Management of measurement and verification uncertainty for industrial 12L tax incentive applications

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ABSTRACT

Title: Management of measurement and verification uncertainty for industrial 12L tax incentive applications

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Keywords: energy efficiency, uncertainty management, measurement and verification, section 12L tax incentive.

South Africa (SA) has committed to reducing its greenhouse gas (GHG) emissions. One of SA's key strategies to minimise GHG intensity is to utilise incentivised energy efficiency initiatives (EEIs). Specifically, the section 12L tax incentive rewards claimants 95c/kWh for verified energy efficiency savings (EES) which can be linked to reduction of GHG emissions. Accurate quantification of EES is critical since it has a direct monetary impact on the claimed amount.

The SANS 50010 standard for measurement and verification (M&V) requires uncertainty management to ensure that reported savings are a conservative reflection of actual savings achieved. The updated version of the standard (officially released in 2018) now also requires that the uncertainty associated with reported savings not only be managed, but also be quantified. This highlights the need for the application of uncertainty management and quantification methods.

In this study, a detailed literature review was conducted to identify the key contributors to EES uncertainty, namely measurement, database, modelling and assessment decision uncertainties. It was found that numerous uncertainty quantification and management (Q&M) methods are available. However, it is important to know which method to use to address specific uncertainty contributors. It is also important to consistently apply the available methods.

A solution in the form of an uncertainty Q&M flowchart was developed for quantifying and managing EES uncertainties. The uncertainty Q&M flowchart is a tool that incorporates a five-step approach to EES quantification. The steps are (1) Energy Saving Measure Isolation, (2) Database Management, (3) Model Development, (4) Uncertainty Assessment and (5) Model Selection. The aim of the flowchart is to provide a structured basis to apply various uncertainty Q&M methods available from literature.

The uncertainty Q&M flowchart was verified by applying it to three industrial EEI case studies. It was found that uncertainty levels can range between 2% and 18% due to varying uncertainty contributors. It is therefore critical to be able to show stakeholders how uncertainty Q&M was applied. The developed methodology provides a basis to validate Q&M by comparing the outcomes of the Q&M flowchart with SANS 50010 requirements.

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"But those who hope in the Lord shall renew their strength" – Isaiah 40: 31 abridged

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LIST OF ABBREVIATIONS

Abbreviation	*Description*
12L	Section 12l of the Income Tax Act, 1962
BFW	Boiler Feed Water
CI	Confidence Interval
EE	Energy Efficiency
EEI	Energy Efficiency Initiative
EES	Energy Efficiency Saving
ESM	Energy Saving Measure
GHG	Greenhouse Gas
M&V	Measurement and Verification
NG	Natural Gas
POM	Point of Measurement
Q&M	Quantification and management
SA	South Africa
SANAS	South African National Accreditation System
SANEDI	South African National Energy Development Institute
SANS	South African National Standard
SARS	South African Revenue Services

GLOSSARY

Accuracy: an indication of how close a reported value is to the true value. The term can be used to refer to a model, set of measured data or to describe a measuring instrument's tolerance.

Assurance techniques: methods for uncertainty management that provide certainty and creditability to the reported value.

Baseline data: the measurements and facts describing operations during the baseline period. This will include energy use and parameters of facility operation that govern energy use.

Baseline model: the set of arithmetic factors, equations or data used to describe the relationship between energy use and other baseline data. A model may also be a simulation process involving a specified simulation engine and set of output data.

Baseline period*:* the period of time selected to be representative of pre-retrofit/energy efficiency initiative operations.

Calibration: to compare the output or results of a measurement or model with that of some standard, determining the deviation and relevant uncertainty and adjusting the measuring device or model accordingly.

Capex: Capital Expenditure.

Energy savings: the reduction in the use of energy from the pre-retrofit/ EEI to the post-retrofit/ EEI, once independent variables (such as weather or occupancy) have been adjusted for.

Error: deviation of measurement from the true value.

Greenfields: the energy saving measure is incorporated into the design, construction and operation of the new system or facility, or new energy carriers.

Independent variables: the factors that affect the energy use but cannot be controlled (e.g. weather or occupancy).

Measurand: a quantity intended to be measured.

Normal operating cycle: an operating cycle that includes all the normal operating modes and is representative of the energy consumption of the system or facility under normal operation.

Opex: operational expenditure.

Performance assessment period*:* the period of time selected to be representative of post retrofit operations/ energy efficiency initiative implementation.

Precision: the repeatability of the measurement

Random error: is caused by inherently unpredictable fluctuations in the measurement readings due to precision limitations of the measurement instruments.

Regression model: a mathematical model based on statistical analysis of some measured data.

Statistical techniques**:** methods for uncertainty determination that involve calculation techniques and yield a numerical value.

Systematic errors: reproducible inaccuracies that are consistently in the same direction.

1 INTRODUCTION

1.1 PREAMBLE

In this chapter background is provided to establish the context and relevance of the study. This includes the present state of climate change mitigation strategies initiated by the South African (SA) government with emphasis placed on the 12L tax incentive. The incentive refers to the allowance awarded for energy efficiency savings (EES) as described by Section 12L of the Income Tax Act (Act No. 58 of 1962) [1].

The chapter includes an investigation of the 12L tax incentive to determine the challenges faced when quantifying and managing (Q&M) the uncertainty associated with reporting EES. This provides the insight needed to understand the formulated problem statement, research objectives and scope of the study. Lastly, an overview of the dissertation is provided.

1.2 BACKGROUND TO STUDY

1.2.1 GLOBAL EFFORT TO REDUCE GREENHOUSE GAS EMISSIONS

In 2015, the United Nations Climate Change Conference (UNCCC), specifically referred to as Conference of the Parties 21 (COP-21) was held. It presented the threat of climate change to the planet and called for the reduction of global greenhouse gas (GHG) emissions. This global effort is referred to as the Paris Agreement [2]. The goal of the agreement is to limit global temperature warming to below 2°C compared with pre-industrial levels by reducing GHG emissions. [2] South Africa is considered a carbon dioxide (CO_2) intensive country since most of its electricity is produced from coal [3]. As a result, SA is amongst the highest GHG emitters in the world as indicated by Figure 1-1 [4].

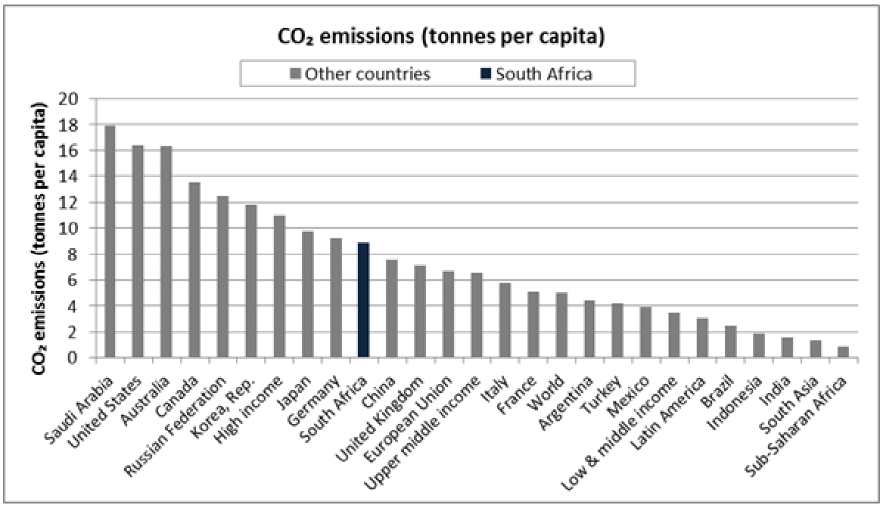


Figure 1-1: National emissions per capita during 2013. Extracted from [4][5]

A move towards a more sustainable and low-carbon economy and society is a national priority [3], [6]–[8]. Hence, in 2015 South Africa ratified the Paris Agreement[1]. The South African government has committed to a 32% reduction in GHG emissions by 2020 and 42% by 2025 [3]. A significant part of SA's strategy to adhere to these agreements is through the use of tax-based incentives and disincentives [7].

