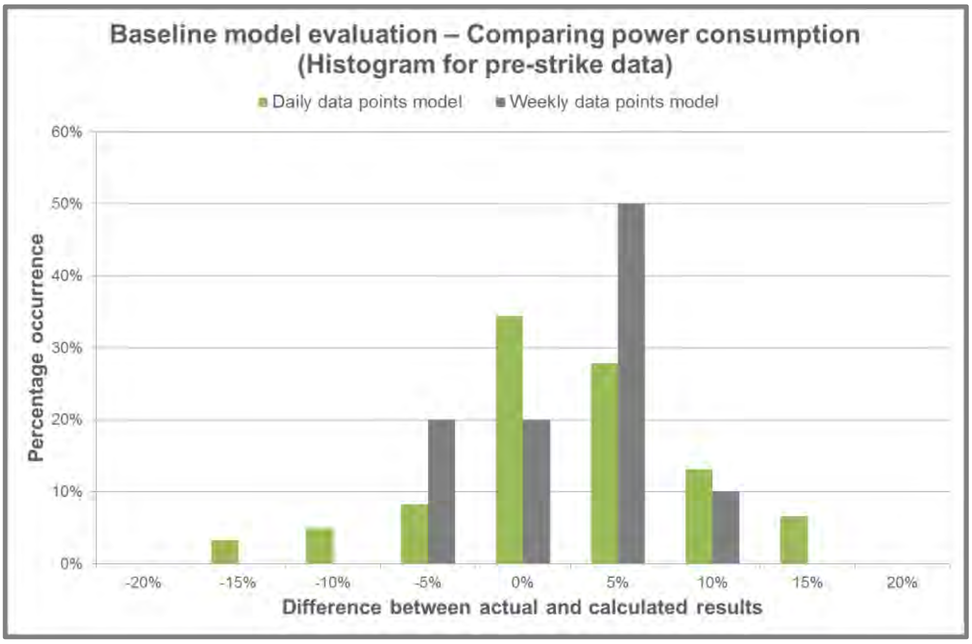

FIGURE 3-27: METHODOLOGY VERIFICATION – SINGLE VARIABLE REGRESSION MODEL (PRE-STRIKE)

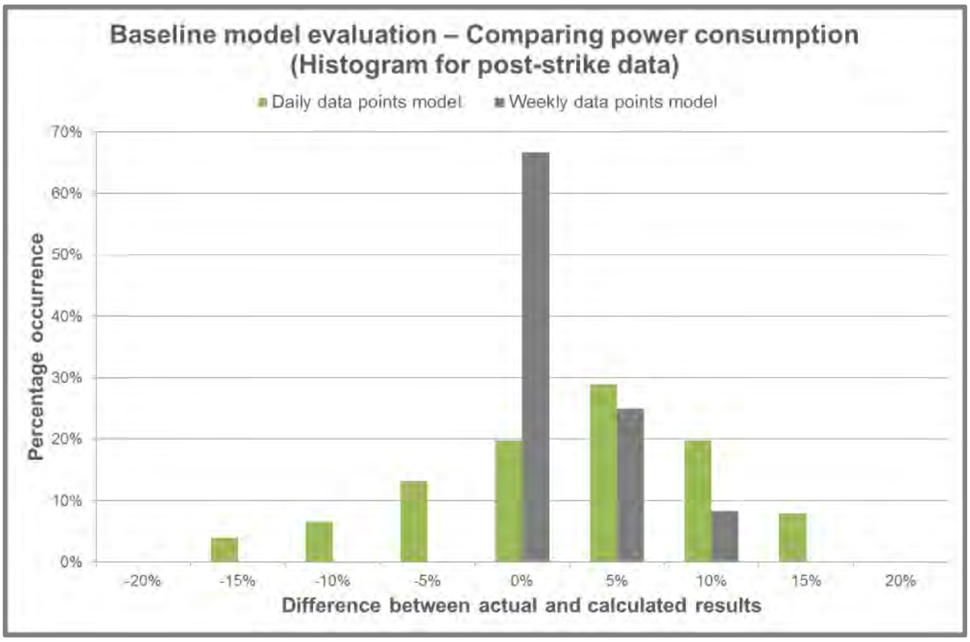

FIGURE 3-28: METHODOLOGY VERIFICATION – SINGLE VARIABLE REGRESSION MODEL (POST-STRIKE)

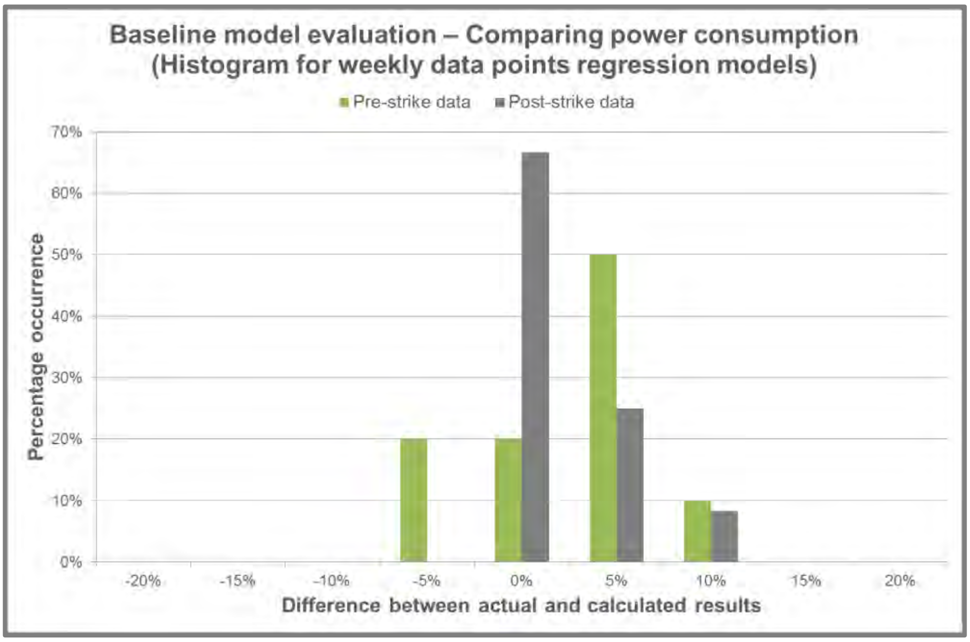

FIGURE 3-29: METHODOLOGY VERIFICATION – SINGLE VARIABLE REGRESSION MODEL (RESULTS)

3.4.4. CASE STUDY 19 – EVALUATING A MULTI-VARIABLE REGRESSION MODEL

Case Study 18 investigated the modelling of a compressed air system using system production as input to the regression model. Case Study 19 will also endeavour to model a compressed air system. This time two variables, namely flow and pressure, will be used to develop potential regression models.

The flow and pressure of the system will potentially be affected by the DSM project. Two different data periods will therefore be used to mitigate the risk. The first data period will include all available data points. The second data period will only use data points taken during the mine's drilling shift where the project impact is assured to be negligible.

Figure 3-30 illustrates the baseline model evaluation methodology results of three different baseline models, each based on a different variable input. An inspection of the results clearly identifies the pressure-based regression model as the least accurate. It is, however, not possible to easily distinguish between the accuracy of the other two models.

Figure 3-31 compares the results from models using the same parameters but different datasets. The results show that the models' accuracy results are very similar. The results from the case study can therefore conclude that there is a minimal difference between the results of a single variable model using flow and a multi-variable model using pressure and flow. It can also be concluded that using a dataset containing all the points or a dataset containing a select dataset will not significantly affect model accuracy.

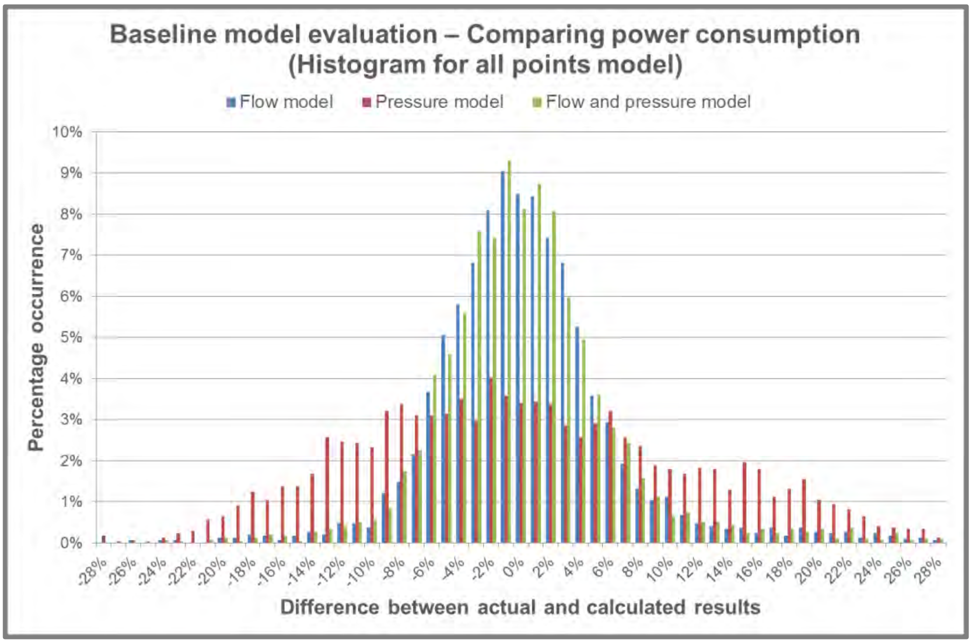

FIGURE 3-30: METHODOLOGY VERIFICATION – TWO VARIABLE REGRESSION MODEL (VARIABLES)

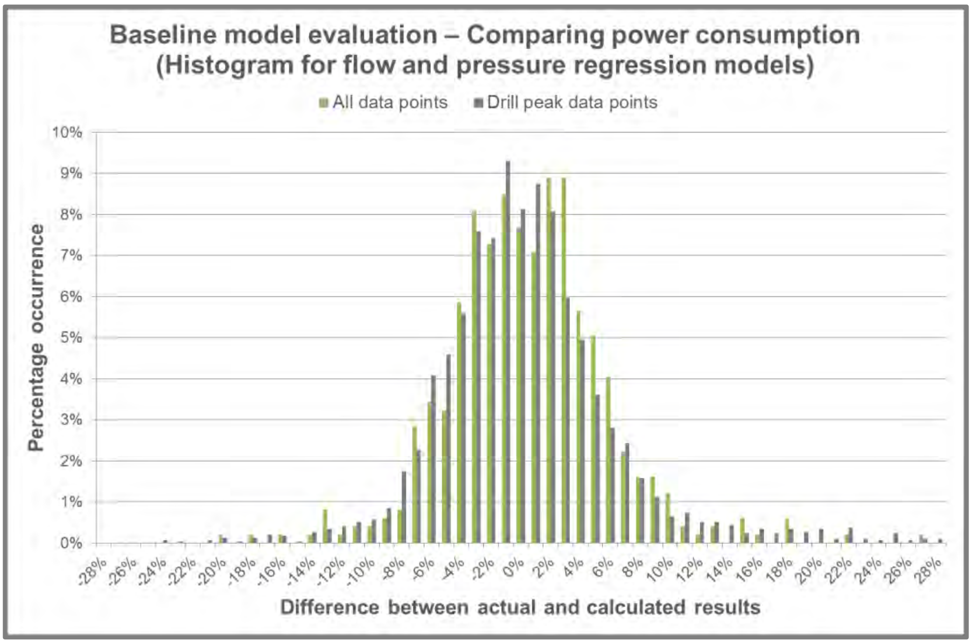

FIGURE 3-31: METHODOLOGY VERIFICATION – TWO VARIABLE REGRESSION MODEL (DATA PERIOD)

3.4.5. Case Study 20 – Evaluating a multi-variable, varied dataset regression model

Case Study 20 investigates the baseline evaluation of a refrigeration plant supplying chilled water to a mining shaft. Various system variables were available and could potentially be used in a baseline model. The measured variables were:

- Delta water temperature (difference between incoming and outgoing water temperature);
- Ambient temperature; and
- Water flow through the plant.

In addition to the different variables, the effect of variable changes had to be examined over different periods of time. The selected periods were:

- Hourly;
- Daily; and
- Weekly.

The various possible combinations of system variables together with the different periods resulted in eighteen different baseline models being developed. The baseline evaluation methodology was applied to all of the possible options and the results compared.

Figure 3-32 illustrates the methodology results for the different variable combinations developed using hourly data. Inspection of the results does not highlight any significant difference between the developed models. The same process was followed for daily and weekly datasets. The results are available in Appendix C.

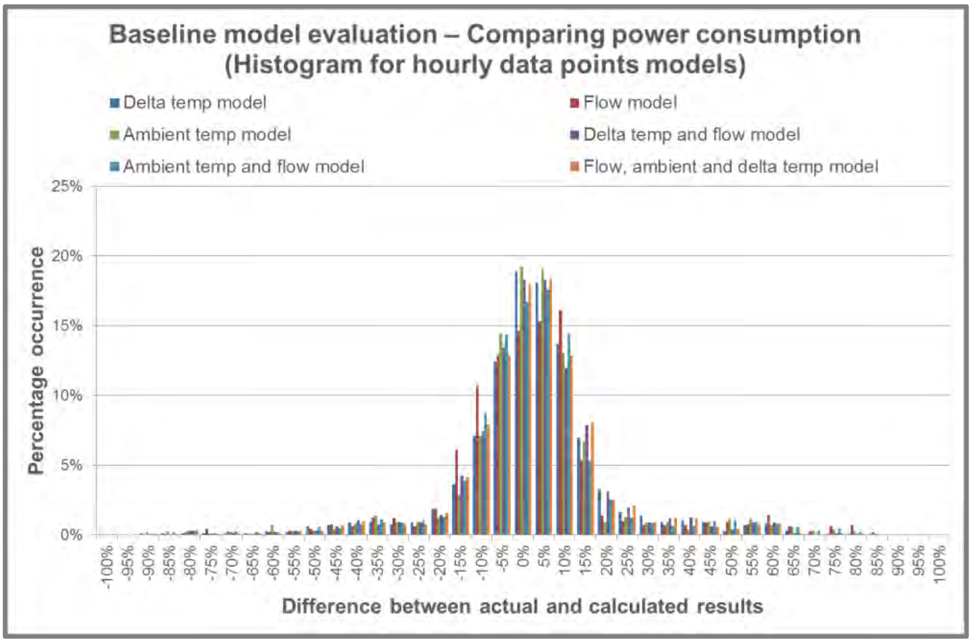

Figure 3-32: Methodology verification – Multi-variable regression model (hourly data)

Grouping all the results on one graph (as in Figure 3-32) renders an image which is too convoluted. The set should therefore be evaluated in smaller groups. Comparing the results of the different periods showed that the model using flow, ambient and delta temperature consistently performed well. Figure 3-33 illustrates the model results for the different periods.

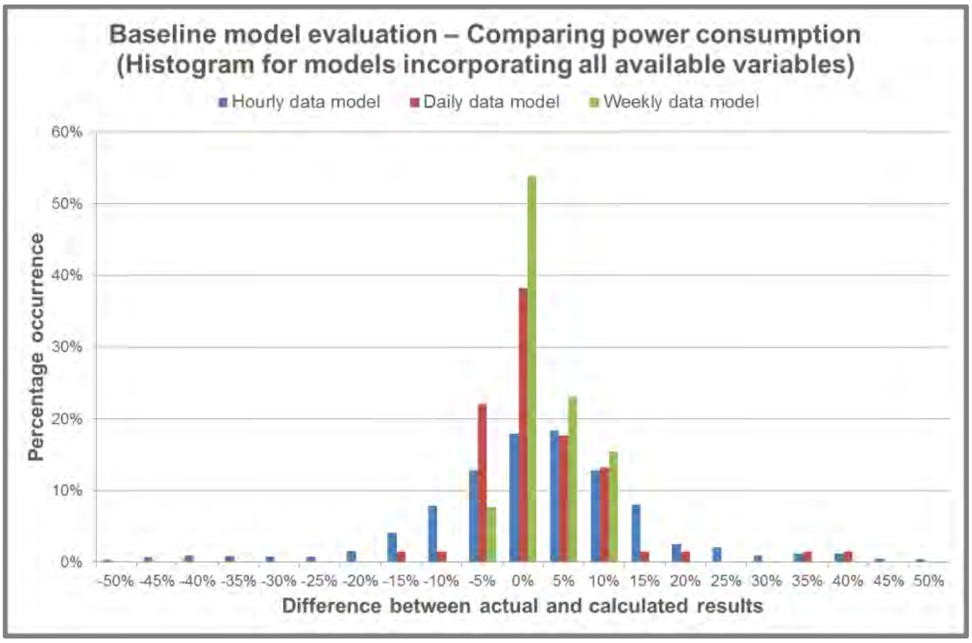

FIGURE 3-33: METHODOLOGY VERIFICATION – MULTI-VARIABLE REGRESSION MODEL (RESULTS)

The results in Figure 3-33 clearly show an increase in model accuracy when increasing the time period of data input. The increase in accuracy can be attributed to various forms of system capacity buffering the effects of changing conditions (ambient temperature and flow).

3.5. CONCLUSION

This chapter developed solutions to improve the baseline model development process. The chapter presented a new guideline to streamline the development of baseline models for industrial DSM projects. The guideline focused on identifying system characteristics and matching the characteristics with the appropriate model. This approach utilised proven models thereby reducing development costs without affecting confidence in the results.

The guideline showed that systems with fixed operational characteristics can be represented by a simple constant baseline model. Systems with a consistent operational profile, but varied power consumption, are best modelled using an energy-neutral baseline model. Regression models are suggested for systems with varied operational profiles and power consumption.

The review in Chapter 1 identified several statistical methods used to evaluate baseline models. The critical literature analysis noted that the evaluation processes were not well documented or explained. An investigation of Anscombe's quartet further highlighted the potential risk of using statistical test results without fully understanding the context. The graphical presentation of the quartet presented an elegant approach to simplify the process of objectively conveying results without resulting in any information loss. This concept formed an integral part of all subsequent methodologies.

The new baseline model evaluation methodology uses a histogram to graphically present results. This enables a comparison of different baseline models by using a common set of histogram classes. The cyclic process of the methodology refines the results before presenting the findings. The simplified presentation of results facilitates the intuitive inspection and selection of a suitable baseline model.

Five industrial DSM projects were selected as practical case studies. A total of 31 different baseline models were developed based on the chapter's guideline. These models were evaluated using the new methodology. The results of each case study were presented for inspection. The case studies clearly verified the ability of the methodology to simplify the baseline model evaluation process. Chapter 4 will now focus on evaluating project performance.

Chapter 4

MEASUREMENT AND VERIFICATION OF INDUSTRIAL DSM PROJECTS

CHAPTER 4

INDUSTRIAL DSM PROJECT PERFORMANCE

4. INDUSTRIAL DSM PROJECT PERFORMANCE

4.1. INTRODUCTION

The literature analysis in Chapter 1 highlighted a strong tendency towards presenting project impact at a high level of accuracy. However, presenting highly accurate results without interpretation cannot objectively convey the true nature of system performance. This identified the need for new methodologies to present project performance.

The application of the methodologies developed in Chapter 2 and Chapter 3 revealed an inherent variance in dataset quality and baseline model accuracy. Project results should therefore be displayed in a manner that clearly describes the characteristics of the project. This chapter employs existing concepts to graphically present results so the project impact becomes clear.

The changing nature of industrial systems will eventually require a review of the baseline model and project performance. Unfortunately, the literature analysis in Chapter 1 found no documented methods to indicate when this review should occur. This creates a scenario where stakeholders prompt a review based on their subjective perception of project performance.

This chapter will use an existing concept to evaluate long-term project performance. The new methodology will track system performance by making use of a control chart. Significant changes in either system operation or project performance will result in a trend change, thereby prompting investigation.

Multiple DSM projects implemented on the same system complicate the process of allocating savings. The chapter will discuss a guideline addressing the issue by presenting a simplified, structured approach to allocating savings. Two scenarios, namely chronological and concurrent implementation of projects, are investigated. The chapter concludes with a set of case studies verifying the developed methodologies.

4.2. METHODOLOGY FOR GRAPHICALLY PRESENTING PROJECT PERFORMANCE

The generalised process of determining project performance entails calculating the difference between the scaled baseline and the actual system profile. This is similar to the process of calculating baseline model accuracy. Chapter 3 introduced the reader to the concept of presenting data in the form of a histogram. The baseline evaluation methodology proceeded to make use of histograms to compare the accuracy of various baselines. This section therefore includes the use of histograms in the methodology for presenting project performance.

The results presented by a histogram indicate the relative frequency of the various classes. The results can be generalised by using the shape of the histogram. The shape is determined by drawing a curve through the various points of the histogram [49]. Figure 4-1 shows an example of a bell curve that approximates the shape of the histogram.

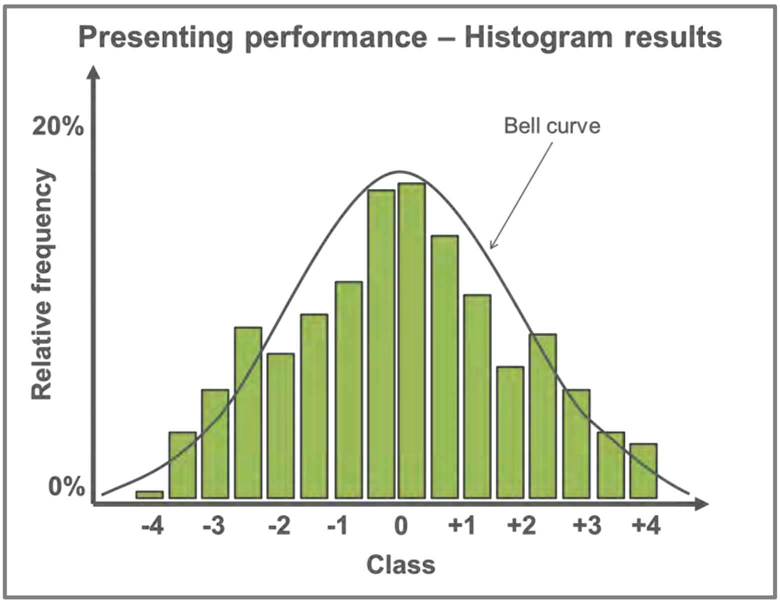

FIGURE 4-1: PRESENTING PERFORMANCE – HISTOGRAM RESULTS

A quick overview of the general shapes illustrated by the case studies in Chapter 3 reveals several histogram shapes. These shapes are dependent on the system characteristics, but can also be influenced by the selection of different classes. Figure 4-2 illustrates some common histogram shapes [49].

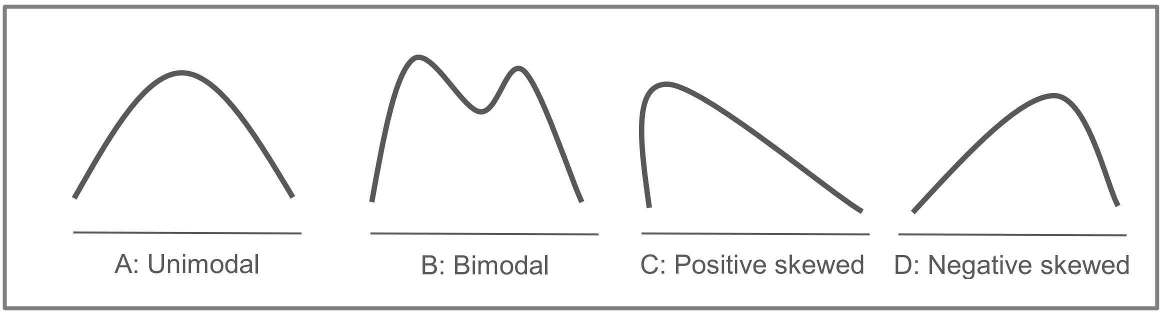

FIGURE 4-2: HISTOGRAM SHAPES

The use of data processing software (such as Microsoft® Excel) enables the user to develop a curve quickly that approximates the histogram shape. The software can also be used to produce a mathematical function (for example *y(x)*) describing the curve. This mathematical function can now be used to estimate the relative frequency of any point in the curve. This function is referred to as the "density function" and must satisfy the following criteria [49]:

$$y(x) \geq 0 \tag{14}$$

$$\int_{-\infty}^{\infty} y(x)dx = 1$$

(15)

The density function can also be used to calculate the density of a selected proportion of the data by using the equation [49]:

$$Density = \int_{a}^{b} y(x)dx$$

(16)

Where *a* denotes the starting point and *b* the end point of the curve presented by the function *y(x)*.

Take the shape in Figure 4-1 as example. Visual inspection of the figure shows that 100% of the results occur between -4 (point *a*) and +4 (point *b*). An estimated 40% of the results occur between -1 and +1. The density function will enable the user to determine the percentage occurrence of any proportion of results without the need for visual inspection. If the histogram shape represents a normal distribution, the calculated results will always follow the same pattern. Figure 4-3 illustrates a normal distribution indicating the mean (μ) and standard deviations (σ) of the distribution [49].

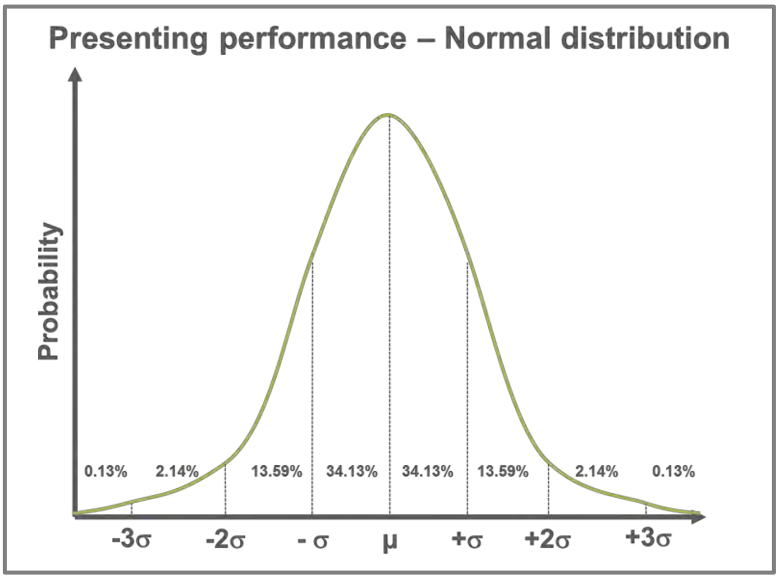

FIGURE 4-3: PRESENTING PERFORMANCE – NORMAL DISTRIBUTION

The mean (μ) can be determined using the following formula:

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n}$$

(17)

Where *n* indicates the number of samples and x_i the specific value of the sample.

The standard deviation (σ) can then be calculated as:

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{n-1}} \tag{18}$$

A normal distribution will always have the same distribution of results [49]. The percentage distribution of the results is indicated in Figure 4-3. This approach enables results to be presented in terms of density. For example, 68% of results occur between $-\sigma$ and $+\sigma$. These basic concepts can now be incorporated into a methodology for presenting project performance. Figure 4-4 illustrates the new methodology.

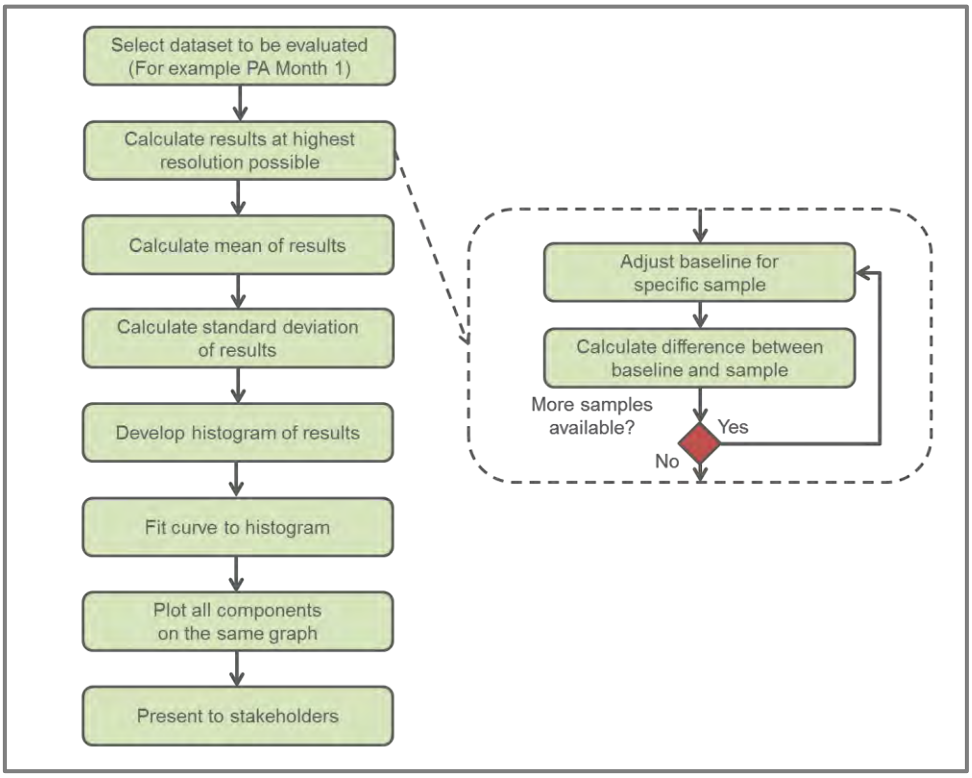

FIGURE 4-4: METHODOLOGY FOR PRESENTING PROJECT PERFORMANCE

The literature and case studies reviewed in Chapter 1 presented project performance only in terms of the mean value. The methodology in Figure 4-4 develops the results further presenting project performance in terms of mean value, standard deviation and histogram shape. Figure 4-5 illustrates an example of the expected result.

Presenting a project's results to the stakeholders in this format will give a detailed graphical illustration of the performance characteristics. The mean value will indicate the average of the results and can be compared with the single value generally used to convey project performance. The profile shape will indicate whether the results follow a normal, skewed, single- or multi-modal distribution. The profile can also be used to determine the density of a selected range. The stakeholders can now focus on selected characteristics to determine project success and remuneration.

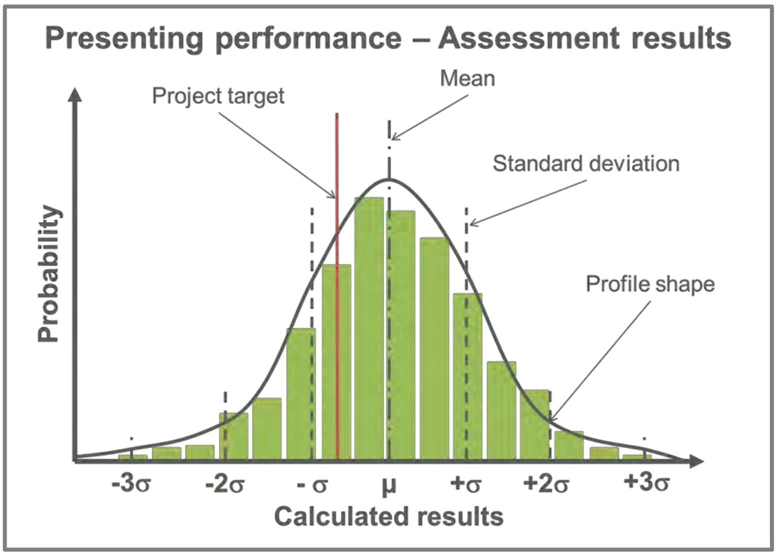

FIGURE 4-5: PRESENTING PERFORMANCE – ASSESSMENT RESULTS

4.3. LONG-TERM EVALUATION METHODOLOGY

The guidelines reviewed in Chapter 1 noted a generalised approach to non-routine baseline adjustment. The literature survey and case studies gave no practical strategies on how to determine when a new model is required. It is the author's experience that baseline models are generally only changed when a stakeholder objects to the reported savings. This approach results in a subjective evaluation based on the stakeholder's expectations of savings.

This section develops an evaluation methodology based on a technique called "sequential analysis". The technique makes use of a control chart to analyse project performance trends graphically. The selected technique is based on the cumulative sum control chart (CUSUM) first developed by E. S. Page and published in 1954 [51].

The CUSUM control chart was developed to monitor the change in output quality of industrial processes. The quality variable θ is plotted on a chart and any significant changes in the direction of the plotted progress are used to indicate changes in output quality [52]. The quality variable is calculated using the following formula:

$$\theta_i = \sum_{j=1}^{i} (x_j - T) \tag{19}$$

Where θ_i is i^{th} the plotted value, x_j the calculated difference for the j^{th} value and T the target value. The calculated value of θ_i is plotted on the control chart for samples 1 to N (where N is the last available sample). Figure 4-6 illustrates an example of the result.

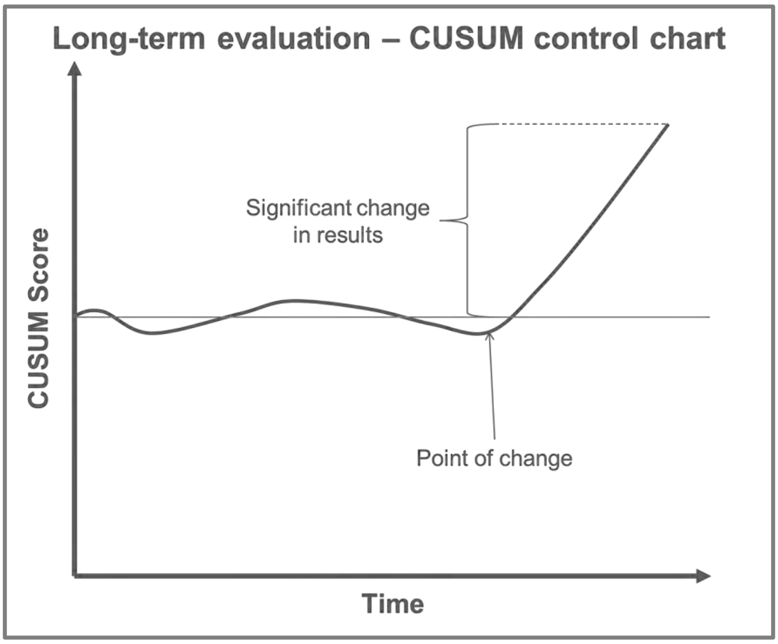

FIGURE 4-6: LONG-TERM EVALUATION – CUSUM CONTROL CHART

The CUSUM control chart will follow the same trend as long as the quality variable fluctuates closely around the target value. A significant or continued change in the quality variable will induce a noticeable change in the control chart trend. The control chart can then be used to estimate the point where the change occurred.

The basic CUSUM control chart can be adapted to evaluate industrial DSM project performance. Figure 4-7 presents the long-term evaluation methodology. The methodology uses the average performance assessment performance as the target value (*T*). The control chart is updated and reviewed on a fixed interval. A significant shift in the trend prompts a detailed investigation into the cause.

The methodology distinguishes between system and project changes. Changes to system operation require a new baseline model to be developed. A decrease in project performance warrants corrective action while overperformance requires the target value (*T*) to be updated. The control chart is reset before the evaluation process resumes.

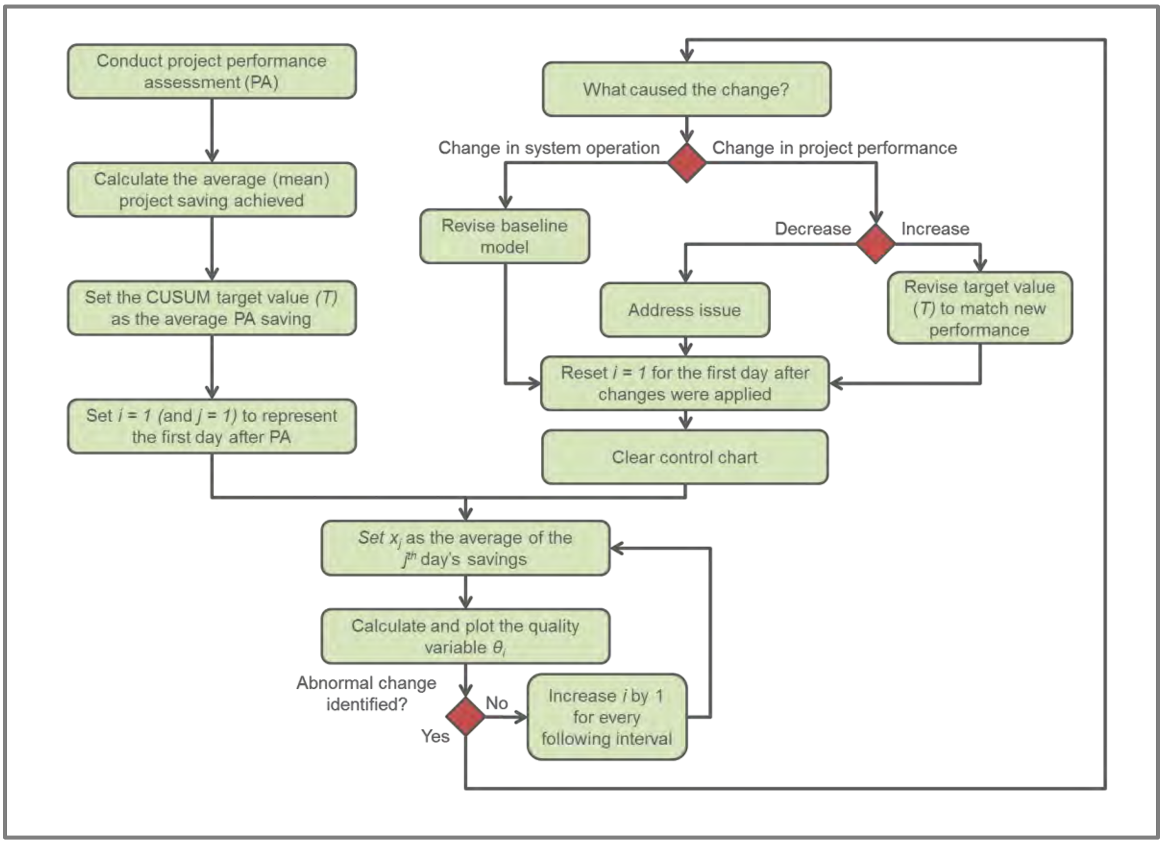

FIGURE 4-7: LONG-TERM EVALUATION METHODOLOGY

4.4. GUIDELINE FOR EVALUATING INTERACTIVE PROJECTS

The process of evaluating multiple projects implemented on the same system can be challenging. The evaluation is further complicated when the projects are implemented by different stakeholders. The evaluation and allocation of savings therefore has to be done in a clear, concise and transparent manner. The evaluation timeline of multiple projects can be split into two scenarios. The first scenario is projects evaluated in a chronological order; the second scenario is projects evaluated at the same time (concurrent).

Figure 4-8 illustrates the impact of two projects implemented in chronological order. The allocation of savings in this scenario is simple. The second project will be evaluated using the assessment period of the first project as the baseline period. The first project will now use the adjusted baseline of the second project (instead of the actual profile) to calculate the impact of the first project. The process can be repeated for any number of projects (*N*) as long as the baseline models remain relevant.

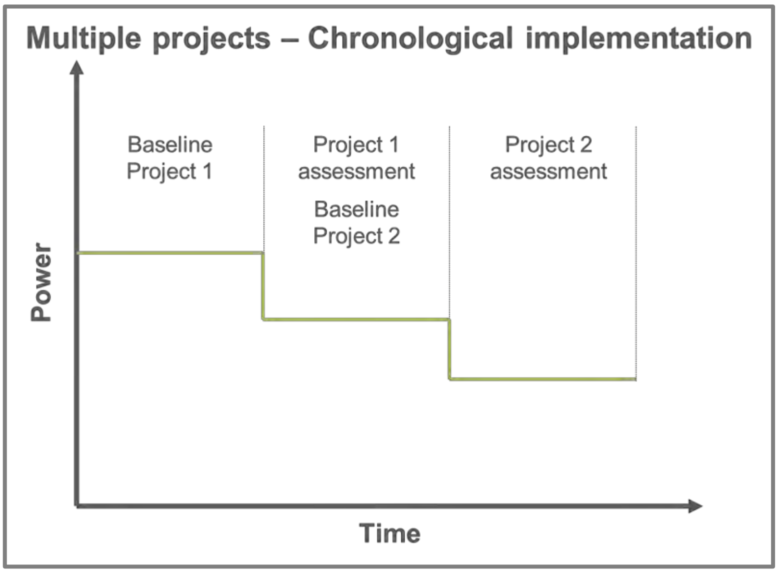

FIGURE 4-8: MULTIPLE PROJECTS – CHRONOLOGICAL IMPLEMENTATION

The process of allocating savings to multiple chronologically implemented projects is illustrated in Figure 4-9. The approach uses the adjusted baseline of the newer project as a reference to determine the impact of the older project. The total impact of the combined projects can be determined by comparing the first baseline (adjusted) to the average of the system profile (after the newest project). This approach will fairly allocate savings while preventing double-counting.

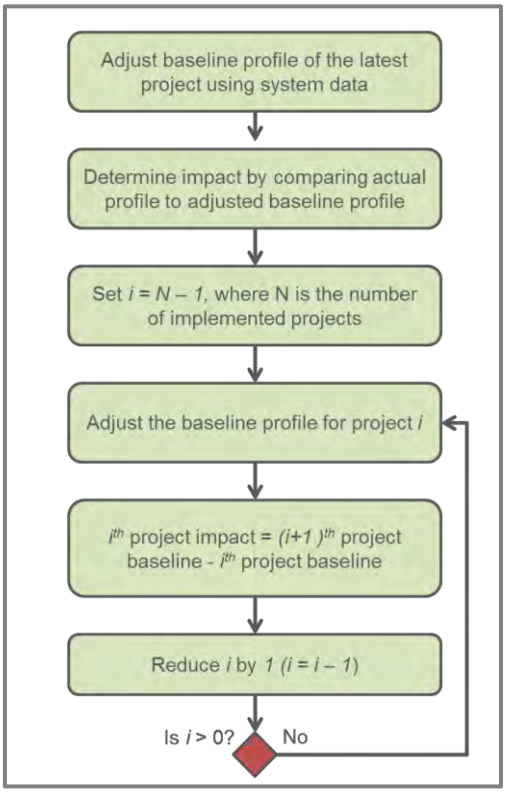

FIGURE 4-9: MULTIPLE PROJECTS – ALLOCATING SAVINGS TO MULTIPLE PROJECTS

Figure 4-10 illustrates the concurrent implementation of two projects. Determining the project-specific impact now becomes more difficult as there is no clear reference point separating project operation. Projects aiming to achieve the same type of impact (24-hour energy efficiency for example) will require the results to be determined experimentally. Projects pursuing different impacts can be evaluated based on the period and nature of the specific project target.

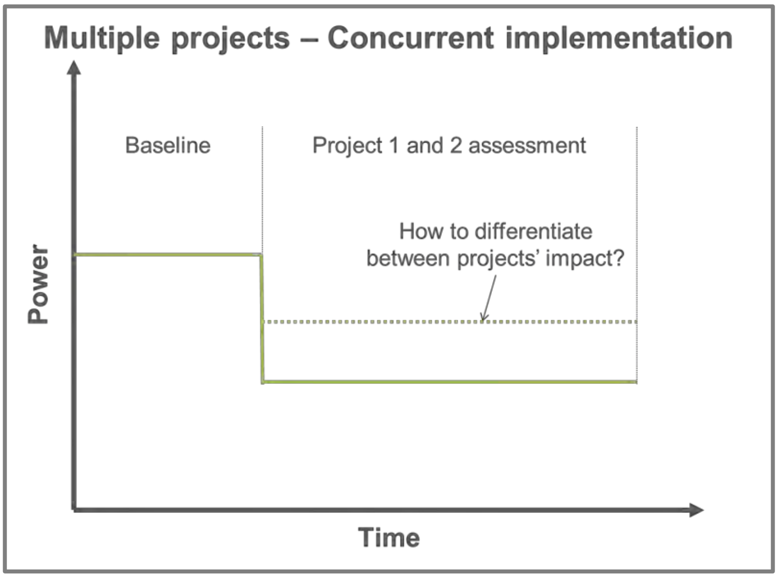

FIGURE 4-10: MULTIPLE PROJECTS – CONCURRENT IMPLEMENTATION

Figure 4-11 illustrates an example of two energy efficiency projects focused on achieving different impacts. Project B aims to achieve general energy efficiency (over 24 hours) while Project A only endeavours to reduce the Eskom evening peak consumption (peak clipping).

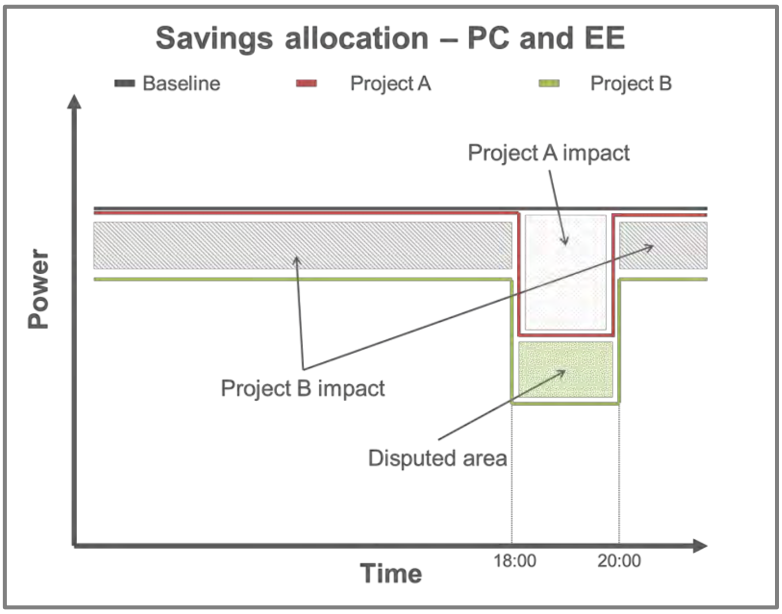

FIGURE 4-11: MULTIPLE PROJECTS – PEAK CLIPPING (PC) AND ENERGY EFFICIENCY (EE) PROJECTS

The savings generated by the projects can be split in two approaches. The first approach will be to allocate the total energy reduction between 18:00 and 20:00 to Project A and the rest to Project B. If Project B influences the evening peak a component of the savings should also be allocated to the project. This amount is illustrated in Figure 4-11 as the disputed area.

The second approach is to estimate the evening peak impact of Project B. This is achieved by calculating the average impact of the day, excluding the peak clip. The result is then extrapolated to estimate project impact during the evening peak. Project A is then allocated all the remaining energy efficiency.

Figure 4-12 illustrates the simultaneous implementation of a load shifting and an energy efficiency project. In this scenario, the difference between the baseline and the actual profile will indicate the energy efficiency. The baseline can then be scaled to be energy neutral with the actual profile to determine the load shift impact.

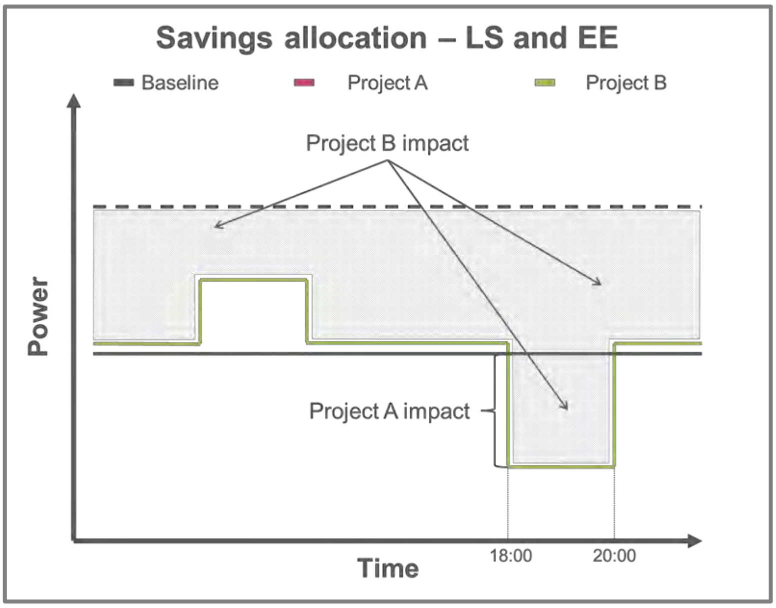

FIGURE 4-12: MULTIPLE PROJECTS – LOAD SHIFTING (LS) AND ENERGY EFFICIENCY (EE) PROJECTS

The methodologies developed in this chapter will be verified by implementing them on industrial DSM projects. Only the relevant results will be given in the next section. The full results of the case studies are available in Appendix D.