In SA, carbon tax refers to one of the tax-based disincentives used by the government to mitigate GHG emissions. Although carbon tax has been delayed several times, it is due for implementation in 2019 [1]. South Africa's carbon tax landscape remains in the development stage with the government publishing the Climate Change Bill as recently as June 2018 [8]. The bill seeks to make provision for a coordinated and integrated response to climate change. Carbon tax is intended to penalise carbon-based emissions; however, several companies who are liable can opt to reduce their GHG emissions pro-actively and voluntarily. Energy efficiency improvement is seen as one the most significant and low-cost measures to reduce GHG emissions [9]. Hence further discussion is provided in the next section.

1.2.2 ENERGY EFFICIENCY IN SOUTH AFRICA

Energy efficiency targets

The National Energy Efficiency Strategy (NEES) approved by Cabinet in 2005 was formulated with the vision of reducing the energy intensity of the economy through energy efficiency (EE). The NEES set a target of an overall energy intensity reduction of 12% by 2015. Specifically, an EE improvement of 15% was set for the industrial and mining sector [10]. The industrial sector also contributes largely towards carbon emissions [3]. The industrial sector was thus targeted in this study as an area where carbon intensity can be reduced by means of energy efficiency.

Energy efficiency tax-based incentives

Energy efficiency has several barriers [11]–[13]. One of these barriers is funding towards Opex and Capex projects to implement and maintain energy saving measures (ESMs)[12]. South Africa's key strategies to minimise GHG emissions in this sector include EE tax-based incentives. These incentives motivate companies toward increase EE efforts. Section 12I and 12L of the Income Tax Act (1962) are examples of these EE incentives which reward specific improvements in energy efficiency performance [14], [15].

Energy Efficiency Initiatives (EEIs) and Energy Saving Measures (ESMs) are observed to play a significant role in the mitigation of GHG emissions [14], [15]. Energy savings can be

[1] DEA, Department of Environmental Affairs. "*South Africa signs Paris Agreement on Climate Change in New York*". Internet: www.environment.gov.za. April 22, 2016 [Oct. 01, 2018].

defined as any action with the response of less energy usage. Energy efficiency is the use of technology in an effective way which results in a lower energy requirement for the same function [16].

ESMs, otherwise referred to as Strategic Energy Management (SEM) initiatives, are geared toward energy efficiency improvements through systematic changes in facility operations, maintenance and behaviours (OM&B) and capital equipment upgrades in large energy-use facilities. Utility ESM programs are a fairly new offering, and evaluators are still developing best practices for evaluation [17]. The 12L tax incentive is a key EE-tax based initiative that drives EE improvements in the industrial sector. Hence, a brief overview of SA's Section 12L regulations is discussed in the following section.

1.2.3 SECTION 12L TAX INCENTIVE

Claimable energy efficiency savings

The National Treasury and South African Revenue Services (SARS) in collaboration with the Department of Energy (DoE) offer a tax allowance to businesses that achieve energy efficiency [10]. The tax allowance is contained in Section 12L of the Income Tax Act, 1962 (Act no 58 of 1962) [14], and is generally referred to as the "*12L tax allowance*". The incentive encourages companies to reduce their energy usage and be more energy efficient [18]. This incentive was implemented by the government on the 1st of November 2013 and is claimable until the 1st of January 2020 [18].

The 12L tax incentive allows a tax deduction on all possible energy carriers that can be measured or converted to an energy (kWh) equivalent with the exception of renewable energy. The verified and measured EES should be over a 12-month period known as the year of assessment or the performance assessment (PA) period. This period is compared with the directly preceding 12-month period known as the baseline (BL) period [13], [19]. Companies that have achieved and verified EES in accordance with the section 12L regulations are allowed a tax deduction of 95c per verified kWh of EE saving achieved (previously 45c/kWh) [13], [19].

Barriers to the 12L process

A number of issues arise when pursuing a 12L claim [20]. In 2016 this was evidenced by the fact that 108 12L applications were submitted to the South African National Energy Development Institute (SANEDI) and only fourteen of those claims were accepted [21]. The 12L application process can be challenging due to strict rules which must be followed [22]. These rules are described in the Income Tax Act [19], the Regulations in terms of Section 12L [14], and the national M&V Standard (SANS 50010) [23]. Important considerations for a 12L application include the verification of the EES, time constraints, and uncertainty in the reported saving [15], [18], [24], [25].

Verification needs to be carried out by an independent South African National Accreditation System (SANAS) accredited measurement and verification (M&V) body. There are also only six of these SANAS accredited M&V bodies in South Africa, making this a limiting factor [18]. Also, these M&V bodies must be employed to verify the calculated EES, and this incurs additional expenditure [18].

Time is a key consideration when approaching a 12L claim, as an entire application must be completed within a certain time frame i.e. before the tax submission date. Also, this incentive is only valid until 1 January 2020, thus there are only two full claimable years left. Time and resource allocation is therefore important when applying for the deduction.

Accurate quantification of the EE saving is a critical component to the 12L claim since the savings cannot be measured directly [26]. Various methods can be employed to calculate the EES. Hence there is uncertainty associated with calculated savings [27]–[29]. An EES should be reported with an uncertainty value for it to be credible [24], [30]. Uncertainty management in both a timeous and effective manner is therefore critical in overcoming a key barrier in the 12L process.

1.2.4 M&V UNCERTAINTY

Uncertainty can be defined as an assessment of the probability that an estimate is within a specified range from the true value. It therefore indicates how well a calculated or measured value represents a true value [29]. American economist Frank Knight aptly stated that “You cannot be certain about uncertainty” [31]. It is nearly impossible to quantify every potential source of uncertainty [29]. However, it is important to include some form of uncertainty assessment when reporting energy savings as it is not possible to judge an estimate’s value without it [29].

Uncertainty of reporting energy savings is mainly governed within the field of Measurement and Verification (M&V). M&V is a tool which delivers an impartial and replicable process that can be used to quantify energy savings in EE and Demand Side Management (EEDSM) projects. M&V reports are used to verify the quantified energy savings achieved by EE projects. [32]

The reported EES always include a degree of uncertainty [24], [30], [32]. To ensure the reported EES are considered accurate, compliant and transparent, an uncertainty value should be stated [24]. However, there is ambivalence regarding how uncertainty should be reported in practice [33]. M&V reports regularly limit uncertainty deliberations to random error (particularly sampling and regression error)[29]. Uncertainty quantification and management can, however, be a much broader topic applied in different levels of rigour.

Reasonable effort should be made to identify and attempt to minimize every potential source of uncertainty [29]. The quality and utility of the uncertainty reported for a result depend on the understanding, critical analysis and integrity of the factors that contributed to the assignment of its value [24], [34]. In order to fully understand the importance and role of uncertainty management it is important to understand the regulatory landscape of the 12L tax incentive.

1.3 REGULATORY LANDSCAPE FOR A 12L APPLICATION

PREAMBLE

The 12L application process includes strict rules and regulations that need to be adhered to as discussed in Section 1.2.3. The process incorporates legislative guidance, governing bodies and multiple stakeholders. The governing regulations for the 12L application process were issued by National Treasury, in 2013 [14] and 2015 [35]. These regulations are referred to as "12L Regulations", as they are relevant to Section 12L of the Income Tax Act of 1962 [14]. The regulatory landscape for a 12L application is illustrated in Figure 1-2 below.

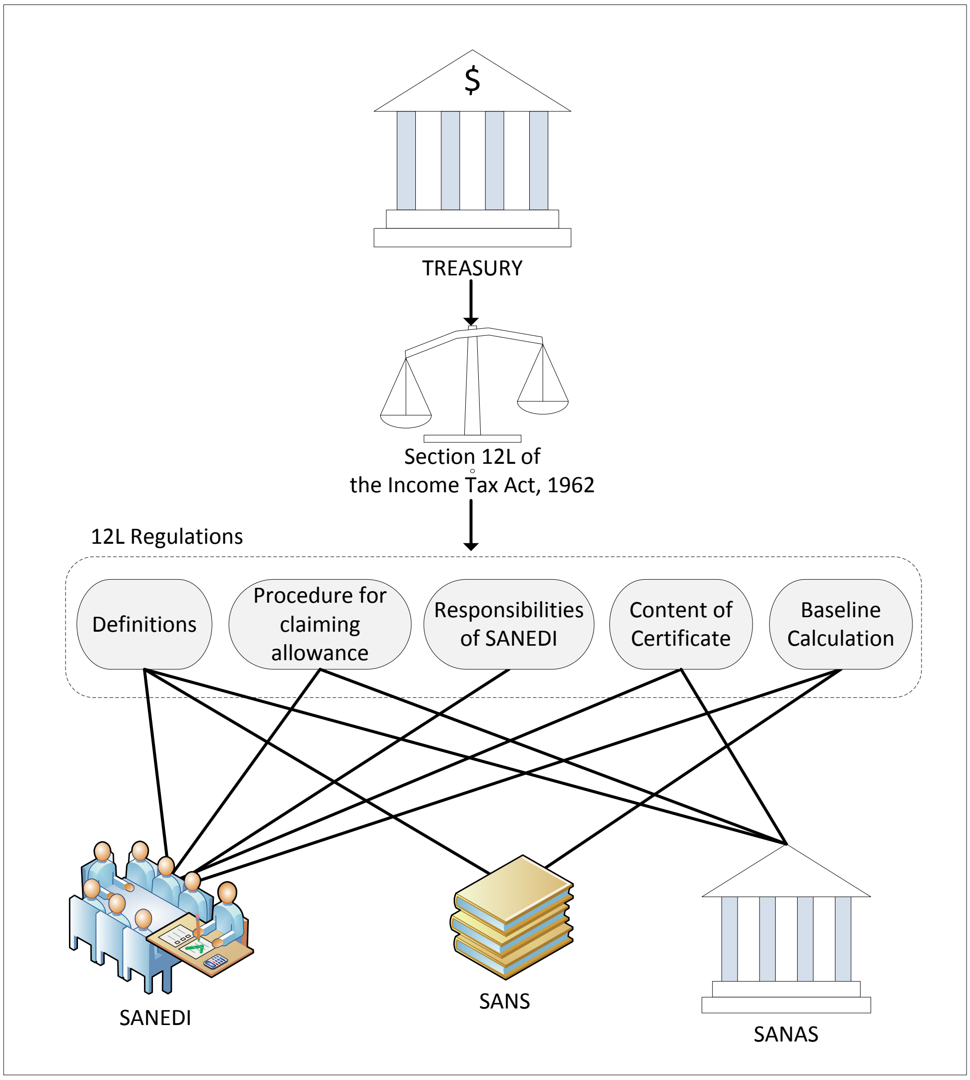


Figure 1-2: Regulatory landscape for 12L application

Figure 1-2 indicates three bodies of government which implement these regulations: the South African National Energy Development Institute (SANEDI), the South African National Standard (SANS) and the South African National Accreditation System (SANAS). The roles of these governing bodies will be discussed hereafter.

SANEDI

SANEDI is Schedule 3A state owned entity that acts as jurisdiction for 12L claims. They appoint experts to review 12L applications. Applications need to be approved within a level of certainty by the SANEDI review panel. SANEDI has the final responsibility of issuing of tax certificates. [13] It is therefore important that uncertainty quantification and management efforts are clearly communicated to SANEDI to allow a review of the 12L applications.

SANS 50010

SANS 50010, hereafter referred to as "the Standard", is a cornerstone of South African M&V practice as it provides an essential resource to prove regulatory compliance [23], [30]. The Standard provides a generic approach to the M&V of energy savings and energy efficiency and is intended for use by organisations of any sector. The main uncertainty management strategy of the Standard is to ensure that reported savings are conservative [23]. In other words, uncertainty should be managed in such a way that the reported savings are likely to be less than actual savings.

The Standard was first published in 2011, and it required stakeholders to manage the uncertainties associated with the reported energy savings. However, the Standard was amended in 2017 to include not only the management of uncertainty, but also the quantification of uncertainty [23], [24]. This indicates a clear need for improved uncertainty disclosures from a standardisation and regulatory viewpoint.

SANAS

The primary function of SANAS relating to 12L is to provide an accreditation to M&V bodies. This provides confidence that qualified and accredited M&V professionals are appointed to report on verified EES. In addition to this function, in 2017 SANAS also published guidelines to assist with uncertainty management in the M&V industry [24].

The SANAS Guideline [24], hereafter referred to as "the Guideline", was intended as a resource for stakeholders. The Guideline was planned as a prescriptive document, to assist M&V teams with a standardized approach to address uncertainty when calculating the EES. Through the input of various stakeholders, the document was changed to a descriptive guide, which could be used by various concerned parties [33]. Hence the guideline is not legally binding [33]. However, it also indicates a clear need for improved uncertainty disclosures from a standardisation and regulatory viewpoint.

The uncertainties associated with the EES can be subdivided into two categories; quantifiable and unquantifiable [32]. There are three typical types of quantifiable M&V uncertainties: sampling, measurement and modelling uncertainty [24], [32] Some aspects of savings determination do not lend themselves to quantitative uncertainty assessment [36]. These unquantifiable errors are errors that are not easily calculated. Although these uncertainties may be practically unquantifiable, SANAS states that they should still be listed, and reasons given as to why they will not be considered.