4.5. Verification of methodologies

4.5.1. Case Study 21 – Load shifting on a cement plant

The first case study of this chapter is a load shifting project implemented on a cement plant. An energy-neutral baseline model was selected to present the system operation. The project scope entailed a manual intervention where mill operators were given a schedule to adhere to. The project performance was tracked over the course of a year. The methodology for presenting project performance was implemented on the dataset. The results are shown in Figure 4-13.

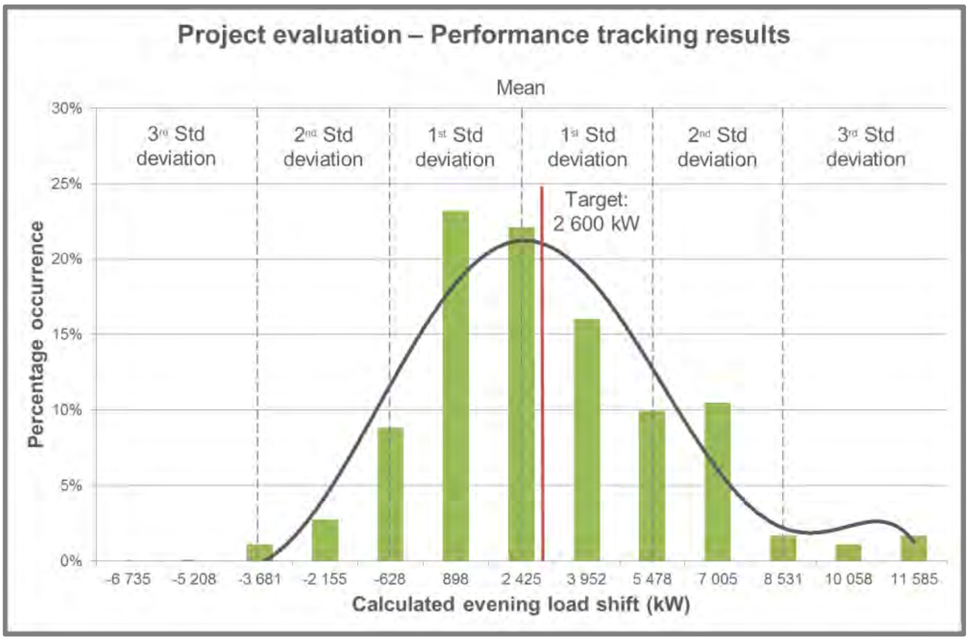

Figure 4-13: Methodology verification – Performance tracking results

An investigation of the results indicates that the project will underperform if evaluated based on the mean of the results. The class with the highest occurrence is 898 kW, shortly followed by 2 425 kW. The unimodal histogram shape is centred on the mean and approaches a normal distribution.

Two interesting results are noted. The first is the size of the standard deviation. For a moment assume that the histogram shape has a normal distribution. The shape will therefore include 95% of the results between the second deviation points (up and down from the mean). It is therefore highly probable that the project performance lies between -3 981kW and 8 531kW. If the project was evaluated based on the conservative approach noted in literature the achieved load shift would have been -3 681 kW. This would clearly misrepresent the project performance.

The second interesting result is the highest achieved load shift values that exceed 8 500 kW. These events do not occur regularly, but their magnitude will affect the mean value. If these results were to be excluded the mean would shift towards the range of 898 kW. Many other observations can be made. It is however clear that presenting the results as directed by the methodology reveals many characteristics of the system performance.

The same dataset was evaluated using the long-term evaluation methodology. The results illustrated in Figure 4-14 show that the project performed well during the first months after implementation. The performance gradually decreased until May 2013 when the project started underperforming. The rest of the chart shows that the project generally continued to underperform for the duration of the performance tracking period.

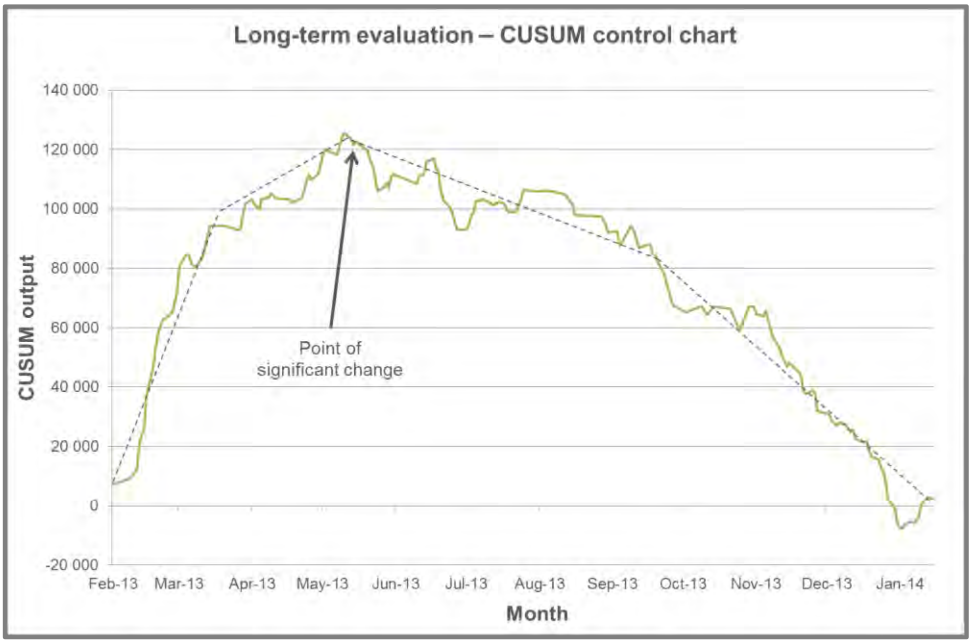

FIGURE 4-14: METHODOLOGY VERIFICATION – LONG-TERM EVALUATION

4.5.2. CASE STUDY 22 – LOAD SHIFTING ON A DEWATERING SYSTEM

Case Study 22 investigates a load shifting project implemented on the dewatering system of a gold mine. The load shift is achieved by an automated control system. An additional agreement is in place where the control system is upgraded and reconfigured as needed. An energy-neutral baseline model is selected to present the pre-implementation system. The project was evaluated over a period of two years and performance results processed using the methodology for presenting project performance.

Figure 4-15 represents the results. The first impression when inspecting the results is that the project is obviously performing well. The mean of the results is 4 061 kW, which is roughly 35% higher than the project target of 3 000 kW. The general shape of the histogram is unimodal, but the histogram shape is definitely positively skewed. The highest occurring results lie in the 4 818 kW class, shortly followed by the 5 575 kW class, which is also one standard deviation from the mean.

Comparing the mean and the target confirms that the project is performing well. The graphical presentation of results suggests that it may be generally performing even better than indicated by the mean.

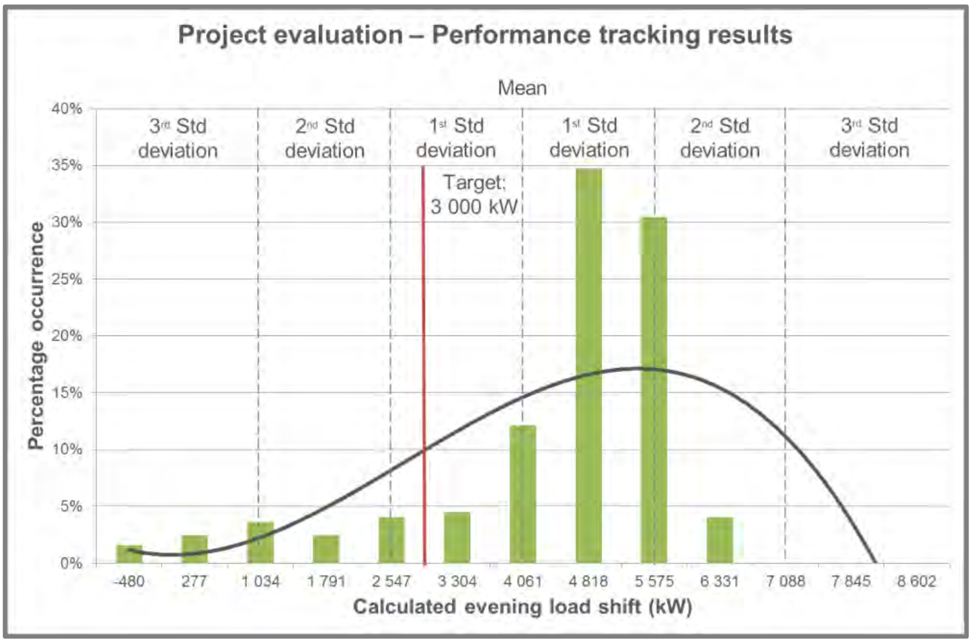

FIGURE 4-15: METHODOLOGY VERIFICATION – PERFORMANCE TRACKING RESULTS

The dataset is evaluated using the long-term evaluation methodology; the results are indicated in Figure 4-16. Inspection of the control chart indicates a significant series of significant events starting in September 2012 and ending in January 2013. It is most likely that the project underperformance illustrated in the histogram occurred during this period. A more detailed analysis of the system and project performance is however required to determine the cause of the events.

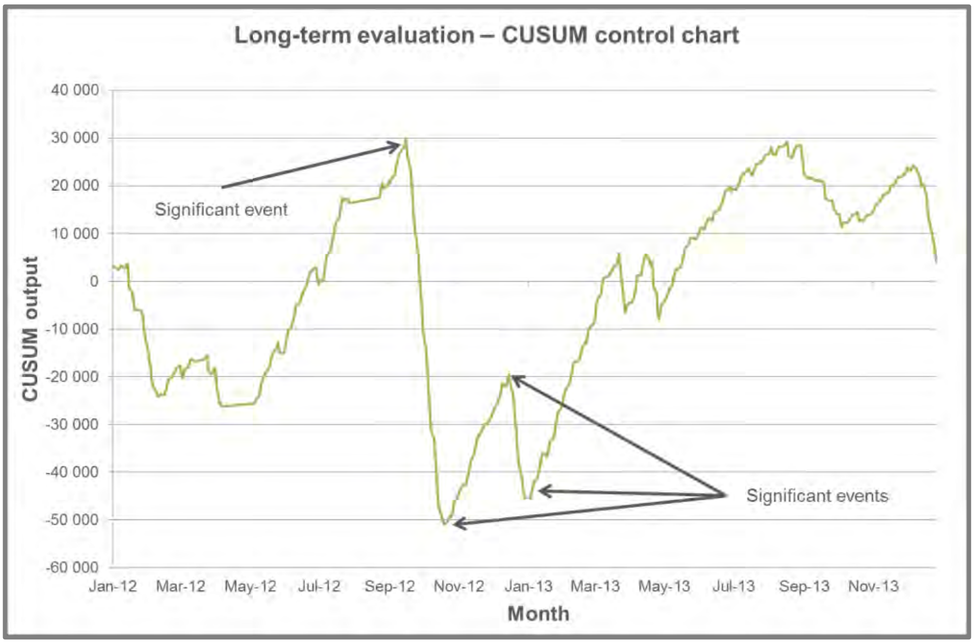

FIGURE 4-16: METHODOLOGY VERIFICATION – LONG-TERM EVALUATION

4.5.3. Case Study 23 – Peak clipping on a compressed air system

Case Study 23 evaluates the performance of an evening peak-clipping project implemented on the compressed air system of a platinum mine. The methodology for presenting project performance was implemented on three months of performance assessment data. The result is illustrated in Figure 4-17.

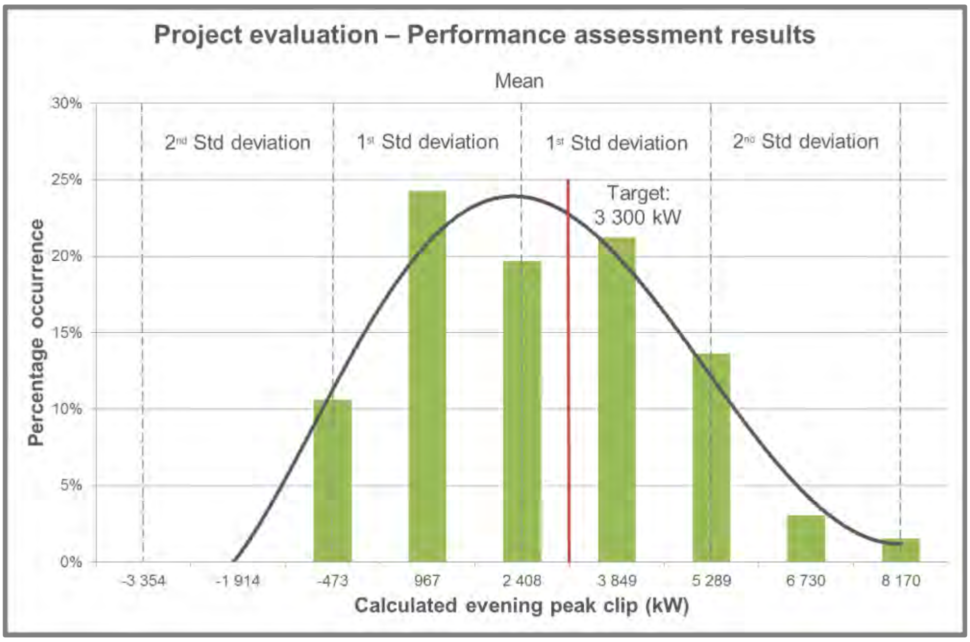

Figure 4-17: Methodology verification – Performance assessment results

The mean of the results falls below the project target of 3 300 kW. The distribution of the results shows a tendency (similar to the results of Case Study 21) for the mean to be positively biased by the occurrence of a few abnormally high results. The long-term performance of the project was evaluated using the developed methodology; Figure 4-18 illustrates the results.

The control chart indicates a decrease shortly after completing performance assessment. The control chart output continues to fluctuate until June 2013 where it again starts degrading until June 2013. A significant event during June 2013 resulted in an increase that is sustained for the remainder of the evaluation period.

An investigation into the cause of the significant change in system operation identified the implementation of another project. The new project utilised the hardware installed as part of the first project to reduce system energy consumption throughout the rest of the day. This realised additional energy savings, but also required the control of the first project to be recommissioned. The change in the control chart can therefore be attributed to the recommissioning and continued operation of the peak-clipping project control. The savings of the two chronologically implemented projects were split based on their period of operation; Figure 4-19 illustrates the results.

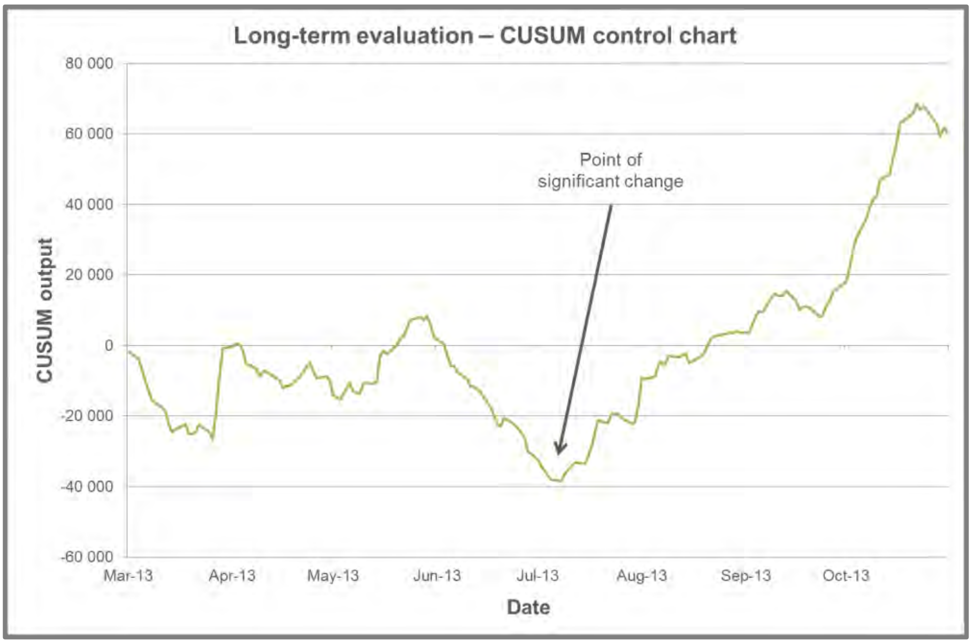

FIGURE 4-18: METHODOLOGY VERIFICATION – LONG-TERM EVALUATION

The original project aimed at clipping energy from the Eskom evening peak period. As a result, all savings achieved during this period are allocated to the first project. The second project made use of the existing hardware to expand the energy efficiency savings. The remainder of the savings is therefore allocated to the second project.

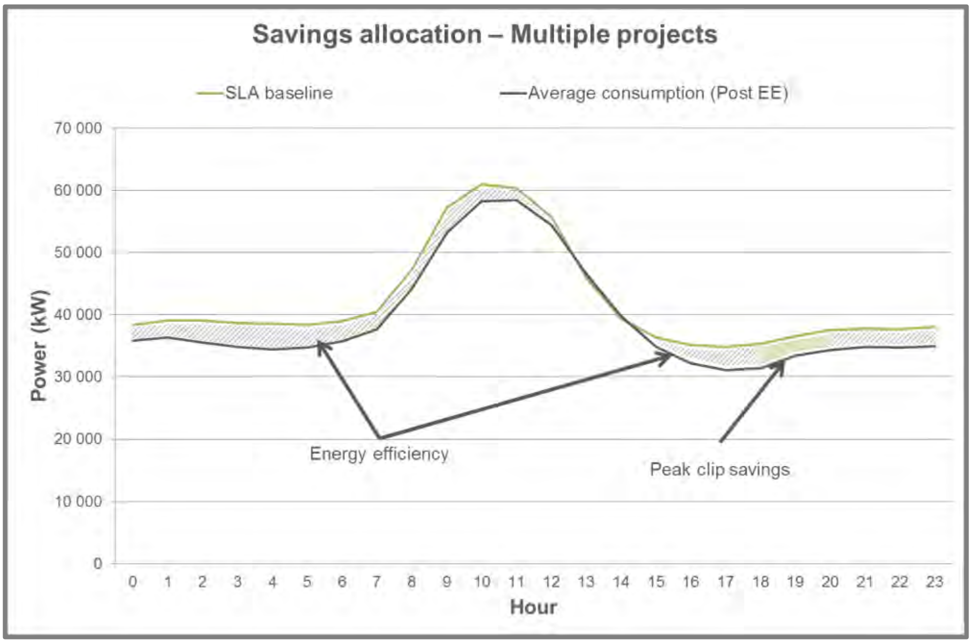

FIGURE 4-19: SAVINGS ALLOCATION – MULTIPLE PROJECTS

4.5.4. Case Study 24 – Energy efficiency on a compressed air system

Case Study 24 investigated the performance of another compressed air project. The project also delivered an evening peak clip. The results of the three-month performance assessment are shown in Figure 4-20. A quick overview of the results confirms that the project successfully achieved its target during the performance assessment phase. The project performance was evaluated over the following year using the long-term evaluation methodology. The results are shown in Figure 4-21.

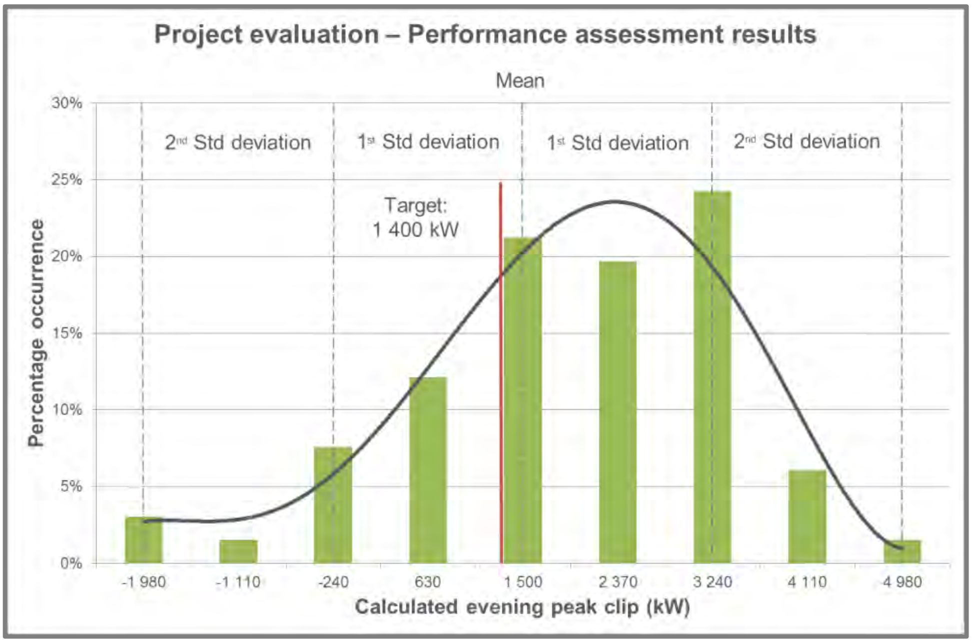

FIGURE 4-20: METHODOLOGY VERIFICATION – PERFORMANCE ASSESSMENT RESULTS

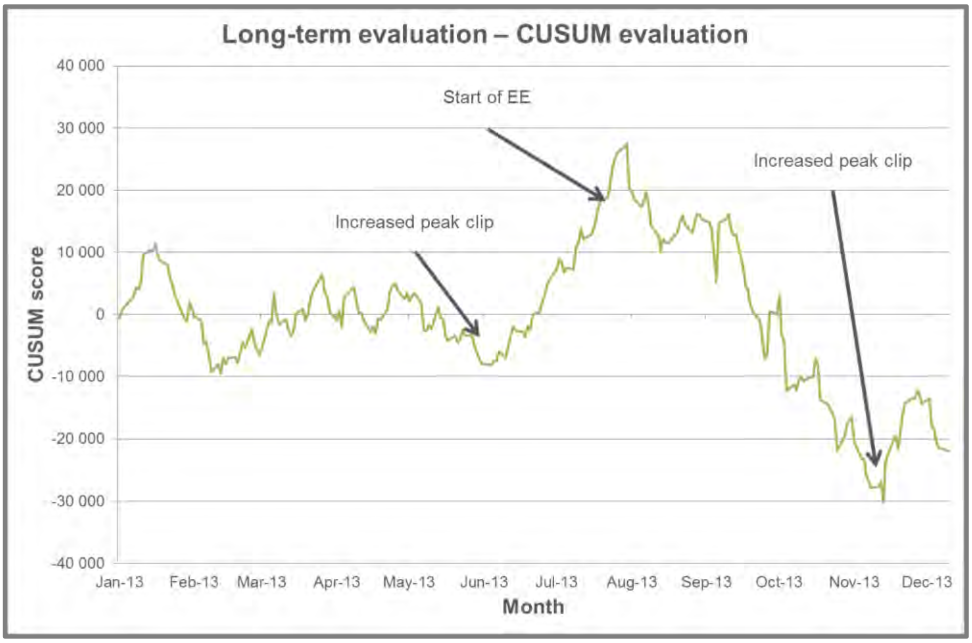

FIGURE 4-21: METHODOLOGY VERIFICATION – LONG-TERM EVALUATION

Figure 4-21 indicates two points of operational change. A more detailed investigation into project performance indicated that the peak clipping was increased during June 2013. The start of an additional project during August 2013 however resulted in a reduction in peak-clipping savings.

The operation of the two projects was evaluated in order to allocate a portion of the savings to each of the projects. System operation did not change so the original baseline model was used to determine the *SLA* baseline. The energy efficiency between the *SLA* baseline and the actual profile was calculated from 00:00 to 17:59, and from 20:00 to 23:59. The *SLA* baseline was then lowered with the calculated average. The saving allocated to the peak-clipping project was then evaluated. The results are shown in Figure 4-22.

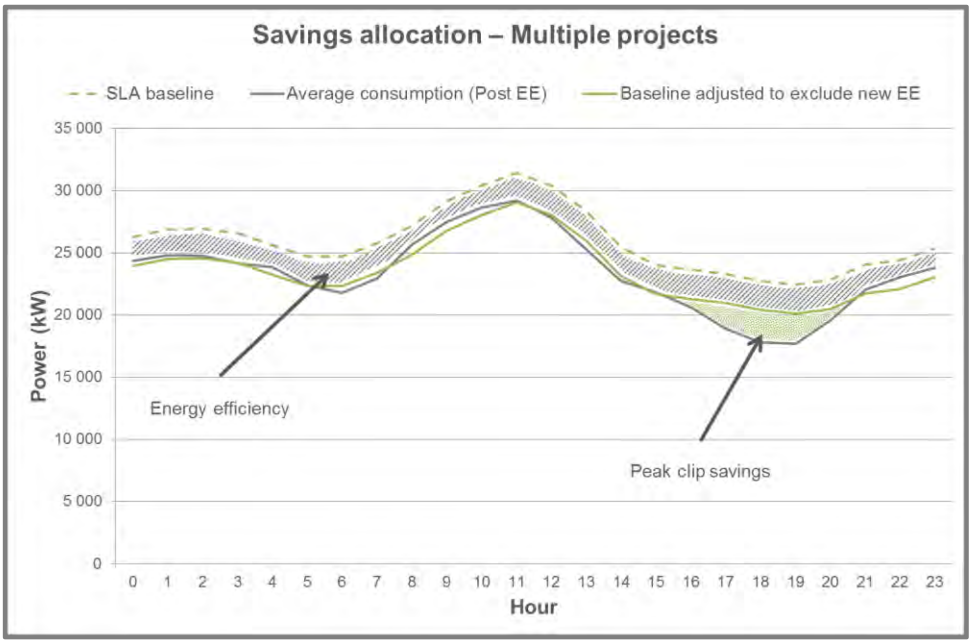

FIGURE 4-22: SAVINGS ALLOCATION – MULTIPLE PROJECTS

4.5.5. CASE STUDY 25 – ENERGY EFFICIENCY ON A REFRIGERATION SYSTEM

The last case study is unique in the sense that it made use of two baseline models to evaluate project performance. The first model was a constant baseline model and it was selected because no system variable data was available at the time of model development. The project performance assessment was subsequently performed using a year-on-year analysis. The required system variables were logged from the beginning of performance assessment and were used to develop a regression baseline model. The average monthly power is illustrated in Figure 4-23.

The new regression baseline model represents system operation during PA. Any change in project performance can be measured using the new *SLA* baseline. The calculated difference must be added to the average performance assessment value to represent system performance. The project performance results are shown in Figure 4-24.

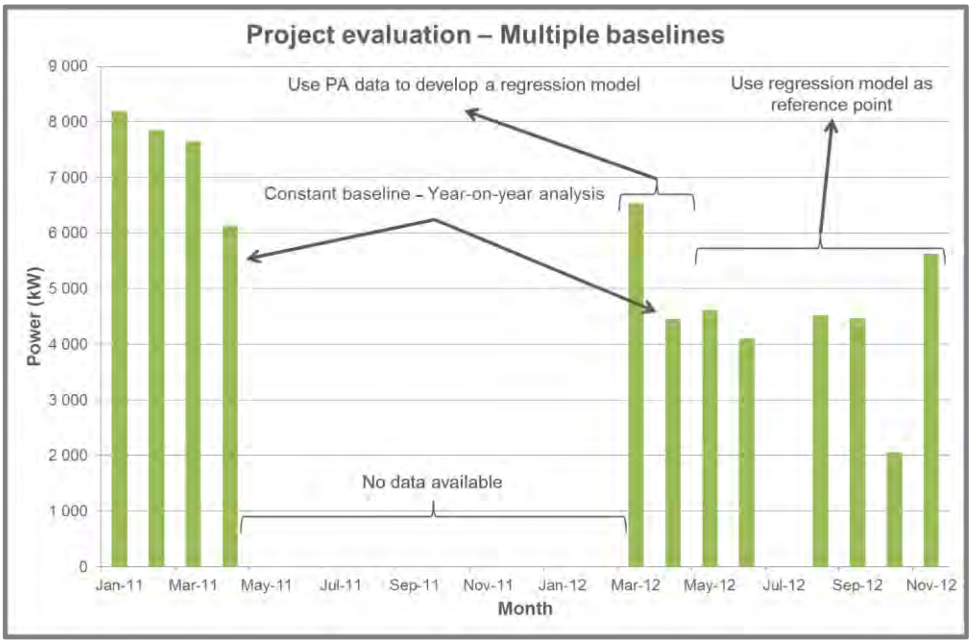

FIGURE 4-23: PROJECT EVALUATION – MULTIPLE BASELINES

The results in Figure 4-24 confirm that the project achieved its target. The histogram profile is centred on the mean. This indicates that the extreme results in the 4 317 kW class did not significantly affect the mean average.

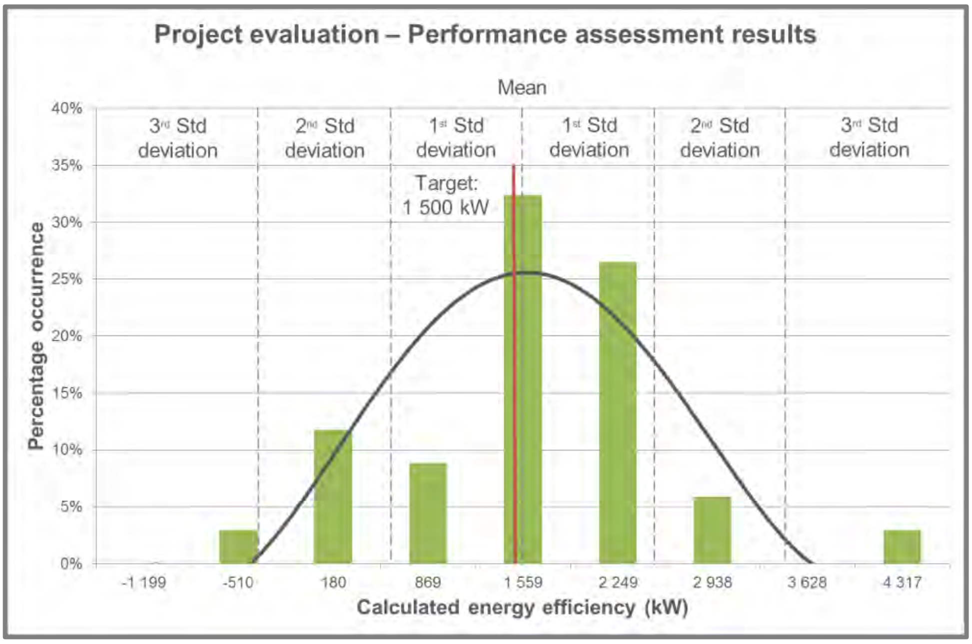

FIGURE 4-24: METHODOLOGY VERIFICATION – PERFORMANCE ASSESSMENT RESULTS

The long-term evaluation methodology was implemented on the post-performance assessment data. The newly developed regression baseline model was used as reference point. The results of the methodology are illustrated in Figure 4-25.

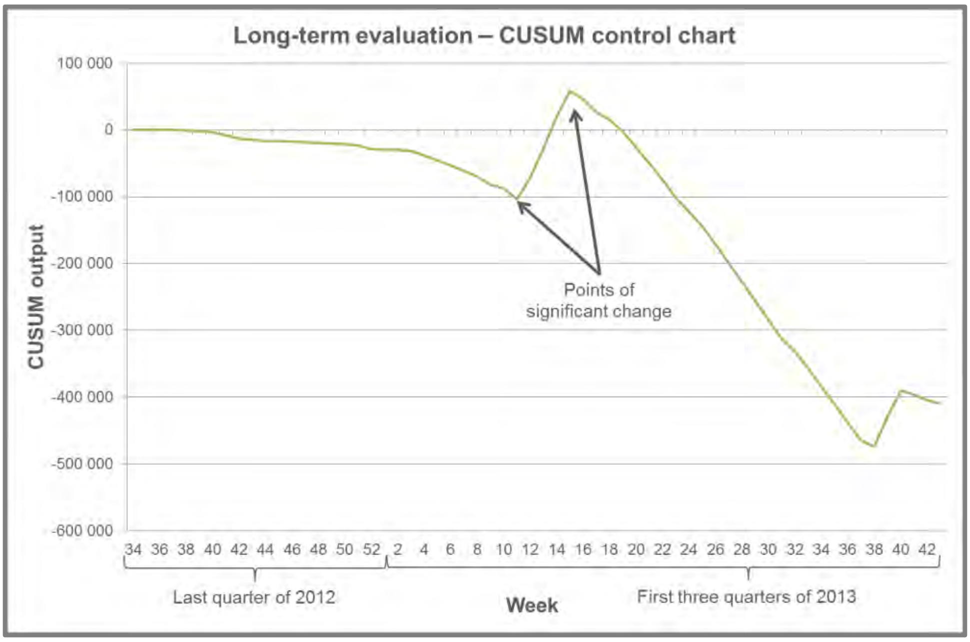

Figure 4-25: Methodology verification – Long-term evaluation

The regression baseline model was developed using average weekly values as input. The control chart subsequently used the same timescale to present results. It is interesting to note that the weekly calculation and presentation has a smoothing effect on the control chart trend. The methodology identified a significant change in operation during Week 12, Week 16 and Week 38.

4.6. Conclusion

This chapter focused on presenting and evaluating industrial DSM project performance. The first methodology was developed with the aim to present a holistic overview of project performance graphically. The methodology presents results in terms of project target, calculated mean and a histogram based on the dataset's standard deviation. The mean indicates the average of the results and represents the single value generally used to indicate project performance. The histogram indicates the occurrence of results while the standard deviations indicate the variance of results. The histogram profile gives further insight into the distribution of the results.

The methodology was verified by presenting five industrial DSM projects. The results highlighted previously unknown characteristics that can significantly influence how stakeholders perceive project success. The verification process illustrated the methodology's ability to objectively present project performance. The new methodology enables stakeholders to use a simplified approach to evaluate project performance holistically. The graphical presentation of results indicates the true nature of project performance thereby enabling an evaluation that is fair to all stakeholders.

The second methodology was developed to evaluate industrial DSM project performance over the long term. The methodology adapted the CUSUM control chart to be used as part of the evaluation process. The chart trend is used to indicate significant changes in system operation and project performance. The period where the change first occurred can be traced using the control chart. The methodology was implemented on the same case studies used for the verification of the first methodology. The results highlighted the degradation of project impact, changes in system operation and the implementation of additional projects. This enables stakeholders to focus their attention on problematic projects.

The long-term evaluation methodology identified two scenarios where project performance changed as a result of new projects being implemented on the system. The guideline for evaluating interactive projects was followed to allocate savings to each of the projects.

This chapter concludes the development of new methodologies and guidelines. Chapter 2, Chapter 3 and Chapter 4 developed several methodologies and verified their impact by implementing them on industrial DSM projects. Chapter 5 will discuss and validate the results of each verification phase.

Chapter 5

MEASUREMENT AND VERIFICATION OF INDUSTRIAL DSM PROJECTS

CHAPTER 5

VALIDATION OF METHODOLOGIES

5. Validation of methodologies

5.1. Introduction

Chapter 1 identified several issues affecting the M&V of industrial DSM projects. The subsequent chapters developed novel methodologies to address these issues. The practical application of each methodology was verified by implementing it on actual industrial DSM projects. Selected results were presented in the relevant chapters while the full set is available in the appendixes.

This chapter will focus on validating the results of the verification processes. The results will be validated using two approaches. The first will be to compare results from the different case studies with each other. The second will be to use results obtained from independent third parties. This will identify general tendencies and allow additional information to be extracted from the results.

The chapter finally investigates the potential impact the new methodologies could have on industry. The financial impact of quantifying the variance in reported savings is calculated and the results extrapolated to indicate the potential international impact. The potential to reduce M&V costs for national projects is also estimated.

5.2. Data evaluation and dataset selection

The data evaluation methodology was developed to evaluate data source and dataset quality. The verification results of three case studies were selected for comparison. The results were compiled presenting the difference between the evaluated sources in terms of percentage deviation. The results were plotted on a histogram. Figure 5-1 illustrates the results.

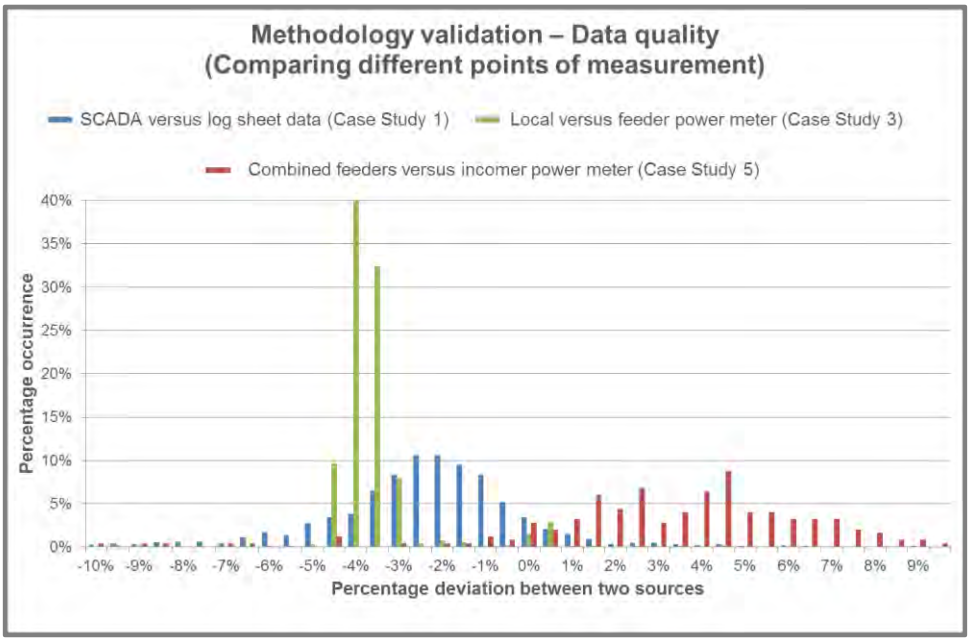

Figure 5-1: Data evaluation methodology – Comparing results

The results illustrated in Figure 5-1 show that the data sources in Case Study 3 had the closest link of all the case studies. In Case Study 3, one meter measured motor power consumption while the other meter measured the motor feeder supplying the motor and all its auxiliaries. The negative deviation values indicate that the feeder measurements were generally between 3–5% higher. The additional power consumption can be attributed to auxiliary equipment such as the motor control system, pumps (oil and water) and lighting. The high percentage occurrence coupled with the narrow band of deviation indicates that the power consumption of the auxiliaries is linked to the power consumption of the motor.

The results from Case Study 1 form a normal distribution around -2.5%. The two sources evaluated in the case study measured power at the exact same point. Under ideal circumstances there would be no difference between the two sources. The results, however, indicate the variance inherent in the manual data-logging process. The variance can be attributed to the low resolution of log sheet measurements not always accounting for fluctuations in system operation.

Case Study 5 evaluated the power consumption of a set of feeders by comparing the totalised feeder power consumption to the power supplied to the plant. The results indicated that the combined power of the incomers is greater than the total power consumption of the entire plant. This indicates the existence of a calibration error or an additional unidentified incomer supplying power to the plant.

Comparing the case studies highlighted the ability of the methodology to evaluate the data source quality. The methodology identified a potential error in Case Study 5. It also highlighted that the two sources used in Case Study 3 form an ideal set to use for source evaluation.

The comparison of results highlights interesting characteristics, but it does not indisputably confirm that the results are accurate. The same problem occurs when attempting to validate results from the dataset evaluation methodology. The case studies used for the verification of the methodology were specifically selected because they clearly represented relevant issues. The significant difference in the presented case studies therefore makes it impractical to cross validate the results.

The ultimate goal of the data evaluation methodology is to deliver a dataset that can be used to develop a baseline model. The methodology results can therefore be validated by comparing the methodology developed baseline profile to the baseline profile developed by an independent M&V team. Case Studies 13, 14 and 15 represent the outcome of the new methodology. Each case study's official baseline profile was obtained from the relevant independent M&V team[1]. Figure 5-2, Figure 5-3 and Figure 5-4 compare the results.

[1] Source details withheld to ensure client confidentiality – contact author for more information.

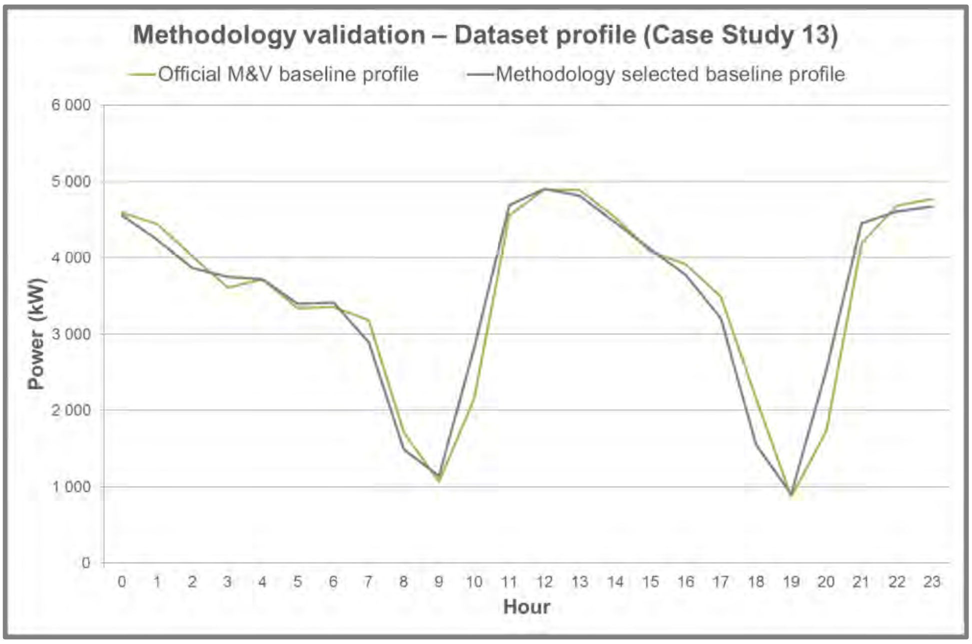

FIGURE 5-2: DATA EVALUATION METHODOLOGY – DATASET PROFILE (CASE STUDY 13)

The profiles in Figure 5-2 represent the average weekday profile of their respective datasets. Any issue with the data source or dataset quality will significantly affect the profile. Comparing the two profiles generated by completely different means and getting similar result clearly validates the methodology results.

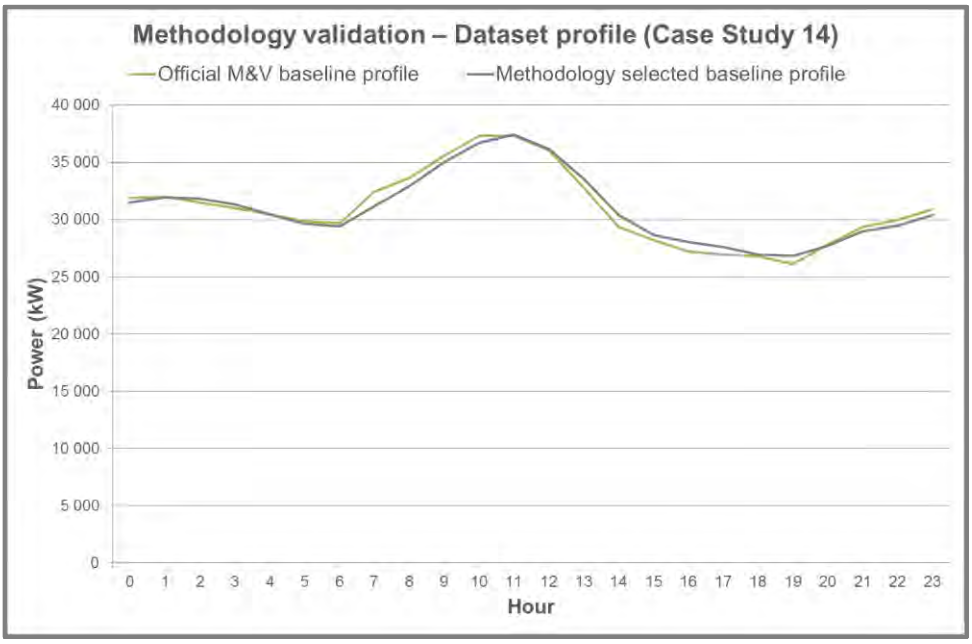

FIGURE 5-3: DATA EVALUATION METHODOLOGY – DATASET PROFILE (CASE STUDY 14)

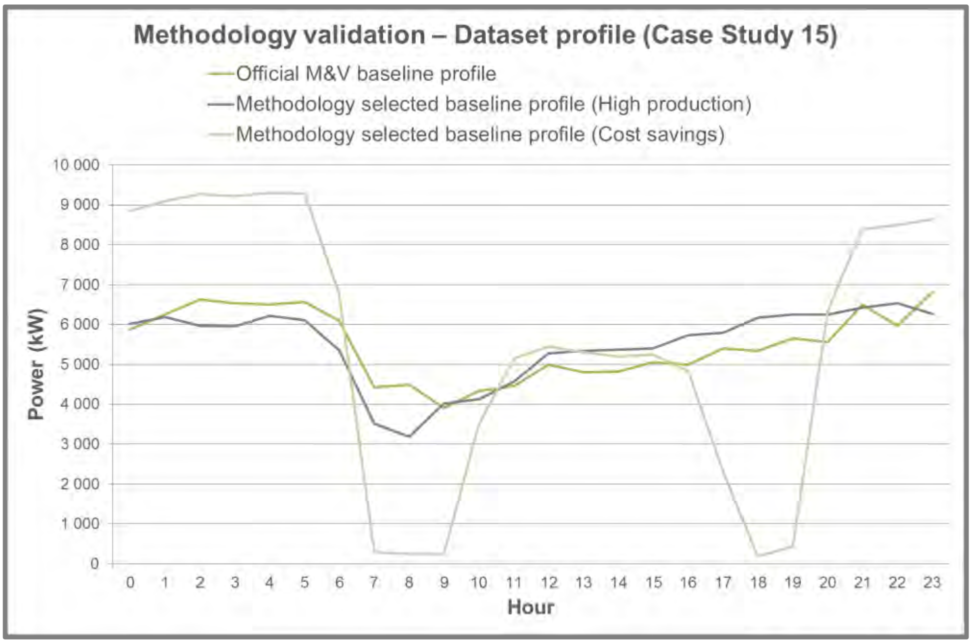

FIGURE 5-4: DATA EVALUATION METHODOLOGY – DATASET PROFILE (CASE STUDY 15)

The profiles illustrated in Figure 5-2 and Figure 5-3 clearly match. This confirms that the new methodology rendered a baseline dataset with an average weekday profile similar to the profile developed by the M&V team. The "high-production" profile in Figure 5-4 matches the profile developed by the M&V team thereby validating the methodology results. The additional profile illustrates the ability of the methodology to identify different modes of operation.

The lack of a significant difference between the methodology selected profile and the official M&V baseline profile can be attributed to two factors. Firstly, it shows that the M&V teams implement some form of data quality evaluation and dataset selection. There are, however, no indication in the general literature or the specific M&V report on how this is done. Secondly, it confirms that the present methods works, and that it manages to deliver similar results while adhering to a clearly defined and structure methodology.

5.3. BASELINE MODEL DEVELOPMENT AND EVALUATION

Investigation into existing methods of baseline model evaluation identified several statistical tests being used. The results of these "traditional" approaches were generally abstract, difficult to present to clients and to compare objectively with other sets of results. This thesis used basic statistical concepts to develop a simplified baseline model evaluation methodology. The outcome is a unique graphical representation of baseline model accuracy. The methodology normalises results enabling the accuracy of several different models to be objectively compared.

The best baseline model from each case study in Chapter 3 is selected for the validation of the methodology. Case study results are presented as a single profile indicating the histogram shape.