The concept of prediction uncertainty is important for determining energy savings uncertainty [36]. The concept can be better understood in terms of confidence limits. The confidence limits define the range of values that can be expected to include the true value with a stated probability. SANAS indicates that the most common confidence limit used in industry is 80/20 [24]. The first number (80) indicates the confidence interval and the second (20) indicates the precision level. SANAS suggests that a reported EES be stated at a confidence level with a precision i.e. a savings precision should be determined.[24]

SANAS states that the uncertainty figure observed for any given energy model is only credible if the assumption used to construct that model has been verified [24], [33]. There is a multitude of tried and tested M&V uncertainty and model validation calculations available, most of them centred on regression. The Guideline focusses on quantifying and managing uncertainty for linear regression models, as these are the most common models used for EES quantification [24]. The main objective of the Guideline is to provide support to M&V professionals [33], to allow more consistent application of uncertainty quantification and management techniques.

CONCLUSION

Regulatory and legislative governance epitomizes the 12L process which makes it administratively strict to navigate. This section only provided a brief overview of the regulatory landscape surrounding the 12L tax incentive (with detailed discussion presented in section 2.2). However, it is clear from the recent updates in this landscape that improved uncertainty quantification and management is required [23], [24]. These updates are aimed at reducing ambivalence regarding how uncertainty should be reported in practice.

The quality and utility of the uncertainty reported for a result depends on the understanding, critical analysis and integrity of the factors that contributed to the assignment of its value. Reasonable effort should therefore be made to identify and minimise potential sources of uncertainty. This is an important challenge in practice considering the regulatory need for improved uncertainty quantification and management. The challenge is explained and developed into a problem statement in the next section.

1.4 PROBLEM STATEMENT DEVELOPMENT

PREAMBLE TO PROBLEM STATEMENT

A change in the Standard now requires M&V bodies not only to ***manage*** the uncertainties associated with a reported EE saving, but to ***quantify*** them as well. This adds a burden to stakeholders as the statistical techniques used to prove model validity and to quantify uncertainty can be complex, time intensive and require expert knowledge [37], [38]. The results of this statistical analysis can also easily be misinterpreted [30].

The 12L tax incentive is part of a strict regulatory environment with a set of rules and regulations that needs to be adhered to. These rules ensure that the claimable EE saving is as compliant, transparent and accurate as possible. Since there are numerous potential errors and sources of uncertainty within the calculation process, the EES needs to be quantified with an uncertainty band [23], [24].

The Standard has provided guidance on which uncertainties to account for, and the Guideline has provided statistical techniques to manage uncertainty (model validation techniques) and quantify uncertainty (uncertainty level tests). However, there is ambivalence on how best to manage and quantify the uncertainties as no prescribed or enforced method is available. Different approaches and techniques can therefore still be applied in different levels of rigour.

Depending on the EE initiative implemented, and the energy savings model chosen, the considerations for managing and quantifying the uncertainty will differ. Hence, the main contributors to uncertainty need to be identified and a simple method for quantifying and managing uncertainty needs to be developed. The expected challenges and issues include:

- Time intensity,
- Complexity of quantification techniques,
- Requirement of specialist/expert knowledge, and
- Examples of practical application not readily available.

In order to test the expected challenges and issues a test was conducted by reviewing M&V reports from existing case studies.

TESTING THE APPLICATION OF AVAILABLE GUIDELINE

The SANAS guideline provides strategies to quantify uncertainty. The statistical methods provided in the guideline are focussed on a linear regression model. As few practical examples of the application of these statistical techniques exist, the methods provided by the Guideline were tested on three real-world South African industrial M&V case studies.

This test was done to identify if case studies would pass the specific uncertainty tests as well as the provided validation tests in hindsight. Additionally, understanding around the need for the tests and the significance thereof was to be established through this initial investigation (details of the calculations are presented in Appendix A). The results of the application of the SANAS statistics to the real-word cases can be seen in the Table 1-1 below.

Table 1-1: Results for SANAS Guideline Statistics Real World Application

STATISTICAL TEST	CASE STUDY 1	CASE STUDY 2	CASE STUDY 3
Savings uncertainty (80/20) test	Fail	Fail	Pass
Monetary Impact	Yes	Yes	No
Model Validation tests	2/3	2/3	3/3
Model Prediction Validation tests	4/4	4/4	4/4

OBSERVATIONS FROM CASE STUDY TESTS

Table 1-1 indicates the results for three types of statistical tests, namely, an 80/20 uncertainty test applied to the savings, a model validation test and prediction validation tests. Additionally, a row was added below the uncertainty test result to indicate whether the failed test would incur a monetary impact. The results for each of three types of statistical tests are provided below.

Expanded uncertainty test

It can be observed in Table 1-1 that two out of the three case studies failed the expanded uncertainty test at an 80/20 confidence limit. This indicates that although it is a common heuristic to use an 80/20 confidence interval, it may not be the best option for industrial EEI applications. Further investigation is necessary to understand why these case studies failed, and how to remedy this. The failure of the 80/20 uncertainty test is critical, as failure means the uncertainty level is too high. As a result, the reported EES would need to be adjusted (monetary impact) and depending on how large the uncertainty is, it could invalidate the claim.

Model validation test

As can be observed in Table 1-1 only one of the case studies (Case study 3) passed all the model validation tests. Correlation (R^2), regression significance (P value) and the Durbin-Watson test for auto-correlation was included in the initial investigation as it could be tested for all the models. The implication of the failed tests is not apparent on the final reported savings. Hence, more investigation is needed to establish this.

Prediction validation test

It can be noted from Table 1-1 that all the models passed the model prediction validation tests. This suggests that all the models are good predictors of the baseline conditions.

Overview of findings

Through this preliminary investigation it was observed that little is evident about the implications of the failed statistical tests or the reason for the failed uncertainty tests. The sources of these uncertainties are not well established and conclusive statements based on this purely statistical evaluation would be inconclusive.

It is also noted there are inconsistent results across the case studies and the relevance and importance of each of the tests is not apparent. More investigation is necessary on how to best quantify and successfully manage the uncertainties, as well as understand and interpret the statistical results of the tests and their implications.

DEVELOPED PROBLEM STATEMENT

Using the findings of the real-world application of SANAS statistics and the background done in the previous sections, the following problem statement was developed:

"A need exists for practical methods to quantify and manage the uncertainties associated with a calculated EE saving."

The following section describes how the problem highlighted in this section will be addressed.

1.5 RESEARCH OBJECTIVES AND SCOPE

RESEARCH OBJECTIVES

The main objective of this study is to provide a means to quantify and manage uncertainty effectively for professionals claiming EES. This methodology will provide M&V professionals with a practical and structured strategy to not only manage but also quantify the uncertainty associated with calculated EES. A few additional objectives are needed to assist in the study and to provide a functional solution. The objectives of this study are hence to:

1. Investigate possible sources of uncertainty associated with the calculation of an EES,
2. Establish the largest contributors to EES uncertainty,
3. Investigate literature for the methods and tools available for the management and quantification of uncertainty,
4. Develop a strategy to manage and quantify uncertainty when calculating an EES,
5. Improve the understanding and interpretation of the results of statistical uncertainty tests,

6. Provide a support tool that assists stakeholders to navigate the decisions associated with the calculation of an EES,
7. Report a final EES with an uncertainty value, and
8. Provide a generic solution that can be applied to industrial EES initiatives.