This simplifies the process of comparing the accuracy of different baseline models. Figure 5-5 compares the accuracy of the two models developed using only energy-consumption data.

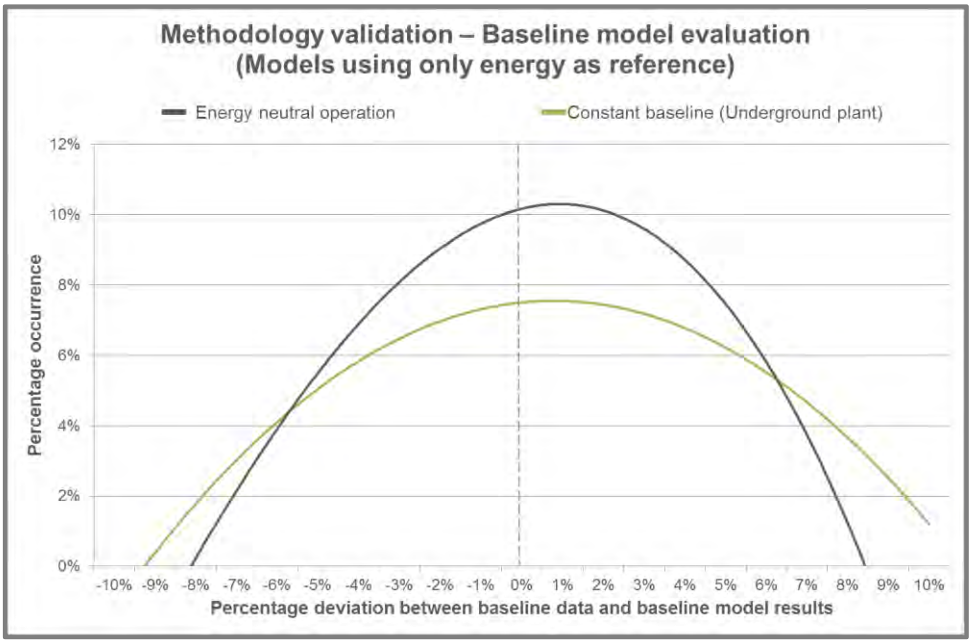

FIGURE 5-5: BASELINE MODEL EVALUATION METHODOLOGY – COMPARING ENERGY-BASED MODELS

Figure 5-6 compares the accuracy of three different regression baseline models.

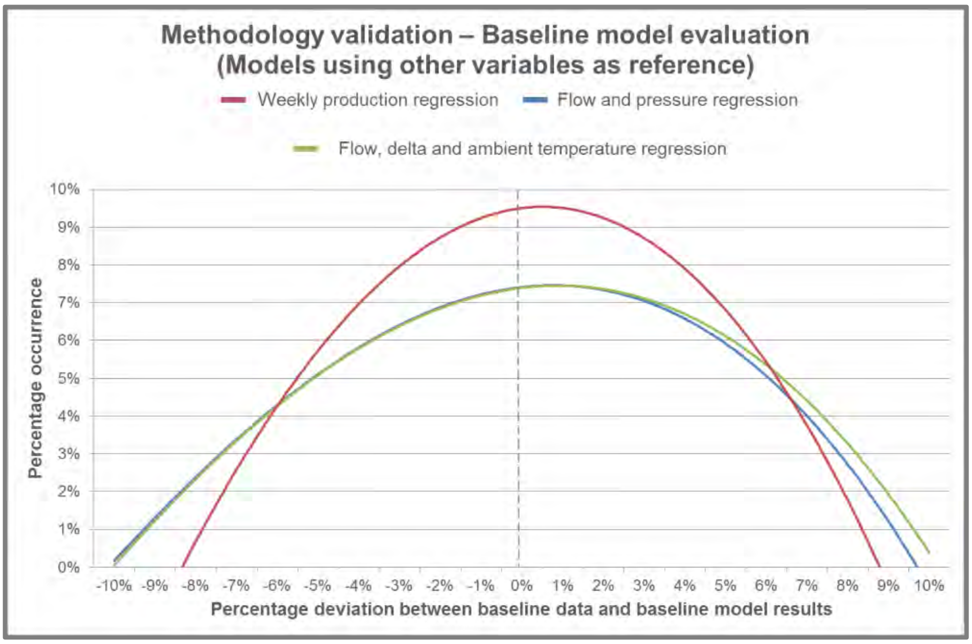

FIGURE 5-6: BASELINE MODEL EVALUATION METHODOLOGY – COMPARING REGRESSION MODELS

Figure 5-5 and Figure 5-6 illustrate the general accuracy of the developed models. The energy-neutral baseline model (Figure 5-5) and the regression model using weekly production data (Figure 5-6) are identified as the most accurate of each set.

It is interesting to note that all five baseline models have a general deviation in the range of ±10%. If this presents the general accuracy of industrial DSM project baseline models it will have a significant effect on the performance assessment phase.

The M&V guidelines discussed in Chapter 1 stipulate that the most conservative results should be reported to compensate for any potential uncertainty. Using any of the developed baseline models implies that reported results can vary within a 20% range of the system power. This is a massive discrepancy and can severely affect the project stakeholders involved, especially if remuneration is linked to performance.

The methodology results are further validated by comparing the results to the outcome of two other evaluation processes. These processes are the "traditional" statistical analysis and the results published by independent M&V teams. Table 5-1 illustrates the results obtained using the three different approaches[2].

TABLE 5-1: METHODOLOGY VALIDATION – COMPARISON OF BASELINE EVALUATION RESULTS

Data integration period	Variables linked to power consumption	R^2	RMSE	Guideline compliant	Best fit	Methodology selection	M&V selection
Case Study 18							
Daily data, pre-strike	Production	0.70	7%	No	Yes	No	No
Weekly data, pre-strike	Production	0.20	4%	No	No	Yes	No
Daily data, post-strike	Production	0.68	8%	No	No	No	Yes
Weekly data, post-strike	Production	0.44	3%	No	No	Yes	No
Case Study 19							
Hourly, all points	Flow	0.71	7%	No	No	Yes	No
Hourly, all points	Pressure	0.11	11%	No	No	No	No
Hourly, all points	Flow and pressure	0.72	6%	No	Yes	Yes	No
Hourly, selected period	Flow	0.25	5%	No	No	Yes	Yes
Hourly, selected period	Pressure	0.08	6%	No	No	No	No
Hourly, selected period	Flow and pressure	0.27	5%	No	No	Yes	No
Case Study 20							
Hourly data	Delta temperature	0.29	19%	No	No	No	No
Hourly data	Flow	0.01	22%	No	No	No	No
Hourly data	Ambient temperature	0.11	21%	No	No	No	No
Hourly data	Delta temp and flow	0.31	18%	No	No	No	No
Hourly data	Flow and ambient temp	0.13	20%	No	No	No	No
Hourly data	Flow, ambient and delta temp	0.31	18%	No	No	No	Yes
Daily data	Delta temperature	0.57	11%	No	No	No	No
Daily data	Flow	0.05	17%	No	No	No	No
Daily data	Ambient temperature	0.25	15%	No	No	No	No
Daily data	Delta temp and flow	0.76	9%	Yes	No	No	No
Daily data	Flow and ambient temp	0.46	13%	No	No	No	No
Daily data	Flow, ambient and delta temp	0.78	8%	Yes	No	No	No
Weekly data	Delta temperature	0.61	9%	No	No	No	No
Weekly data	Flow	0.02	14%	No	No	No	No
Weekly data	Ambient temperature	0.46	10%	No	No	No	No
Weekly data	Delta temp and flow	0.90	5%	Yes	No	No	No
Weekly data	Flow and ambient temp	0.54	10%	No	No	No	No
Weekly data	Flow, ambient and delta temp	0.90	4%	Yes	Yes	Yes	No

[2] Source details withheld to ensure client confidentiality – contact author for more information.

The “Data Integration Period” column in the table indicates the data period used to develop the regression model. The second column describes the variables linked to power consumption. Chapter 3 noted how the time period represented by a single data point and the combination of different variables affect regression model accuracy. The case studies therefore selected several different combinations of data periods and variables to investigate the effect on baseline model accuracy.

The R^2 and *RMSE* results represent the “traditional” statistical analysis results. The results were evaluated based on the M&V guideline requirements of $R^2 > 0.75$ and *RMSE* < 15%. The best-fit column identifies the model with the best fit in terms of the “traditional” analysis.

The methodology selection model highlights the suitable models identified by the new evaluation methodology. Several models are indicated as the methodology aims to present results to enable objective selection, thereby not producing a single result. The last column (M&V Selection) indicates the model selected by the M&V team.

An inspection of the results from Case Study 18 indicates that none of the developed models was compliant with the existing M&V guidelines. The results also show no link between an increase in R^2 and a decrease in *RMSE*. This makes it difficult to select the best model based only on the statistical results. The evaluation methodology identified the models using weekly data as being more accurate. The model using post-strike data presented the best results. The M&V team also selected the model based on post-strike data, but used daily data instead to develop their model. Comparing the two post-strike models using the evaluation methodology (Figure 3-29) shows the weekly data model to be more accurate.

Case Study 19 delivered six different baseline models. None of the models complied with the “traditional” statistical requirements. The flow and pressure regression model using hourly data delivered the best statistical fit. The evaluation methodology identified four potential baseline models. One of these models was also selected by the M&V team. Inspection of the results shows that the models using flow and pressure are slightly more accurate when compared with the flow-based model (Figure 3-30). The small increase in accuracy may, however, not be enough to justify the use of the additional variable. In this case, the evaluation methodology and M&V team selected the same regression model thereby validating the results.

Case Study 20 presented eighteen different models for evaluation. In this scenario four models managed to adhere to the statistical requirements. The evaluation methodology identified the model using weekly flow, ambient and delta temperature as the best fit. The M&V team selected the same model, but made use of daily data. A comparison of the two models based on the new methodology indicated an increased accuracy as a result of the increased data period (Figure 3-33).

The new evaluation methodology and M&V teams selected the same combination of variables for every case study. The evaluation methodology results indicated an increase in regression model accuracy when a longer period is selected. The M&V teams, however, did not optimise regression model accuracy in this regards.

This section compared the accuracy of different baseline models based on the evaluation methodology results. The comparison showed that the models all had an accuracy of in the range of ±10% of system power consumption. The results were further validated by evaluating three case studies based on statistical, methodology and independent M&V team results. The comparison successfully validated the methodology results.

5.4. INDUSTRIAL DSM PROJECT PERFORMANCE

The first methodology of Chapter 4 was developed to illustrate project performance objectively. The methodology was used to present results graphically in order to simplify the evaluation process without incurring any data loss. The practical application of the methodology was verified with the implementation of several case studies.

In this section results from the case studies are normalised and displayed as a percentage of project target for further evaluation. Only the histogram shapes are shown to prevent the figures from becoming too cluttered. The methodology results will be compared to the single value results obtained from the independent M&V teams assigned to evaluate each project.

Figure 5-7 illustrates the performance results of two load shifting projects. The M&V results are superimposed onto the relevant histogram shape. The “PA” and “PT” notations indicate values represented by the M&V performance assessment and performance tracking reports respectively[3].

Inspection of the Case Study 21 histogram profile indicates that the highest peak in occurrence falls below the project target. This peak, situated close to 40%, indicates a general project underperformance. The average performance value shown in the figure seems to be biased towards the target due to some extremely high savings (>300%+). The M&V performance assessment results are all above project target and are spread around a second smaller peak. The M&V performance tracking results are situated closer to the peak occurrence. The comparison of results indicates that the project performed well during performance assessment, but predominantly underperformed afterwards.

The Case Study 22 histogram shape shows a general overperformance. The distribution of the M&V results shows that the project performed well during the performance assessment phase. The project, however, managed to overperform even further during the performance tracking phase with only two reports indicating underperformance.

Figure 5-8 illustrates the performance assessment results of two projects using regression baseline models to represent the relevant systems. The results from the independent M&V reports are superimposed onto the histogram shapes. Inspection of the figure indicates that the independent M&V teams reported an overperformance for both projects during PA. The histogram shapes,

[3] Source details withheld to ensure client confidentiality – contact author for more information.

however, indicate a significant underperformance for Case Study 23 and a significant overperformance for Case Study 24.

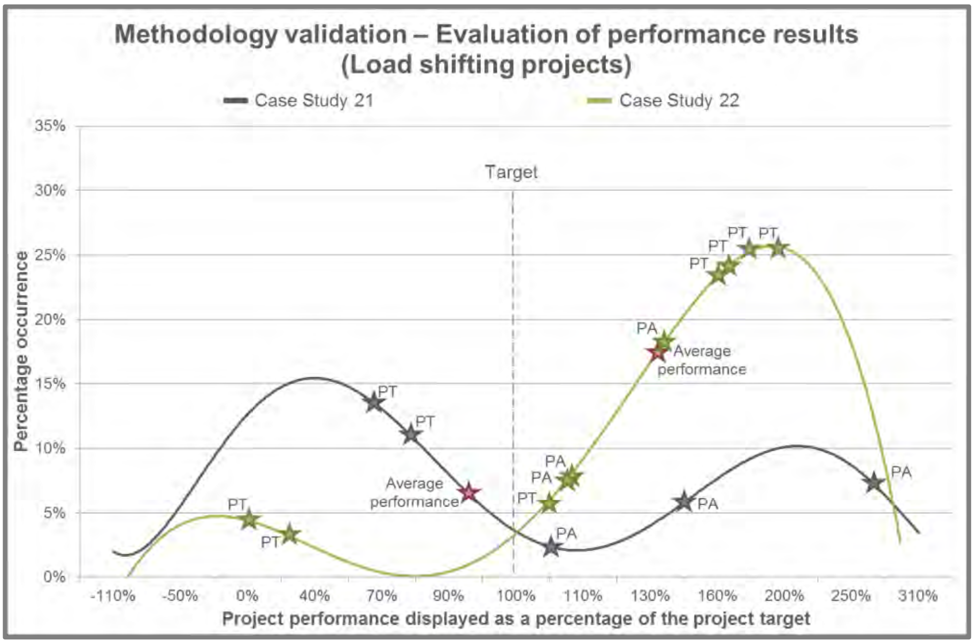

FIGURE 5-7: METHODOLOGY PRESENTING PROJECT PERFORMANCE – LOAD SHIFTING PROJECTS

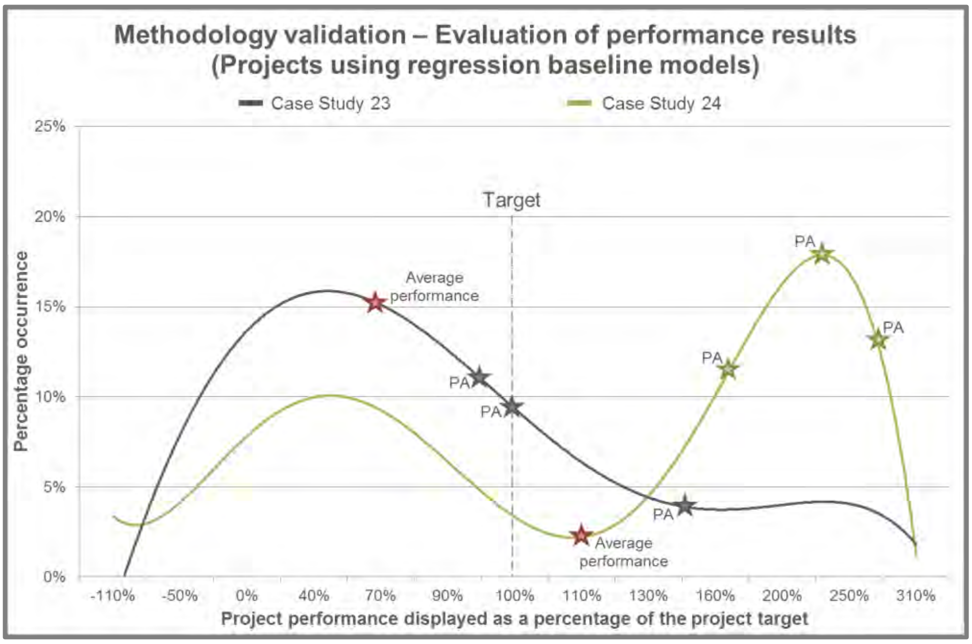

FIGURE 5-8: METHODOLOGY PRESENTING PROJECT PERFORMANCE – ENERGY EFFICIENCY PROJECTS

A detailed investigation into Case Study 23 indicated that different baseline models were used to represent the system. The baseline models used the same variables but selected different integration periods to develop the regression models. The variance in results can therefore be attributed to the inherent inaccuracies of the baseline models. The discrepancy between results illustrates the significant effect baseline model accuracy can have on reported savings.

The M&V performance assessment results for Case Study 24 closely match the peak in occurrence presented by the histogram. It is, however, interesting to note that the histogram has a second peak with a significant level of occurrence. The second peak clearly influences the average performance value and causes the average performance to be much closer to project target. The M&V results do not reflect this and indicate a much higher project performance.

The validation of methodology results presents a great deal of information that remains open for interpretation. It, however, clearly illustrates how the methodology gives an objective and holistic overview of project performance. The methodology's graphical presentation of results will therefore enable stakeholders to understand the true nature of project performance better.

The last methodology in this thesis was developed to identify changes in system operation or project performance. The verification results of three case studies were selected for further validation. The methodology results were validated by linking changes in the control chart trend to documented events[4]. Figure 5-9 and Figure 5-10 illustrate the verification results from Chapter 4, but also includes added information obtained from official media statements.

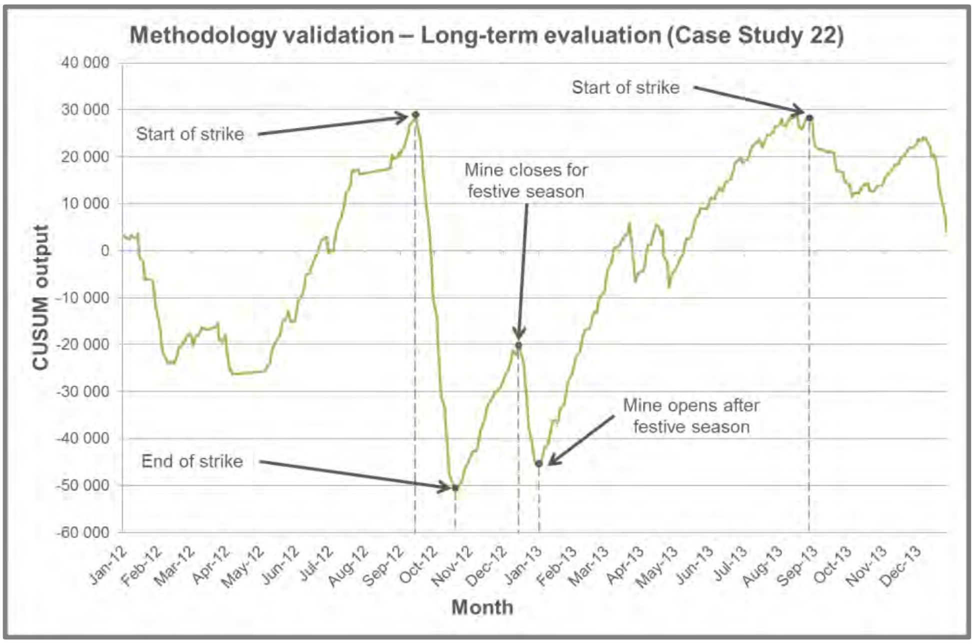

FIGURE 5-9: METHODOLOGY VALIDATION – LONG-TERM PROJECT EVALUATION (CASE STUDY 22)

The significant changes in the control chart illustrated in Figure 5-9 and Figure 5-10 can all be linked to changes in system operation due to the absence of miners. The regular occurrence of strikes together with the closure over the festive season may have overshadowed changes in project performance.

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[4] Source details withheld to ensure client confidentiality – contact author for more information.

Figure 5-10 illustrates the smoother trend of weekly results, while still clearly indicating changes in operation. The prolonged strike, mine closure and subsequent reopening significantly affected the system. These major changes were, however, easily identified and validated.

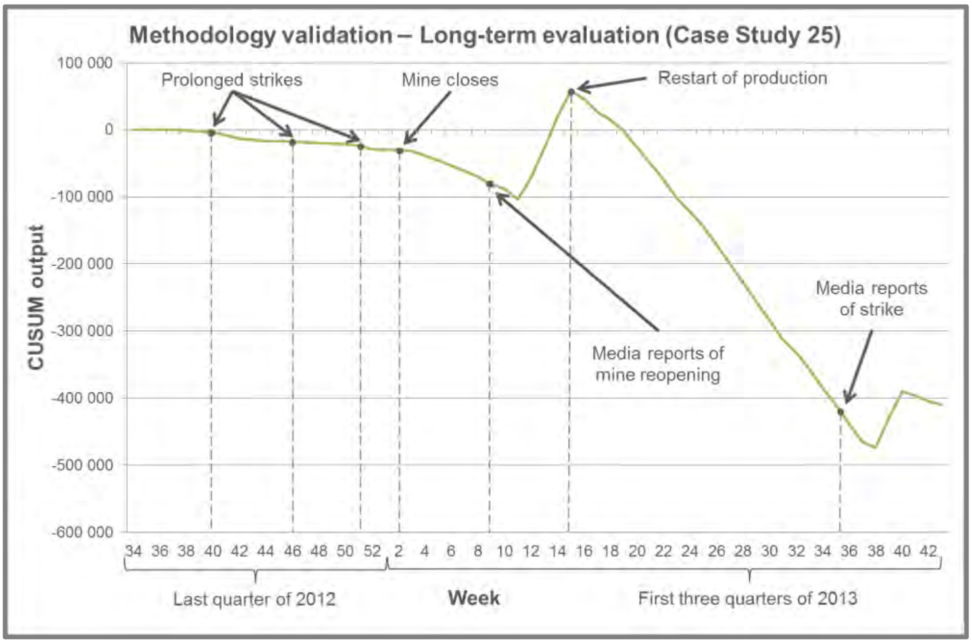

FIGURE 5-10: METHODOLOGY VALIDATION – LONG-TERM PROJECT EVALUATION (CASE STUDY 25)

The validation process indicates the methodology's ability to identify significant changes in system operation. These major events made it difficult to identify changes in project performance. Figure 5-11 illustrates the methodology results as well as the monthly project impact (presented as percentage of project target) as reported by the independent M&V team.

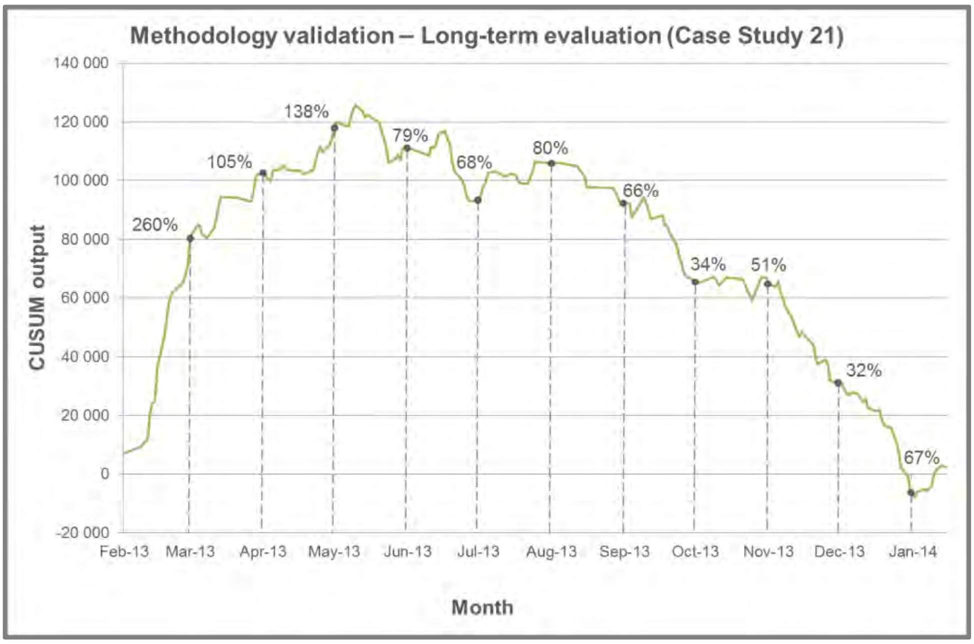

FIGURE 5-11: METHODOLOGY VALIDATION – LONG-TERM PROJECT EVALUATION (CASE STUDY 21)

The angle of the control chart changed between the months of May and June 2013. The independent M&V results also indicate that the project started underperforming in June 2013. The control chart's upward trend can be likened to overperformance; the downward trend to underperformance. The results in Figure 5-11 validate the methodology's ability to identify changes in system operation.

By linking the control chart trend to events using independent data, the methodology's ability to identify changes in system operation and project performance was confirmed. The validation process indicated that events such as strikes and mine closures would result in a much larger and quicker change in the trend. The magnitude of these events may overshadow smaller and prolonged changes in project performance.

5.5. POTENTIAL IMPACT OF NEW METHODOLOGIES

The validation section confirmed that the new methodologies produce accurate results. These results can now be used to estimate the potential financial impact of the methodologies. Two areas of impact will be investigated. The first area of impact is the ability to quantify the accuracy of reported savings and the repercussions it may have on stakeholders. The second area of impact is the potential reduction in M&V costs as a result of more efficient processes. The potential impact will be estimated using figures relevant to the South African market. The results will be extrapolated to indicate the international potential.

The review and literature analysis in Chapter 1 found no formal approach as to how to incorporate the impact of accuracy into the process of allocating savings. A generalised approach stated that the most conservative results should always be reported. The new methodologies enable stakeholders to gauge the financial impact of this decision objectively.

The validation of results indicated that the evaluated baseline models all produced results within a range of ±10% of the actual value. The presentation of project impact indicated a significant deviation in calculated results that will further increase the range of results. Using available DSM (0.22 c/kWh with a load factor of 55%)[5] and 12L tax incentive funding values (0.126 c/kWh)[6] the potential impact of variance in reported savings can be calculated. Figure 5-12 and Figure 5-13 illustrate the results.

The impact of a 1% to 20% variance in calculated results is presented. The 10% line is highlighted in red as it presents a conservative, yet objective indication based on results obtained from the case studies. Eskom's integrated report for the year ending 31 March 2013 reported an annual DSM energy efficiency of 2 244 GWh [53]. This equals an average energy efficiency of approximately 256 MW over the year. The green dot in Figure 5-12 and Figure 5-13 indicates the potential impact the 10% variance will have had on the 2013 projects.

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[5] Letter written by demand side manager, Monkwe Mpye, to ESCOs (dated 6 October 2011).
[6] SANEDI 12L Energy Efficiency Tax Incentive – FAQ Example.

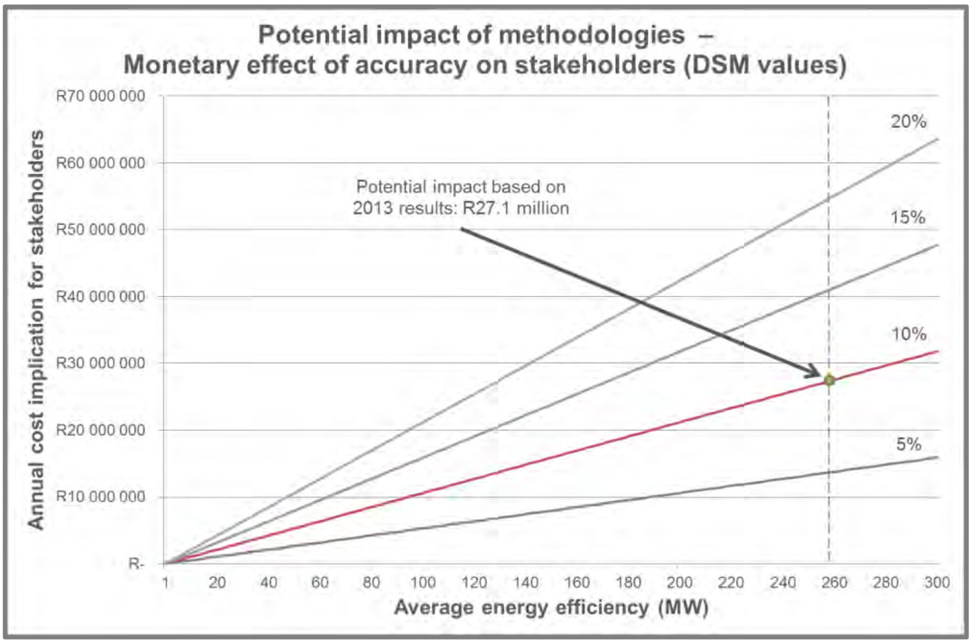

FIGURE 5-12: POTENTIAL IMPACT OF METHODOLOGIES – IMPACT ON STAKEHOLDERS (DSM VALUES)

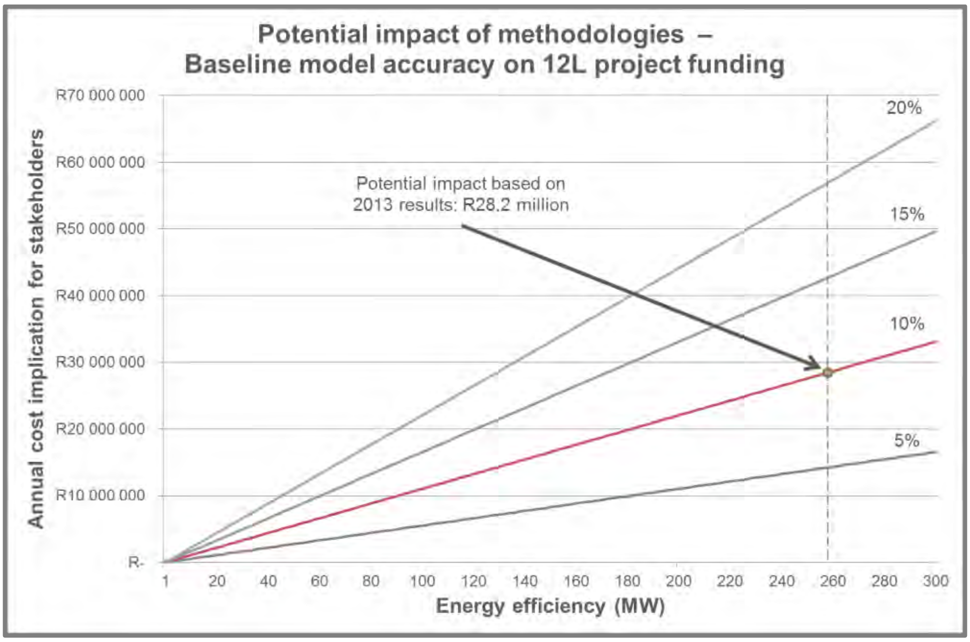

FIGURE 5-13: POTENTIAL IMPACT OF METHODOLOGIES – IMPACT ON STAKEHOLDERS (12L VALUES)

Figure 5-12 indicates a potential impact of R27 million on DSM projects. Figure 5-13, assuming that the 12L tax incentive scheme will be just as successful as the DSM scheme, indicates a potential impact of R28 million. The combined effect falls in the range of R55 million. These results are merely estimations of the potential impact. The scale of the results, however, indicates a significant impact potential on stakeholders. The methodologies therefore have the potential to improve the feasibility of projects and enable the stakeholders to claim more savings.

The new methodologies and guidelines also improve the M&V process by standardising several processes. The transparency of these processes allow for the reuse and improvement of existing models. This will ultimately reduce the cost of M&V, thereby contributing to the financial viability of projects.

Ideally, the new methodologies and guidelines will reduce M&V costs from the maximum cost of 10% down to the general minimum of 3% as identified in Figure 1-2 [7], [9]. The potential impact of this improvement on national M&V is estimated using figures presented in Eskom's 2013 integrated report [53]. The potential impact on M&V costs is calculated based on the conservative assumption that only Eskom funding was used to develop the energy efficiency projects presented in Eskom's report. The results are shown in Figure 5-14.

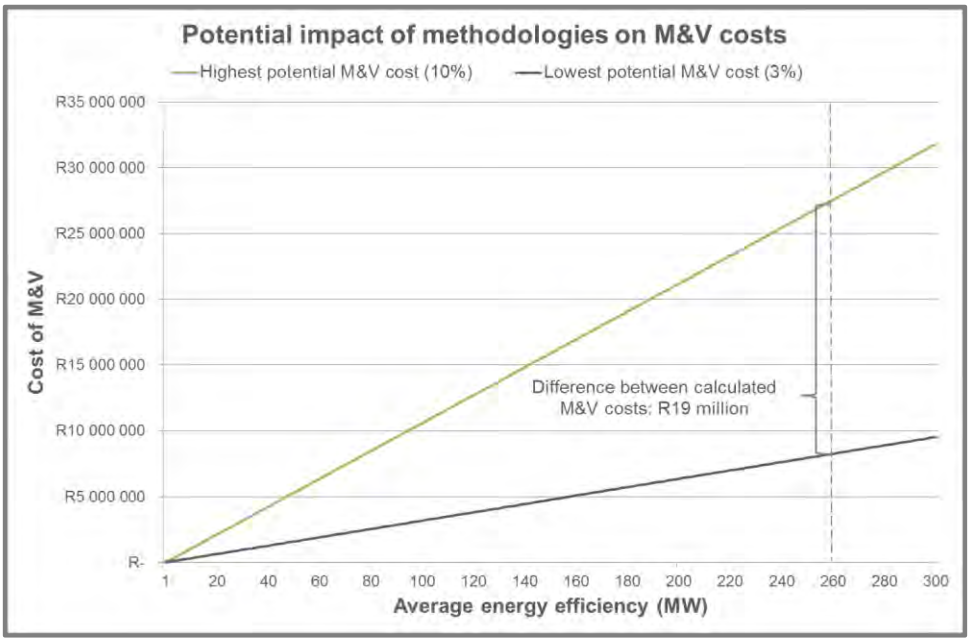

FIGURE 5-14: POTENTIAL IMPACT OF METHODOLOGIES – M&V COSTS

Figure 5-14 illustrates that M&V costs can ideally be reduced by R19 million. The methodologies will therefore not only contribute by improving the M&V process but also by reducing costs. This will benefit all stakeholders by making more projects feasible. The calculated results are summarised in Table 5-2. The potential impact of the methodologies on international projects can now be estimated using these results.

Statistics regarding the world's electricity generation from 1985 to 2012 was collected for analysis[7]. The assumption was made that only 10% of the generated electricity is available for energy efficiency projects. Figure 5-15 illustrates the estimated annual impact based on 2012 generation data. The results indicate a significant potential impact.

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[7] BP Statistical Review of World Energy June 2013 (http://www.bp.com/statisticalreview).

TABLE 5-2: CALCULATED RESULTS

Description:	Value:	Unit:	Notes:
DSM funding	0.220	c/kWh	Based on a load factor of 55%
12L EE tax incentive	0.126	c/kWh	Based on tax rate of 28%
2013 Eskom DSM impact	2 244	GWh	Reported EE results
2013 Eskom DSM impact	256	MW	Average impact
Methodology impact on annual DSM costs	27.1	R million	Annual impact based on 256 MW EE
Methodology impact on annual 12L costs	28.2	R million	Annual impact based on 256 MW EE
Methodology impact on annual M&V costs	19.0	R million	Based on 7% reduction in M&V costs
Methodology impact on DSM lifecycle	172	R million	Five year cycle including once-off M&V cost and 6% inflation
Methodology impact on 12L lifecycle	47	R million	Annual impact including once-off M&V cost
Average DSM impact	134 000	R/MW	Average annual impact per MW EE
Average 12L impact	185 000	R/MW	Average annual impact per MW EE
Average impact	160 000	R/MW	Average impact of DSM and 12L

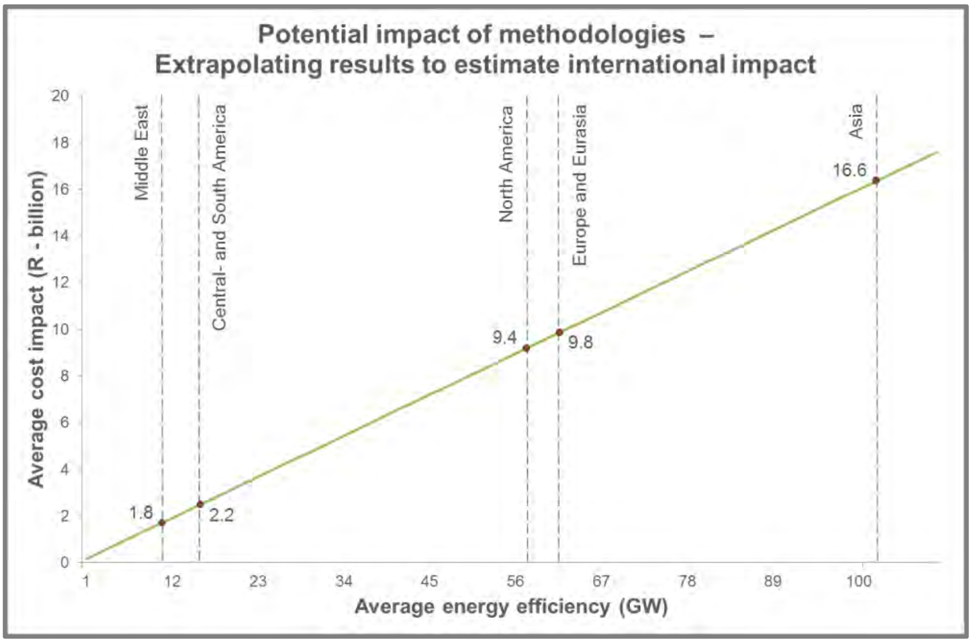

FIGURE 5-15: POTENTIAL IMPACT OF METHODOLOGIES – EXTRAPOLATED RESULTS

5.6. Conclusion

This thesis developed several novel methodologies to address the needs identified in Chapter 1. The practical implementation of these methodologies was verified using actual industrial DSM projects as case studies. The results of the verification processes were validated in this chapter by using data obtained from independent sources as reference.

The methodologies in Chapter 2 were developed to ensure that a high quality dataset representative of system operation is selected for baseline model development. The validation process compared the methodology verification results to baseline profiles developed by independent M&V teams. The comparison showed that the methodologies managed to deliver suitable baseline datasets and subsequent profiles consistently.

Chapter 3 presented a methodology to simplify the baseline model development and evaluation process. The verification results were first evaluated by comparing the five most accurate baseline models. The comparison of the models indicated an average accuracy of ±10% (of measured power). A set of eighteen baseline models, developed in three of the verification case studies, were selected for further validation.

The verification results were compared with the “traditional” statistical evaluation results as well as with the selection made by the independent M&V teams. It indicated that the methodology and M&V teams consistently selected baseline models using the same variable combinations. The methodology, however, selected different periods of data integration. The verification results in Chapter 3 compared the impact of the different integration periods and illustrate the increased accuracy of the methodology selected period. The validation process thereby illustrated ability of the methodology to improve the baseline development process.

The validation process confirmed the ability of the methodology to evaluate and present baseline model accuracy. The process highlighted critical characteristics which can be used to ensure model accuracy and compliance to present statistical requirements.

The last set of methodologies presented project performance in a graphical format. The aim of the first methodology was to enable an objective evaluation of project performance. The second methodology tracked project performance indicating significant changes in system operation or project performance. The methodology verification results were validated by superimposing results obtained from independent third parties onto the relevant graphical presentation.

The histogram shape produced by the first methodology combined with the single values reported by independent M&V teams highlighted the methodology’s ability to represent results objectively. The evaluation also revealed the significant impact the use of different baseline models has on the calculated results.

The verification results from the long-term evaluation methodology were validated by linking documented events to significant changes in the control chart trend. The validation process found that the methodology clearly indicated system changes due to strikes and mine closures. An evaluation of a site with no system changes showed how the control chart could be used to identify the point where project savings started to degrade.

The validated results were used to estimate the potential impact of the methodologies. The calculated results illustrated the impact for various levels of variance that can be determined using the new methodologies. The ideal scenario impact based on a 10% variance amounted to R27 million for DSM projects, and R28 million for 12L tax incentive projects, when based on the average energy efficiency of 256 MW achieved by the Eskom DSM programme in 2012. The results were further processed indicating an average impact of R160 000 per average MW energy efficiency per annum.

Chapter 6

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS FOR FUTURE WORK

6. Conclusion and recommendations for future work

6.1. Conclusion

A review of official M&V documents identified a lack of practical methodologies and guidelines. This prompted a detailed investigation of national and international publications in search of practical examples. A vast collection of published literature consisting of articles, books and conference papers were evaluated with the final selection consisting of 62 cases. The graphical presentation of the normalised analysis results gave a unique insight into the nature of M&V and identified several areas of need. This prompted the development of new methodologies and guidelines for the M&V of industrial DSM projects.

Three chapters were dedicated to the development of new methodologies, each focusing on a specific core M&V step. Every chapter discussed a specific need and the theoretical concepts utilised to develop the relevant new methodologies to address the identified need. The presented methodologies were significantly simplified and generalised to easily convey the solution. Their design, however, enabled the methodologies to handle large and complex solutions.

The methodologies presented in Chapter 2 evaluated system data with the goal of producing a high quality dataset. The verification case studies found that even the best data source produced intermittent errors. This highlighted the importance of dataset quality especially in a context where a small measurement error can have a significant financial impact on stakeholders. The new dataset selection guideline illustrated the importance of evaluating system operation and variables holistically. Applying the new methodologies and guideline from the beginning of the project can mitigate significant errors. These errors would usually only surface much later in the project lifecycle potentially resulting in additional costs and delays.

Chapter 3 devised a guideline to aid the process of developing baseline models. The guideline presented simplified examples of project characteristics and utilised three common baseline models to represent the relevant systems. The three generalised models presented can be used to model most industrial DSM projects. The guideline therefore eliminated the need to develop new models, thereby reducing costs and inherent risks. This information combined with the methodologies from Chapter 2 will guide new developers from project onset mitigating potentially costly mistakes.

The baseline model evaluation methodology was developed to evaluate the accuracy of a selected model. The methodology's unique graphical presentation of results allowed for a multitude of different models to be objectively compared. The methodology therefore enabled the optimisation of existing models and the development of new models.

Chapter 4 utilised the theoretical principles discussed in Chapter 3 in conjunction with additional basic statistical concepts to develop the methodology for graphically presenting project performance. The methodology output presented project performance in terms of the mean, standard deviation, relative frequency of results and the subsequent histogram shape. The mean represented the single value usually selected to convey project performance. It was, however, in the graphical comparison of the various characteristics that the true nature of the project performance was revealed. This was a unique and novel indication of project performance and allowed stakeholders to objectively evaluate and discuss the results.

The long-term evaluation methodology repurposed the CUSUM control chart concept and used it to evaluate project performance. The specific goal of the methodology was to identify significant changes and prompt a detailed review of the baseline model and project performance when necessary. This unique application could significantly reduce the amount of labour required to monitor project performance continuously. It could also give stakeholders the ability to quickly identify and address issues thus preventing unnecessary losses.

The final guideline presented an approach to evaluating interactive projects. The occurrence of interactive projects was noted in literature, but no publications were found that detailed practical solutions for this issue. The guideline presented simplified approaches to evaluate chronological and concurrently implemented projects. The guideline’s structured process prevented double-counting and allocated savings in an unbiased logical manner.

The practical application of all the guidelines and methodologies developed in this thesis were verified with the use of selected case studies. Chapter 5 validated methodology results by comparing results obtained from the verification case studies with results obtained from independent third parties. The majority of the results were verified by using official M&V reports. The CUSUM control chart results were, however, validated using a combination of media reports, official company statements and M&V results.

The 25 case studies presented in the thesis were selected to verify and validate the developed methodologies and guidelines. The studies were purposefully selected to cover a wide range of projects, scenarios and issues. The transparent implementation of the methodologies presented the reader with a roadmap to use on similar projects. The selection of case studies therefore doubled as a library of proven solutions and a starting point for future developments.

The methodologies and guidelines presented in this thesis were developed to address the various needs identified in the literature study. Their clear and concise design contributes a novel approach without compromising the M&V process. Their simplified presentation and application make them open to all stakeholders. The use of graphics to convey complex and abstract information enables the objective and intuitive evaluation of results. The potential impact of the new methodologies amounts to an estimated R27 million for the energy efficiency projects implemented by Eskom in 2013 alone. Further extrapolation shows that worldwide application of the methodologies can have a monetary impact amounting to billions of Rands.

6.2. RECOMMENDATIONS FOR FUTURE WORK

The thesis presented several new methodologies aimed at addressing the needs identified by the literature analysis. The development process together with the verification and validation of the methodologies briefly touched on several subjects that warrant additional investigation. This final section of the thesis presents the author's recommendations for future work.

The first recommendation is to implement the new methodologies on projects from different sectors including commercial and domestic sectors. The implementation results should be evaluated and the models adjusted where necessary. The models should also be implemented on actual 12L energy efficiency tax incentive projects when the first group of projects have been officially evaluated.

The developed methodologies all used the graphical presentation of results to simplify the evaluation process. This approach also enables the objective comparison of different results. The second recommendation for future work is to apply these methodology characteristics to quantitative studies. The studies should investigate a large collection of projects, implement the methodologies and compare the results to ascertain whether specific tendencies exist. The comparison will hopefully present statistical significant information on subjects such as general baseline model accuracy and project performance.

The results from the quantitative studies can be further evaluated to develop benchmarking tools. These tools can be used by stakeholders to evaluate project feasibility and risk quickly. The study can also highlight general issues and develop checklists to be used as part of project feasibility studies. The application of these checklists will ensure that the relevant variables are logged and evaluated as part of the project feasibility phase. This will greatly reduce the errors and resulting loss (time and money) to redo inadequate M&V models.

The verification and validation processes identified the inherent inaccuracy of the process. The author suggests that additional work be done on present M&V standards and policy. This should include formal rules depicting what constitutes acceptable accuracy and what to do if these rules cannot be adhered to.

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MEASUREMENT AND VERIFICATION OF INDUSTRIAL DSM PROJECTS

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7. REFERENCES

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Appendix
A

MEASUREMENT AND VERIFICATION OF
INDUSTRIAL DSM PROJECTS

APPENDIX A

LIST OF PUBLISHED LITERATURE USED IN CRITICAL ANALYSIS

APPENDIX A: PUBLISHED LITERATURE USED IN CRITICAL ANALYSIS

Nr	Title	Reference
1	A Compact Fluorescent Lamp Mass Roll-out Case Study in Gauteng Province	[54]
2	A Large-scale Energy Reporting System for the Process Industry	[55]
3	A New Approach to Ensure Successful Implementation of Sustainable Demand Side Management (DSM) in South African Mines	[56]
4	A New Clustering Algorithm for Load Profiling Based on Billing Data	[34]
5	Accumulation Periods and Accuracy of M&V Baseline Models	[46]
6	Air Conditioner Intelligent Switch Control in Commercial Buildings	[57]
7	Air Conditioning Systems Replacement at Industrial Facilities	[58]
8	Analysis and Forecasting of Non-residential Electricity Consumption in Romania	[59]
9	Assessing Energy-saving Measures in Buildings through an Intelligent Decision Support Model	[60]
10	Assessment of the National DSM Potential in Mine Underground Services	[61]
11	Awareness Programmes in the Residential Sector (Case Study 1)	[62]
12	Awareness Programmes in the Residential Sector (Case Study 2)	[62]
13	Baseline Service Level Adjustment Methodologies for Energy Efficiency Projects on Compressed Air systems in the Mining Industry (Case Study 1)	[48]
14	Baseline Service Level Adjustment Methodologies for Energy Efficiency Projects on Compressed Air systems in the Mining Industry (Case Study 2)	[48]
15	Baseline Service Level Adjustment Methodologies for Energy Efficiency Projects on Compressed Air systems in the Mining Industry (Case Study 3)	[48]
16	Building Energy Efficiency Projects	[63]
17	Clustering Techniques in Load Profile Analysis for Distribution Stations	[35]
18	Co-operative Strategies for Control of Industrial Energy Systems	[64]
19	Demand Side Management in South Africa at Industrial Residence Water Heating System using in Line Water Heating Methodology	[38]
20	Development of an Energy Monitoring and Targeting Methodology for the Most Efficient Operation of Chilled Water Systems	[36]

Nr	Title	Reference
21	Development of an Energy Management System: Case Study of Serbian Car Manufacturer	[65]
22	Domestic Electricity Use: A High-resolution Energy Demand Model	[66]
23	Dust Suppression System on an Open-pit Mine	[67]
24	Dynamic Energy-consumption Indicators for Domestic Appliances: Environment, Behaviours and Design	[68]
25	Energy and Demand Impact of Compact Fluorescent Light Distribution Programmes (Case Study 1)	[69]
26	Energy and Demand Impact of Compact Fluorescent Light Distribution Programmes (Case Study 2)	[69]
27	Energy and Demand Impact of Compact Fluorescent Light Distribution Programmes (Case Study 3)	[69]
28	Energy Efficiency Improvement and Load Reduction on Refrigeration at Supermarket Stores	[70]
29	Energy Efficiency Improvement on the Cooling Auxiliary Equipment in the Mining Industry	[71]
30	Energy Efficiency Savings in Industrial Facilities: The Flaw of using Energy Intensities to Determine Savings	[72]
31	Energy Efficiency through Behaviour Change	[73]
32	Energy Models for Demand Forecasting: A Review	[39]
33	Energy Saving and Energy Efficiency Concepts for Policy Making	[74]
34	ENERNET: Studying the Dynamic Relationship between Building Occupancy and Energy Consumption	[45]
35	Forecasting Turkey's net Electricity Energy Consumption on Sectorial Bases	[43]
36	High Pressure Solar Water Heating Systems with Backup Heating Elements	[75]
37	Industrial Compressed Air Load Management	[76]
38	Industrial Energy Management: The Role of Distributed Control Systems	[77]
39	Industrial Heat Pumps	[78]
40	Industrial Lighting Project Case Study	[79]
41	Industrial Load Shifting Using an Online Energy Management System	[80]
42	Industrial Sector Energy Conservation Programs in the People's Republic of China during the Seventh Five-Year Plan (1986–1990)	[81]

Nr	Title	Reference
43	Irrigation Pumping Systems	[82]
44	IT Based Energy Management through Demand Side in the Industrial Sector	[83]
45	LED Lighting Retrofit at Commercial Buildings	[84]
46	Load Shifting Using Intelligent Pumping in a Water Reticulation System	[44]
47	Low Flow Shower Head Retrofits at Multiple Sites in the Western Cape	[85]
48	Low Pressure Solar Water Heating Systems	[86]
49	Methodology to Measure and Verify the Demand-Side Management Impact of a Residential Load Management Project	[87]
50	Methodology, Challenges and Lessons from Commercial Heat Pumps	[88]
51	On a Compact Fluorescent Light Distribution Project and Lessons Learnt in Lighting Projects	[89]
52	Optimisation of Compressed Air Networks at a Deep Level Mine (Case Study 1)	[90]
53	Optimisation of Compressed Air Networks at a Deep Level Mine (Case Study 2)	[90]
54	Optimisation of Compressed Air Networks at a Deep Level Mine (Case Study 3)	[90]
55	Overview and Performance Assessment of the Clustering Methods for Electrical Load Pattern Grouping	[33]
56	Reduction on Cooling Loads through the Implementation of Energy Management Systems	[91]
57	Residential Heat Pump Rebate Programme	[92]
58	Residential Load Management of Geysers in the Western Cape	[47]
59	The Challenge of Reducing Energy Consumption of the Top-1000 Largest Industrial Enterprises in China	[93]
60	The Development of a Proper Measurement and Verification Plan	[94]
61	Using Indicators to Profile Energy Consumption and to Inform Energy Policy in a University: A Case Study in Ireland	[32]
62	Water Optimisation at a Deep Level Mine with an Existing Load Shifting Intervention	[95]

Appendix
B

MEASUREMENT AND VERIFICATION OF INDUSTRIAL DSM PROJECTS

APPENDIX B

INDUSTRIAL CASE STUDIES – DATA EVALUATION AND DATASET SELECTION

APPENDIX B: DATA EVALUATION AND DATASET SELECTION

CASE STUDY 1 – EVALUATING SCADA DATA USING LOG SHEETS

Case Study 1 evaluates data obtained from a SCADA system by comparing it to log sheet data. The log sheet data was obtained from a panel meter measuring power consumption at the same point as the SCADA power meter. The data source evaluation methodology was applied to determine whether the SCADA could be used as data source. Figure B-1 illustrates the complete dataset.

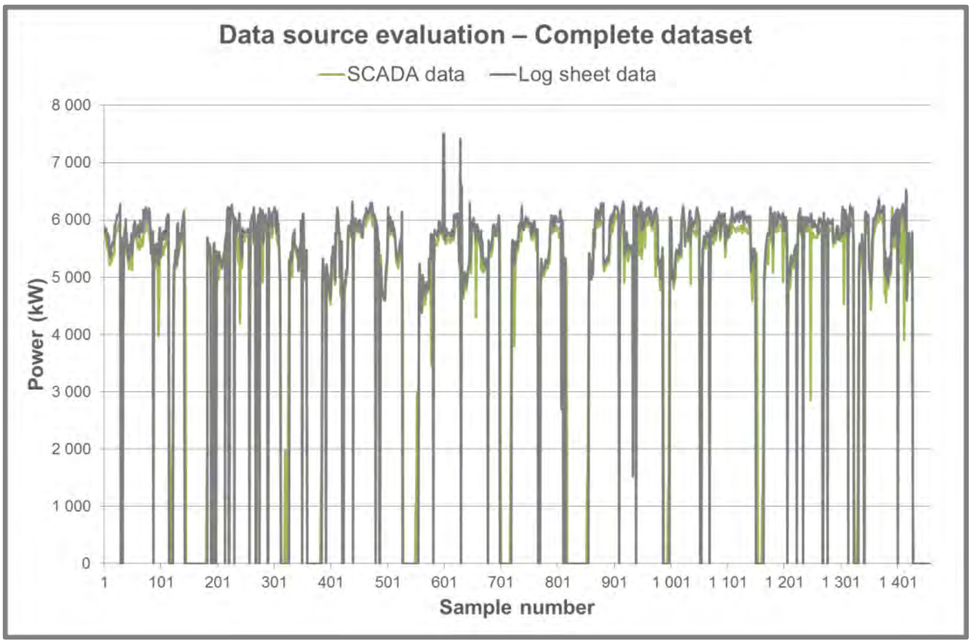

FIGURE B-1: DATA SOURCE EVALUATION – COMPARING SCADA AND LOG SHEET DATA (FULL DATASET)

The data's high resolution makes it difficult to discern the differences between the two sources visually. A subset of data is therefore selected to further inspect the two sources. The subset is illustrated in Figure B-2. Inspection of the subset reveals a continued offset combined with larger sporadic discrepancies.

The visual inspection alone is not sufficient to quantify the difference between the sources. The dataset was therefore processed to determine the difference between the two sources. The results are illustrated in Figure B-3. The figure illustrates the frequency of major differences between the two data sources. The amplitudes of the discrepancies are generally in excess of 1 000 kW (absolute value) with the highest peak reaching almost 6 000 kW.

The frequency of discrepancies combined with their amplitude indicates the occurrence of several abnormalities. It is, however, still unclear whether the SCADA and/or log sheets should be discarded as data sources. The results are therefore sorted to obtain more information on the data sources characteristics. The results are shown in Figure B-4.

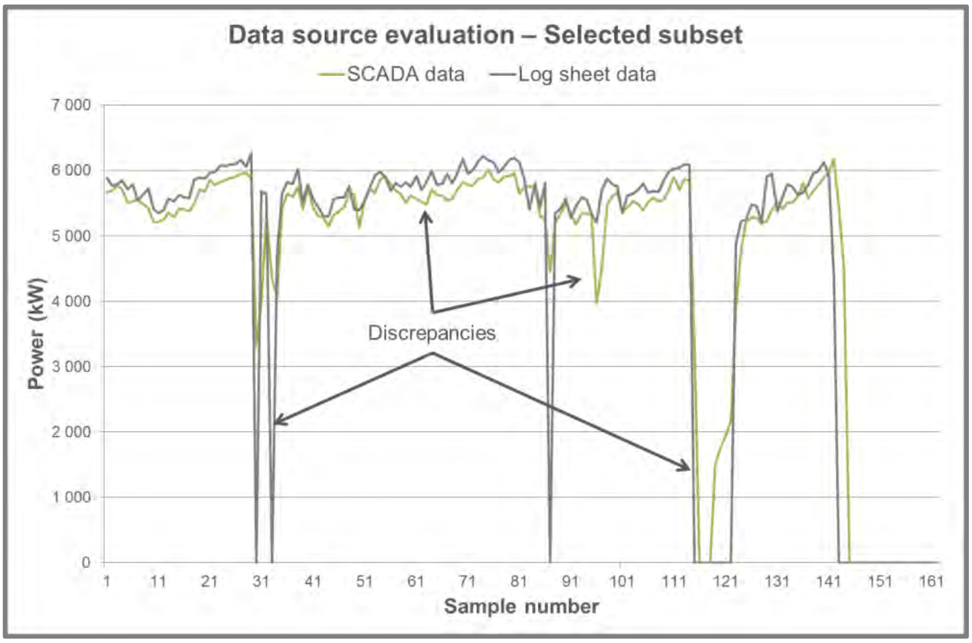

FIGURE B-2: DATA SOURCE EVALUATION – COMPARING SCADA AND LOG SHEET DATA (DATA SUBSET)

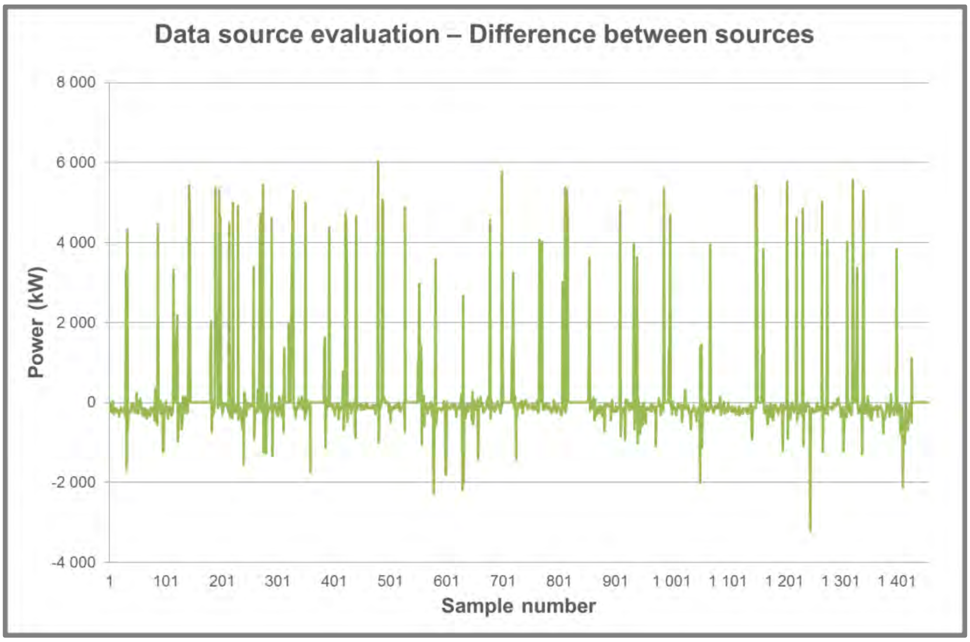

FIGURE B-3: DATA SOURCE EVALUATION – COMPARING SCADA AND LOG SHEET DATA (RESULTS)

The results in Figure B-4 convey important system information. The constant difference can be attributed to the presence of zero value data in one of the datasets. The positive offset indicates that the zero values were present in the log sheets. This is most probably due to the lower resolution of the log sheets missing the precise moment of consumer start-up. The same logic can be used to explain some of the negative values, although the smoothed curve indicates slight measurement inconsistencies. The vast majority of the values however fall within 7% of each other thereby quantifying the data source quality.

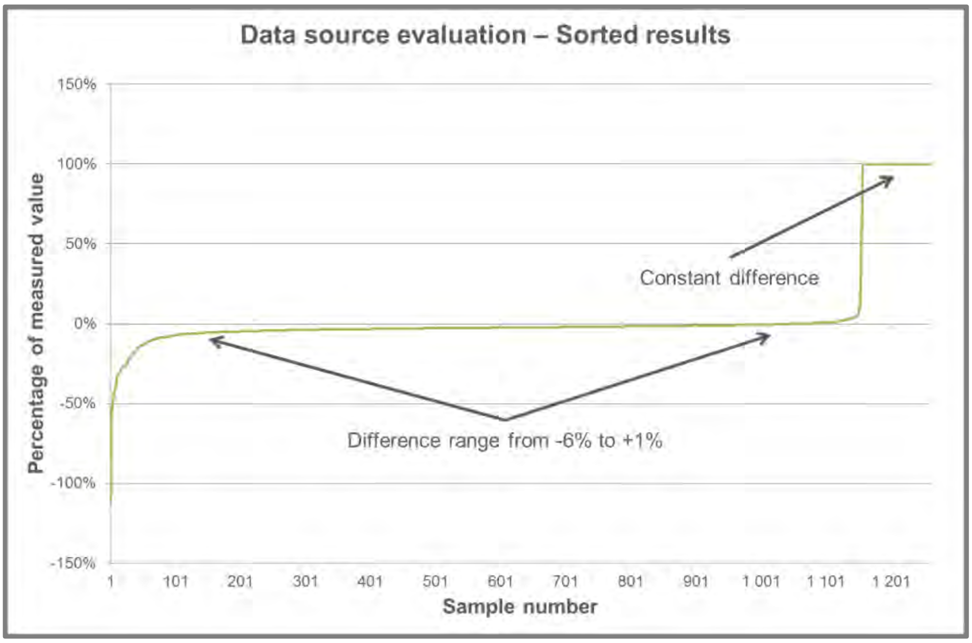

FIGURE B-4: DATA SOURCE EVALUATION – COMPARING SCADA AND LOG SHEET DATA (SORTED RESULTS)

CASE STUDY 2 – EVALUATING PORTABLE POWER METER DATA USING LOG SHEETS

Case Study 2 evaluates a portable power meter as data source by comparing its measurements to log sheet data. The measurements were taken at the same point using different equipment. Figure B-5 displays the complete dataset.

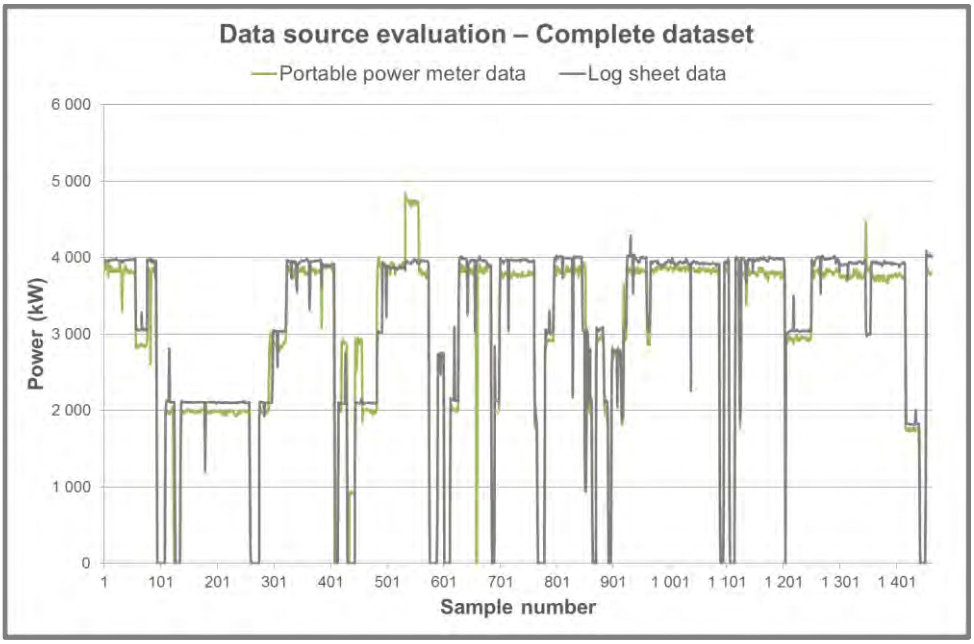

FIGURE B-5: DATA SOURCE EVALUATION – COMPARING PORTABLE METER AND LOG SHEET DATA (FULL DATASET)

Inspection of the complete dataset shows a definite continuous discrepancy between the two sources. A subset of the data is selected for a more detailed inspection. The subset is shown in Figure B-6.

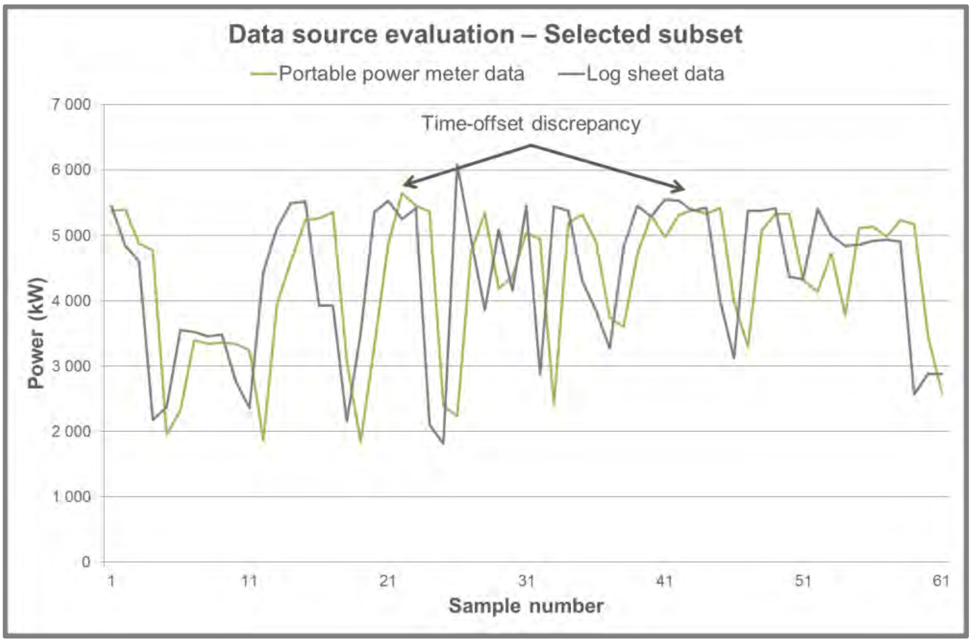

FIGURE B-6: DATA SOURCE EVALUATION – COMPARING PORTABLE METER AND LOG SHEET DATA (DATA SUBSET)

The subset indicates the occurrence of a time-offset discrepancy. This is due to the use of different timestamp conventions (forward filing and backward filling). The offset is resolved and the datasets adjusted follow the same convention. The adjusted dataset is shown in Figure B-7.

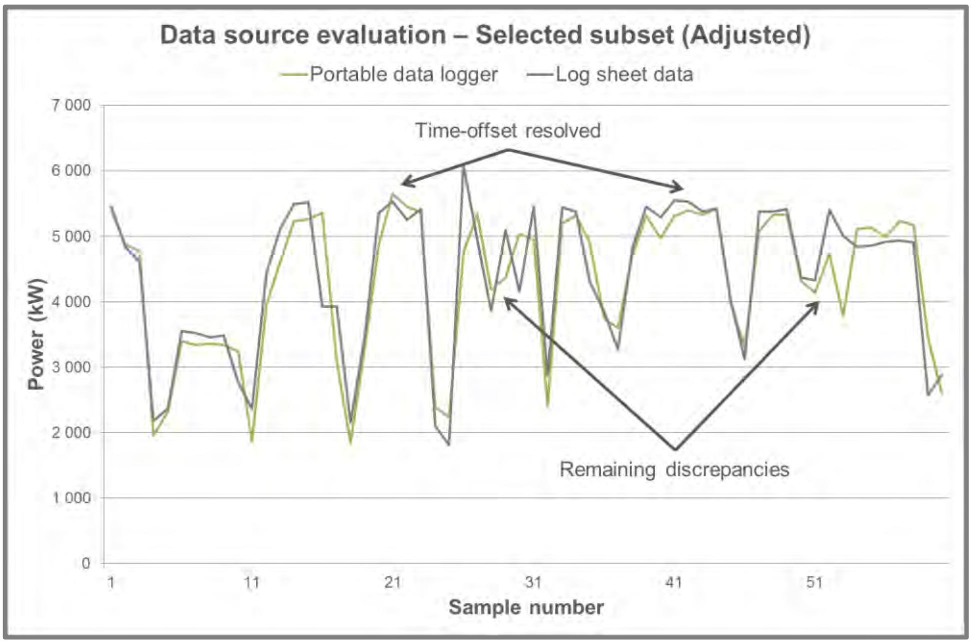

FIGURE B-7: DATA SOURCE EVALUATION – COMPARING PORTABLE METER AND LOG SHEET DATA (ADJUSTED SET)

The time stamp discrepancy has the potential to seriously affect the evaluation process. The original and adjusted dataset are therefore both included in the evaluation so the impact of the discrepancy can be quantified. Figure B-8 illustrates the calculated difference between the two sources.

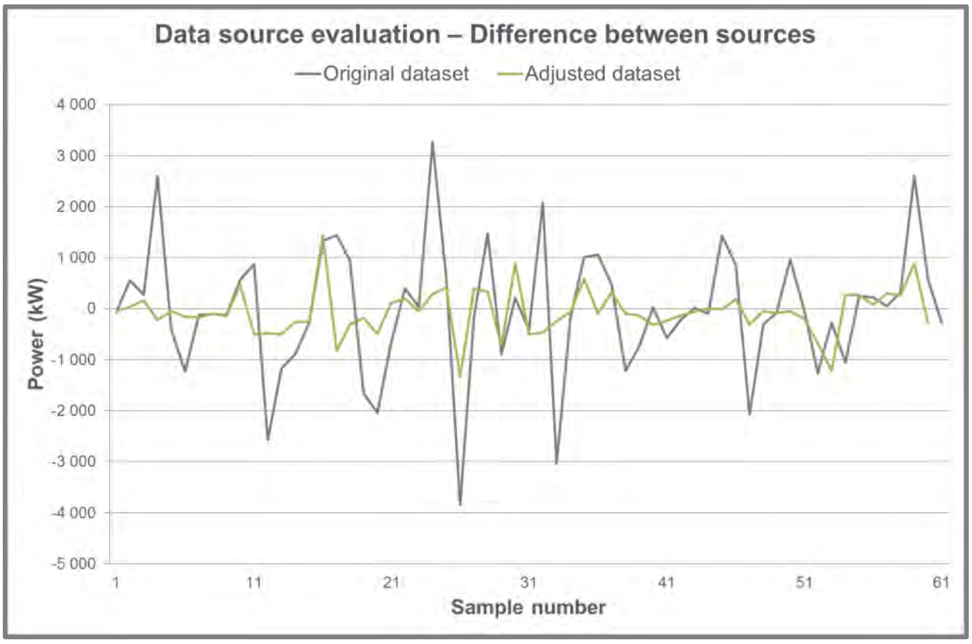

FIGURE B-8: DATA SOURCE EVALUATION – COMPARING PORTABLE METER AND LOG SHEET DATA (RESULTS)

The significant results shown in the comparison highlights the significant impact of the time-offset discrepancy. There are, however, other discrepancies indicated by the comparison. The results are sorted to determine the significance of their impact. Figure B-9 presents the results.

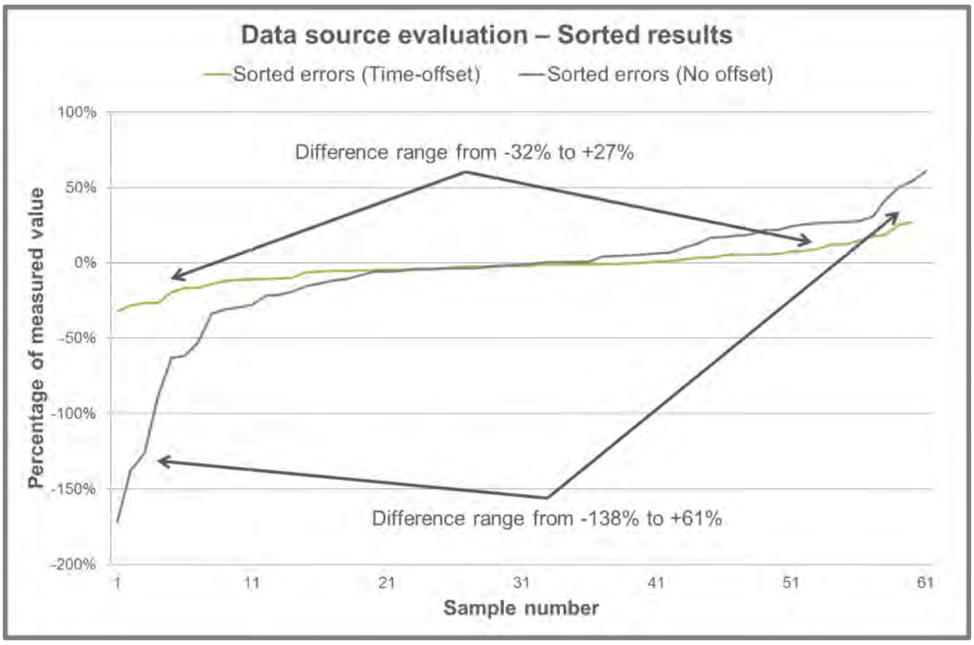

FIGURE B-9: DATA SOURCE EVALUATION – COMPARING PORTABLE METER AND LOG SHEET DATA (SORTED)

The sorted results clearly indicate the significant impact of the time-offset discrepancy. If the discrepancy went unnoticed, the data source would definitely be deemed unusable. Inspection of the adjusted dataset (no time offset) highlights a large discrepancy between the two sources. The gradual distribution of the differences indicates a varied error. Additional inspection of the two sources will be required before the quality of the portable data logger can be confirmed.

Case Study 3 – Evaluating local meter using feeder meter

Case Study 3 uses the evaluation methodology to evaluate a local power meter installed to log the power of an electric motor. The source is evaluated by comparing its measurements to that of a meter situated on the feeder supplying the motor circuit. The datasets are shown in Figure B-10.

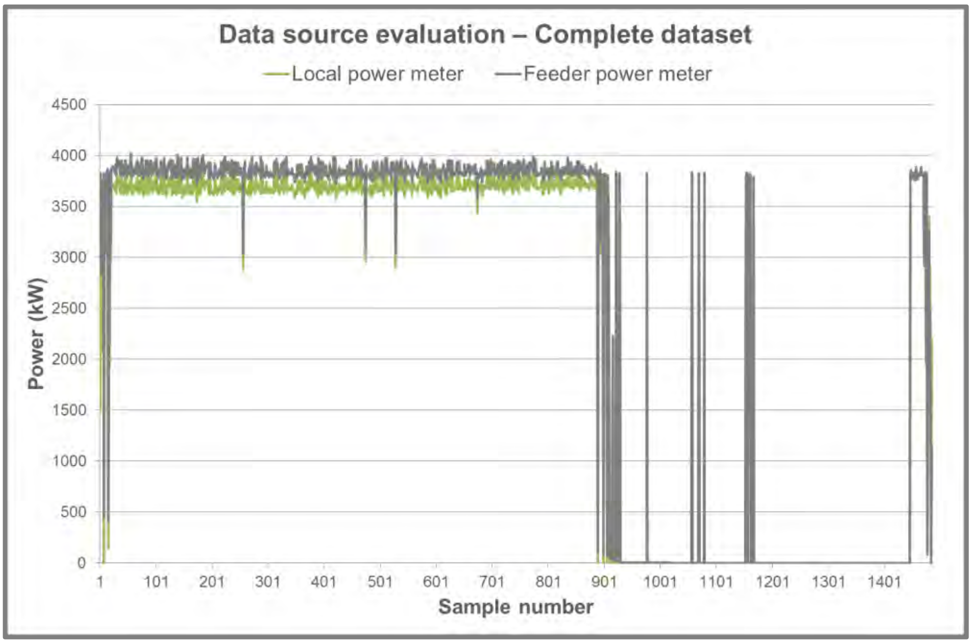

Figure B-10: Data source evaluation – Comparing local and feeder power meter data (full dataset)

Inspection of the complete dataset shows a general discrepancy between the two sources. It seems that the feeder value remains slightly above the local power meter value at all times. Inspection of a subset illustrated in Figure B-11 confirms this.

The difference between the two sources is calculated and sorted. The results in Figure B-12 indicate a minimal difference between the sources with a very small amount of outliers resulting in large discrepancies. The evaluation of the data sources confirms the quality of the local power meter. The general discrepancy between the two sources can be attributed to small users being supplied by the feeder.

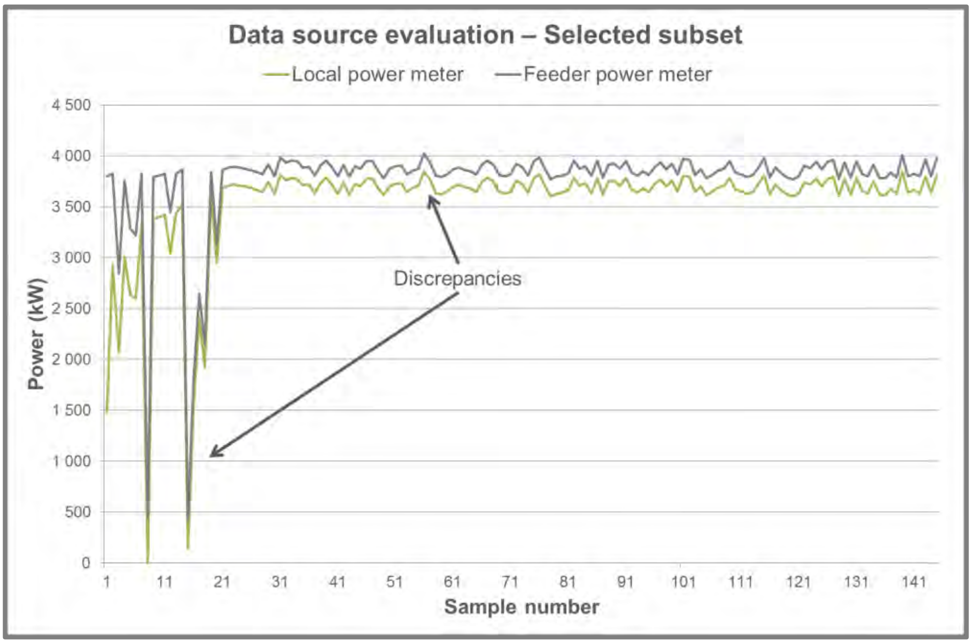

FIGURE B-11: DATA SOURCE EVALUATION – COMPARING LOCAL AND FEEDER POWER METER DATA (DATA SUBSET)

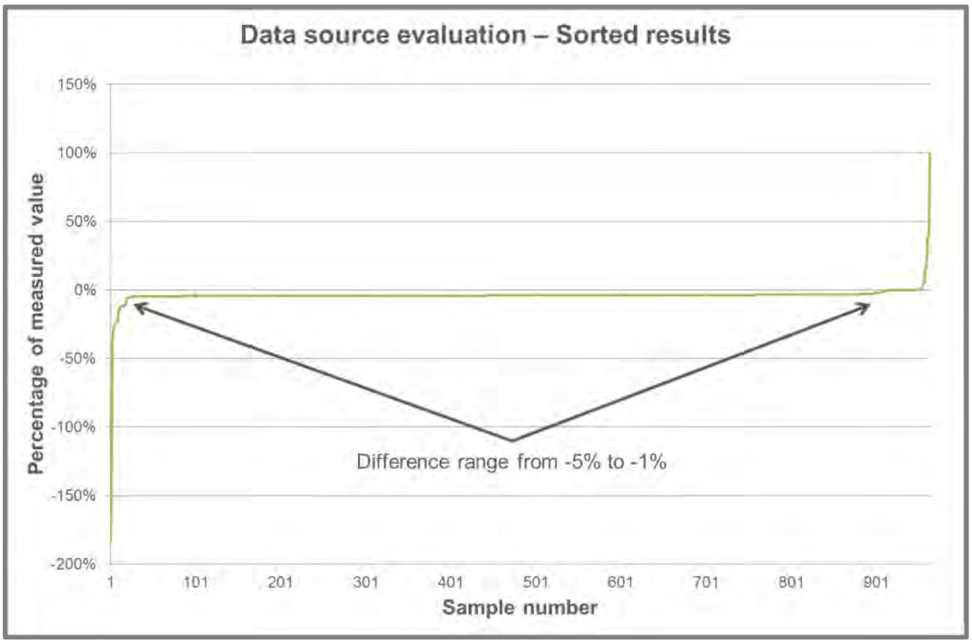

FIGURE B-12: DATA SOURCE EVALUATION – COMPARING LOCAL AND FEEDER POWER METER DATA (SORTED)

CASE STUDY 4 – EVALUATING POWER METER USING BILLING METER

Case Study 4 endeavoured to evaluate the quality of a power meter by comparing it to data obtained from a billing meter. The power meter is situated on a feeder supplying power to a compressor house. The billing meter measures the same supply. Only the totalised monthly consumption figures were available from the billing meter. The power meter measurements therefore had to be processed to reflect total monthly consumption to enable an objective comparison. The low resolution of results required a large data sample to enable a comparison. Figure B-13 illustrates the complete dataset.

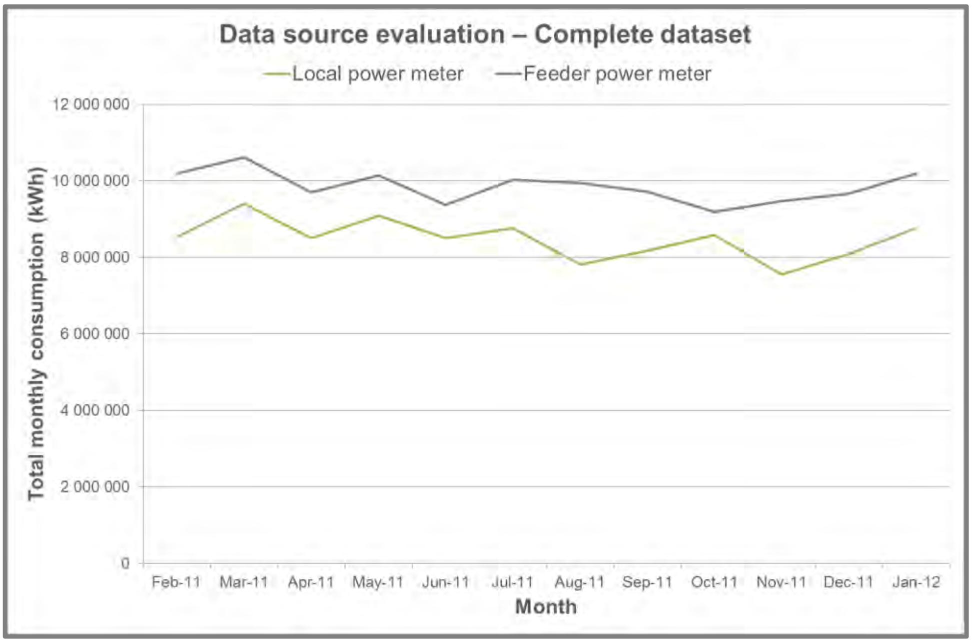

FIGURE B-13: DATA SOURCE EVALUATION – COMPARING LOCAL AND FEEDER POWER METER DATA (MONTHLY DATA)

Inspection of the dataset shows that the two sources followed a similar trend. Comparing the two sources in terms of total monthly consumption makes it difficult to evaluate the difference objectively. This is especially because the rest of the case studies present results in terms of average power consumption. The difference is therefore calculated and presented as an average value to match the rest of the case studies. The results are shown in Figure B-14.

The difference between the two sources fluctuates between 1 000 kW and 3 000 kW (absolute values). The consistent negative values indicate that the billing meter generally reports a higher consumption. The sorted results displayed in Figure B-15 do not indicate a consistent pattern. This together with the low resolution of results and the extended period of data required makes the evaluation of a data source using a billing meter less ideal.

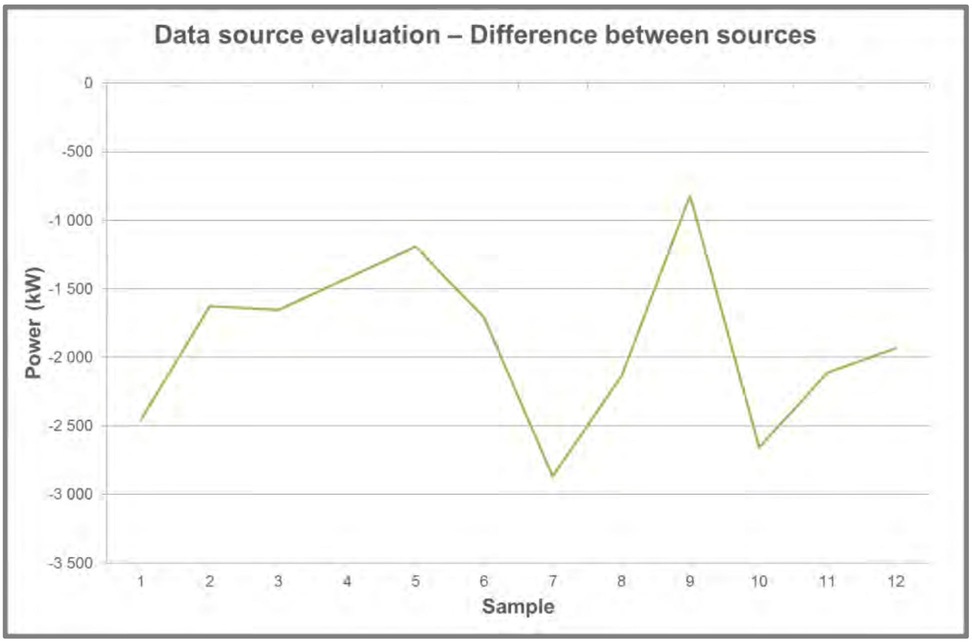

FIGURE B-14: DATA SOURCE EVALUATION – COMPARING LOCAL AND FEEDER POWER METER DATA (RESULTS)

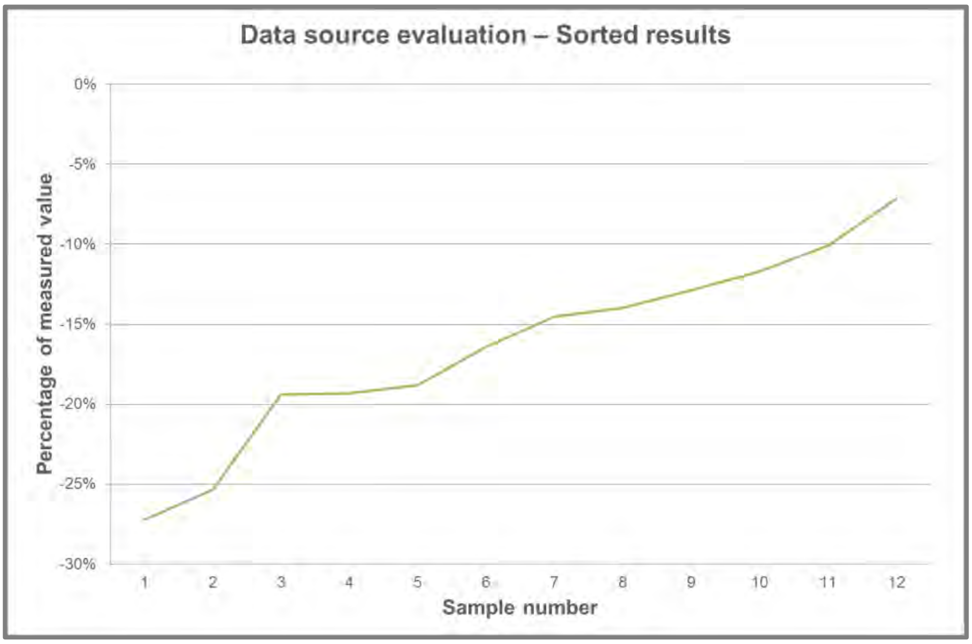

FIGURE B-15: DATA SOURCE EVALUATION – COMPARING LOCAL AND FEEDER POWER METER DATA (SORTED)

Case Study 5 – Evaluating totalised feeders using incomer

Case Study 5 evaluated a set of power meters situated on feeders by comparing their combined power measurements to that of the combined power supplied by the Eskom incomers. If the feeders supply the vast majority of the plant the evaluation will be able to use the Eskom incomers as reference. The complete dataset is displayed in Figure B-16.

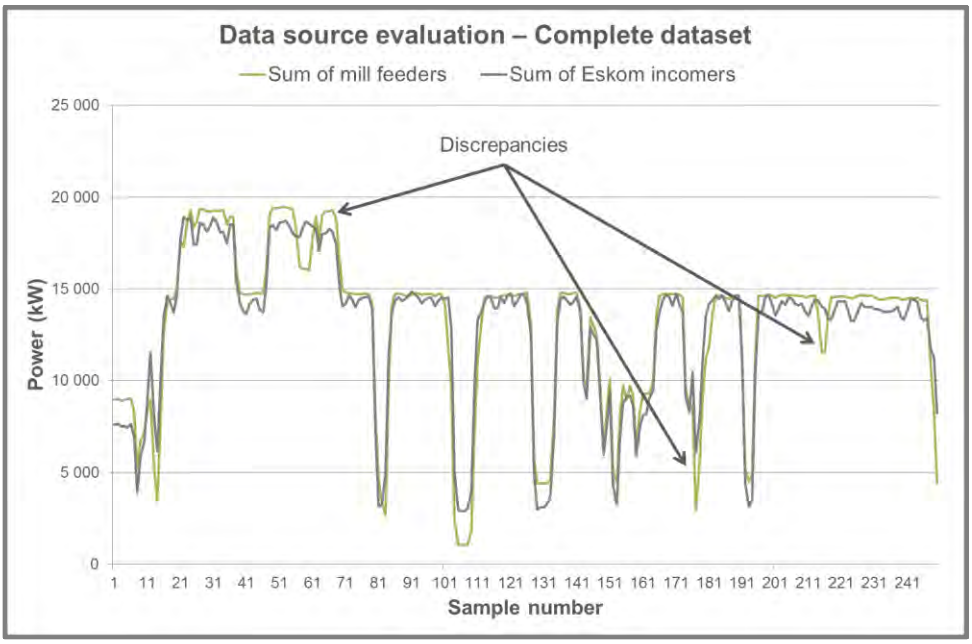

FIGURE B-16: DATA SOURCE EVALUATION – COMPARING FEEDER AND INCOMER DATA (FULL DATASET)

The two sources seem to follow the same trend with some discrepancies occurring. Figure B-17 illustrates the calculated difference between the two sources.

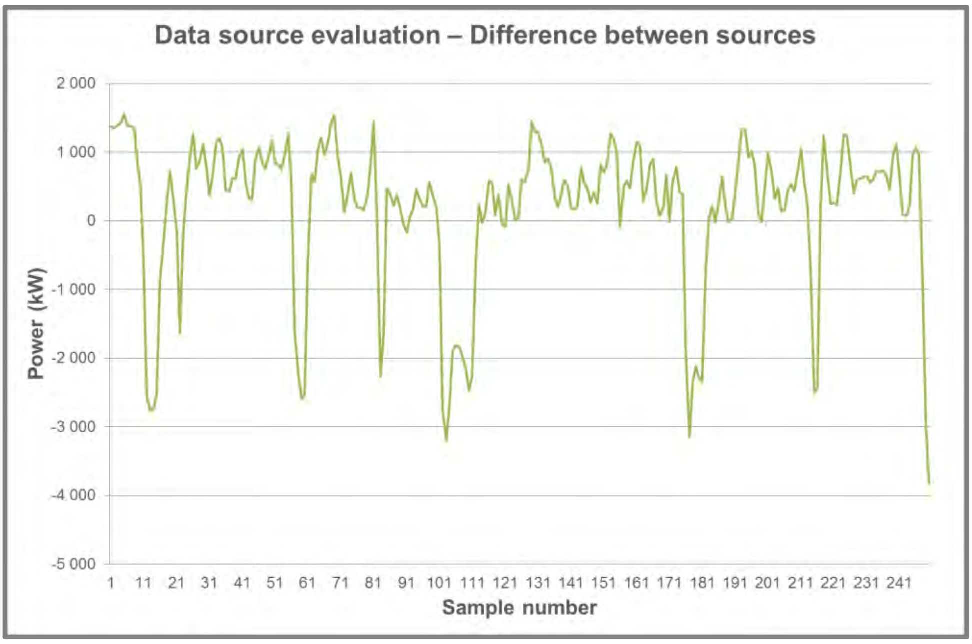

FIGURE B-17: DATA SOURCE EVALUATION – COMPARING FEEDER AND INCOMER DATA (RESULTS)

The calculated difference between the two sources indicates that the majority of results are positive with negative spikes of significant magnitude occurring intermittently. The positive values indicate that the sum of the feeders generally exceeds the sum of the incomers. The large negative spikes either indicate metering malfunction, or the presence of additional consumers unaccounted for by the feeders.

The calculated results are sorted and displayed in Figure B-18. The general difference between the two sources shows that the assumption of a balanced feeder usage and incomer supply is feasible for the majority of the time. The outliers indicated in the rest of the figure do, however, indicate the presence of either metering malfunction or unaccounted users and suppliers.

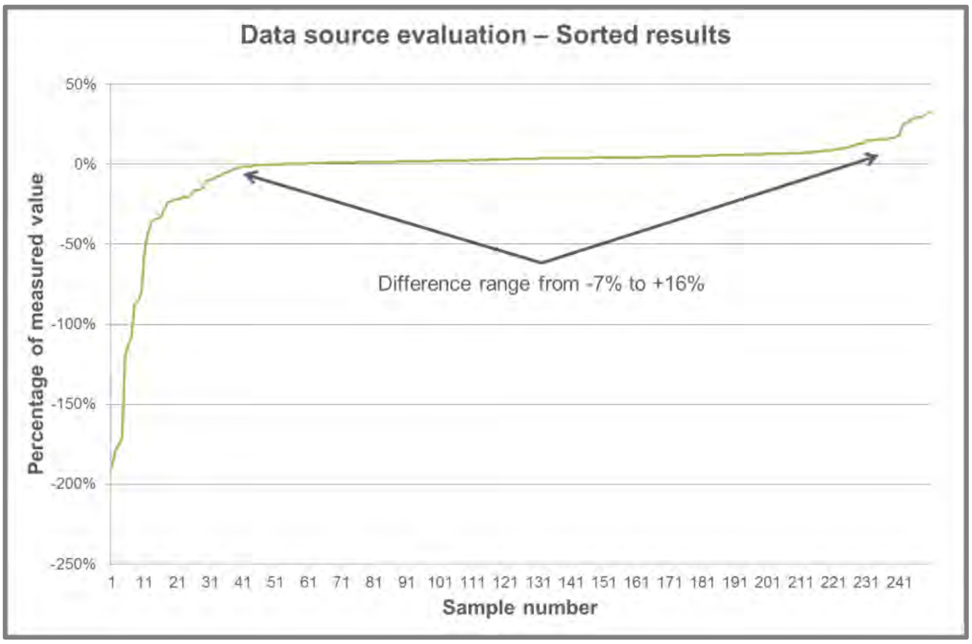

FIGURE B-18: DATA SOURCE EVALUATION – COMPARING FEEDER AND INCOMER DATA (SORTED)

CASE STUDY 6 – DATASET EVALUATION: IDENTIFYING VOLTAGE DIP

Case Study 6 used the dataset evaluation methodology to evaluate a dataset obtained from a power logger. Figure B-19 illustrates the logged power consumption. A brief examination of the power profile does not indicate the presence of any major abnormalities except for the occurrence of few brief data spikes.

The same process is repeated for the phase currents that were used to calculate the logged power values. The logged phase current values are shown in Figure B-20. The logged values are shown to remain within the selected bounds. The data spike originally identified in the power consumption profile are also found in the current profiles indicating that a spikes in the measured current resulted in the power spikes.