This study will therefore assist industries to understand, manage and quantify the uncertainties associated with calculated EES.

SCOPE OF STUDY

The fields of interest for this study include energy efficiency, statistics and uncertainty management. The study reviews the energy efficiency of industrial facilities, with specific reference to EE initiatives carried out to reduce energy intensity and the subsequent calculation of the reported savings. The key focus of this study is the management and quantification of uncertainty; specifically, the uncertainty associated with the EES reported for a 12L tax deduction.

1.6 OVERVIEW OF DISSERTATION

This study consists of five chapters. A brief description of each chapter is provided as follows.

CHAPTER 1: INTRODUCTION

This chapter provides a brief background to establish the context and relevance of the study. Recent changes in the regulatory landscape are identified for driving the need for improved uncertainty quantification and management. Results from an initial investigation of three case studies are also provided to assist with the development of a problem statement. This offers readers the insight needed to understand the formulated problem statement and the research objectives of the study.

CHAPTER 2: LITERATURE REVIEW

A review of relevant literature such as research papers, journals, articles, books, etc. is carried out in Chapter 2. Firstly, the administrative, legal and technical requirements of a 12L application are established. Measurement and verification (M&V), and uncertainty quantification and management (Q&M) techniques are then investigated. Finally, two decision support tools used in the M&V industry are discussed. The information gathered from the literature study is used to generate a strategy which helps M&V practitioners navigate the EES quantification process while addressing key uncertainties.

CHAPTER 3: METHODOLOGY

The developed methodology is presented in this chapter. A decision-making flowchart is presented as a solution to assist M&V practitioners navigate the EES quantification process. This flowchart is called the *'Uncertainty Quantification and Management (Q&M) Flowchart'*. The construction of the flowchart is discussed in this section, with specific reference to a Five-Step Approach to EES quantification. A discussion on how the developed methodology can be used to quantify and manage key uncertainties while adhering to 12L regulations and the SANS 50010 standards is provided.

CHAPTER 4: RESULTS AND DISCUSSION

This chapter presents the results from the application of the methodology to three industrial case studies. This is done to verify the methodology and critically evaluate its effectiveness. A validation of the results of each case study is also provided by evaluating the results of the case study against the requirements of the SANS 50010 standard.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

This chapter provides a summary of the findings of the study, as well as a discussion of how the study objectives were met. Recommendations for additional studies in this field are presented and concluding remarks are provided.

1.7 CONLUSION

South Africa's key strategy to minimise GHG emissions in the industrial sector is to utilise incentivised energy efficiency (EE) initiatives. Industrial corporations can utilise a 12L tax deduction to fund these initiatives, but several barriers arise when pursuing a 12L claim. A key barrier refers to the management and quantification of the uncertainties associated with the reported EES.

In this chapter, recent changes in the regulatory landscape were identified which highlight the need for improved uncertainty quantification and management. However, results from an initial investigation of three case studies showed that several challenges remain in addressing uncertainties. These findings were used to assist with the development of a problem statement, research objectives and scope of the study.

2 LITERATURE REVIEW

2.1 PREAMBLE

In Chapter 1, it was established that there is ambivalence regarding how uncertainty should be reported in practice when calculating energy efficiency savings (EES). This chapter is dedicated to critically reviewing available literature to determine different uncertainty Q&M techniques in the field of measurement and verification (M&V).

Firstly, this chapter provides context on the current 12L tax incentive regulatory landscape by reviewing the associated regulations and supporting resources. Given this context, the main contributors to uncertainty are established and a wide range of available literature is reviewed to investigate the techniques for quantifying and managing these uncertainties. These uncertainties are grouped into four categories, namely measurement, database, modelling and assessment decisions.

From the literature review, several credible techniques are identified that can be used to quantify and manage uncertainty. However, it is a challenge to correctly identify which technique to utilise from the multiple available options to address specific uncertainties. In order to address this challenge decision support tools are also investigated as part of the literature review. The findings from the literature review serve as the knowledge basis on which a methodology is developed in Chapter 3.

2.2 12L REGULATIONS AND SUPPORTING RESOURCES

2.2.1 INTRODUCTION

The 12L tax allowance is awarded to taxpayers who have attained verified EES [14]. However, the 12L application process includes strict rules and regulations that need to be adhered to. The following section will discuss these requirements as well as important supporting resources which include the SANS 50010 standard and SANAS uncertainty guideline.

2.2.2 SECTION 12L ACT AND REGULATIONS

Introduction

The 12L tax allowance is subject to administrative, legal and technical requirements. These requirements are explained in this section.

Administrative requirements

There are administrative procedures that must be followed when constructing a 12L application. This procedure is indicated in Figure 2-1.

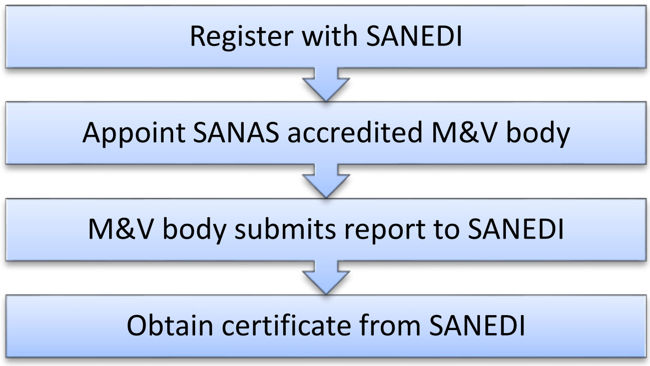


Figure 2-1: 12L tax allowance procedure for claiming

The business must register with SANEDI, which is an agency of the DoE. It must appoint a SANAS accredited M&V body to perform the necessary reports towards the claimed energy amounts. It must ensure the M&V body submits the reports to SANEDI for evaluation. Finally, it must obtain a certificate from SANEDI that confirms and provides proof for energy savings claimed.[14]

Besides the administrative aspects of the 12L application mentioned above, there are technical and legal considerations that need to also be addressed.

Technical requirements

EES models should be constructed using the technical guidance provided in the Standard. A list of the considerations that should be made when approaching uncertainty is provided in APPENDIX B.1. The Standard does not provide practical examples of how to address the uncertainty. This is where the SANAS guideline assists, as it provides statistical techniques to address uncertainty, and report a level of certainty with the stated energy saving figure.

Legal requirements

The Income Tax Act [9] states the legal requirements for a 12L application. It includes the exclusion of any limitations and concurrent benefits in the calculation of the EES. (See APPENDIX B.1 for the 12L Regulations). Limitations on the tax allowance refer to savings obtained as a result of energy generation from renewable resources or due to co-generation (other than waste heat recovery), which is not claimable. Concurrent benefits refer to savings that were achieved as a part of a different government funded project, or as a power purchase agreement.

Conclusion

Although the 12L tax allowance is claimable, various administrative, legal and technical requirements must be adhered to. The Standard is a key resource for technical guidance, hence it will be discussed in the next section.