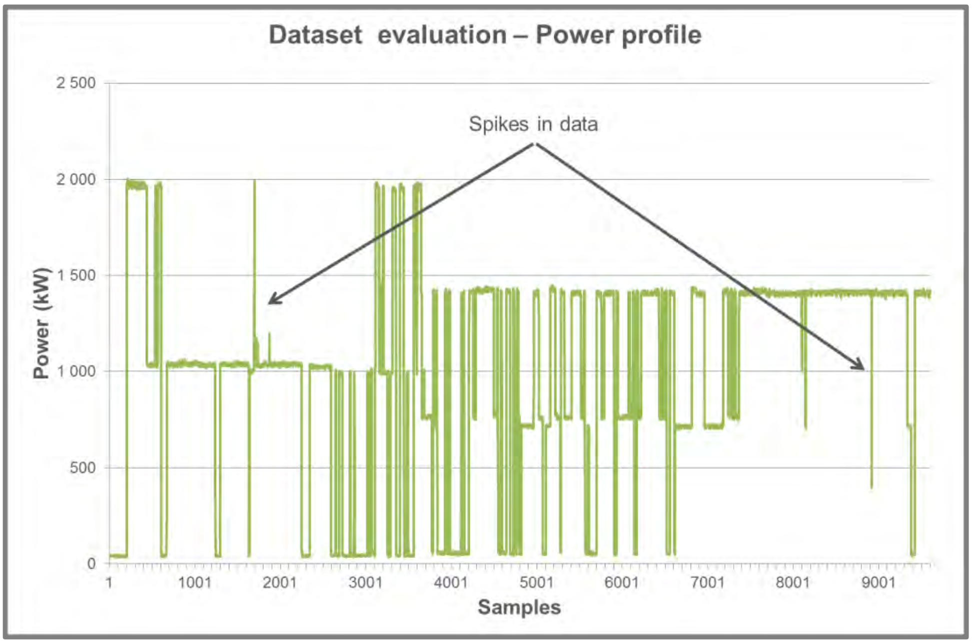

FIGURE B-19: DATA SOURCE EVALUATION – POWER PROFILE EVALUATION

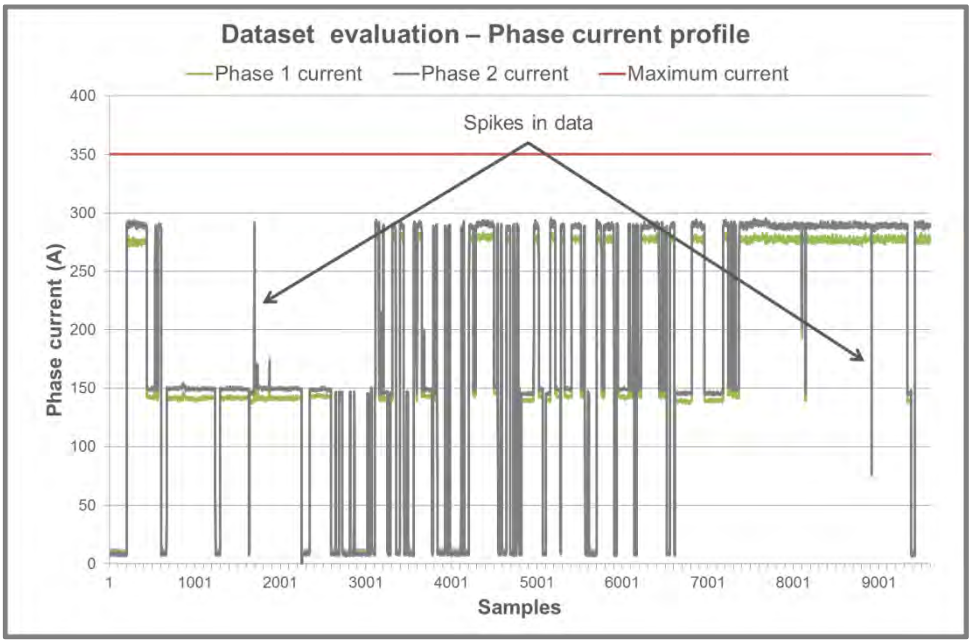

FIGURE B-20: DATA SOURCE EVALUATION – CURRENT PROFILE EVALUATION

The last set of evaluated data is the logged voltage profiles. Visual inspection of Figure B-21 immediately identifies a dip in the Phase 2 voltage. This dip falls outside the minimum allowable voltage, thereby indicating a potential problem with either the meter or the supply. Reinspection of the power profile now indicates the significant effect of the voltage dip that would usually have gone by unnoticed.

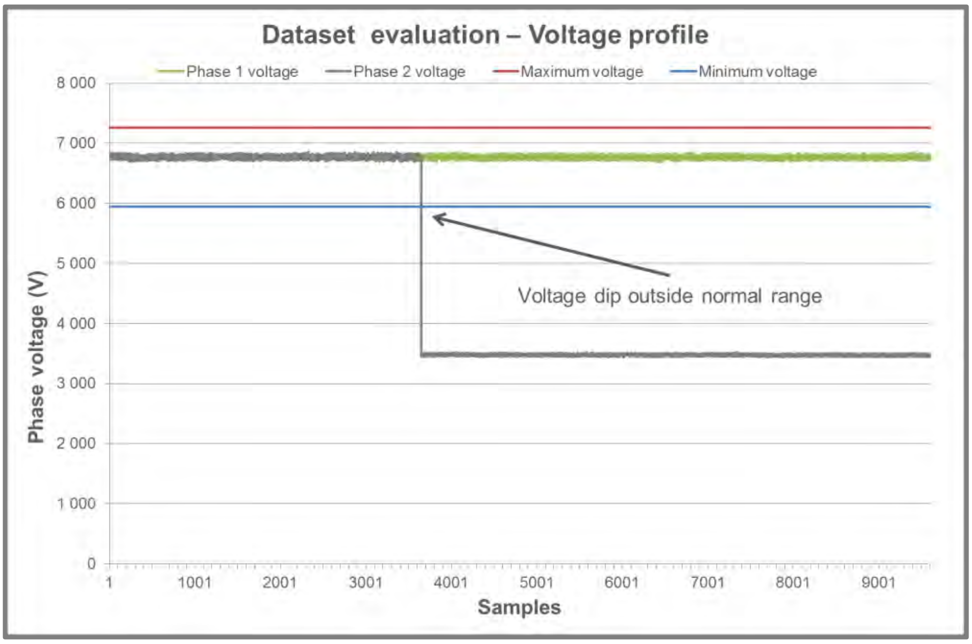

Figure B-21: Data source evaluation – Voltage profile evaluation

Case Study 7 – Dataset evaluation: Identifying multiple abnormalities

Case Study 7 evaluates data recorded by a portable power meter. Figure B-22 illustrates the logged power profile. A maximum limit of 480 kW is added as this is the installed capacity of the measured motor. The minimum limit is set as zero and therefore not displayed. Visual analysis of the data shows that the maximum limit is never exceeded. Only a few data spikes are observed.

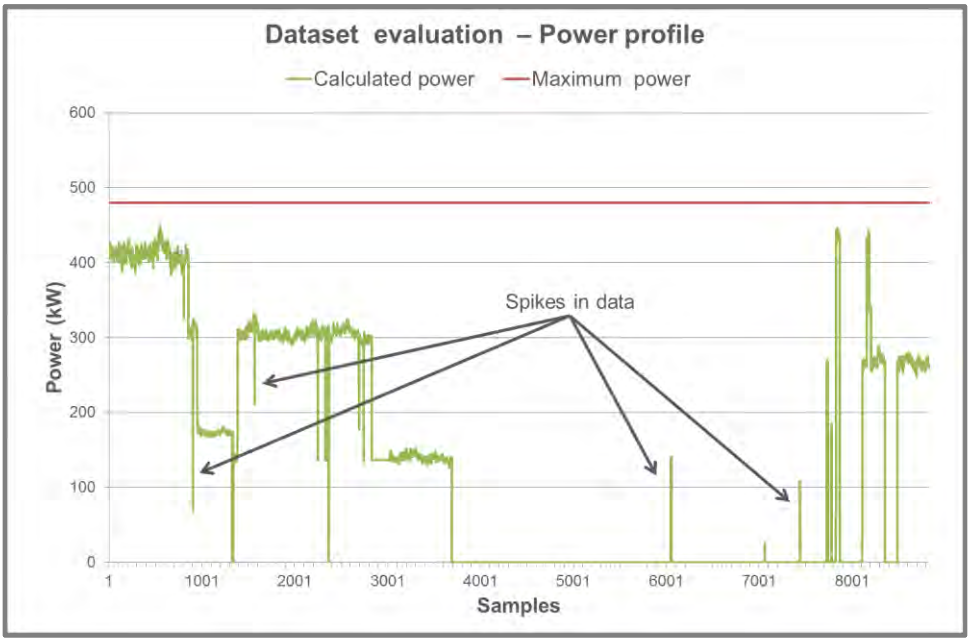

Figure B-22: Dataset evaluation – Power profile evaluation

The logged data is further analysed by inspecting the voltage and current measurements. The logged voltage measurements are displayed in Figure B-23. The only suspicious components identified are some data spikes and a very short period of constant values being logged.

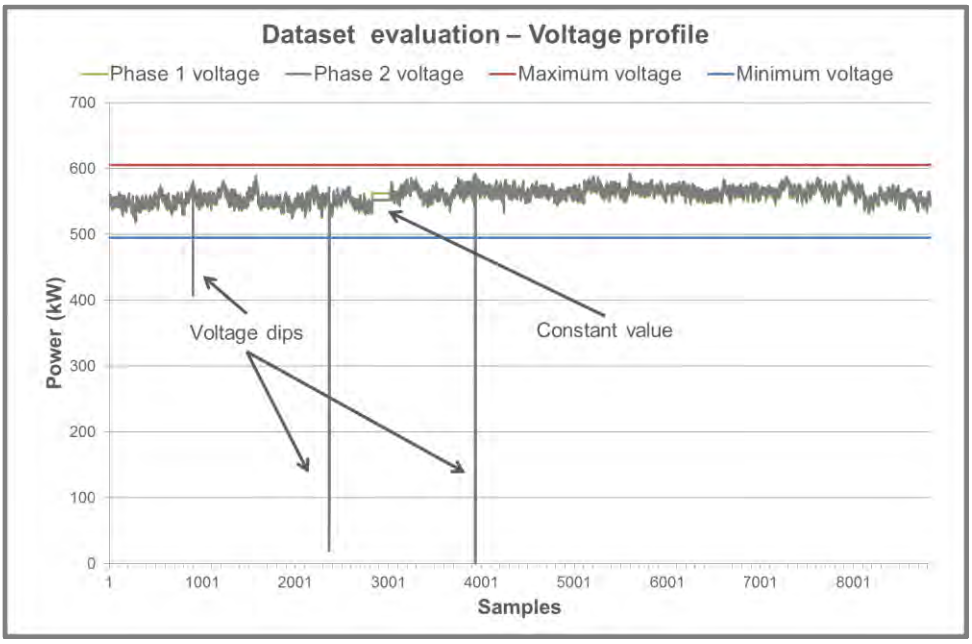

FIGURE B-23: DATASET EVALUATION – VOLTAGE PROFILE EVALUATION

The logged current profile is displayed in Figure B-24. Visual inspection of the results immediately indicates the presence of several issues. The first identified issue is the complete loss of values for the Phase 1 current. The second issue is that the Phase 2 values become constant at the same point where the Phase 1 data loss occurs. The last issue is the occurrence of significant data spikes in the Phase 1 current dataset.

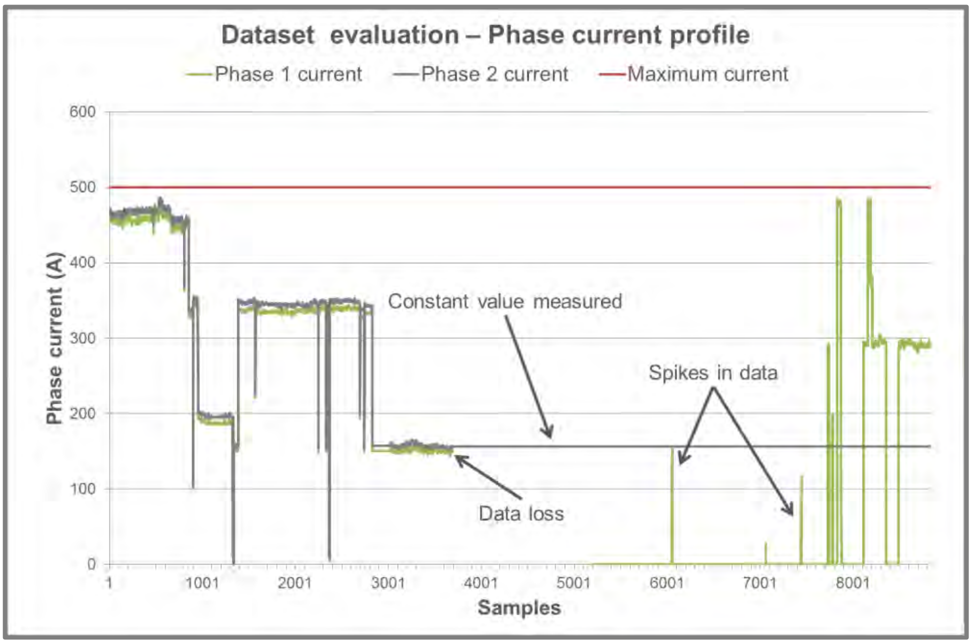

FIGURE B-24: DATASET EVALUATION – CURRENT PROFILE EVALUATION

Case Study 8 – Dataset evaluation: Identifying constant values

Case Study 8 investigates a dataset consisting of only power data. The absence of voltage and current data requires the power profile to be evaluated in more detail. The dataset is displayed in Figure B-25. Inspection of the profile indicates the occurrence of two significant data spikes with a section containing a constant value. The constant value is of the same magnitude as the rest of the measurements and will as a result bias calculations without resulting in any obvious discrepancies. This highlights the importance of evaluating data quality before using the data in any calculations.

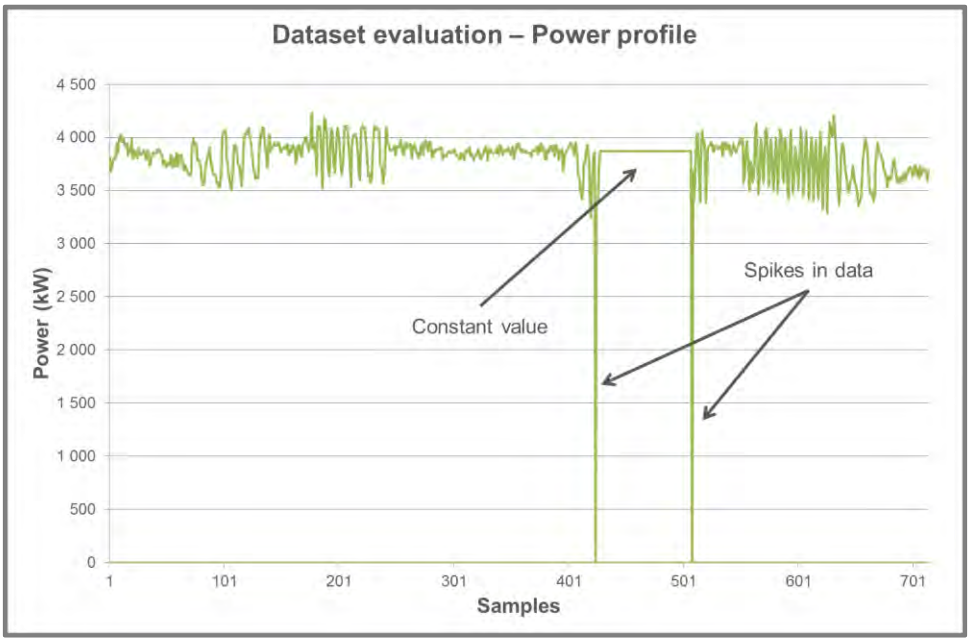

FIGURE B-25: DATASET EVALUATION – POWER PROFILE EVALUATION

Case Study 9 – Dataset evaluation: Identifying a data spike

The data collected for Case Study 9 also only consists of power data. The results are shown in Figure B-26. A brief inspection of the data immediately reveals a massive data spike. The spike has a relative short duration, but the significant amplitude will definitely affect subsequent calculations.

Further inspection shows that almost half of the dataset indicates that no power was consumed during the latter part of the sample period. The irregular use combined with the data spike and large set of zero data will require that the data source be evaluated to ensure that the logged measurements are correct.

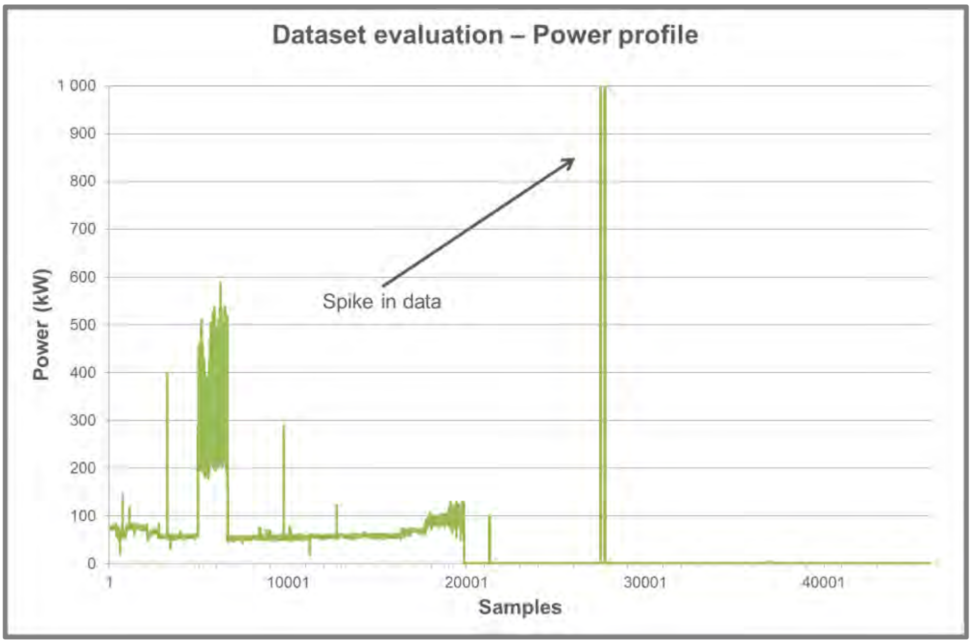

FIGURE B-26: DATASET EVALUATION – POWER PROFILE EVALUATION

CASE STUDY 10 – DATASET SELECTION: IDENTIFYING ABNORMAL OPERATION

Case Study 10 presents a power profile of a pumping system. It can be assumed that the data source and dataset quality has been evaluated. The power profile presented in Figure B-27 can now be processed to investigate the different operational modes of the system.

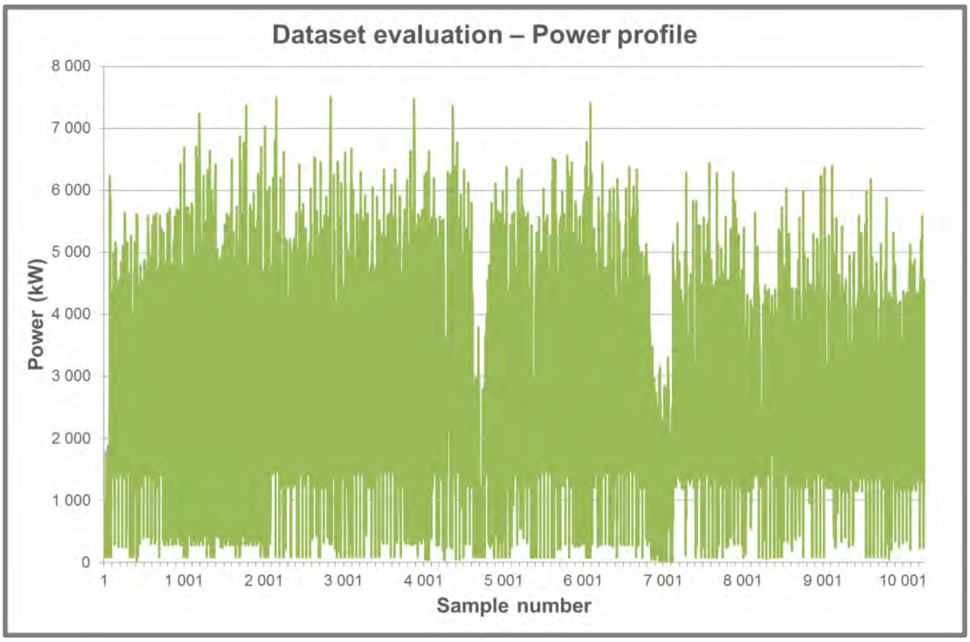

FIGURE B-27: DATASET EVALUATION – POWER PROFILE EVALUATION

Figure B-28 illustrates the average consumption for each month included in the dataset. Inspection of the average profiles does not indicate any significant changes in operation. The next step is to determine the average 24-hour weekday profile for each month.

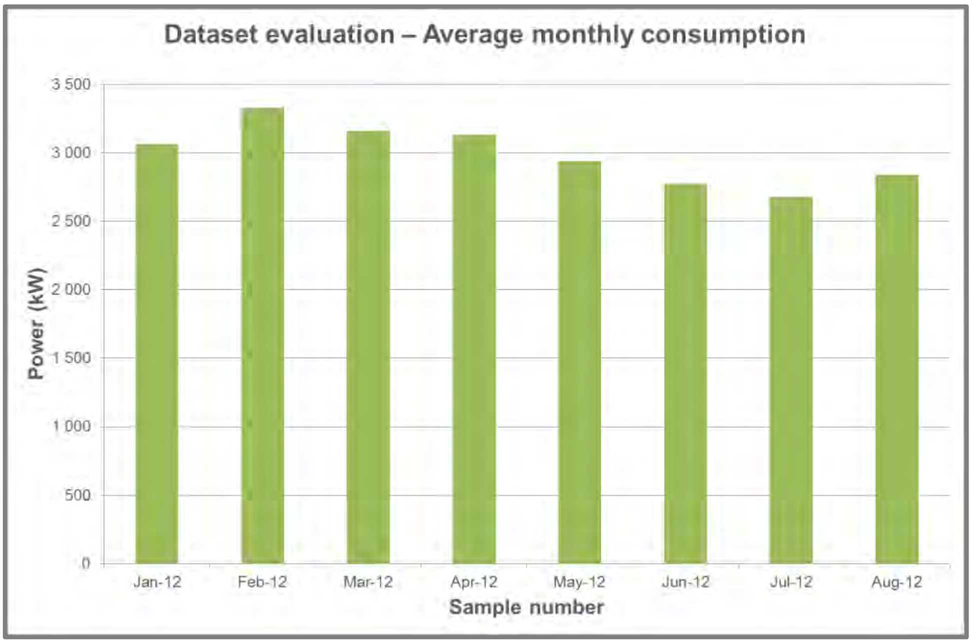

FIGURE B-28: DATASET EVALUATION – AVERAGE MONTHLY CONSUMPTION EVALUATION

Figure B-29 illustrates the average weekday profile of each month included in the dataset. Inspection of the results indicates the occurrence of one abnormal profile. The relevant month can now be inspected in more detail.

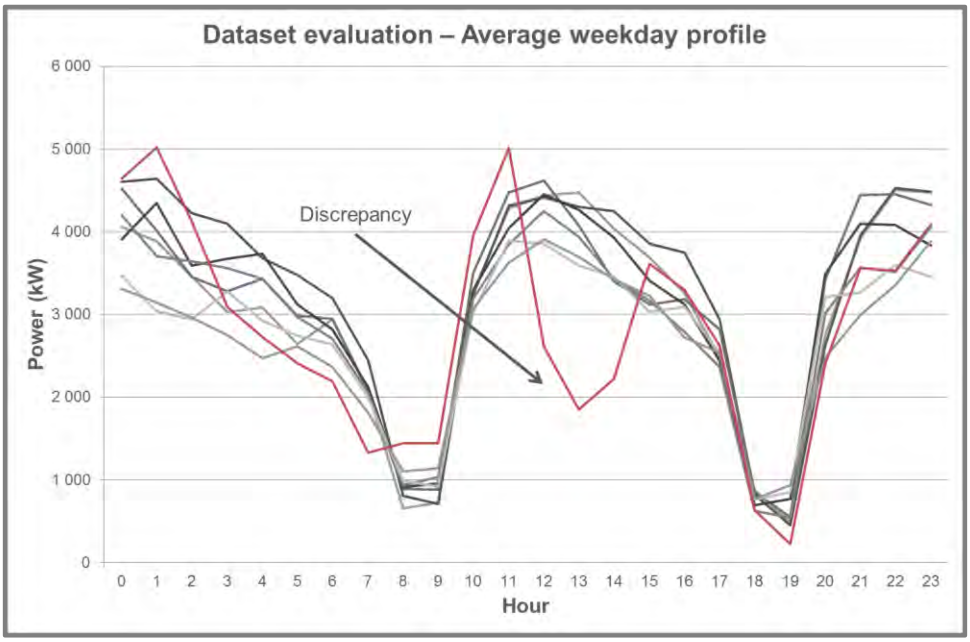

FIGURE B-29: DATASET EVALUATION – MONTHLY CONSUMPTION PROFILE EVALUATION

Case Study 11 – Dataset selection: Identifying a complete dataset

Case Study 11 illustrates the application of the dataset selection guideline. Figure B-30 illustrates the complete dataset collected to develop a baseline model. Inspection of the dataset shows that high-resolution power data is available for a span of almost two years. The figure, however, shows that other system variables namely, pressure and flow are not always available. The average pressure is intermittently available while a usable set of flow data occurs only once in the two-year stretch.

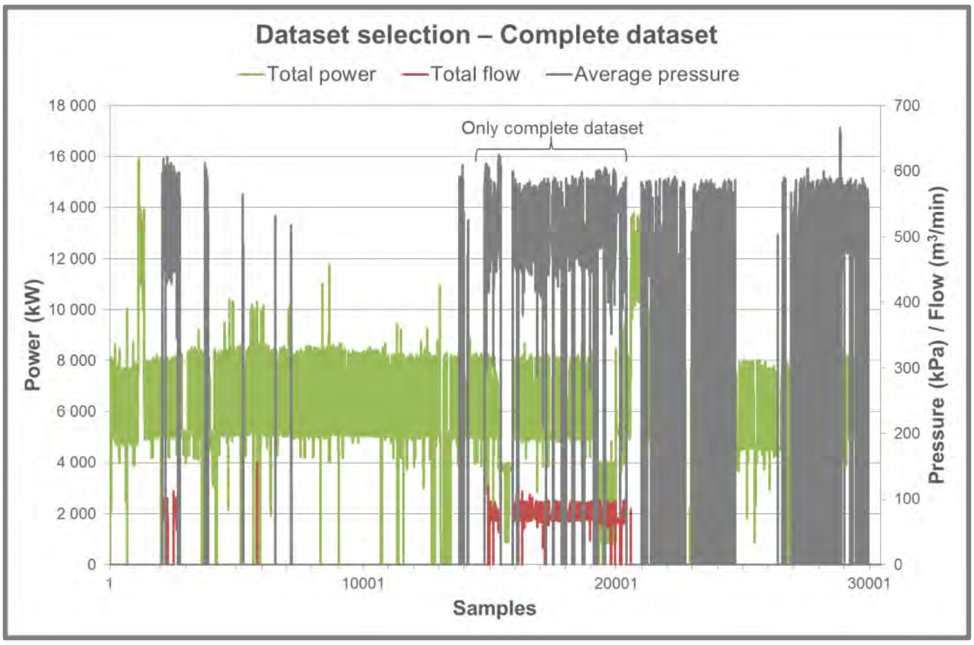

Figure B-30: Dataset selection – Data availability evaluation

The availability of data severely limits available options when developing a baseline model. The large set of electrical data will make it possible to develop and evaluate several energy-based baselines. However, if a regression baseline model is required the availability of variable data will severely limit the usable dataset.

Case Study 12 – Dataset selection: Identifying seasonal cycle (fridge plant)

Case Study 12 investigates the dataset selection to incorporate the seasonal cycles of a mining fridge plant. Data depicting the total consumption of the refrigeration system was collected and processed to illustrate the average monthly power consumption. Figure B-31 illustrates the results. The figure clearly illustrates the occurrence of two seasons (summer and winter) separated by transition phases.

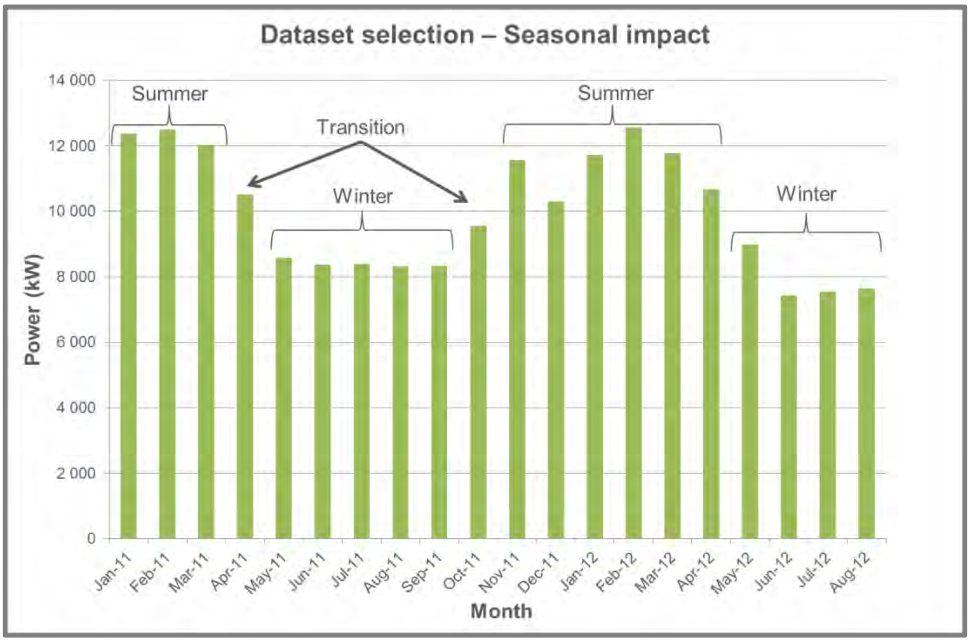

FIGURE B-31: DATASET SELECTION – AVERAGE MONTHLY CONSUMPTION (SEASONAL IMPACT)

The total power consumption of the system identifies a seasonal component. Figure B-32 illustrates the total power consumption of the system in terms of the different users. The details in Figure B-32 indicate that only the surface cooling system is seasonally dependent.

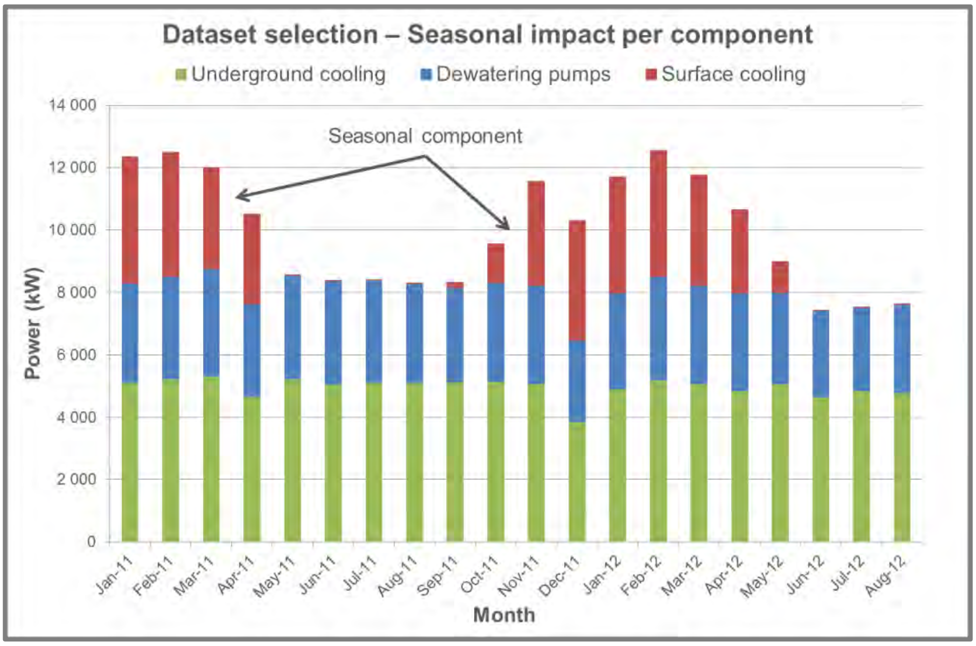

FIGURE B-32: DATASET SELECTION – AVERAGE COMPONENT CONSUMPTION (SEASONAL IMPACT)

Inspection of the dataset revealed a seasonal impact on the surface plants. This distinguishes the surface plant from the rest of the refrigeration system. The underground cooling and dewatering pumps can each be modelled using a single baseline. The surface plants will, however, require at least two baseline models (summer and winter) as well as a structured approach on how to handle the transitional phases.

Case Study 13 – Dataset selection: Identifying operational profiles (pumping)

Case Study 13 illustrates the process of evaluating different modes of operation in order to select a suitable dataset. Figure B-33 illustrates the average monthly power consumption of the system. The results illustrate a variance in average power consumption with no discernable pattern.

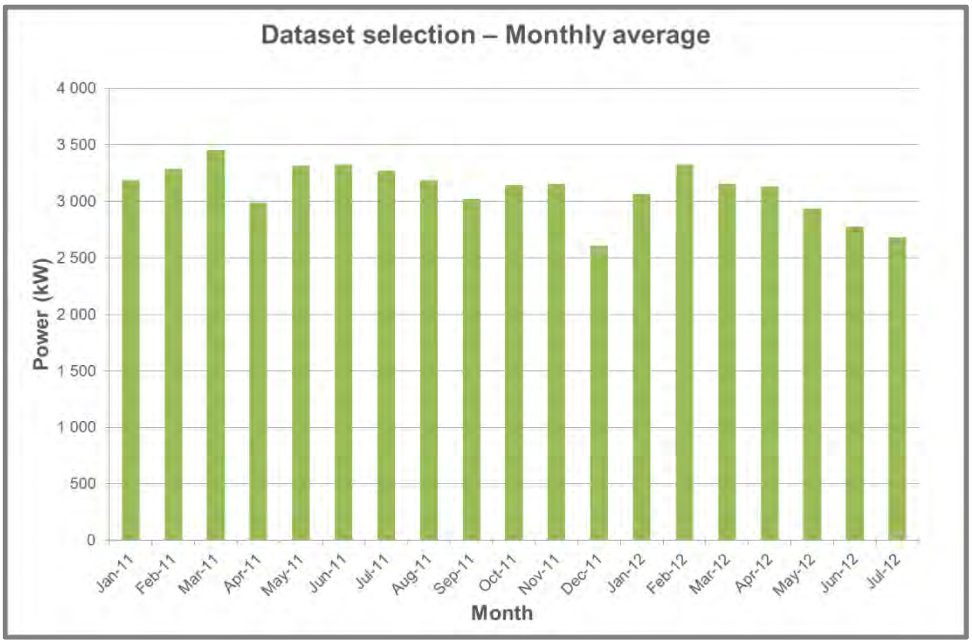

FIGURE B-33: DATASET SELECTION – AVERAGE MONTHLY CONSUMPTION (NO CYCLIC OPERATION)

The dataset is further processes to determine the average 24-hour weekday profile for each month included in the dataset. The results are shown in Figure B-34.

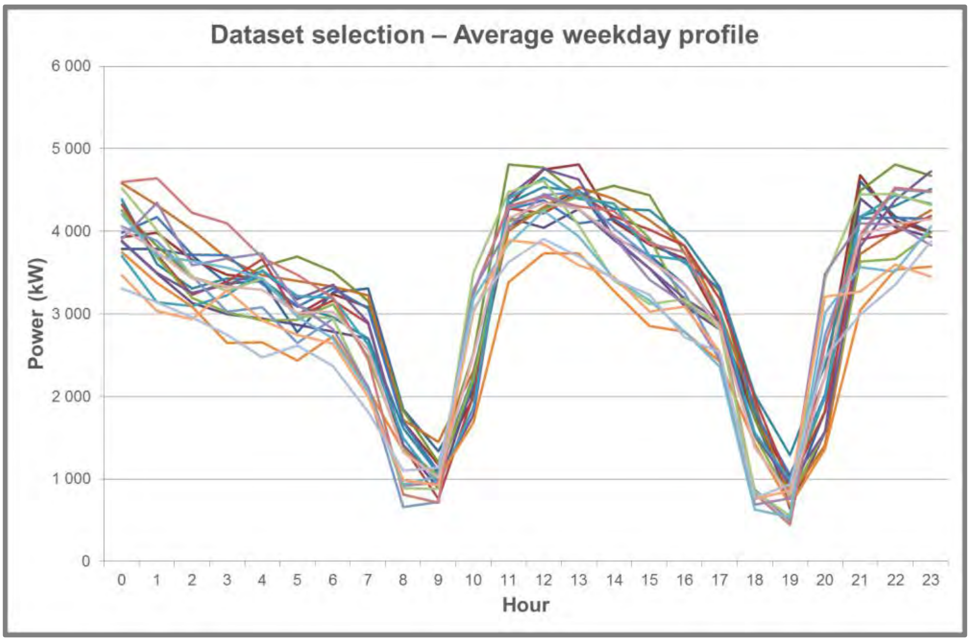

FIGURE B-34: DATASET SELECTION – AVERAGE MONTHLY PROFILE EVALUATION

The average weekly profiles seem to follow the same trend. The variance in average monthly power affects the average amplitude of the profiles. The profiles are therefore normalised to enable an objective comparison. The results are shown in Figure B-35. The normalised comparison shows that the system always follows the same operational profile. The significance is that any selection made from the dataset will result in a similar baseline model.

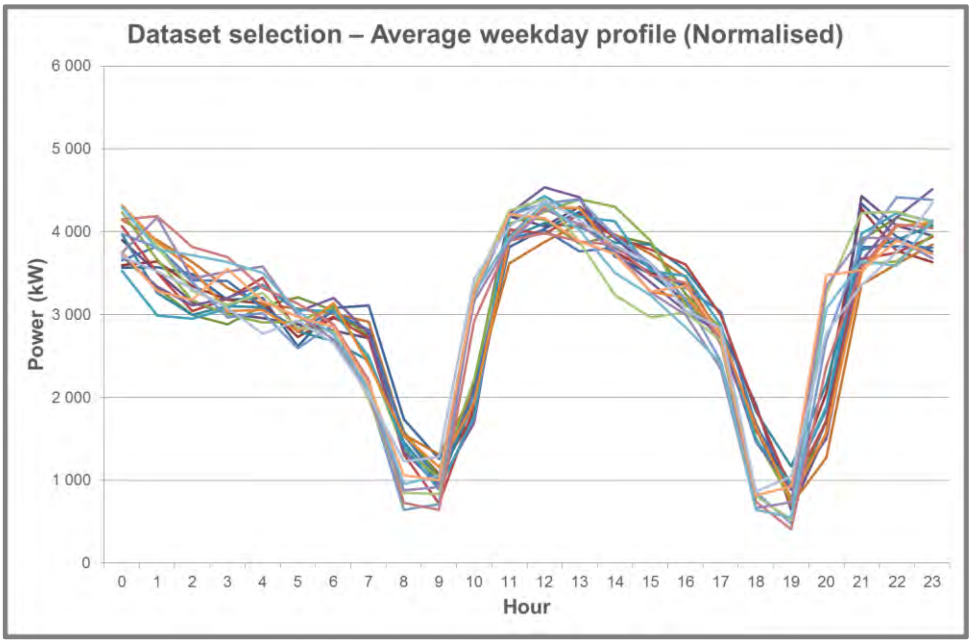

FIGURE B-35: DATASET SELECTION – AVERAGE MONTHLY PROFILE EVALUATION (NORMALISED)

CASE STUDY 14 – DATASET SELECTION: IDENTIFYING OPERATIONAL PROFILES (COMPRESSED AIR)

Case Study 14 follows the same process of dataset selection as illustrated in Case Study 13. The major difference is that the system inspected in Case Study 14 is a compressed air system. Figure B-36 presents the average monthly power consumption. Inspection of the results indicate variance, but with no identifiable pattern.

The dataset is processed to determine the average 24-hour weekday profile for each month in the dataset. Figure B-37 illustrates the results. Inspection of the profiles shows that the December weekday profile is significantly lower than the rest of the group. This corresponds with the average power consumption shown in Figure B-36.

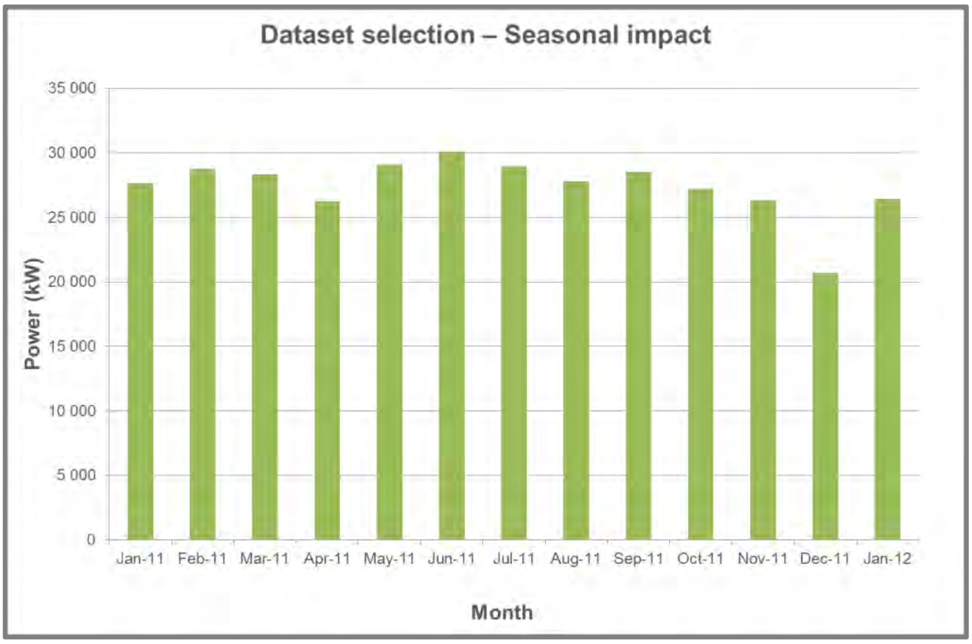

Figure B-36: Dataset selection – Average monthly consumption (No cyclic operation)

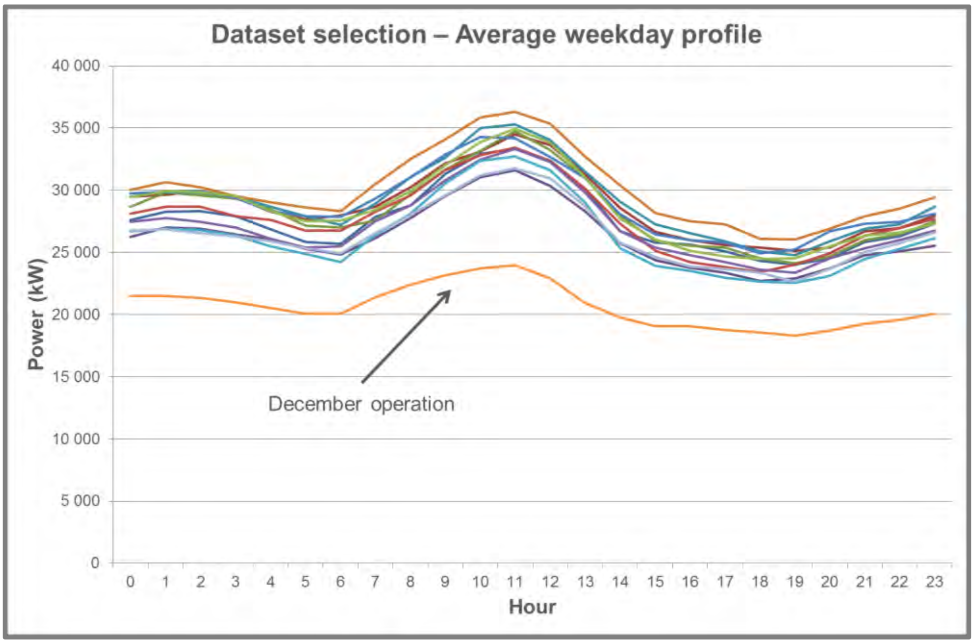

Figure B-37: Dataset selection – Average monthly profile evaluation

The weekday profiles are normalised to simplify the evaluation of the profile shape. The results are shown in Figure B-38. Inspection of the results indicates that the compressed air system (similar to the pumping system) follows the same operational profile throughout the year. It is therefore possible to use any of the months as baseline dataset.

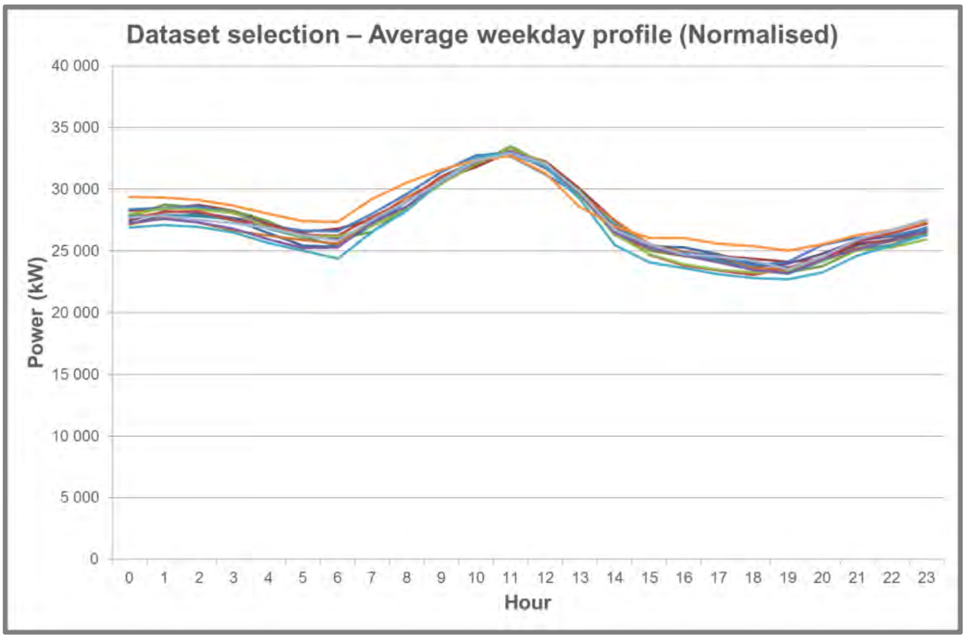

FIGURE B-38: DATASET SELECTION –AVERAGE MONTHLY PROFILE EVALUATION (NORMALISED)

CASE STUDY 15 – DATASET SELECTION: IDENTIFYING OPERATIONAL PROFILES (MATERIAL PROCESSING)

Case Study 15 illustrates the operation of a cement plant. The average monthly power consumption illustrated in Figure B-39 shows a significant variance in monthly power consumption. It is, however, not possible to determine any operational cycle that would account for the changes in monthly power consumption.