2.2.3 SANS 50010 STANDARD

Introduction

The Standard provides a generic approach to the measurement and verification (M&V) of energy efficiency savings. Hence it can be used independently or with other standards and protocols [23]. It is valid for all M&V activities such as residential, industrial and commercial EE projects [30].

Measurement and verification (M&V) refers to the process used to quantify the savings delivered by an ESM, and the sub-sector of the energy industry involved with this practice.[2] Several EE-related initiatives have been introduced by the government since 2005 [12], [39]. Since then the M&V process has become vital in ensuring accurate, independent and auditable results are reported [5], [40], [41]. The M&V process has an impact on the monetary value that may be claimed in accordance with the 12L regulations [42]. Thus, the M&V process is very important to a 12L application.

M&V Approach

The M&V approach provides a reliable and impartial method to quantify EES [32]. However, there are various challenges when performing the M&V approach which include time limitations, resource intensity and the accuracy of the reported saving [20], [42]. Figure 2-2 below shows the hierarchy for M&V practice relating to the Section 12L process. The hierarchy has four levels.

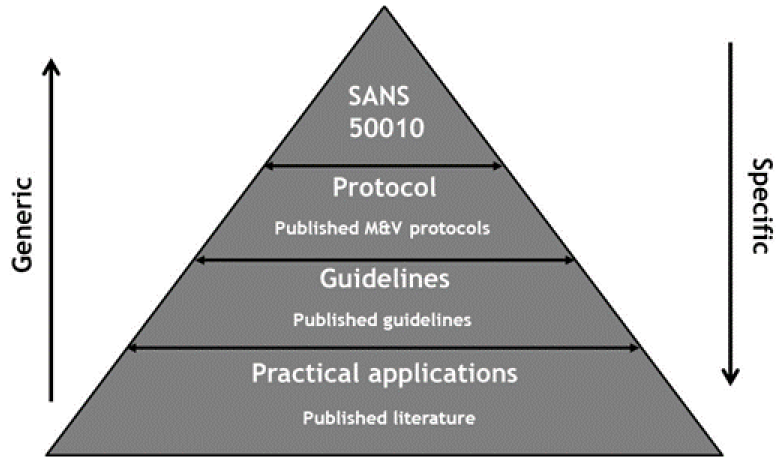


Figure 2-2: Hierarchy of M&V practice regarding 12L. Extracted from [5]

Figure 2-2 indicates the Standard at the top position of the hierarchy, as it is the most important resource for regulatory compliance and is the most generic guideline available.

[2] SANEDI, South African National Energy Development Institute. *"Mark Rawlins SAEEC 2016 Presentation – Measurement and Verification: Example Project with Principles*". Internet: www.sanedi.org.za. Sep 2016 [Oct. 09, 2018].

The Standard represents the minimum requirements for acceptable M&V practice [5]. As one moves down the pyramid the resources are more specific in nature.

There is a variety of M&V approaches available in literature. Internationally popular M&V guidelines include the IPMVP [29], ASHRAE Guideline 14 [36] and the Federal energy management program (FEMP)[43]. International standards organisation (ISO)[44] also provide general principles and guidance for the M&V process [32]. Figure 2-3 indicates two M&V approaches in relation to the Standard.

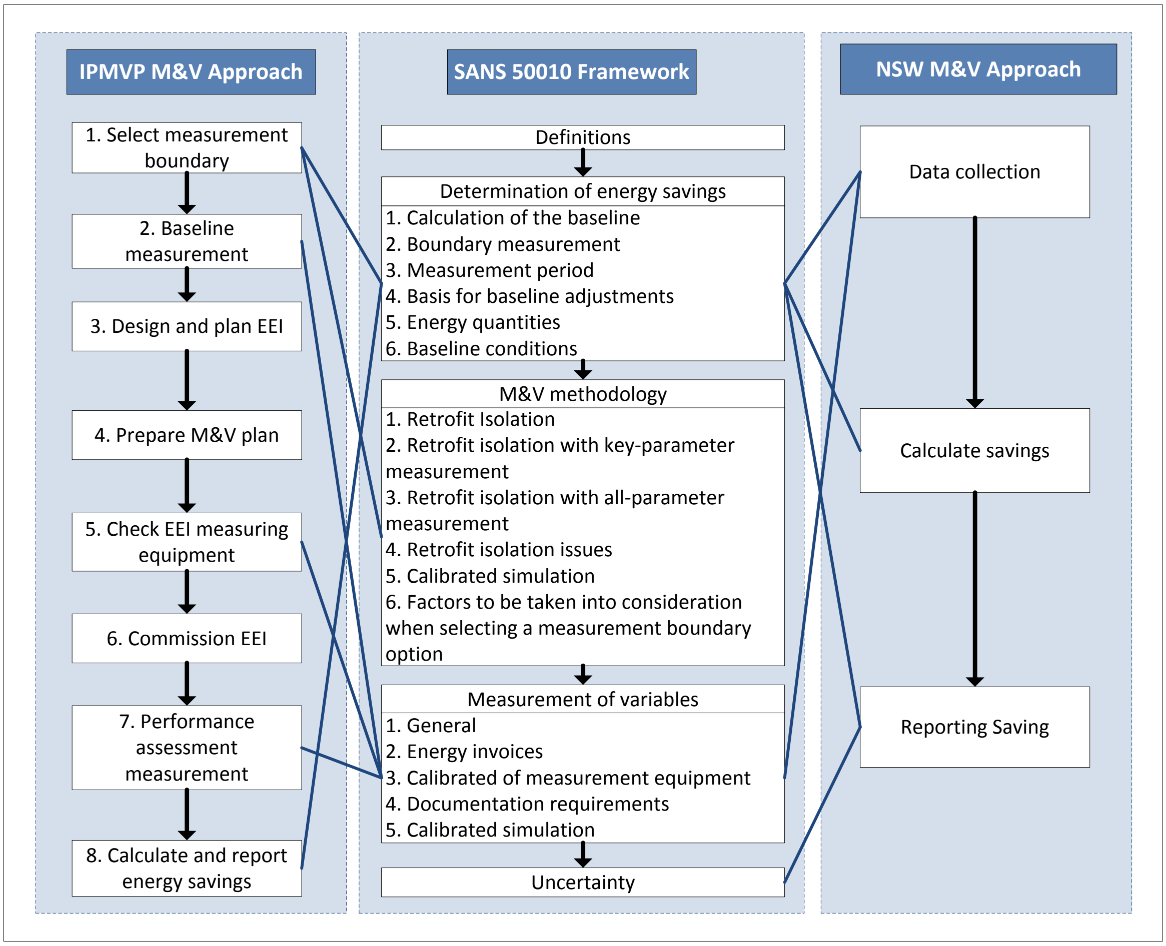


Figure 2-3: M&V approach to EES determination

The *'IPMVP M&V Approach'* provides clear definitions of terms, and transparent methods which incorporate best practices from around the world. It has been successfully applied to a variety of EE applications, for thousands of initiatives worldwide. [45]

Figure 2-3 indicates that the IPMVP M&V approach consists of seven steps. Some align with the requirements set out in the Standard. These steps include measurement boundary selection, measurement of the baseline and performance assessment period, checking EEI measuring equipment and the calculation and reporting of energy savings.