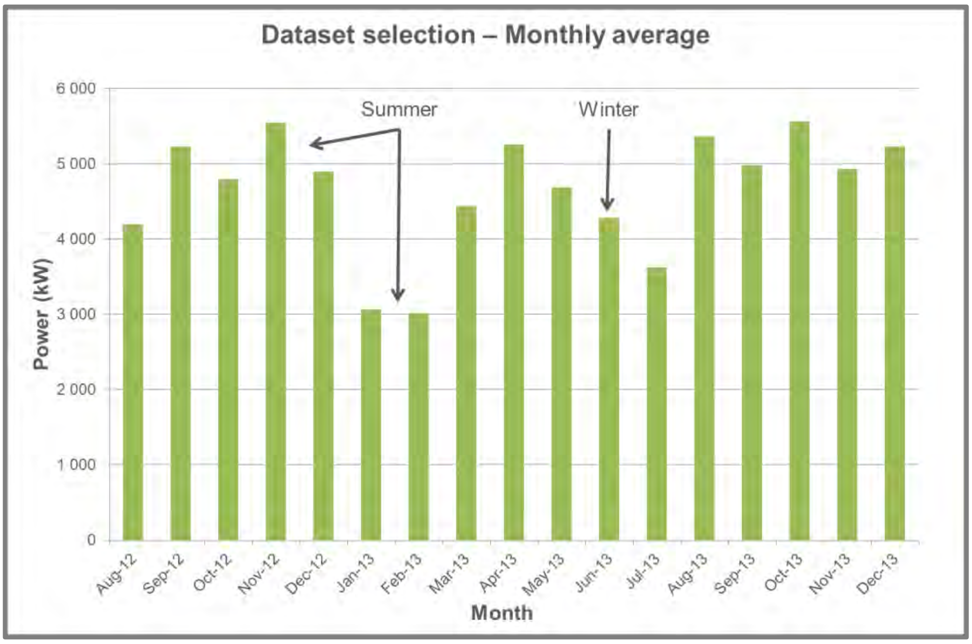

FIGURE B-39: DATASET SELECTION – AVERAGE MONTHLY CONSUMPTION (VARIED OPERATION)

The dataset was processed further to determine the average 24-hour weekday profile for every month in the dataset. Figure B-40 illustrates the results. The profiles indicate various different modes of operation. Attempts to normalise the profiles did not aid the process of determining the different operational modes.

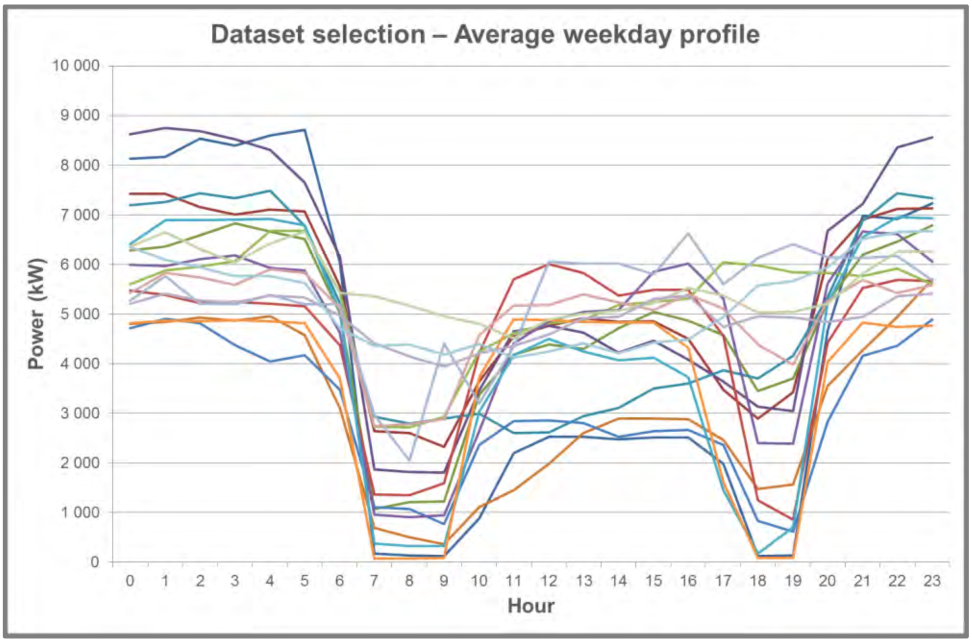

FIGURE B-40: DATASET SELECTION – AVERAGE MONTHLY PROFILE EVALUATION

The calculated profiles were further processed to enable a normalised comparison indicating different operational modes. This was done by calculating a ratio representing the relationship between the Eskom evening peak and the average profile power consumption. Figure B-41 illustrates the results.

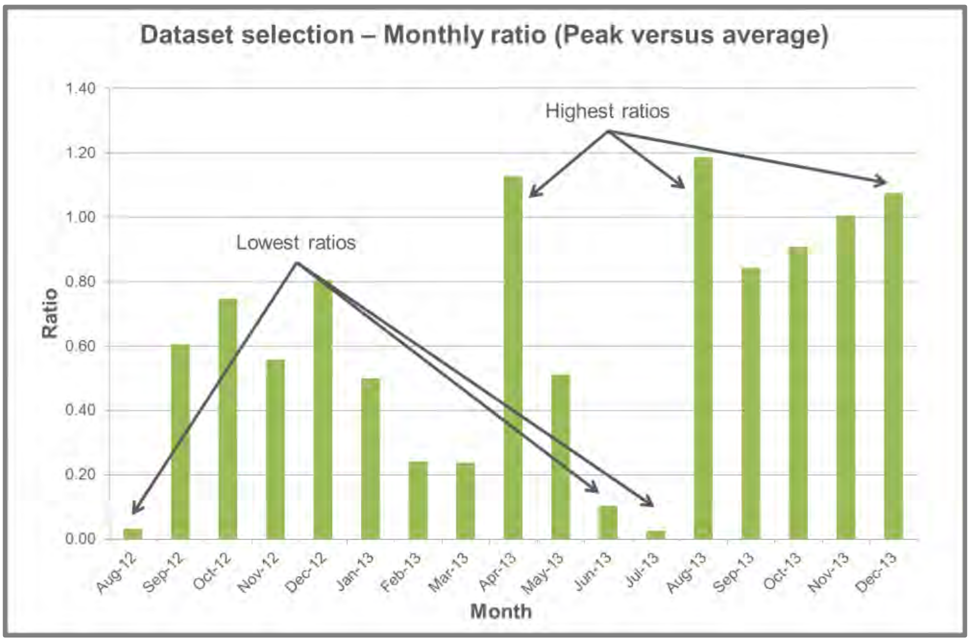

FIGURE B-41: DATASET SELECTION – MONTHLY RATIO EVALUATION

Inspection of the results enables the lowest and highest ratios to be identified. Figure B-42 illustrates the three profiles with the lowest ratios while Figure B-43 illustrates the figures with the highest profiles. The two figures illustrate two different strategies of plant operation.

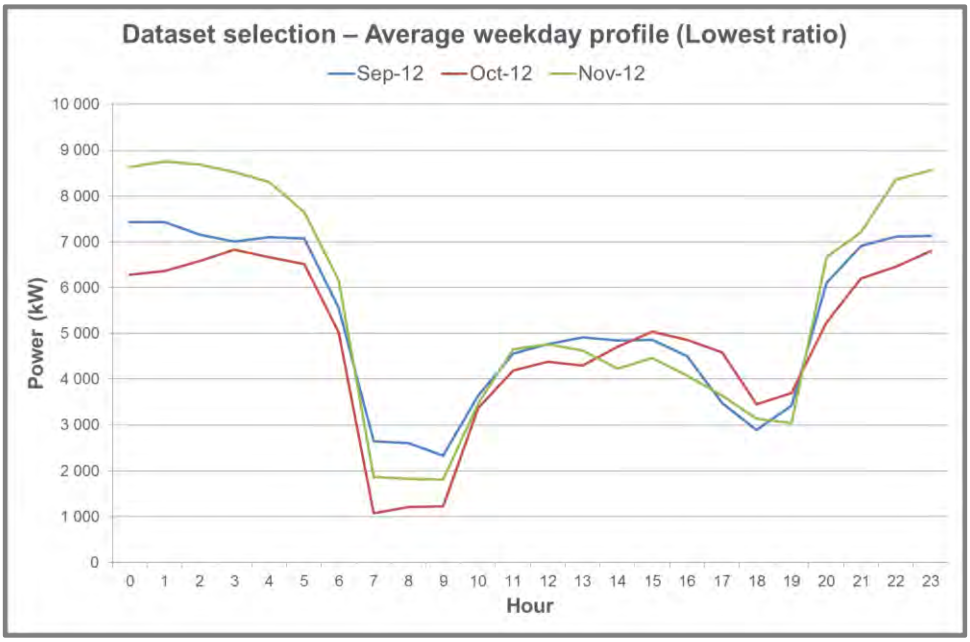

FIGURE B-42: DATASET SELECTION – AVERAGE MONTHLY PROFILE (LOWEST RATIO)

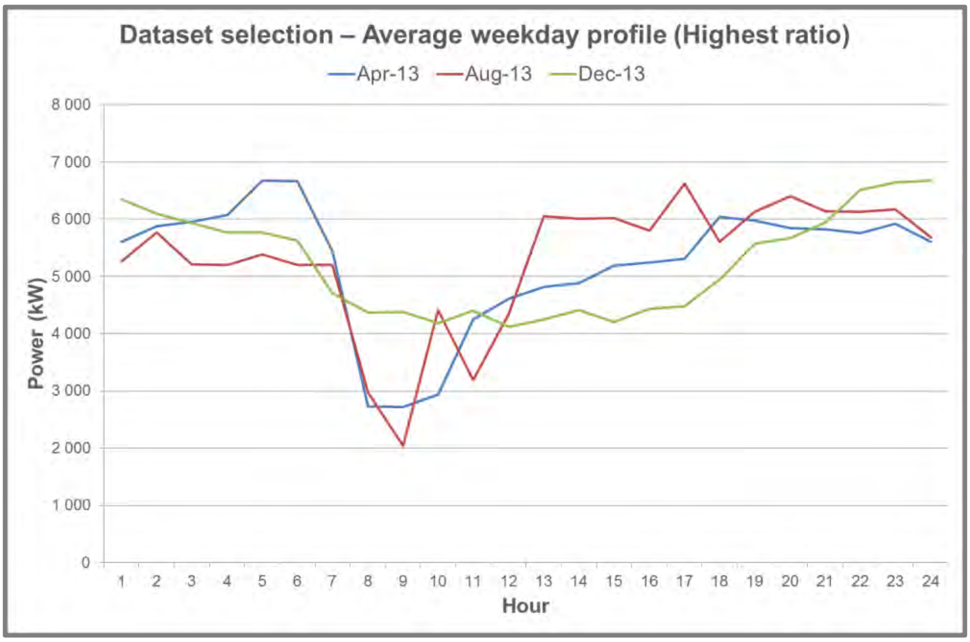

FIGURE B-43: DATASET SELECTION – AVERAGE MONTHLY PROFILE (LOWEST RATIO)

Figure B-44 illustrates the average profiles depicting two different modes of system operation. The process followed to identify these two different strategies also identified which datasets to use to model each of these strategies. The project stakeholders can now decide on the relevant system operation to model.

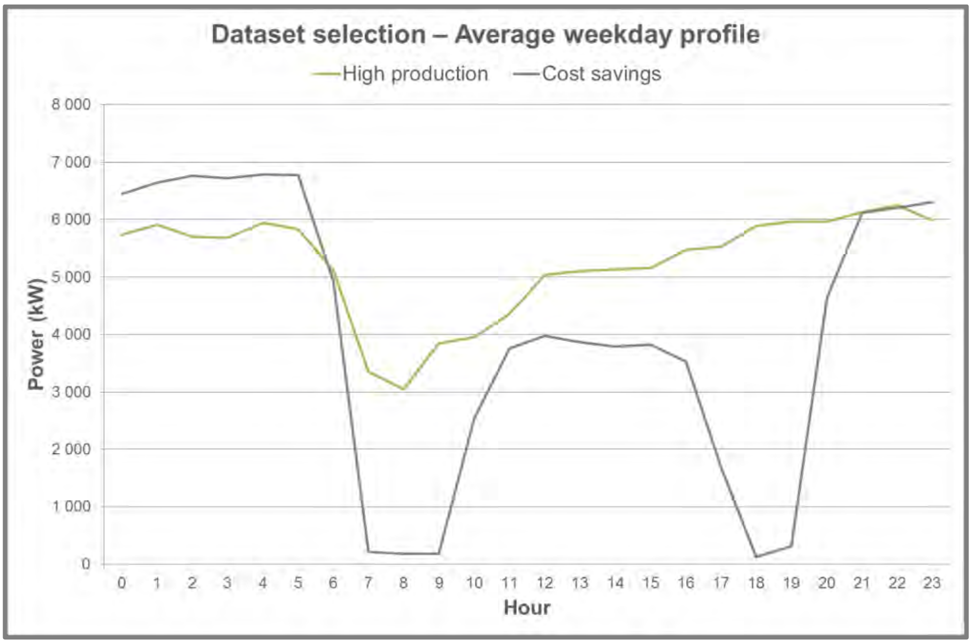

FIGURE B-44: DATASET SELECTION – AVERAGE WEEKDAY PROFILES (DIFFERENT MODES)

Appendix
C

MEASUREMENT AND VERIFICATION OF
INDUSTRIAL DSM PROJECTS

APPENDIX C

INDUSTRIAL CASE STUDIES –
BASELINE MODEL DEVELOPMENT AND EVALUATION

APPENDIX C: BASELINE MODEL DEVELOPMENT AND EVALUATION

CASE STUDY 16 – CONSTANT BASELINE MODEL FOR SURFACE AND UNDERGROUND REFRIGERATION PLANTS

Case Study 16 presents the baseline development of two fridge plants. No variable data was available at the start of the project so only power data could be used to develop a baseline. Figure C-1 illustrates the average power consumption of the underground plant.

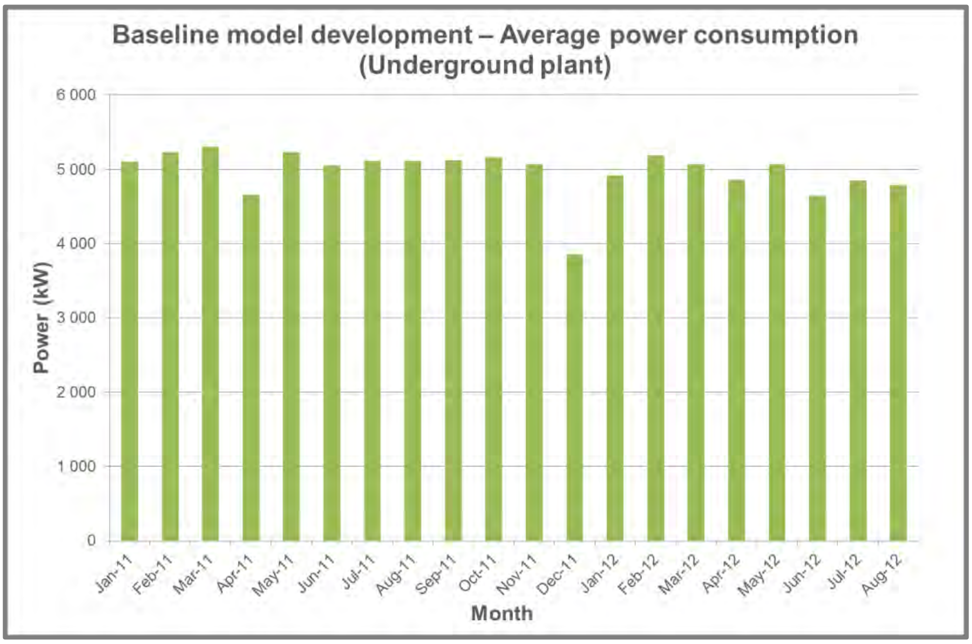

FIGURE C-1: BASELINE MODEL DEVELOPMENT – AVERAGE POWER CONSUMPTION (UNDERGROUND PLANT)

Inspection of the average monthly power consumption reveals a variance in power consumption. The cause of the variance is, however, not clear. The average 24-hour workday profile is determined for every month included in the dataset. The results are shown in Figure C-2. Inspection of the profiles indicates a consistent system operation with only December 2011 being significantly lower than the rest.

The profiles are normalised to have the same average power to enable the operational profile shapes to be compared. Figure C-3 illustrates the results. Inspection of the normalised profiles confirms that the plant operates under the same operational profile throughout the year. The consistent operation of the plant means that a single baseline model can be used to present system operation.

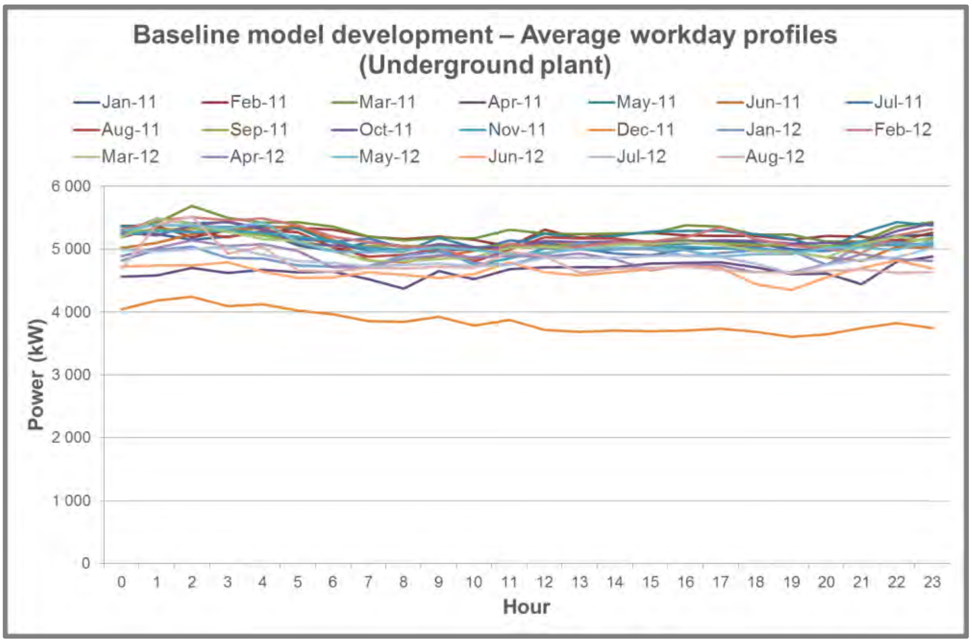

FIGURE C-2: BASELINE MODEL DEVELOPMENT – AVERAGE WORKDAY PROFILES

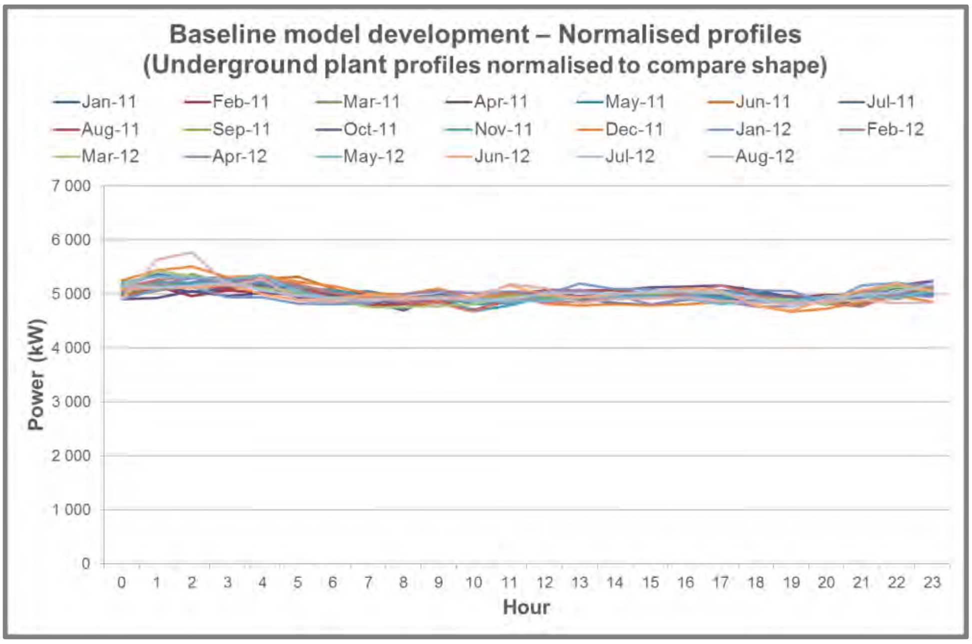

FIGURE C-3: BASELINE MODEL DEVELOPMENT – AVERAGE WORKDAY PROFILES (NORMALISED)

January and February 2011 are selected as the baseline months. The average power consumption of the two months is calculated and compared to the average monthly power consumption. Figure C-4 illustrates the results. Inspection of the results shows that the baseline model average approximates average monthly power consumption within 10% of the actual values. The only month that does not fall within this margin is December 2011.

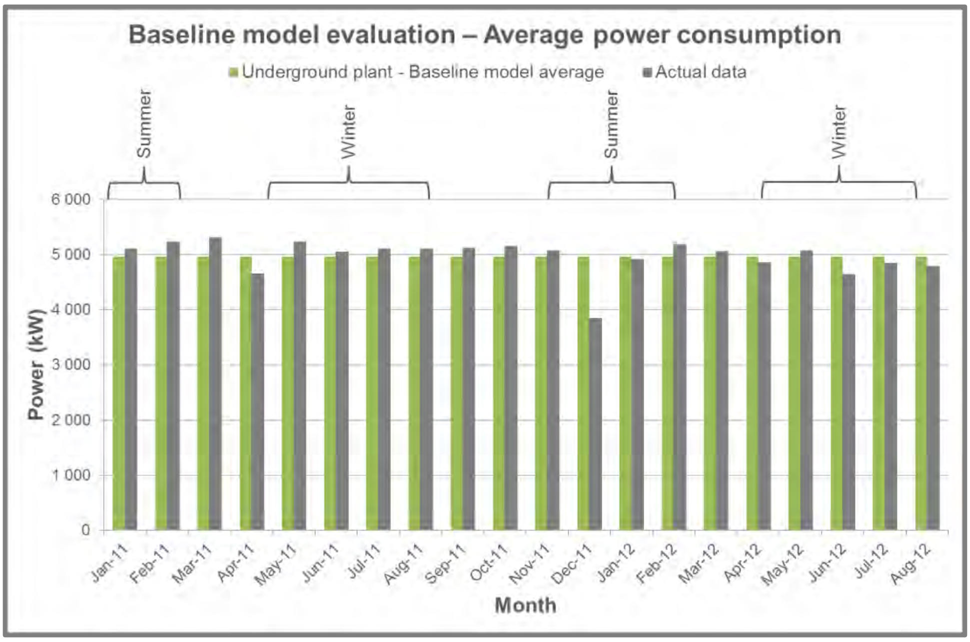

FIGURE C-4: BASELINE MODEL DEVELOPMENT – AVERAGE POWER CONSUMPTION

Figure C-5 illustrates the average monthly power consumption of the surface plant. Inspection of the results clearly indicates a seasonal impact on power consumption. The extended period of available data enables the inspection to confirm the operational trend of the plant. The data shows that the plant is always running during the summer months and always shutdown over the winter months. It also indicated the existence of a transitional period between seasons. The different power consumption in May 2011 and May 2012 confirms this.

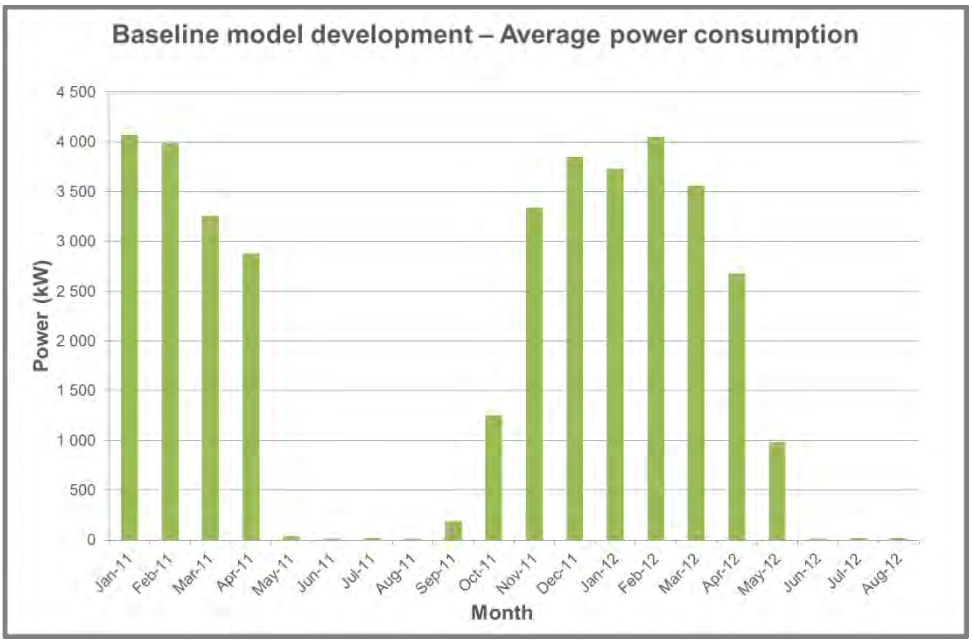

FIGURE C-5: BASELINE MODEL DEVELOPMENT – AVERAGE POWER CONSUMPTION

The investigation into plant operation is continued by determining the average 24-hour workday profiles for every month in the dataset. The results are illustrated in Figure C-6.

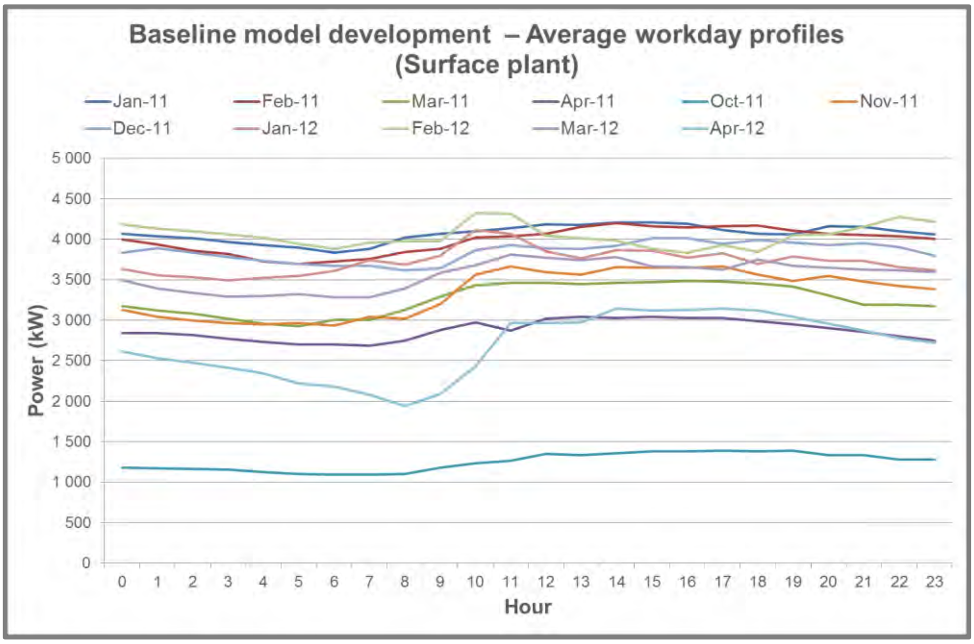

FIGURE C-6: BASELINE MODEL DEVELOPMENT – AVERAGE WORKDAY PROFILES

The average workday profiles are normalised to compare the profile shape. Figure C-7 illustrates the results. Inspection of the figure confirms that the plant follows the same operational procedure although the average power consumption decreases during the transition months.

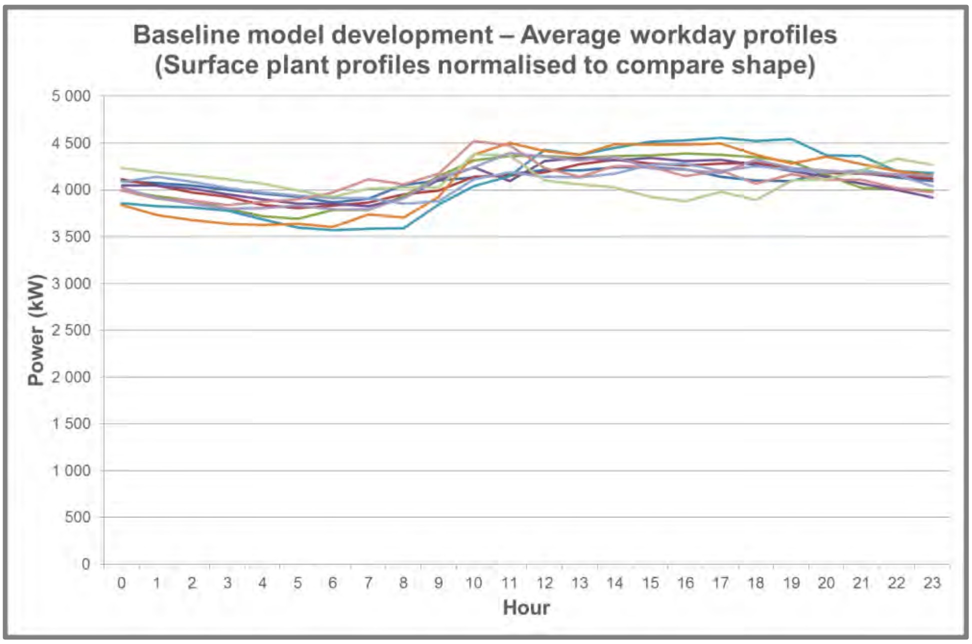

FIGURE C-7: BASELINE MODEL DEVELOPMENT – AVERAGE WORKDAY PROFILES

January and February 2011 were selected as dataset to develop the baseline model. Figure C-8 illustrates the baseline model average. The average power consumption of the two months is used to indicate the average summer power consumption. The value is then proportionally reduced to approximate the transition months. The winter power consumption is estimated to be zero at all times.

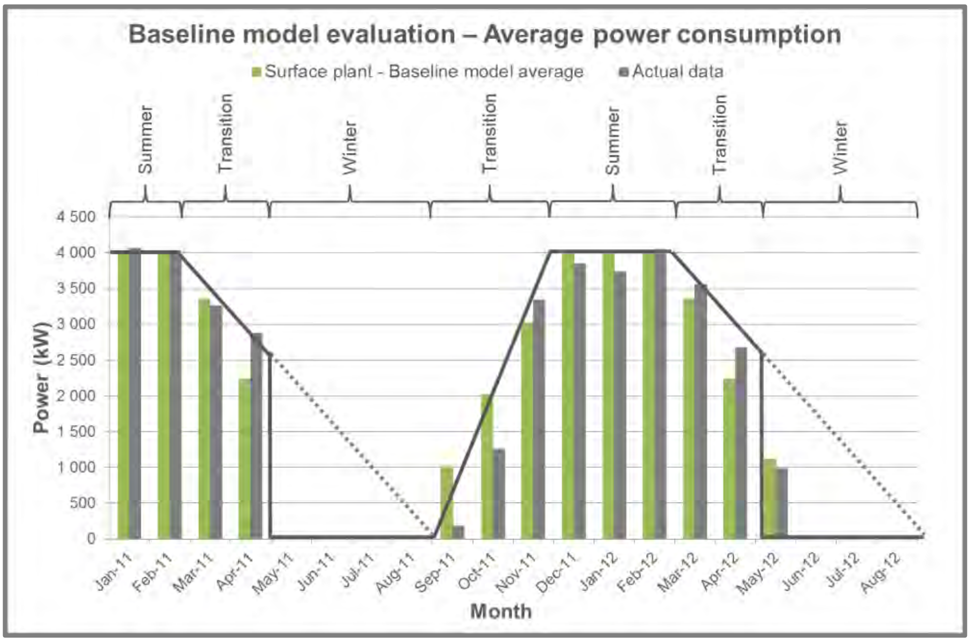

Figure C-8: Baseline model development – Average power consumption

The two baseline models devised as part of this case study were evaluated using the baseline model evaluation methodology. The evaluation results are shown in Figure C-9.

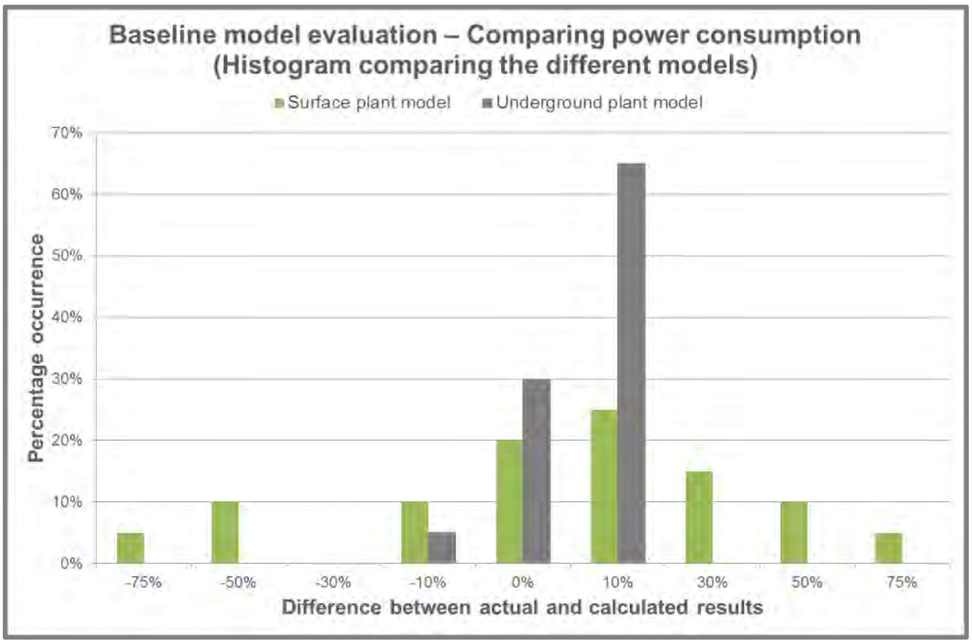

Figure C-9: Baseline model evaluation – Power consumption histogram

The baseline model evaluation results indicate that the majority of the underground plant's estimated values fell within 10% of the actual results. This implies that the model estimation will generally be higher than the true plant power consumption. This bias can be attributed to the use of January and February 2011, which are generally higher consumption months, as baseline dataset.

The evaluation results of the surface plant model indicate that the model was not able to estimate plant power consumption nearly as well as the underground plant model. The occurrence of results is also biased towards 10%, but the wide range of variance casts serious doubt on the model's general accuracy.

Case Study 17 – Energy-neutral baseline model for water-pumping scheme

Case Study 17 presents the baseline model development of a large pumping scheme. The average monthly power consumption of the scheme is illustrated in Figure C-10. The slight variance in monthly consumption can be attributed to changes in system demand.

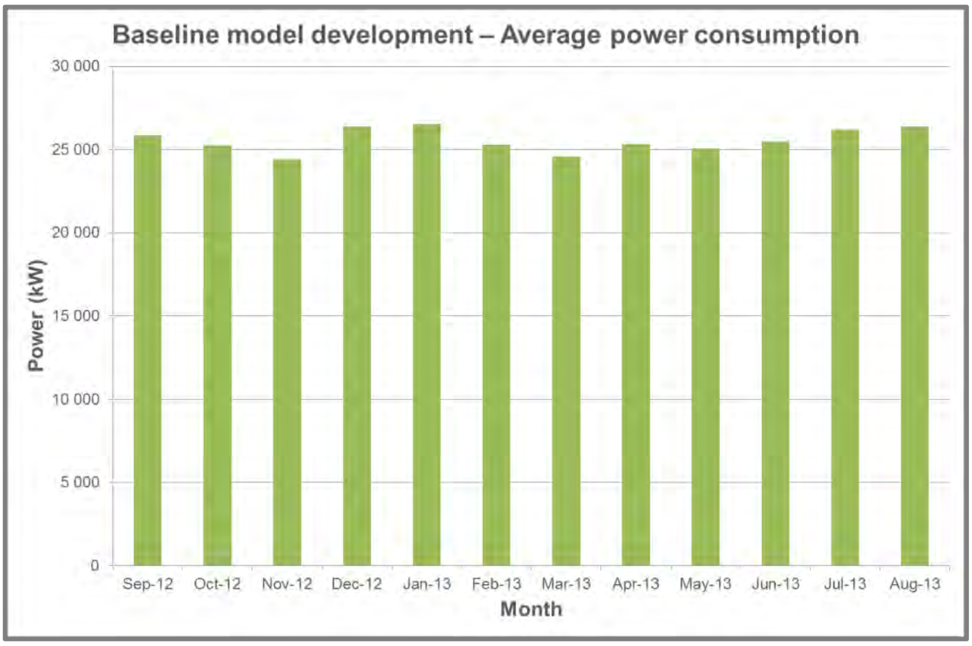

Figure C-10: Baseline model development – Average power consumption

The average 24-hour workday profiles were developed for every month in the dataset. Figure C-11 illustrates the results. The consistency of the operational profiles is evaluated by normalising all of the profiles to reflect the same average power consumption. The results are illustrated in Figure C-12. Inspection of the results confirms that the plant operates under a consistent mode of operation. A single baseline model can therefore be used to approximate the system operation.

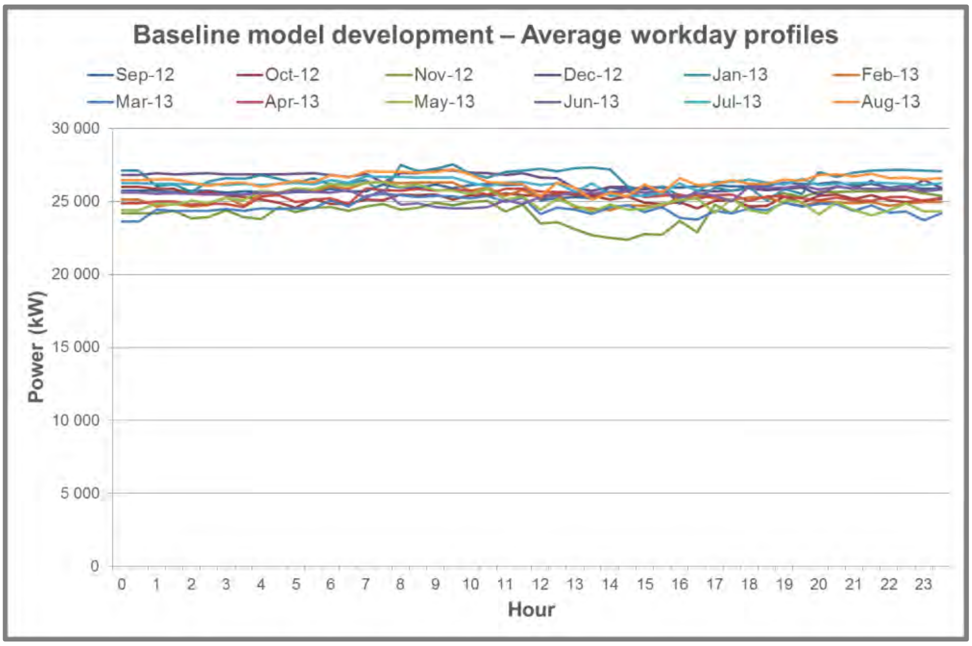

FIGURE C-11: BASELINE MODEL DEVELOPMENT – AVERAGE WORKDAY PROFILES

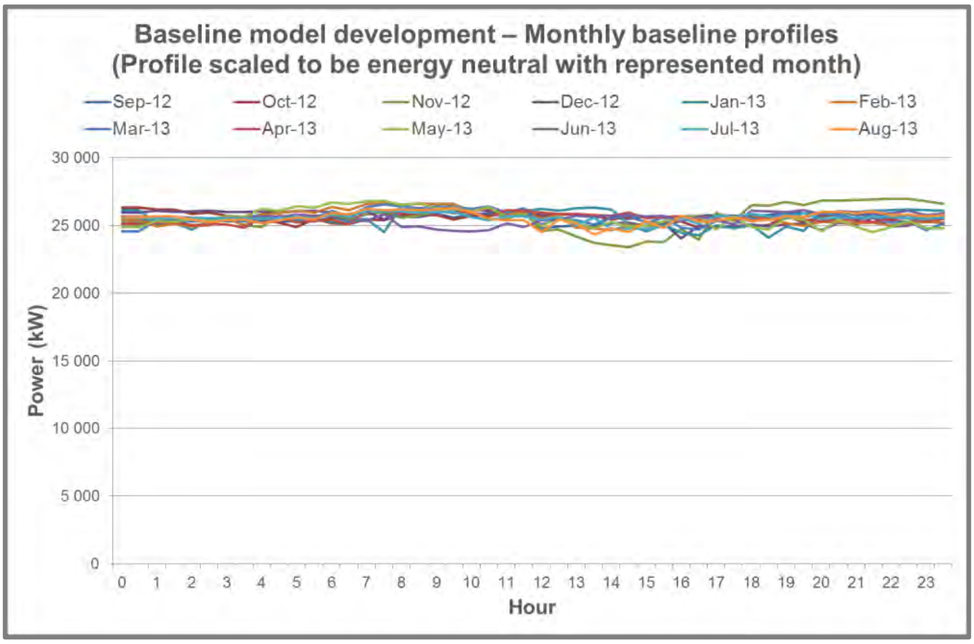

FIGURE C-12: BASELINE MODEL DEVELOPMENT – AVERAGE WORKDAY PROFILES

The project developer proposed a load shifting project to be implemented on the pumping scheme. This will alter the operational profile but not the power consumption. An energy-neutral baseline model is developed using the average profile of the dataset. The model is tested by scaling it to be energy neutral for every month in the dataset. The results are illustrated in Figure C-13. Inspection of the results confirms that the average energy consumption of the model cannot be used to measure it's accuracy as it will always be exactly the same as the dataset. The Eskom evening peak (18:00–

20:00) values of the dataset and model are therefore compared to test model accuracy. The results are illustrated in Figure C-14.

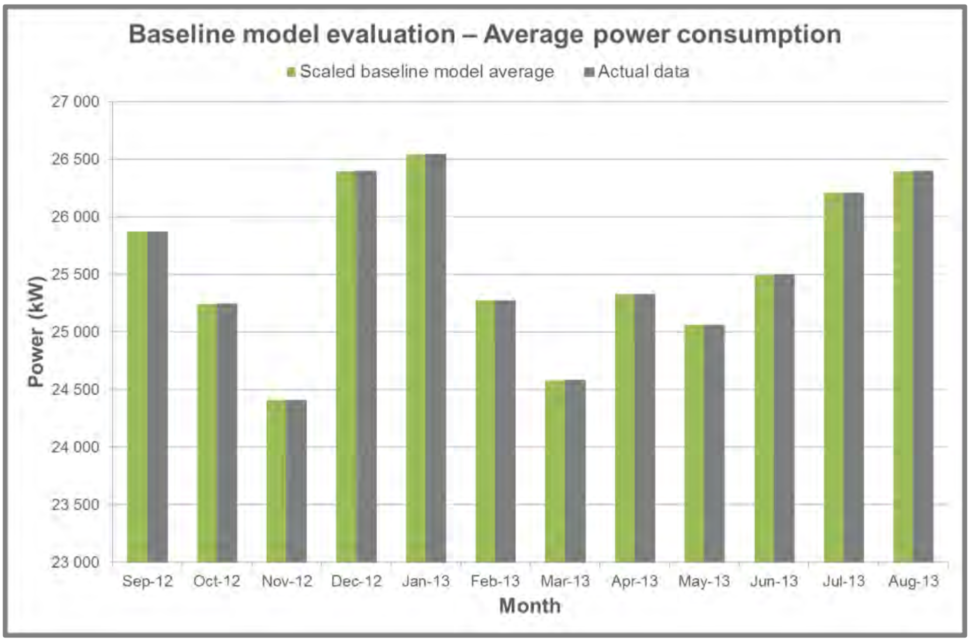

FIGURE C-13: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM

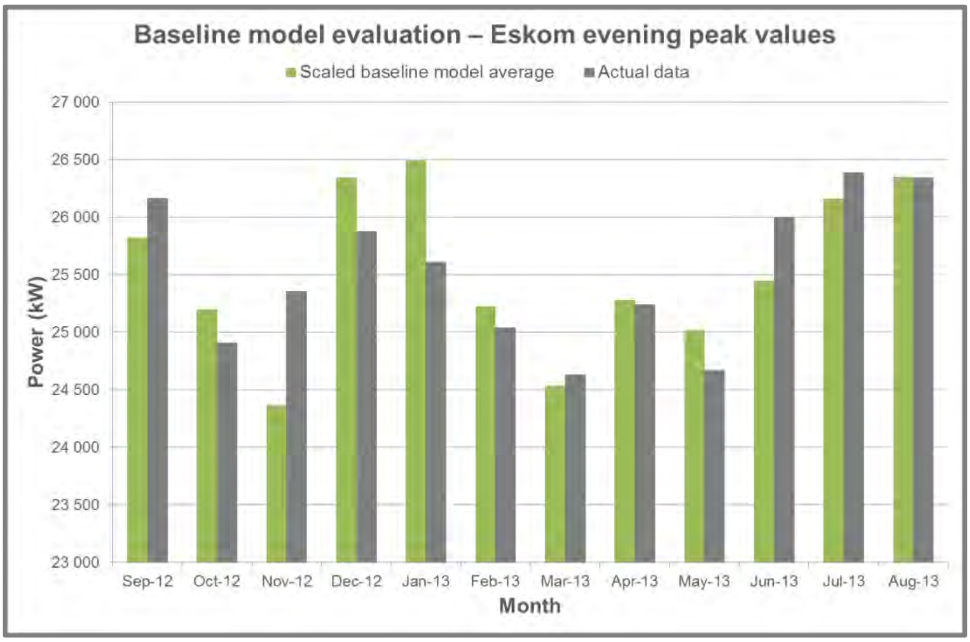

FIGURE C-14: BASELINE MODEL EVALUATION – ESKOM EVENING PEAK VALUES

The baseline model evaluation methodology is used to evaluate the accuracy of the new baseline model. The results are illustrated in Figure C-15. Inspection of the results reveals that the model bias is situated very close to zero. The majority of the results also fall within 1% of the actual values. The model evaluation therefore confirms that the energy-neutral baseline model can accurately approximate system power consumption.

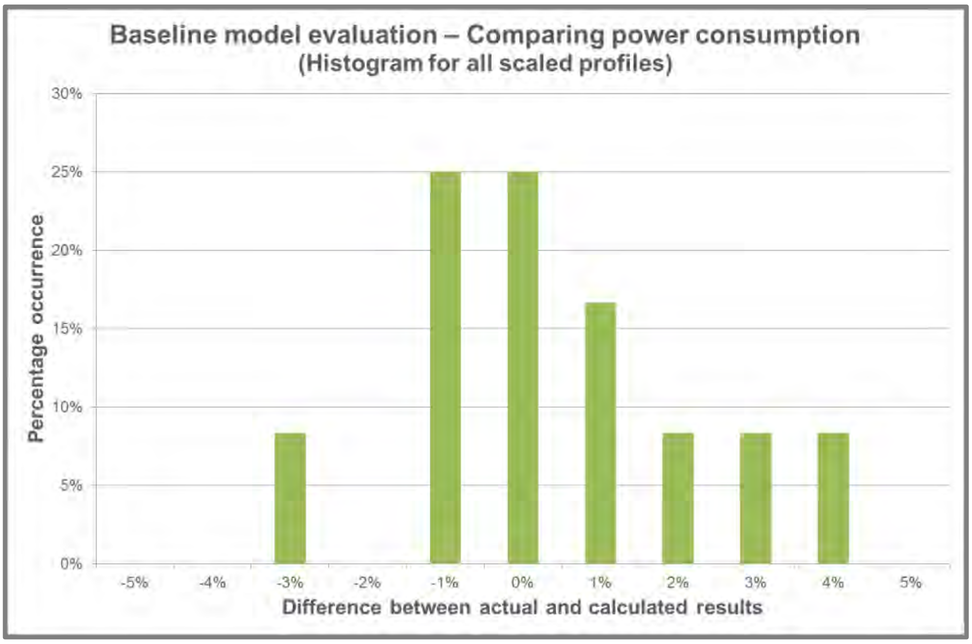

FIGURE C-15: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM

CASE STUDY 18 – REGRESSION BASELINE MODELS USING PRODUCTION AS INPUT

Case Study 18 presents the development of a regression baseline model to represent the operation of a compressed air system. A labour strike occurred shortly after the first model was developed. The system operation changed as a result and required the development of a new baseline model. Figure C-16 illustrates the effect by comparing pre- and post-strike workday profiles.

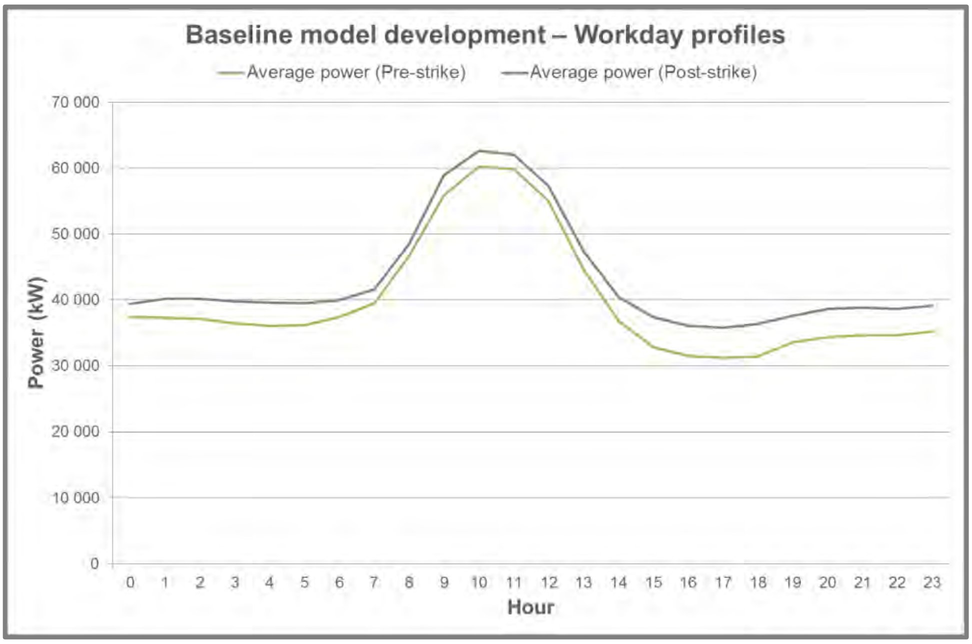

FIGURE C-16: BASELINE MODEL DEVELOPMENT – AVERAGE WORKDAY PROFILES

The regression models were developed using compressor power consumption and mine production data. Data from the two datasets (pre- and post-strike) are presented in the original daily format as well as average weekly values. Figure C-17 illustrates the four different sets.

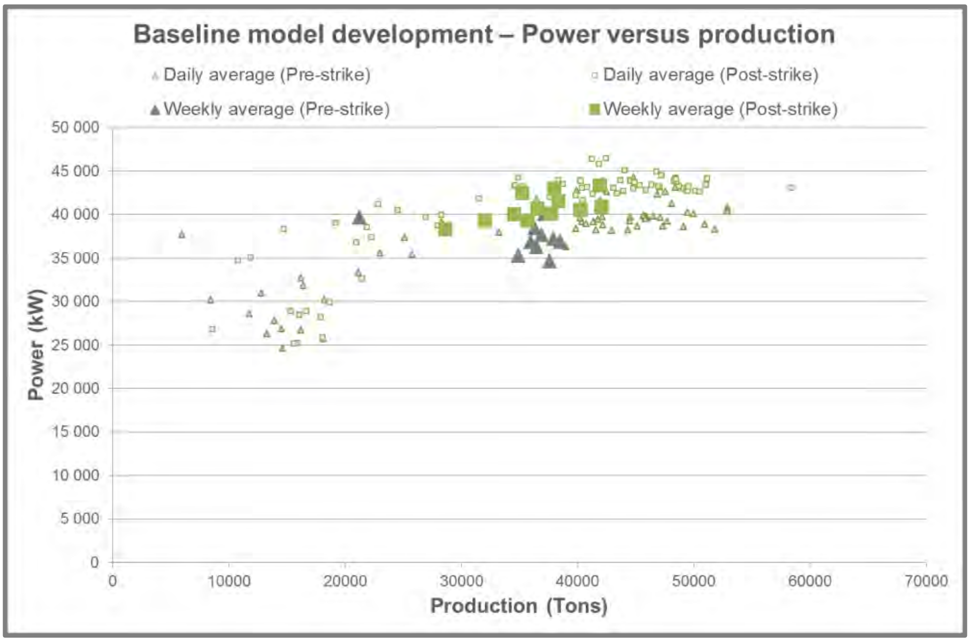

FIGURE C-17: BASELINE MODEL DEVELOPMENT – POWER VERSUS PRODUCTION

The different datasets were used to develop four different baseline models. The formulas for the models are summarised in Table C-1.

TABLE C-1: REGRESSION MODEL VALUES

Data integration period	m*Variable	Constant	R^2	RMSE
Pre-strike daily data	0.30	26 388.36	0.70	7%
Pre-strike weekly data	-0.15	42 694.05	0.20	4%
Post-strike daily data	0.36	27 361.02	0.68	8%
Post-strike weekly data	0.26	31 161.03	0.44	3%

The models were tested by using the available production data to estimate the system power consumption. The calculated results were then compared to the actual power data. A highly accurate model will be able to closely predict the actual power consumption. Figure C-18 illustrates an example.

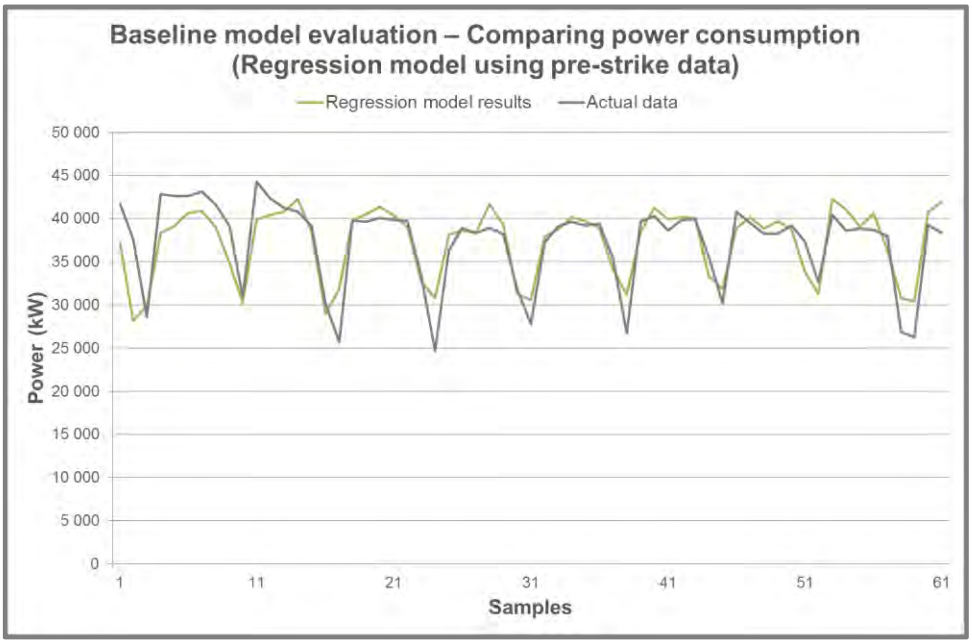

Figure C-18: Baseline model evaluation – Actual vs calculated power consumption

Visually comparing the different models' output will give an indication of the accuracy. However, a more detailed analysis is required to select the best model objectively. The baseline model evaluation methodology is therefore used to evaluate the four different models. Figure C-19 illustrates the result of the model developed using pre-strike data.

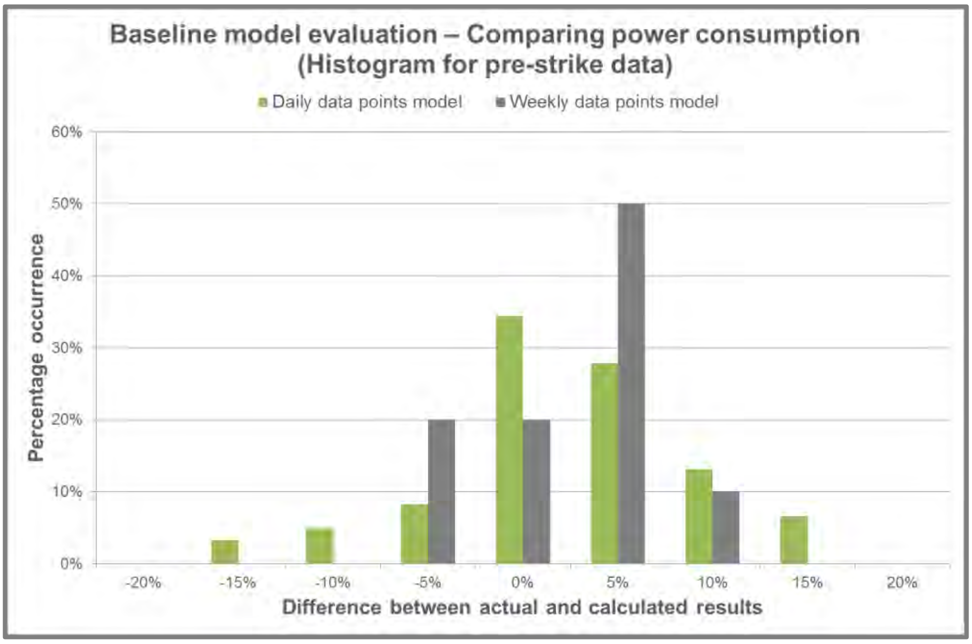

Figure C-19: Baseline model evaluation – Power consumption histogram (Pre-strike data)

The model developed using weekly data points is revealed as the more consistent model. It produced results between -5% and +10% of the actual value with the majority of results biased towards +5%. The model using daily data produced a wider range of results varying from -15% to +15% of the actual values with results biased around 0%. Figure C-20 illustrates the post-strike model results.

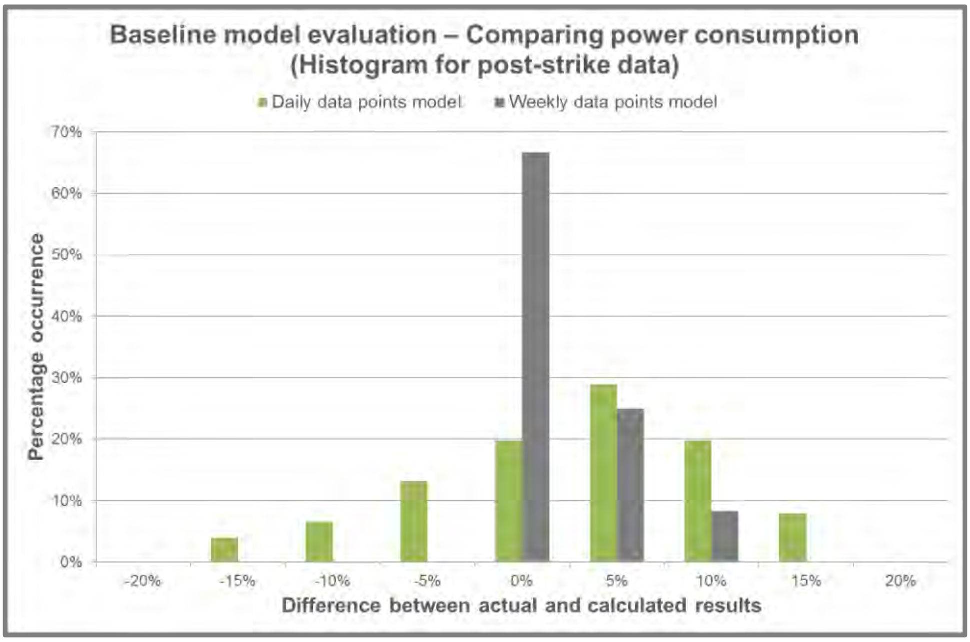

FIGURE C-20: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM (POST-STRIKE DATA)

Inspection of the results in Figure C-20 indicates that the model using weekly data is more consistent and accurate. Results from the weekly data model range from 0% to +10 and will be biased above 0%. The model using daily data again produces results that fall in the -15% to +15% range, the results are biased towards +5%. Figure C-21 compares the pre- and post-strike models using daily data points. The comparison confirms that the models produce similar results.

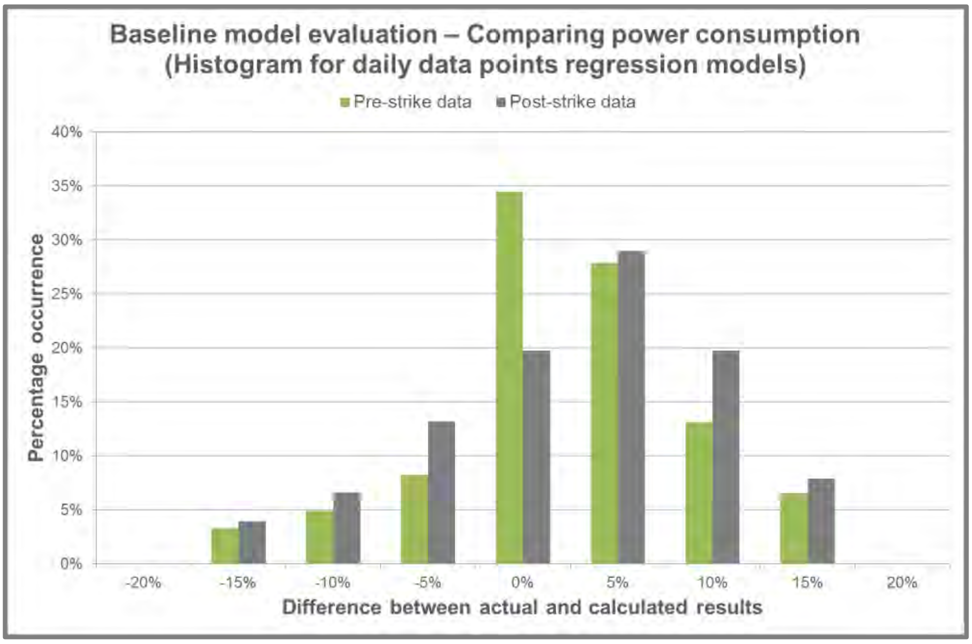

FIGURE C-21: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM (DAILY DATA POINTS)

The baseline model evaluation methodology indicated that the models using weekly data produce the more consistent results. Figure C-22 indicates that the post-strike model is more accurate.

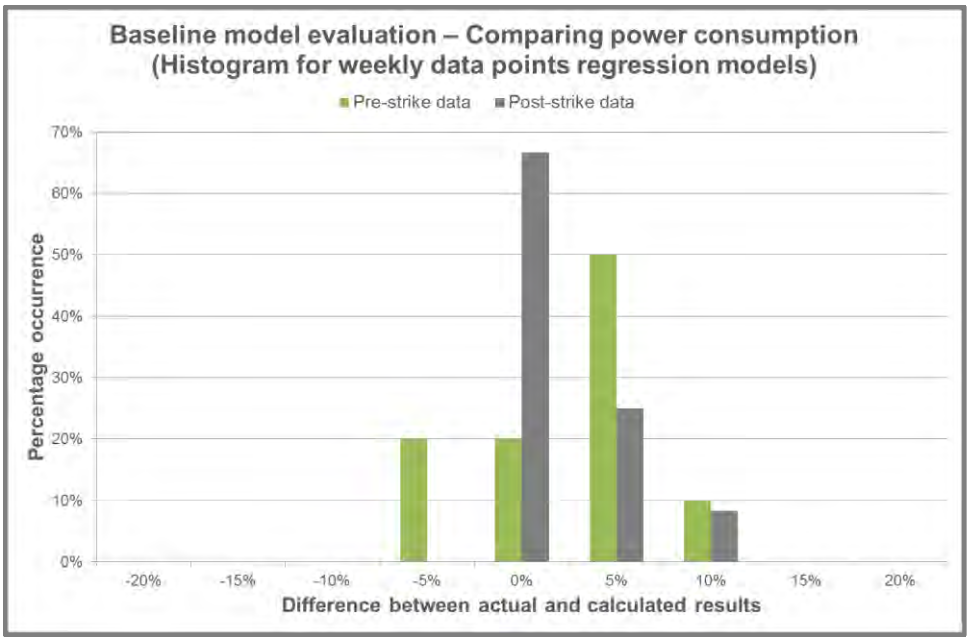

FIGURE C-22: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM (WEEKLY DATA POINTS)

CASE STUDY 19 – REGRESSION BASELINE MODELS USING FLOW AND PRESSURE AS INPUTS

Case Study 19 presents the baseline model development of another compressed air system. This study develops several regression models using compressor power, as well as compressed airflow and pressure. Figure C-23 illustrates average workday profiles for each of the variables.

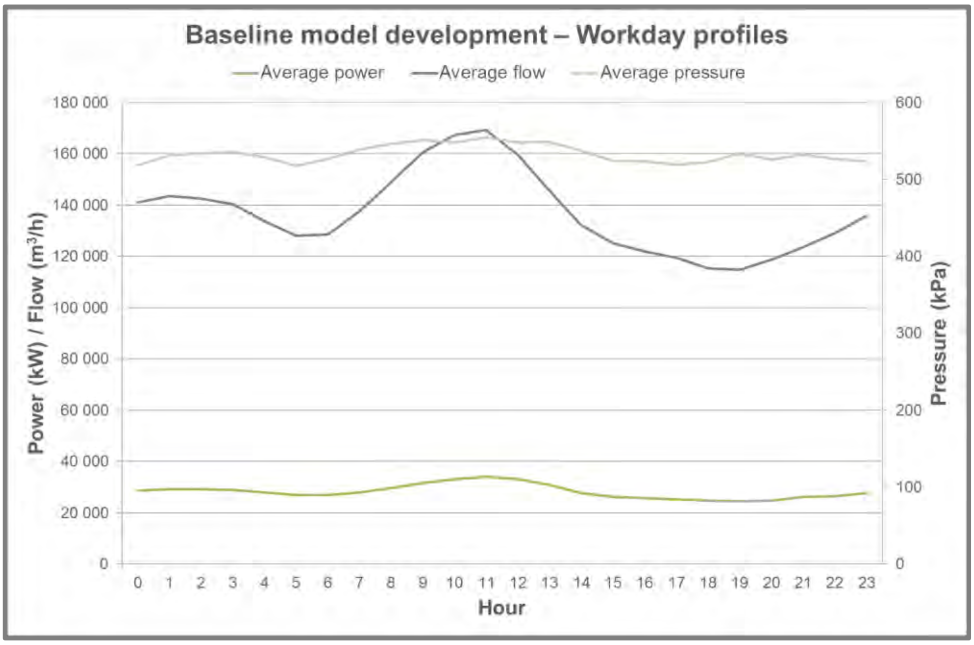

FIGURE C-23: BASELINE MODEL DEVELOPMENT – AVERAGE WORKDAY PROFILES

Inspection of the profiles presented in Figure C-23 indicates an increase in flow and power consumption from 09:00 to 12:00. This period is referred to as the drill shift. The shift is a scheduled and recurring event where the maximum available flow and pressure are required to drill holes for the blasting shift. The interventions implemented on the compressed air system are not allowed to affect the system in anyway during the drill shift. It can therefore be used as a reference point when evaluating changes in system operation.

Figure C-24 illustrates the available power and flow data points. Figure C-25 illustrates the available power as well as the pressure data points. Both the figures present all the available data as well as the data points depicting the drill shift operation. The different combinations of the power, flow and pressure variables will be used to develop various baseline models. The number of models is further increased by developing models using the different combinations of dataset (complete and drill shift data).

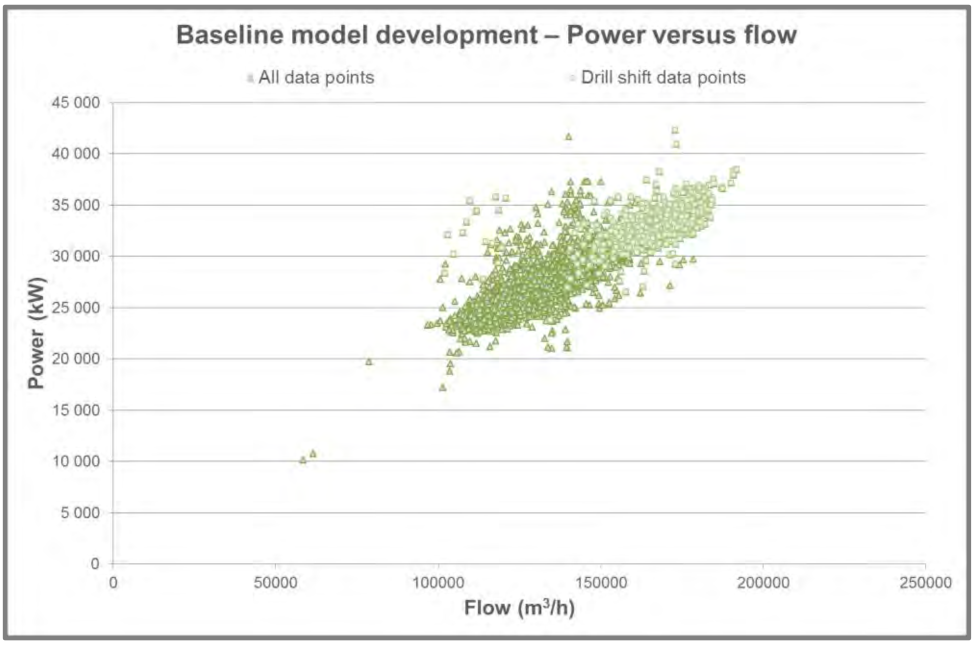

FIGURE C-24: BASELINE MODEL DEVELOPMENT – POWER VERSUS FLOW

The different regression models are developed, the formulas for the models are summarised in Table C-2. The baseline models' accuracy are tested using the same variables to calculate the power consumption of the baseline dataset. The results are compared to the actual power consumption data. The difference between the actual and calculated results is determined. Figure C-26 presents an example of the results.

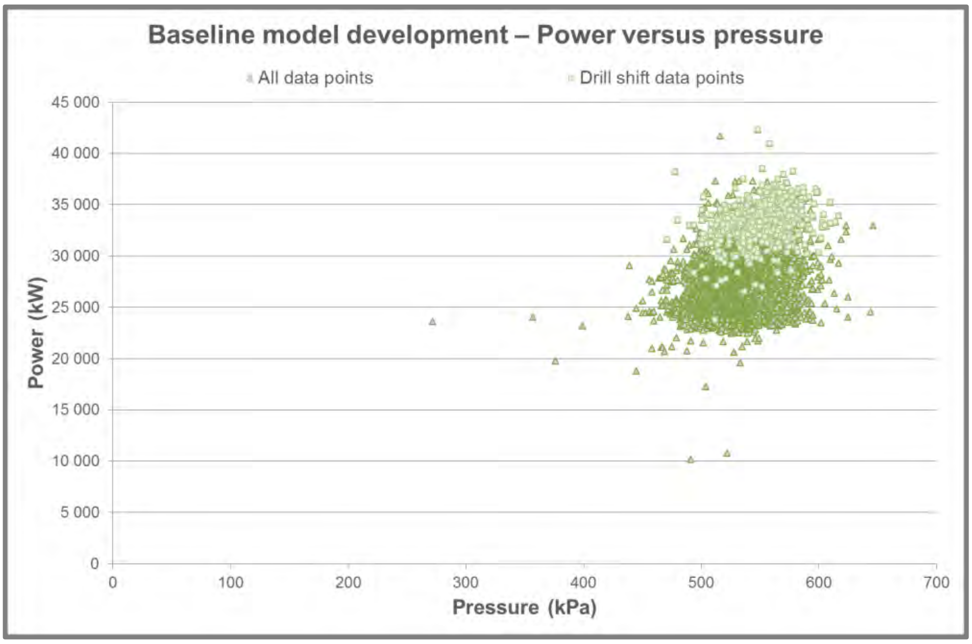

FIGURE C-25: BASELINE MODEL DEVELOPMENT – POWER VERSUS PRESSURE

TABLE C-2: REGRESSION MODEL VALUES

Data integration period	m*Variable1	m*Variable2	Constant	R^2	RMSE
All points, flow data	0.16	-	6 832.70	0.71	7%
All points, pressure data	-	38.28	7 814.71	0.11	11%
All points, flow and pressure data	0.15	10.96	1 655.10	0.72	6%
Drill peak, flow data	0.07	-	21 122.33	0.25	5%
Drill peak, pressure data	-	23.91	19 951.57	0.08	6%
Drill peak, flow and pressure data	0.07	12.46	15 293.70	0.27	5%

Figure C-26 presents three different models developed using all the available data. The models make use of flow, pressure and a combination of the two variables to predict power consumption. The results presented in Figure C-26 makes it difficult to determine which model is more accurate or suitable to represent system operation. The methodology for baseline model evaluation is therefore used to evaluate the results. Figure C-27 presents the methodology results when applied to the models presented in Figure C-26.

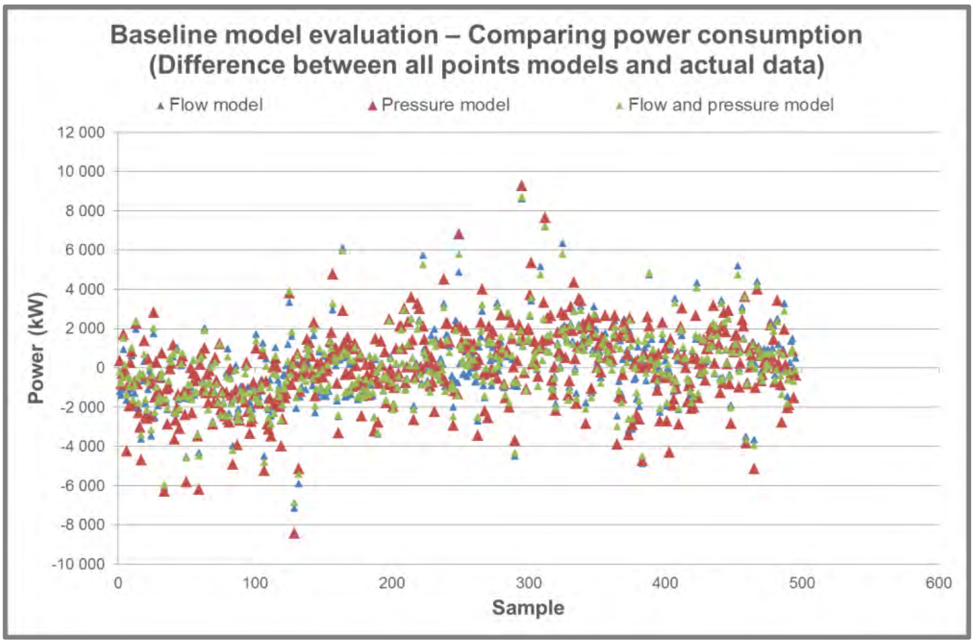

FIGURE C-26: BASELINE MODEL EVALUATION – CALCULATED POWER CONSUMPTION (ALL POINTS)

The methodology results presented in Figure C-27 immediately clarifies the nature of the different models. The model developed using system pressure is clearly inferior to the other two. There is a minimal difference in accuracy of the other two models with the flow and pressure-based model being biased around zero.

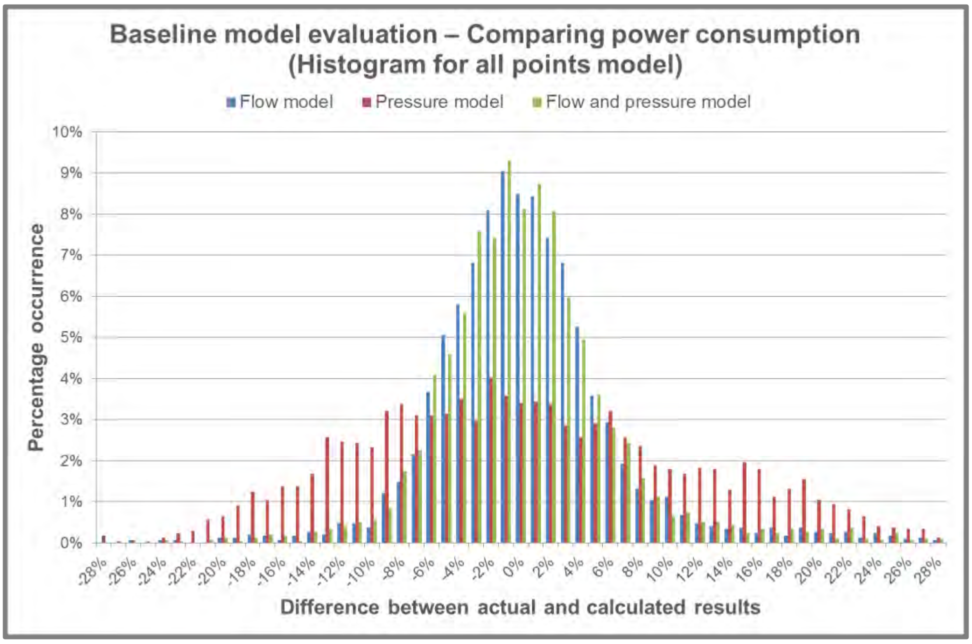

FIGURE C-27: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM (ALL POINTS)

The same evaluation process is repeated for baseline models developed using only the drill shift dataset. The results are illustrated in Figure C-28. Inspection of the results indicate that the three models' characteristics are fairly close to one another.

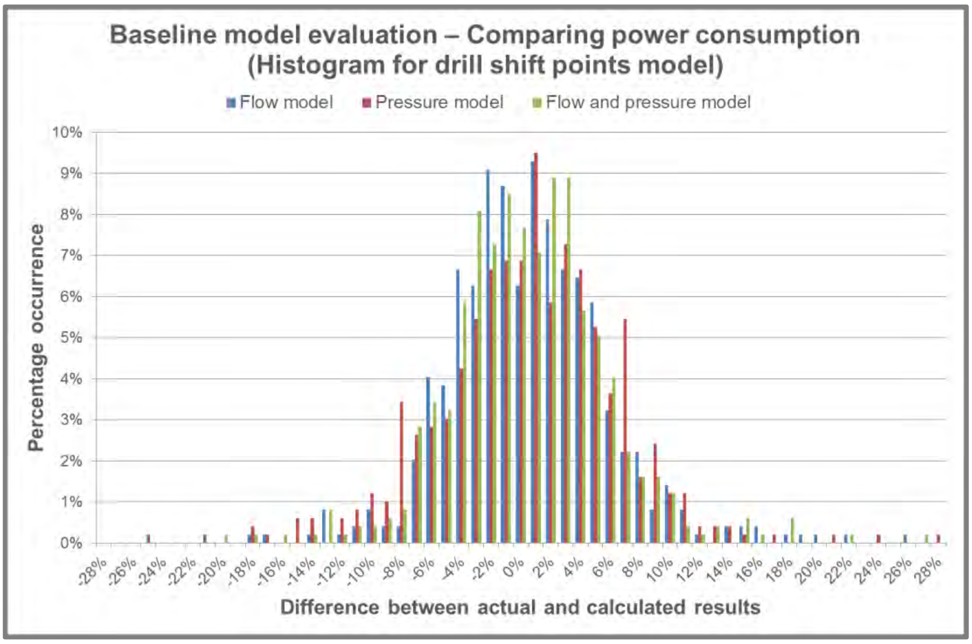

FIGURE C-28: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM (DRILL SHIFT POINTS)

Figure C-29 compares the flow and pressure regression models developed using the different datasets. The comparison indicates that there is no significant difference in accuracy as a result of the different datasets used. The evaluation can therefore conclude that any of the two models can be used to represent the system. The final choice will only be influenced by how the proposed project will affect the variables used in the model.

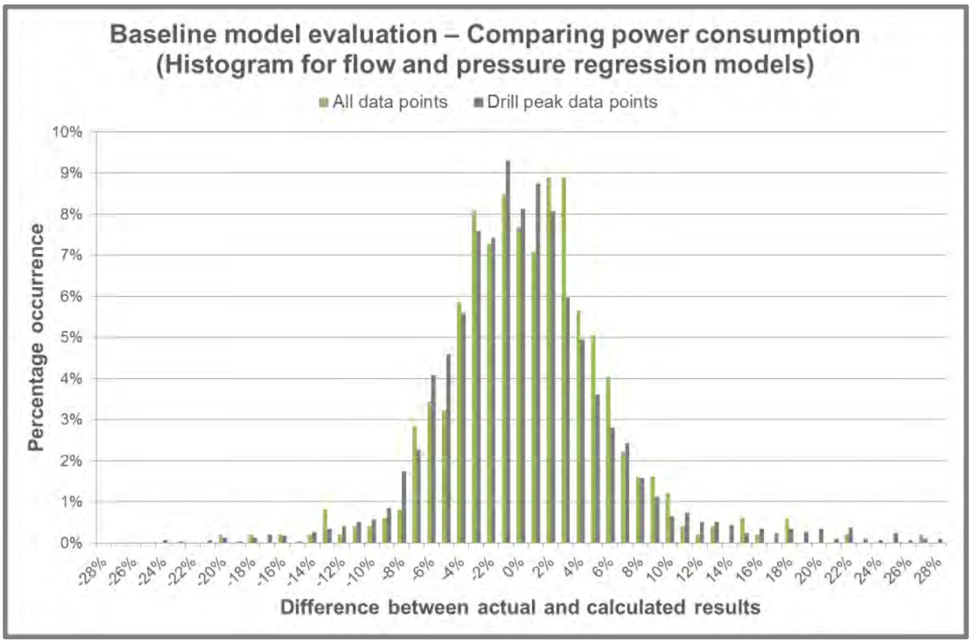

FIGURE C-29: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM

Case Study 20 – Regression baseline model using multiple inputs

Case Study 20 presents the baseline model development of a fridge plant system. The fridge plant is sensitive to changes in system variables and as a result a regression model is selected to match power consumption to the relevant system variables. Figure C-30 illustrates a year-on-year comparison of system power consumption to illustrate the variance in operation.

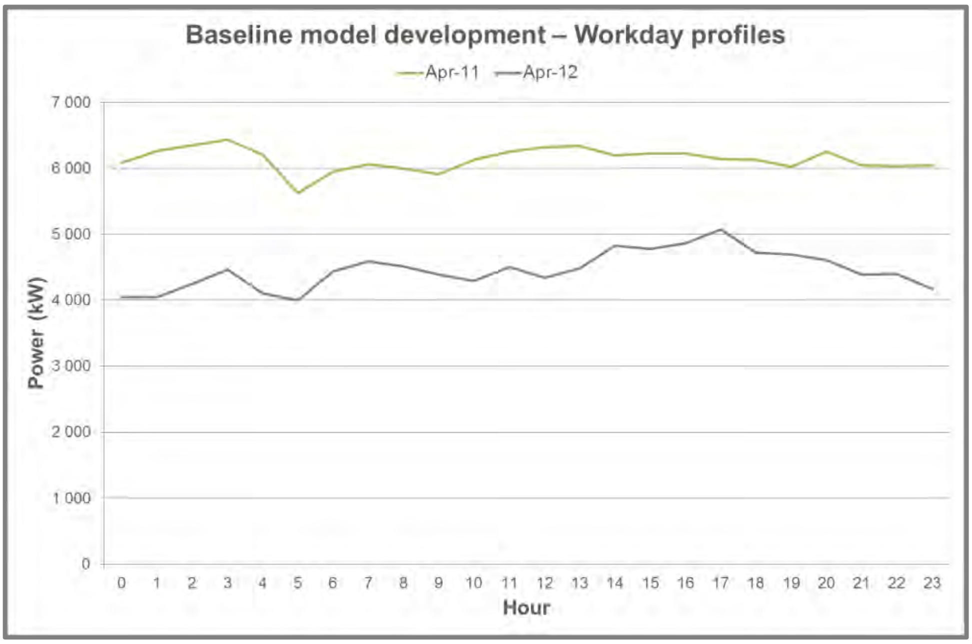

Figure C-30: Baseline model development – Average workday profiles

Several variables are available for use in the regression model. Several combinations of the variables will be selected for evaluation. Different integration periods will also be evaluated to improve the model accuracy further.

Figure C-31 gives an example of a single variable (flow) and its relation to plant power consumption. Three different integration periods are selected for model development. The first is raw data consisting of hourly data points. The second is daily data points developed by integrating the daily data points. The last set represents weekly data which an additional level of integration.

This process is repeated for the following variables: ambient temperature, delta temperature (difference between inlet and outlet water temperature) and water flow volume. Different combinations of these variables are used to develop regression models. The formulas for the models are summarised in Table C-3. The developed regression models are evaluated by using the baseline dataset values to calculate power consumption. The calculated results are then compared to the actual baseline power consumption. Figure C-32 gives an example of a comparison.

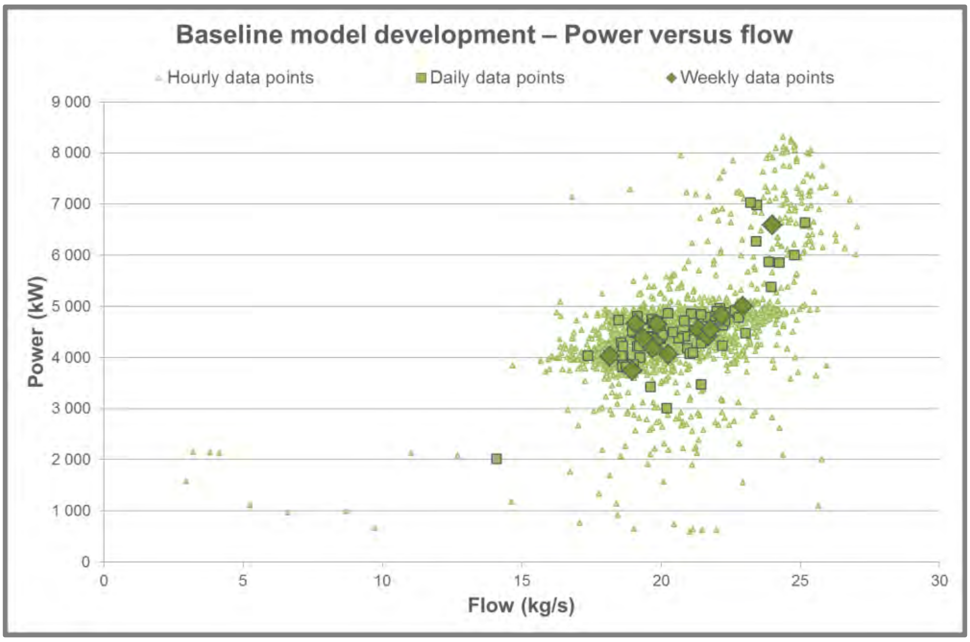

FIGURE C-31: BASELINE MODEL DEVELOPMENT – POWER VERSUS PRESSURE

TABLE C-3: REGRESSION MODEL VALUES

Data integration period	m*Variable1	m*Variable2	m*Variable3	Constant	R^2	RMSE
Delta temp (Hourly)	222.26	-	-	-25.31	0.29	19%
Flow (Hourly)	-	0.89	-	4 241.49	0.01	22%
Ambient temp (Hourly)	-	-	71.39	3 486.98	0.11	21%
Delta temp and flow (Hourly)	225.41	1.11	-	-476.86	0.31	18%
Flow and ambient temp (Hourly)	-	1.28	76.57	2 964.04	0.13	20%
Delta, ambient temp and flow (Hourly)	206.99	1.19	18.36	-397.55	0.31	18%
Delta temp (Daily)	306.61	-	-	-1 756.39	0.57	11%
Flow (Daily)	-	3.38	-	3 392.12	0.05	17%
Ambient temp (Daily)	-	-	113.22	2 873.41	0.25	15%
Delta temp and flow (Daily)	354.86	6.94	-	-5 165.27	0.76	9%
Flow and ambient temp (Daily)	-	7.71	158.48	-483.76	0.46	13%
Delta, ambient temp and flow (Daily)	306.48	7.68	44.93	-5 097.37	0.78	8%
Delta temp (Weekly)	309.21	-	-	-1 822.30	0.61	9%
Flow (Weekly)	-	-2.48	-	5 422.88	0.02	14%
Ambient temp (Weekly)	-	-	137.29	2 500.58	0.46	10%
Delta temp and flow (Weekly)	513.15	12.41	-	-10 335.03	0.90	5%
Flow and ambient temp (Weekly)	-	5.71	176.68	-71.38	0.54	10%
Delta, ambient temp and flow (Weekly)	480.91	12.40	19.98	-9 966.38	0.90	4%

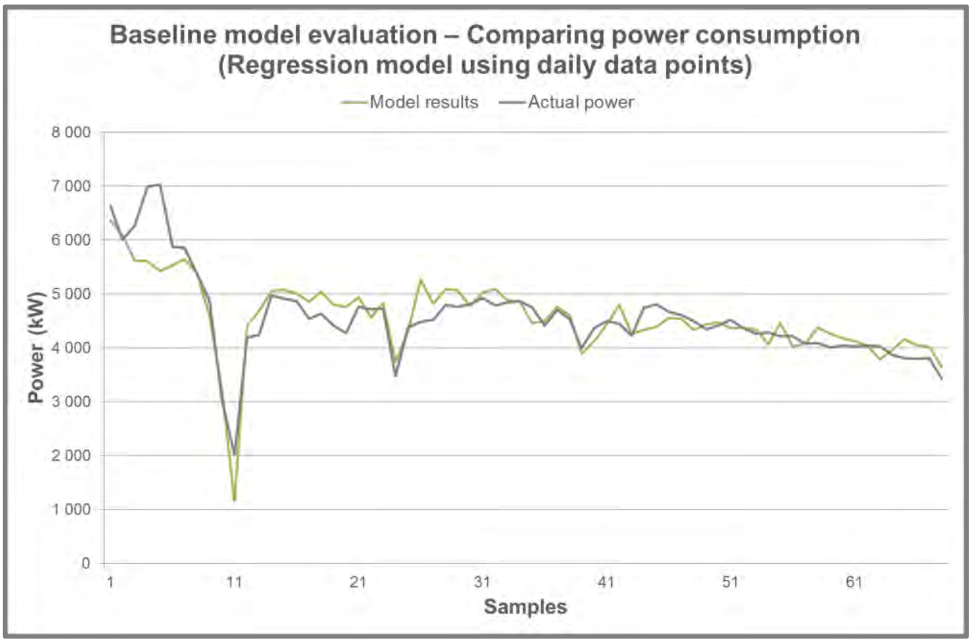

FIGURE C-32: BASELINE MODEL EVALUATION – ACTUAL VS CALCULATED POWER CONSUMPTION

The results of each regression model are calculated and compared to the actual power consumption. Figure C-33 illustrates the result obtained when evaluating the various models developed using the daily data points. The results in the figure do not clearly illustrate the characteristics of the different models. The baseline evaluation methodology is therefore used to evaluate the results.

The results for the different variable combinations are displayed in three figures, each presenting the results of a specific period of data points. Figure C-34 indicates results from models using hourly data, Figure C-35 results from daily data and Figure C-36 results from weekly data.

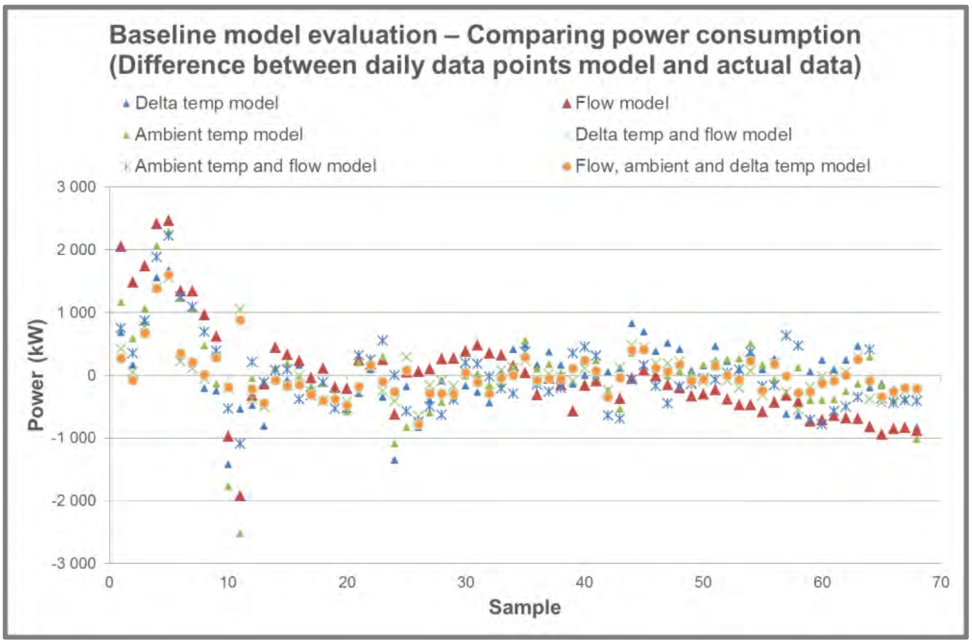

FIGURE C-33: BASELINE MODEL EVALUATION – CALCULATED POWER CONSUMPTION

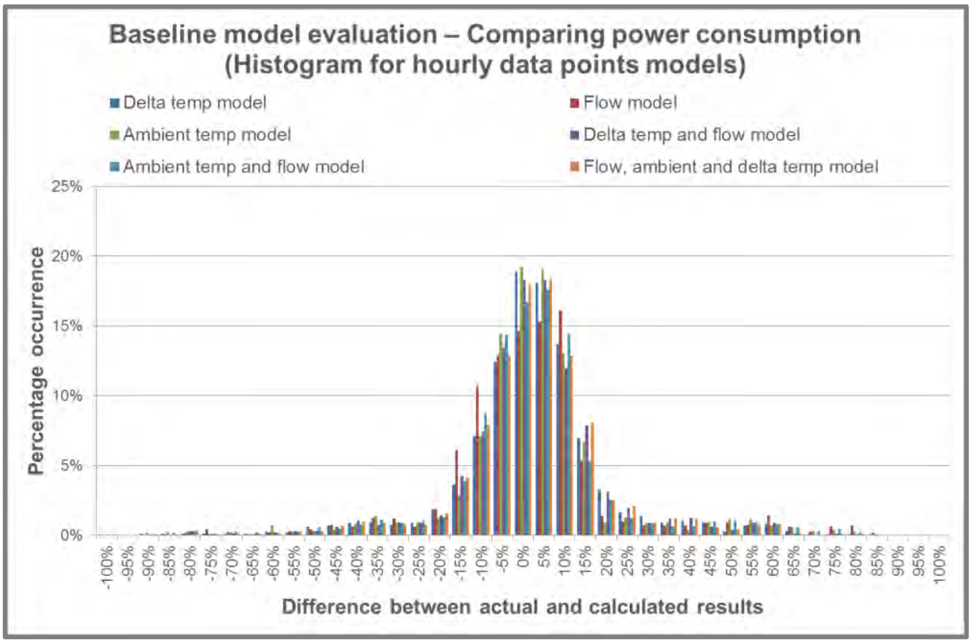

FIGURE C-34: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM

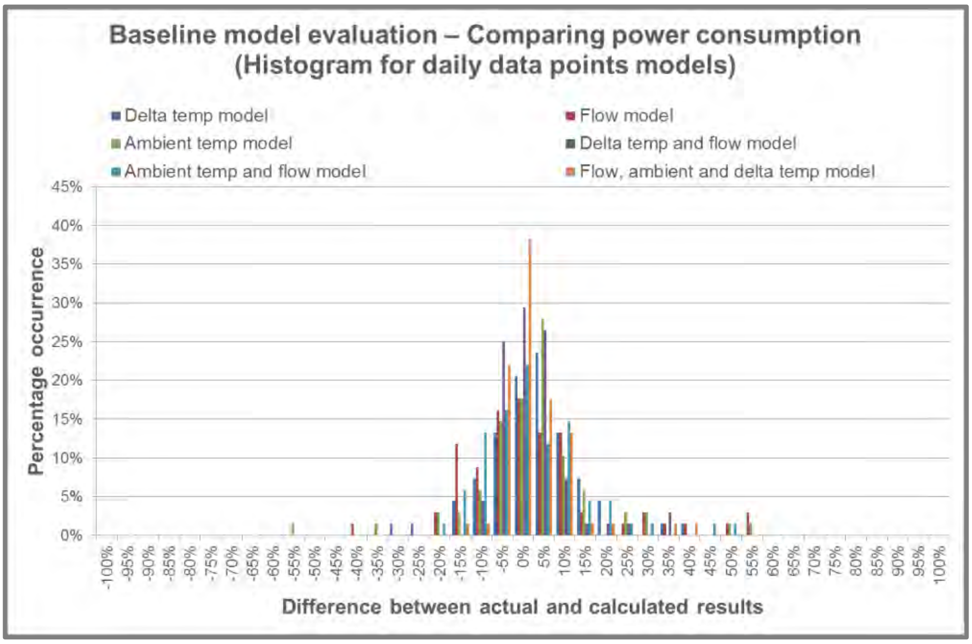

FIGURE C-35: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM

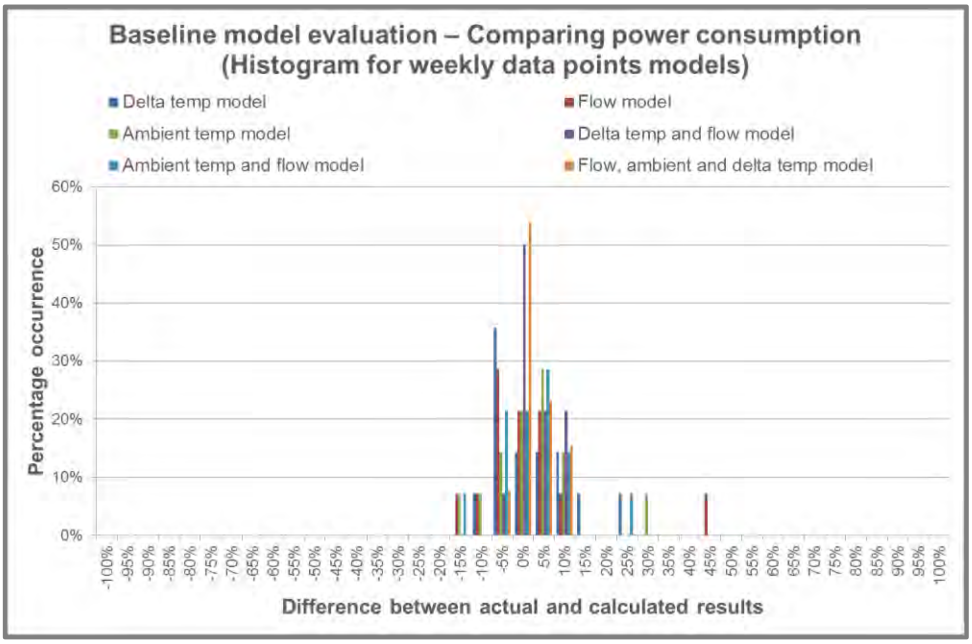

FIGURE C-36: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM

The results displayed in Figure C-34, Figure C-35 and Figure C-36 are all plotted using the same x-axis configuration. The fine resolution of the axis is selected to illustrate the increase in accuracy. Unfortunately, it also makes it difficult to clearly distinguish between the different models. Figure C-37 illustrates the effect on the regression model using all available variables. This presentation confirms that the regression model using all available variables, integrated to present weekly values produces the most accurate results.