In Figure 2-3 an example of a simplified M&V approach is provided by the New South Wales (NSW) approach [46]. This M&V approach represents a more simplified approach to M&V, with only three steps. The three steps include data collection, savings calculation and savings reporting. As seen in Figure 2-3 these steps also align with some of the requirements of the Standard.

There are various M&V approaches that can be used in the EES quantification process. It is important that the M&V approach includes a clear definition of why the saving occurred and understanding of the level of uncertainty in the savings. [3]

Uncertainty management strategies

The Standard requires the quantification and management of the uncertainty associated with the reported EES. There exists an inherent uncertainty in the reported energy savings as they represent calculated values. Figure 2-4 below indicates this uncertainty between the actual EES achieved and the reported EES.

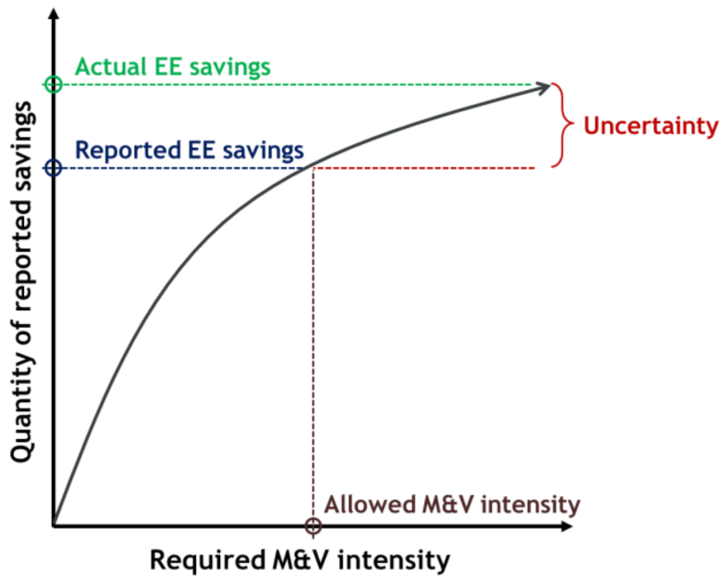


Figure 2-4: Uncertainty associated with EES. Extracted from [5]

Figure 2-4 indicates that the lower the M&V intensity the more conservative the reported EES is. In other words, a decrease in the reported saving mitigates the associated uncertainty. Increasing the M&V intensity may also be used to mitigate uncertainty. However, an increase in M&V intensity is often linked to additional cost. The methods provided by the standard are all geared toward producing a conservative result, as this reduces the uncertainty of the reported EES [23]. Specific requirements for what should be

[3] SANEDI, South African National Energy Development Institute. *"Mark Rawlins SAEEC 2016 Presentation – Measurement and Verification: Example Project with Principles*". Internet: www.sanedi.org.za. Sep 2016 [Oct. 09, 2018].

considered when quantifying and managing uncertainty are provided in the Standard (See Appendix B.1). However, no examples or calculation methods to do this in practice are provided.

Conclusion

The Standard offers a generic approach to measurement and verification of an EES. The M&V approach provides a reliable and impartial method for EES calculation. The Standard sets the minimum requirements for good M&V practice.

The review of the Standard indicates that there is a need for EES uncertainty management and quantification. Although the Standard provides a clear strategy to conservatively manage uncertainty, it does not provide specific practical techniques for uncertainty quantification. Hence investigation of additional resources for uncertainty quantification in M&V is necessary. The SANAS Guideline is one such resource, which presents the best practical calculation techniques for uncertainty quantification. Hence, it will be discussed in the following section.

2.2.4 SANAS GUIDELINE

Introduction

The Guideline is a resource which provides clarity regarding how best to address the uncertainty requirements contained in the Standard. The Guideline is not legally binding and is intended to be used as a resource by M&V teams. It synthesises international best practices for uncertainty quantification and management.[33]

Breakdown of the Guideline construction

The best practices from international M&V uncertainty guidelines were combined to create the SANAS Guideline. The Guideline was constructed using four main resources as indicated in Figure 2-5.

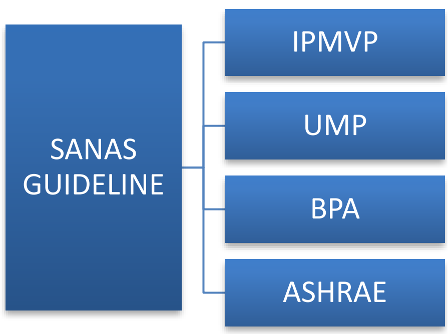


Figure 2-5: SANAS Guideline breakdown

The most well-known M&V resource used is the International Performance Measurement and Verification Protocol (IPMVP) [45]. The statistics and uncertainty supplement to IPMVP is a very useful resource [47]. The Uniform Methods Project (UMP) provides practical guidance for a variety of M&V projects. The Bonneville Power Administration's (BPA) Regression Reference Guide [48] provides statistical model validation tests and explanations on how they work. American Society of Heating, Refrigeration and Air Conditioning Engineers (ASHRAE) Guideline 14 [36] prescribes uncertainty limits (68/50) [33] and suggests indices for the evaluation of model uncertainty.

Review of SANAS Guideline

Uncertainty needs to be quantified to manage risk. For M&V, this refers to the risk of reporting an energy saving that was not achieved.

The Guideline provides practical methods that can be used for reporting savings uncertainty. Two questions to ask in the M&V process are: what level of uncertainty is acceptable, and what action should be taken when the uncertainty is not within acceptable bounds and cannot be improved. The Guideline provides techniques to help M&V practitioners answer these questions.

Table 2-1 indicates the concepts covered in the Guideline. The guideline is made up of two parts; part one covers savings uncertainty reporting and part two suggests validation techniques for regression models.

Table 2-1: SANAS Guideline uncertainty reporting and validation

Part I: Savings uncertainty reporting	Part II: Validation
Uncertainty Levels	**Unquantifiable Uncertainties**
Reporting savings	**Data Validation**
Calculating savings uncertainty	Statement on measurement error
Statements of uncertainty	Mismeasurement
	Regression sample size
	Outliers
	Independent variable
	Model Selection
	Model Validation
	Normality of residuals
	Auto-correlation
	Collinearity
	Model Prediction Validation
	K-fold cross validation
	Satisfactory predictor
	Over/under prediction of savings
	Model goodness of fit
	Savings Validation

Table 2-1 indicates the main headings in the Guideline stated in bold, and the statistical techniques for validation are listed below the 'data validation', 'model validation' and 'model prediction validation' headings. The specific tools used for model validation and model prediction validation can be found as add-ins in commonly available software (e.g. MS Excel). A summary of part one and two of the Guideline is provided below.

Part I: Savings uncertainty reporting

It is obligatory to quantitatively indicate the quality of the reported results. The first part of the Guideline hence covers how the uncertainty level can be quantified, and what should be considered in the assignment of its value.