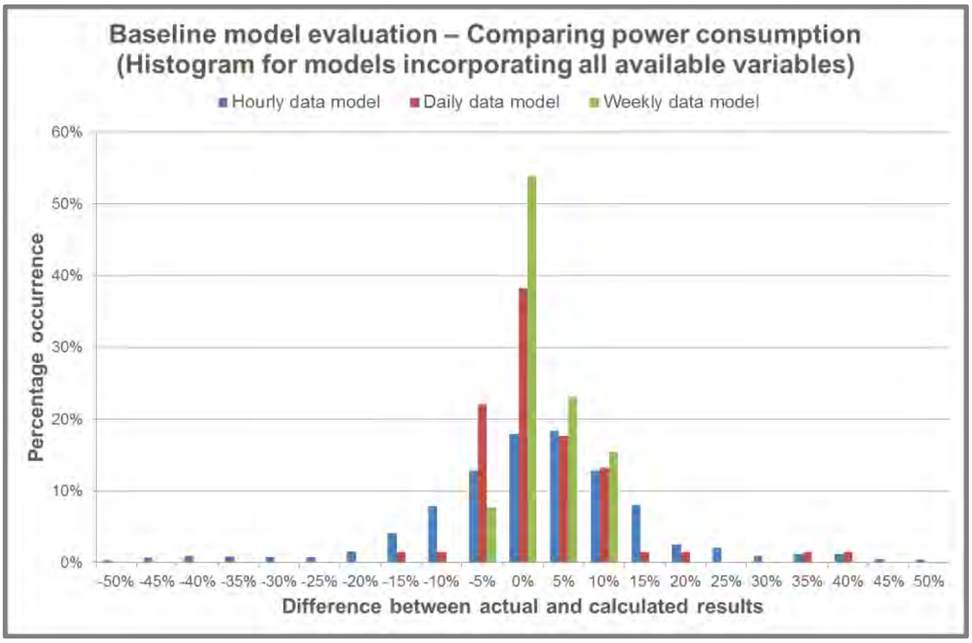

FIGURE C-37: BASELINE MODEL EVALUATION – POWER CONSUMPTION HISTOGRAM

Appendix

D

MEASUREMENT AND VERIFICATION OF INDUSTRIAL DSM PROJECTS

APPENDIX D

INDUSTRIAL CASE STUDIES –
INDUSTRIAL DSM PROJECT PERFORMANCE

Appendix D: Industrial DSM project performance

Case Study 21 – Cement plant project performance assessment

Case Study 21 presents the performance evaluation of a load shifting project implemented on a cement plant. The project aimed to shift energy consumption out of the Eskom evening peak and recovering it during lower cost period. An energy-neutral baseline model was selected to represent the system as the project would only change operational profiles and not result in any energy efficiency.

Hourly performance data was collected from February 2013 to January 2014. The dataset included the three-month project performance assessment period. Figure D-1 illustrates the average power consumption as well as the original and scaled baseline.

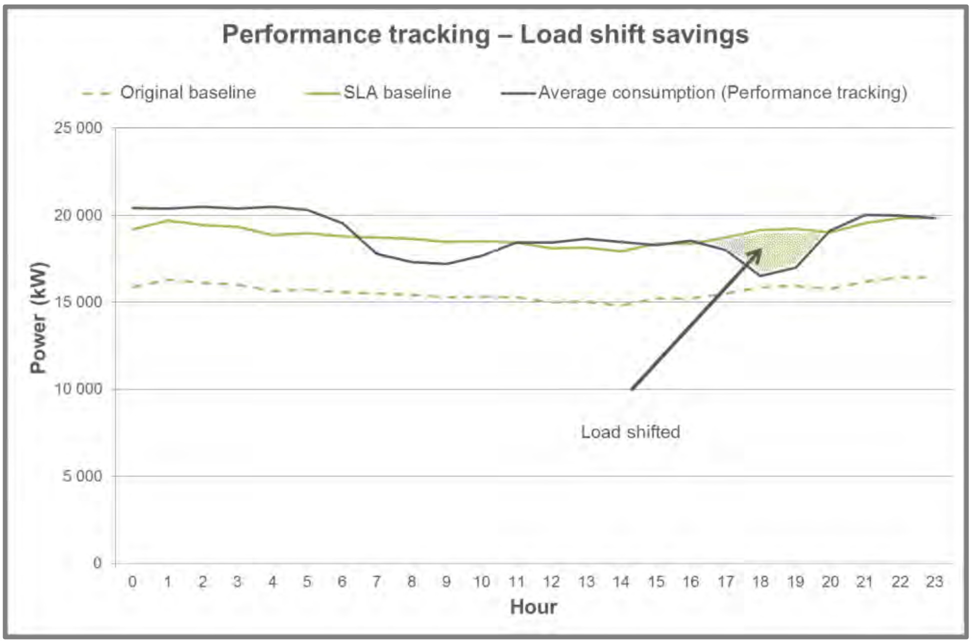

Figure D-1: Performance tracking – Load shift savings

The profile in Figure D-1 clearly indicates the evening load shift of the project. It also indicates that the system power consumption is higher than it was during the baseline period. Unfortunately, inspection of the graph does not clearly indicate the true nature of the project performance, but rather presents a generalised overview. The methodology for graphically presenting project performance was implemented on the dataset to gain a better understanding of the project performance characteristics. The performance tracking results are shown in Figure D-2.

Investigation of the results depicted by Figure D-2 indicates that the project is underperforming. A comparison of the mean and target values suggests that the project is only slightly underperforming achieving 2 425 kW of a target of 2 60 0kW (93% of target). The occurrence of results, however, indicates that the majority of results fall within the range of 898 kW. Further investigation of the graph also indicates the rare occurrence of extremely high savings exceeding 8 500 kW.

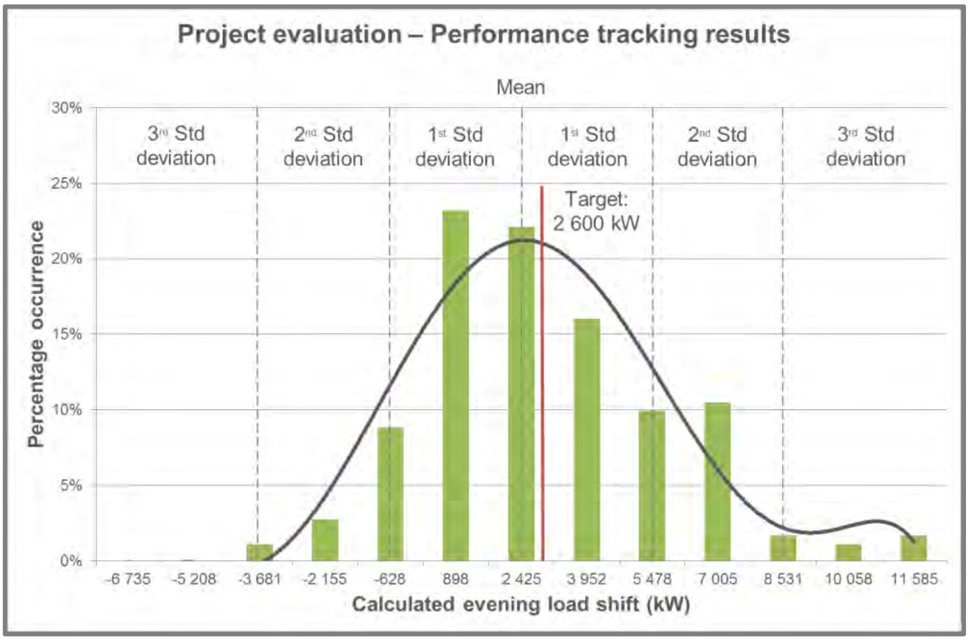

FIGURE D-2: PROJECT EVALUATION – PERFORMANCE TRACKING RESULTS

The occurrence of large savings will result in the mean being positively biased. This will explain why the general histogram shape is not centred towards the 898 kW class. The occurrence of extreme performance values also affected the size of the standard deviation. Assuming that the histogram shape approaches the form of a normal distribution 95% of the results will therefore fall between -3 681 kW and 8 531 kW. This is a massive range stretching from -140% to 330% of project target. If the project performance was reported as the most conservative value the project would have underperformed by more than a 100%. This confirms the importance of the methodology and its ability to present result in this format thereby allowing stakeholders to evaluate performance objectively.

The performance tracking dataset was also evaluated using the long-term evaluation methodology. The results of the evaluation are presented in Figure D-3. Investigation of the results indicates that the project performed really well during the first four months after project completion. The sharp increase in the control chart indicates that the project consistently overperformed on its target.

The angle in the control chart trend changed shortly after performance assessment was completed. Changes in the angle indicate that the project started to underperform gradually. The underperformance, however, increased during the year resulting in a sharper decline. The long-term underperformance probably resulted in the high occurrence of results in the 898 kW class.

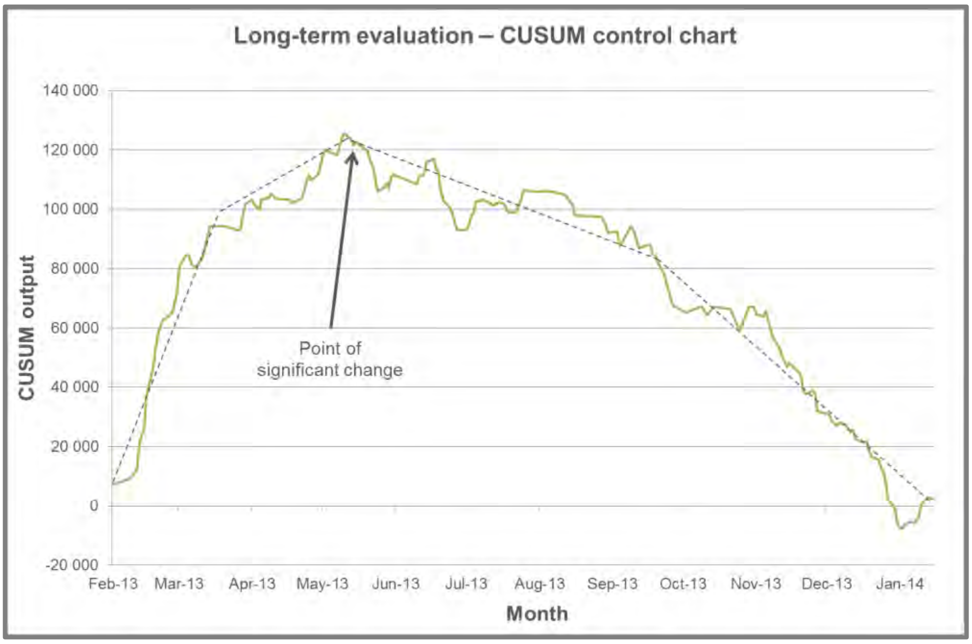

FIGURE D-3: LONG-TERM EVALUATION – CUSUM EVALUATION RESULTS

CASE STUDY 22 – MINE DEWATERING PROJECT PERFORMANCE TRACKING

Case Study 22 presents another load shifting project. This project was implemented on the dewatering system of a gold mine. The project implemented an automated control system that was upgraded and reconfigured when required. The expectation therefore is that the project will perform consistently well. An energy-neutral baseline model was used to represent system operation before project implementation. Figure D-4 illustrates the average performance over a two-year period.

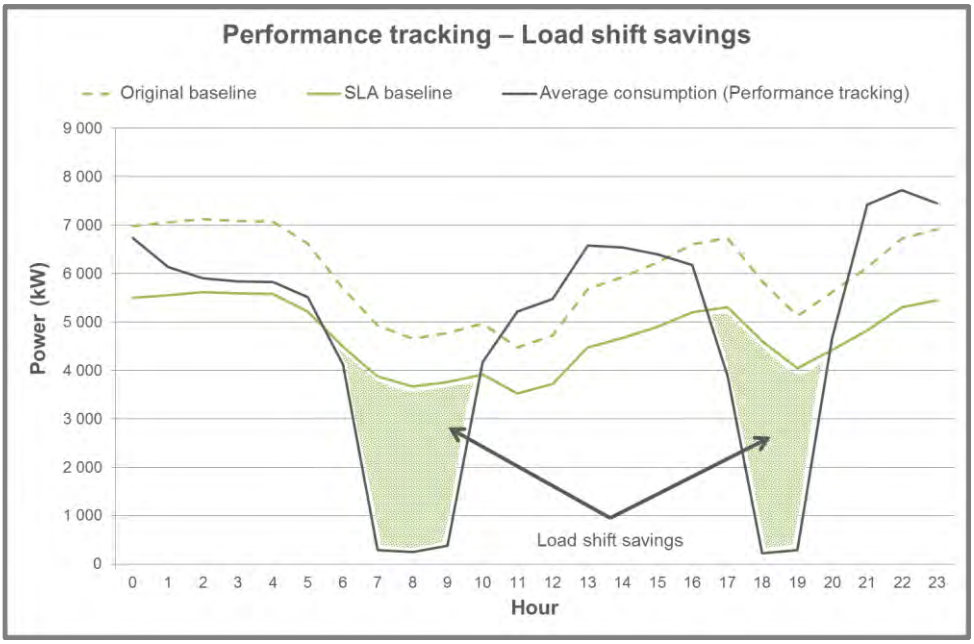

FIGURE D-4: PERFORMANCE TRACKING – LOAD SHIFT SAVINGS

The average profile indicates that the system power consumption is generally lower than it was during the baseline period. The average power consumption profile also indicates that the system almost manages to consistently achieve a complete load shift. The project performance is processed using the newly developed methodology. The results are illustrated in Figure D-5.

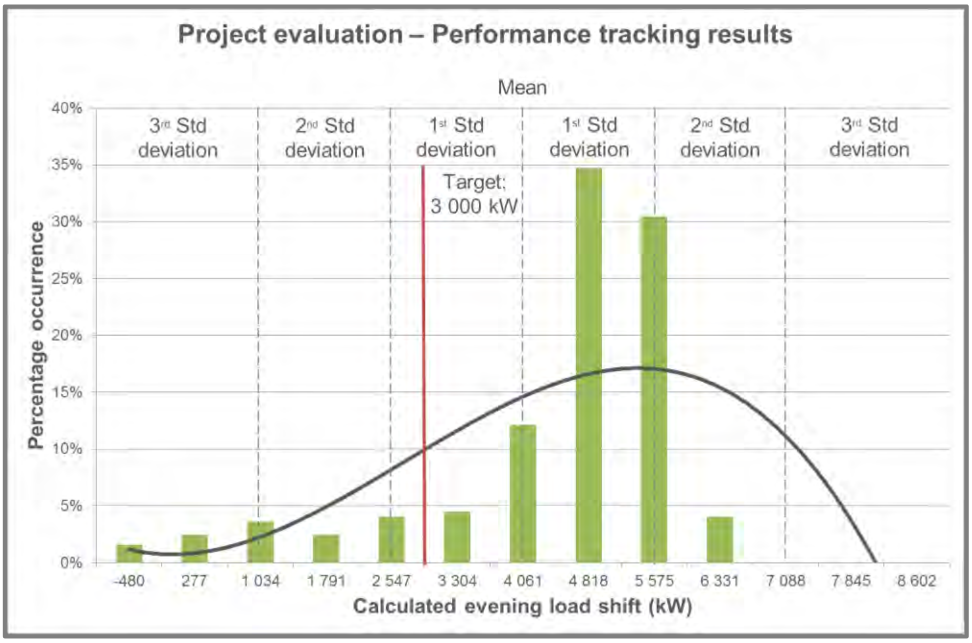

FIGURE D-5: PROJECT EVALUATION – PERFORMANCE TRACKING RESULTS

The results presented in Figure D-5 clearly indicate the project's overperformance. The mean of the results is situated at 4 061 kW, which is approximately 135% of the project target. The highest occurrence of results is situated at 4 818 kW and 5 575 kW which is one standard deviation above the mean. In this case study the sporadic occurrence of underperformance results in a lower mean value.

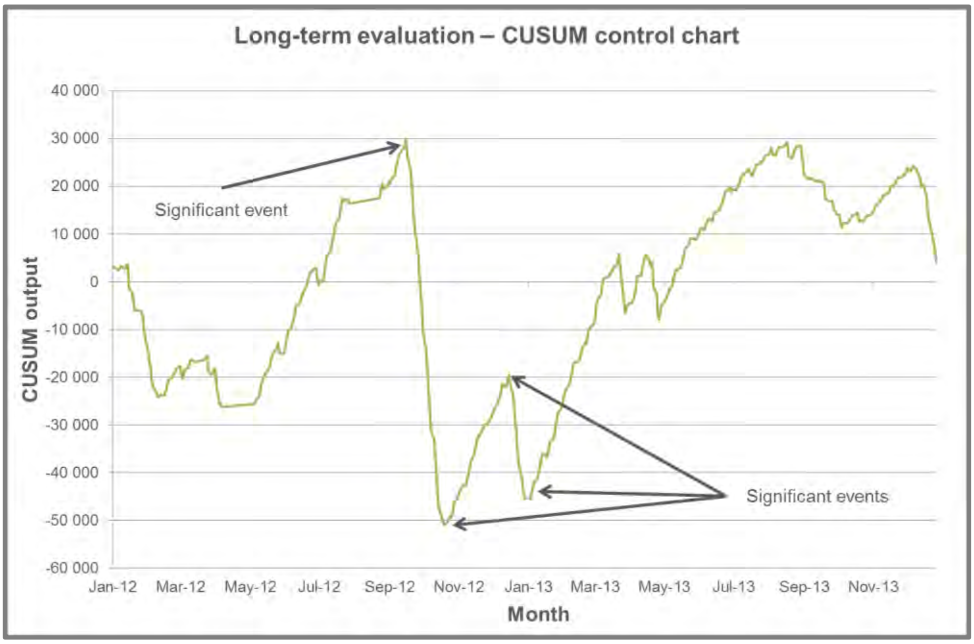

FIGURE D-6: LONG-TERM EVALUATION – CUSUM EVALUATION RESULTS

The long-term evaluation methodology was implemented on the collected data to analyse the project performance further. The resulting control chart is illustrated in Figure D-6. Inspection of the control chart indicates the occurrence of several significant events that negatively affected project performance for brief periods. It is also evident that the project managed to quickly rectify the issue and continue with normal operations.

Case Study 23 – Compressed air project performance assessment

Case Study 23 presents an evening peak-clipping project implemented on a compressed air system of a platinum mine. The project used a regression baseline model to determine what the system power consumption would have been without the project. The case study started by investigating the project performance for the performance assessment period only. Figure D-7 presents the results.

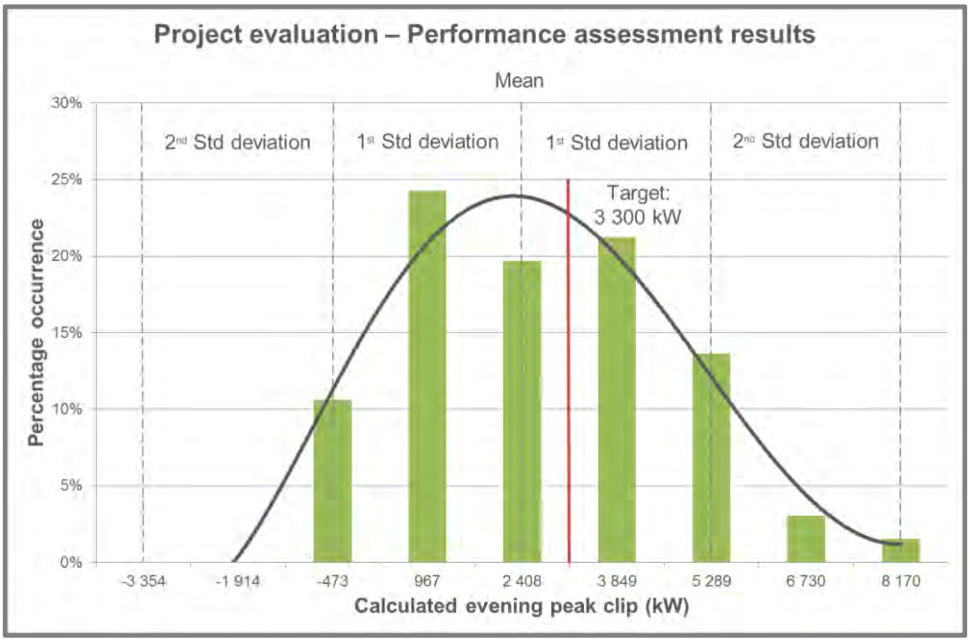

Figure D-7: Project evaluation – Performance assessment results

The results indicate that the project is underperforming. The mean value of 2 408 kW is significantly lower than the target of 3 300 kW (73% of project target). Further inspection of the graph indicates that the peak in occurrence falls within the 967 kW class. The occurrence of high impact results (falling in the classes above 6 730 kW) positively biases the mean value.

The project evaluation continued by increasing the data sample to include all performance data. This dataset consisted of the three-month performance assessment as well as an additional six months of performance tracking data. The long-term evaluation methodology was applied to the dataset. Figure D-8 illustrates the results.

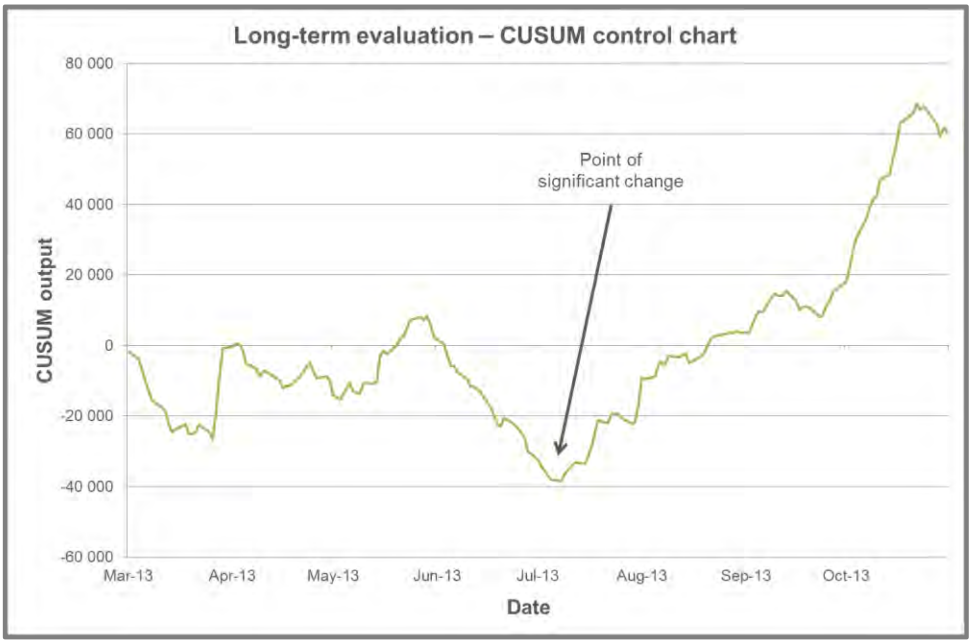

FIGURE D-8: LONG-TERM EVALUATION – CUSUM EVALUATION RESULTS

The results depicted in the control chart indicate that the project performance fluctuated but remained close to target during the performance assessment phase. The project performance then slowly started to degrade during June. The control chart indicates the occurrence of a significant event during July 2013 that resulted in a steep increase in reported savings.

The investigation found that the change was due to the implementation of another project. The project used the hardware installed as part of the original project to increase energy savings to periods outside the evening peak. The change in control philosophy also resulted in an increase in evening peak-clipping savings. The significant change in the control chart can be attributed to the increase in the peak-clipping savings.

The increase peak-clipping savings are generated by the control philosophy and hardware implemented by the first project. The second project will therefore only be able to claim savings outside the evening peak.

Figure D-9 illustrates the allocation of savings between the two projects. The baseline is scaled using the regression model. The savings achieved during the evening peak is allocated to the first project while the remainder is allocated to the second project.

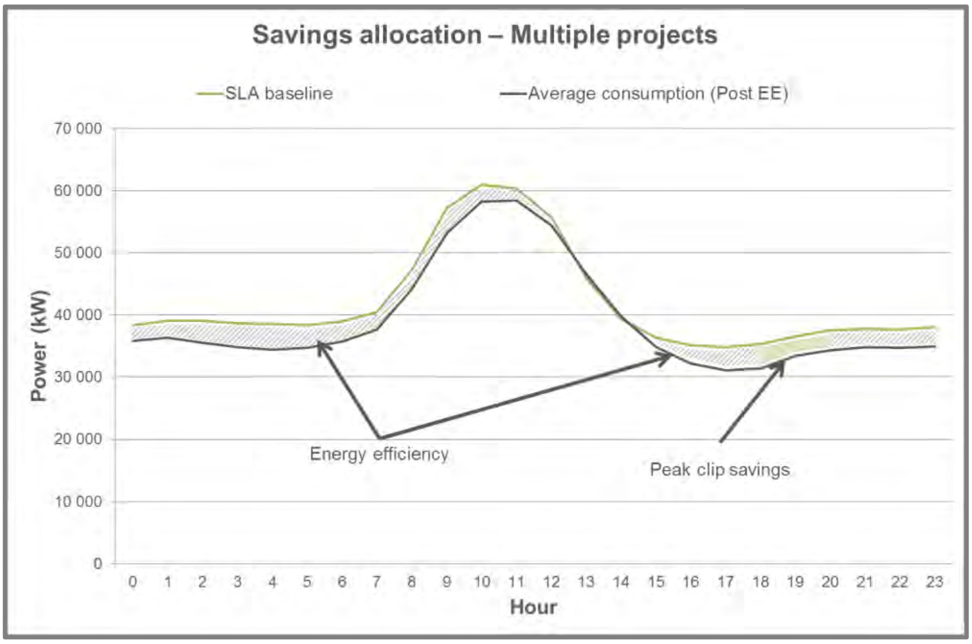

FIGURE D-9: SAVINGS ALLOCATION – MULTIPLE PROJECTS

CASE STUDY 24 – COMPRESSED AIR PROJECT PERFORMANCE ASSESSMENT

Case Study 24 presents another compressed air peak-clipping project. The project used a regression baseline model to determine what the system power consumption would have been without the project. The results of the project performance assessment period were evaluated using the new methodology. The results are presented in Figure D-10.

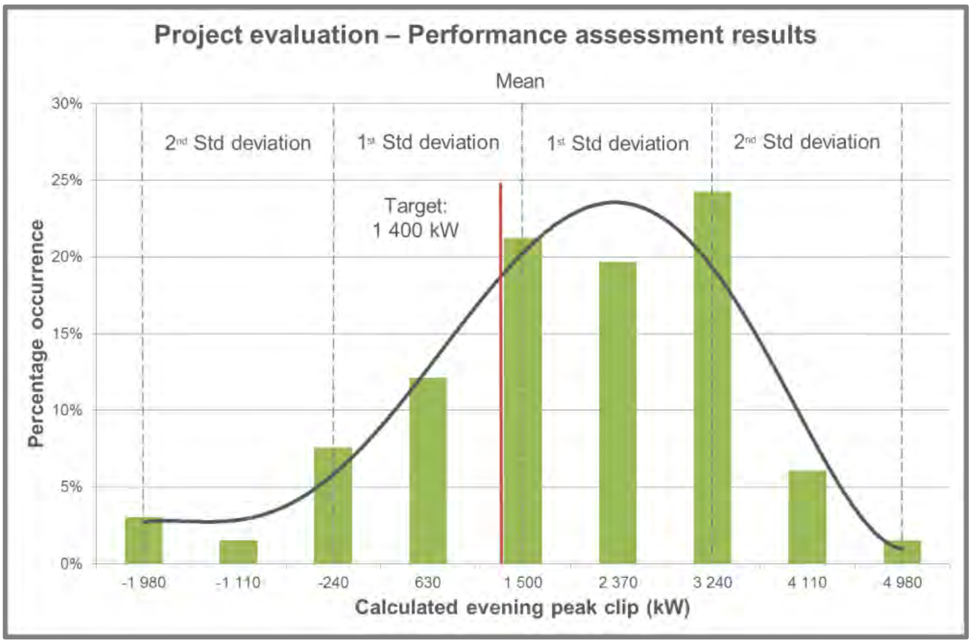

FIGURE D-10: PROJECT EVALUATION – PERFORMANCE ASSESSMENT RESULTS

Investigation of the project results indicates that the project achieved its target of 1 500 kW. The occurrence of results is, however, more dominant in the 3 240 kW class suggesting that the project regularly overperformed on its target. The occurrence of significant under performance resulted in the mean value remaining close to the target.

The project dataset was increased to include a year's performance tracking data. The data was also processed using the new methodology. Figure D-11 presents the results.

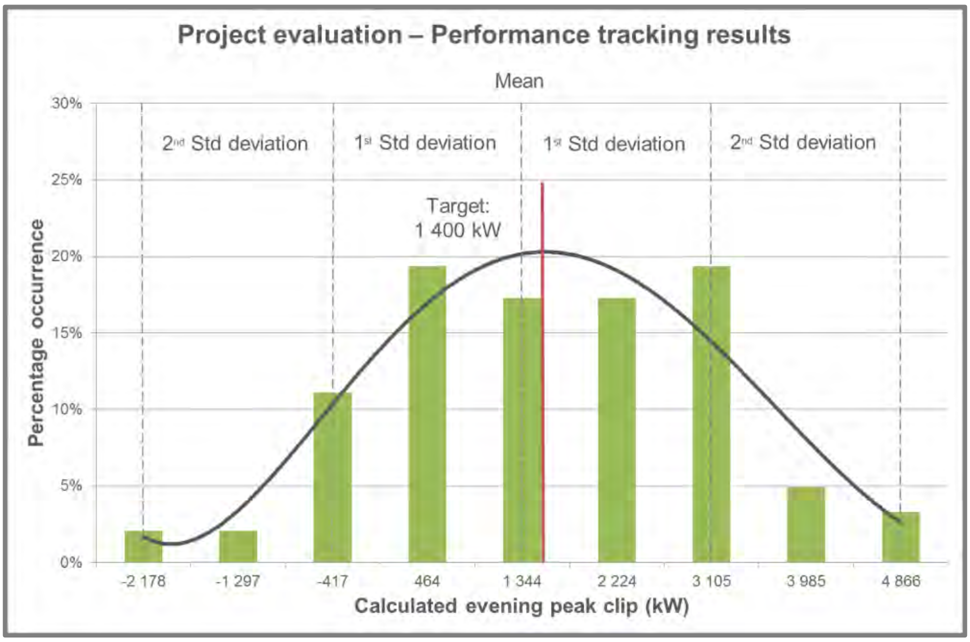

FIGURE D-11: PROJECT EVALUATION – PERFORMANCE TRACKING RESULTS

The performance tracking results indicate the project slightly underperformed during the tracking phase. The results indicate that the project managed to achieve 96% of the target savings. The general occurrence of results indicated that the project is performing fairly consistently with the performance tracking results slightly lower than the performance assessment results. The performance tracking dataset was also evaluated using the long-term methodology. The results are displayed in Figure D-12.

The results illustrated by the control chart indicate that the project started to underperform in January, but managed to regain and maintain good performance until June. During June, the calculated savings increased and continued to increase until August where it suddenly started decreasing again. The downward trend continued until December where it started to improve until the mine closed for the festive season.

Investigation of the system operation indicated the implementation of an additional project focusing on energy efficiency. The project started off by increasing only the evening peak savings, thereby resulting in the increase noted from June. The completion of the required hardware installations resulted in a general increase in system efficiency noticeable from August. The full implementation of the energy efficiency project in August, however, negatively affected the evening peak-clipping savings.

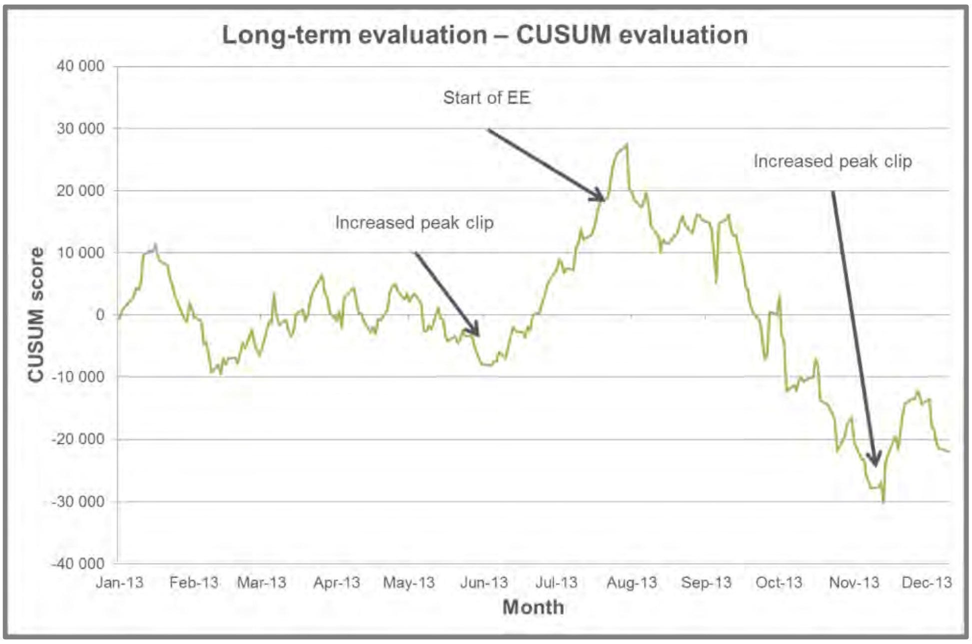

FIGURE D-12: LONG-TERM EVALUATION – CUSUM EVALUATION RESULTS

The concurrent operation of the two projects required the savings to be objectively allocated. The developed guideline was therefore followed. The same baseline model was used to present pre-implementation system operation. The impact of the energy efficiency project was calculated by determining the average energy efficiency from 00:00 to 17:59 and from 20:00 to 23:59. The average value was then used to allocate the energy efficiency impact during the evening peak period. The remainder of the savings were allocated to the peak-clipping project.

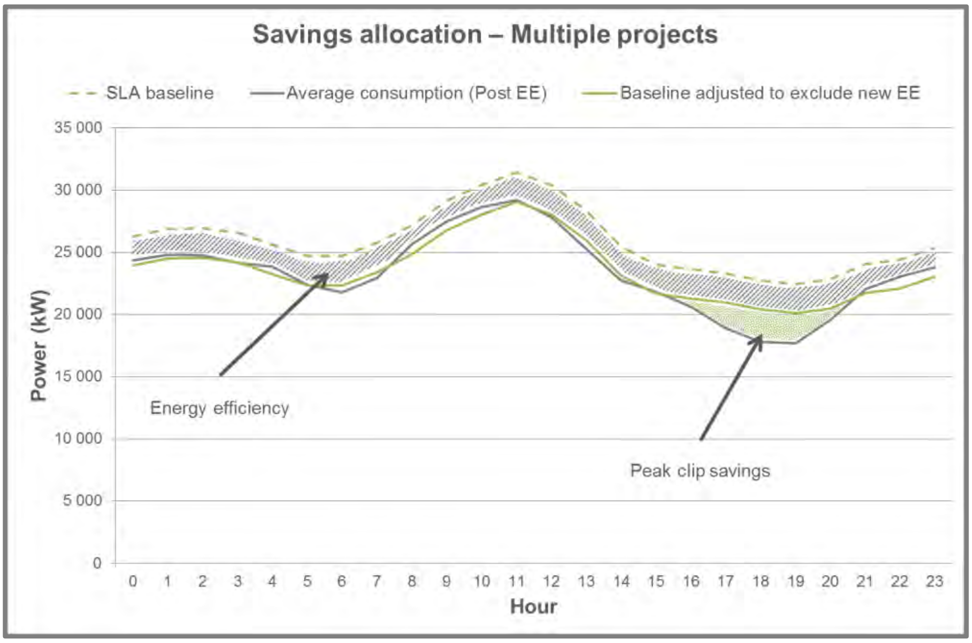

FIGURE D-12: SAVINGS ALLOCATION – MULTIPLE PROJECTS

Case Study 25 – Mine refrigeration project performance assessment

Case Study 25 presented an energy efficiency project implemented on a mine refrigeration system and its auxiliaries. Only power data was available during the baseline period of the project. This resulted in the use of a constant (year-on-year) baseline model to evaluate the project during performance assessment. Figure D-13 illustrates the constant baseline and the average power consumption during performance assessment.

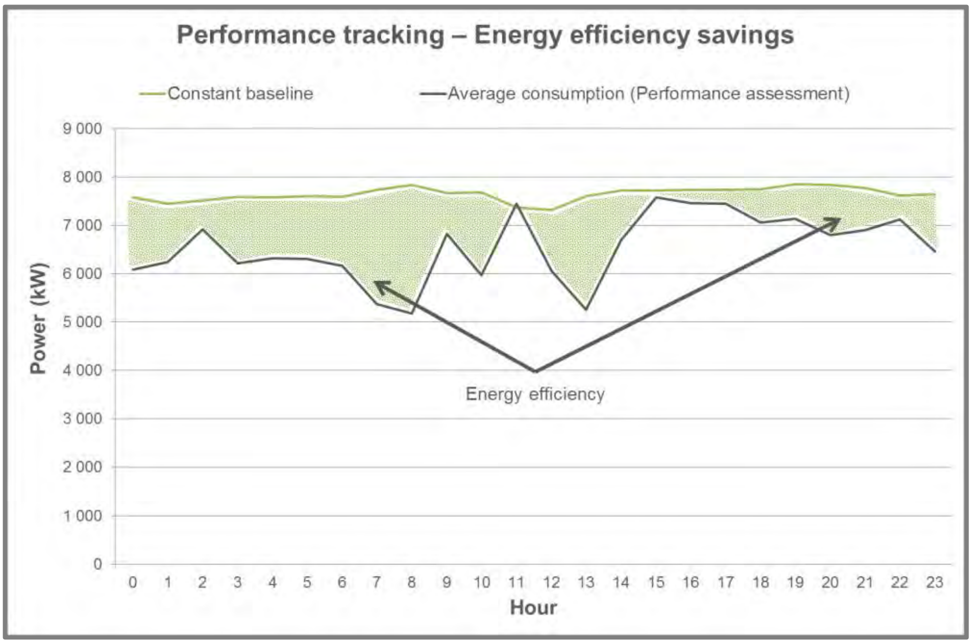

Figure D-13: Performance tracking – Energy efficiency savings

The impact of seasonal variance was mitigated by analysing project performance based on a year-on-year assessment. This entailed using a constant baseline developed using March 2011 data to assess the performance of March 2012. The same process was followed for the assessment of April 2012. The results are presented in Figure D-14.

Inspection of the results indicates that the project achieved its target. The occurrence of results confirms that the project managed to regularly achieve target and also overperformed regularly. The occurrence of extreme cases of reported savings seems not to have significant effect on the mean value.

The process of developing the two baseline models is illustrated in Figure D-15. The figure shows the availability of data before and after, but not during project implementation. The performance assessment dataset was subsequently used to develop a regression model. The regression model can therefore not be used to depict system operation before project implementation, but rather system operation during PA. The model can now be used for the performance tracking phase.

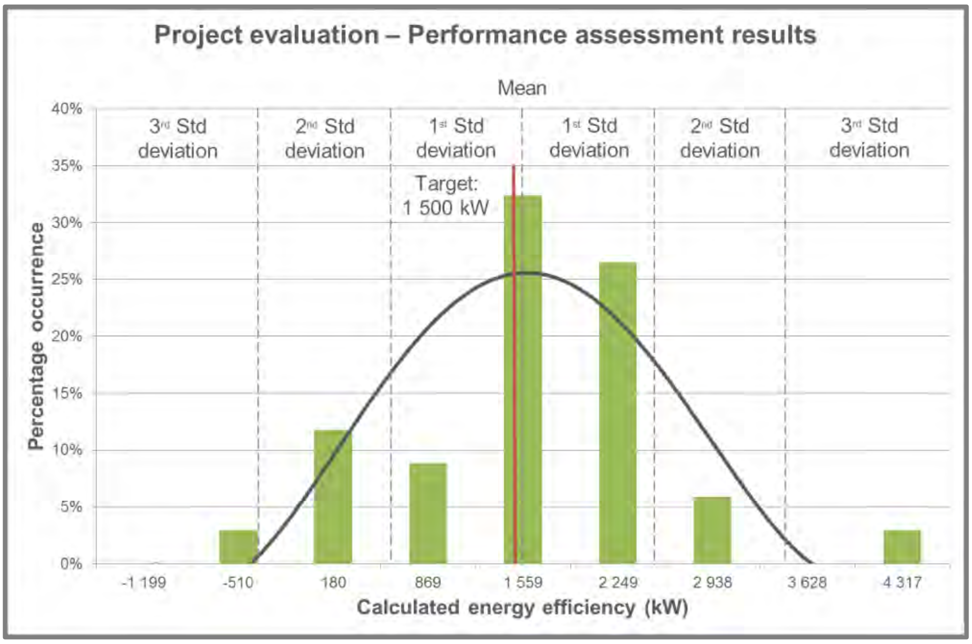

FIGURE D-14: PROJECT EVALUATION – PERFORMANCE ASSESSMENT RESULTS

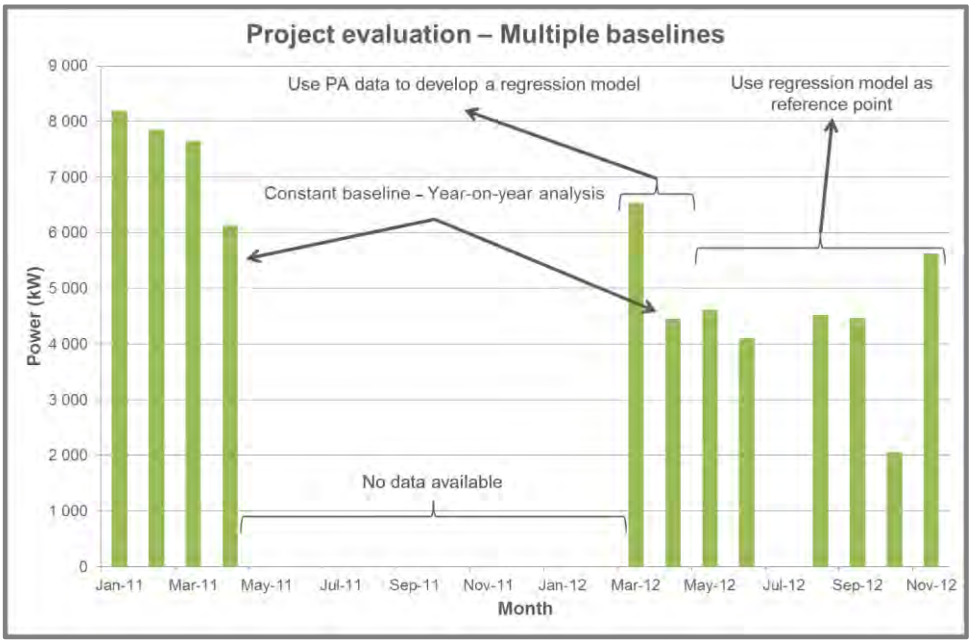

FIGURE D-15: CALCULATING SAVINGS – CONSTANT BASELINE

The performance tracking results were evaluated using the long-term evaluation methodology. The results are illustrated in Figure D-16. The control chart indicates a slow decline in project performance. The decline continued for approximately 30 weeks until a significant change resulted in a steep upward trend. The change was shortly followed by an extreme decline that continued for almost 20 weeks. Investigation into the cause of the massive shifts in operation identified labour strikes, mine closure and reopening as the main drives of the change.

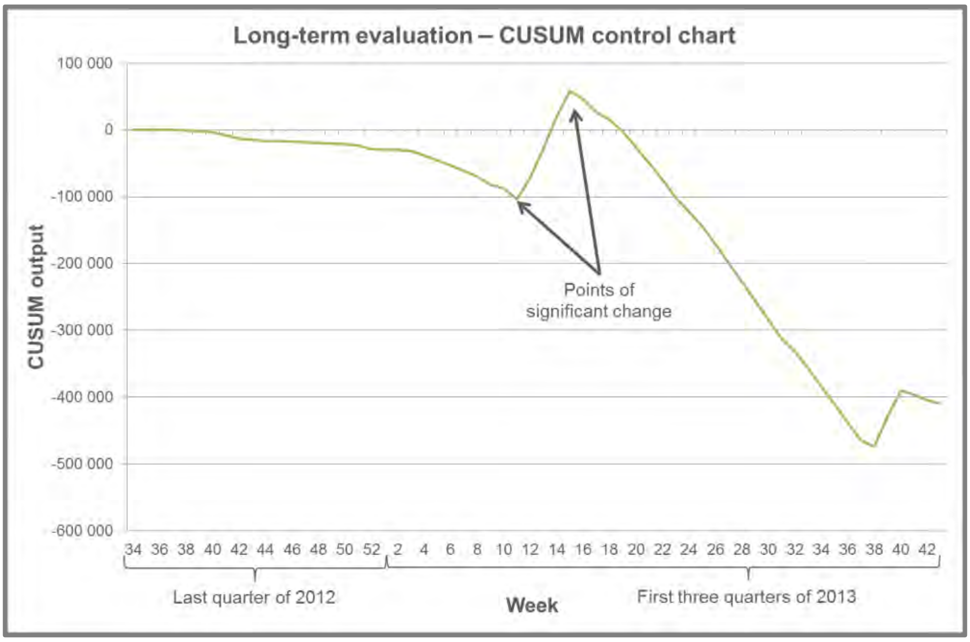

FIGURE D-16: LONG-TERM EVALUATION – CUSUM EVALUATION RESULTS