Uncertainty Levels

M&V uncertainty is expressed as "*expanded uncertainty*", as codified by the ISO Guide to the Expression of Uncertainty [26]. Expanded uncertainty is represented by two numbers: the first number represents the confidence limit and the second represents the (relative) precision [33]. International uncertainty levels range from ASHRAE's 68/50 requirement, to 90/10 where high M&V funding is available. The most popular uncertainty level is 80/20. A suggestion by a South African M&V company is to use 80/7.5 for 12 data points, 80/15 for up to 52 data points and 80/20 for more than 52 data points. [26]

The reported uncertainty can be improved by using more accurate measurement instruments and savings models. Intuitively, this is sensible: if the savings claimed is a small percentage of the total energy (has a small significance), more accurate instruments must be used i.e. you need small precision values e.g. 1% precision.

Reporting savings

The Guideline proposed two methods for reporting uncertainty depending on whether there are symmetrical or skewed savings distributions. Symmetrical distributions represent the default case. Alternatively, skewed distributions are usually not of concern for most projects, as normal distributions are often assumed and are produced by linear regression. [26] An example on how to manage the uncertainty if it is higher than the threshold is provided for both these types of distributions in Appendix B.2.

Calculating savings

M&V uncertainty quantification usually includes measurement, sampling and modelling uncertainty as a minimum. The uncertainty values for each of the component uncertainties can then be stated. Also, an overall uncertainty can be provided using a method for combining uncertainties. [26]

Statements of uncertainty

High quality M&V reports will include statements of expanded uncertainty for variables of interest. Additionally, assurance for measurement instruments can be provided by including manufacturers' accuracy specifications and calibration certificates. Variables such as; population size, sample size and inter-sample coefficient of variance is expected on M&V where sampling was done. [26]

Part II: Validation

A large reported uncertainty value is not always an indicator of poor M&V. It could be due to limitations in data or unquantifiable uncertainties, etc. Likewise, a small uncertainty is not indicative of high quality M&V. Validation of the reported value is thus important. The second part of the Guideline hence discusses validation techniques. [26]

<u>Data Validation</u>

Various factors should be considered when approaching data validation. A few of the main considerations outlined in the Guideline are provided below.

- Statement of measurement errors for all variables

The precision of measurements is commonly stated at 95% confidence; this should be assumed where no information is provided by the supplier. Class 1 meters are accurate to 1% of its full-scale reading value. By law a utility meter should be calibrated. Typical measurement error uncertainty values can be found in ASHRAE G14 [36]. [26]

- Mismeasurement

Mismeasurement is not valid if the error is in the dependent variable (energy carrier), but is if the error is in the independent variable (temperature, occupancy, production, etc.) This becomes significant if the error in the measurement of the independent variable exceeds 5%.[26]

- Regression sample size

The Guideline suggests that state-of-the-art M&V regression models only need 3-6 months hourly data to characterise the baseline adequately if data reflects all operating conditions. This does not mean that <u>*all*</u> M&V models only need three months hourly baseline data. It also emphasises that there are significant implications for regression that need to be tested if the sample size is smaller than 15. [26]

- Outliers

It is standard practice to discuss and explain all outliers in data. Outliers that represent normal operating conditions should not be removed. Robust regression techniques and methods for large multidimensional datasets are suggested in the Guideline. When utilising these methods discussions should always be provided as justification for removing outliers. [26]

- Independent variables

Independent variables are the energy governing factors which are expected to change e.g. temperature, production, occupancy, etc. Plotting the magnitudes of the independent variable for the baseline and performance assessment period provides an indication of this change. The energy model is designed to adjust to these changes. Where the difference between pre-and-post EEI is vastly different and extrapolation is necessary, discussion should be provided. [26]

Model selection

Multiple modelling options exist to model energy use. Linear regression models are the most popular modelling option in M&V as they are simple and powerful. The Guideline hence only provides validation tests for linear regression models. For other model types, tests and threshold values used should be described and referenced to prove due diligence has been carried out. [26]

Model Validation

The linear regression model only holds under certain assumptions. These assumptions should be stated and motivated when necessary. The assumptions are: the independent data has a linear relationship with energy use, the residuals follow normal distribution, there is no autocorrelation, little to no collinearity, and the variance in data is constant over the range of data (homoscedastic). Table 2-2 below indicates various techniques provided in the Guideline for testing the above-mentioned criteria.

Table 2-2: Model validation tests

Test	Conditions	Method	Requirement
Normality of residuals	n<15	q-q plots	Points in a straight line.
		Histogram of residuals	The result should approximate normal distribution
		Anderson-Darling	H0: The data follows the normal distribution H1: The data do not follow the normal distribution For 10<n<20, 0.683<AD limit <0.704.
Auto-correlation	-	Durbin-Watson	d=2 acceptance value indicates no auto-correlation [0<d<4]
Collinearity	Program: Minitab	Variance Inflation Factor	VIF>5 indicates collinearity
	Program: Python	Condition Number	CN>20 indicates collinearity

In Table 2-2 three testing criteria are indicated: normality of residuals, auto-correlation and collinearity. It is well established that normality of residuals is not an issue if the sample size is greater than fifteen. Auto-correlation can be tested using the Durbin-Watson statistic. If the value is less than one, it could indicate serial correlation is occurring which is a cause for concern. Collinearity is relevant only to multi-variate linear regression models. Collinearity can be reduced using methods such as PCA, LASSO or Ridge regression.

Central Limit Theorem (CLT) is often used to justify the assumption of normality. However, this is not good practice. If data is not normally distributed it is better to use regression methods such as Generalised Linear Models or Bayesian methods. [26]

Model Prediction Validation

The usefulness of a model is its performance on future or "unseen" data. Table 2-3 indicates methods for validating the ability of the model to predict future data.

Table 2-3: Model prediction validation tests

Test	Conditions	Method	Requirement
K- Fold cross validation	-	Leave-one-out cross validation	Low prediction error
Useful Regression (satisfactory predictor)	Program: ANOVA	F-test	Fobs>= 4 x Fcrit
	-	$\left(\frac{Max\,\hat{Y}_t - Min\hat{Y}_t}{\sqrt{p\times\frac{s^2}{n}}}\right) \geq 4$	LHS >= 4
Over/under prediction of savings	-	Net Determination Bias (NDB)	Acceptable limit of NDB<=0.005%
Model goodness of fit	-	Coefficient of Variation on the Root Mean Square Error [CV(RMSE)]	CV(RMSE) < 25% (EE projects)

The parameters to be tested as indicated in Table 2-3 include whether the model is a satisfactory predictor (F-test), whether the model over- or under-predicts the saving (NDB), and how well the model fits the data (CV(RMSE)).

On the use of R^2 and p value

R^2 describes the proportion of data variation in a model. It is a relative measure of goodness of fit. It is not a valid measure for uncertainty or model precision; a better measure is the CV (RMSE) value. The p-value can indicate how incompatible the data are with a specific statistical model. R^2 and p-values should be used as a part of a broader diagnostic framework but cannot be used as a valid measure for uncertainty or model precision on their own.

Savings validation

Measurement, sampling and modelling uncertainty need to be combined to yield overall uncertainty. The ASHRAE Guideline provides equations that can be used to combine the uncertainty values from different sources of uncertainty. See Appendix B.2 for these equations. Monte Carlo or ASUE method for combining uncertainties can be used. However, for linear regression models ASHRAE G14 is recommended.

Sensitivity analysis can be carried out to provide additional confidence in the energy model. A tornado diagram, Sobol's sequence, Morris method and Latin Hypercube sampling schemes are methods that are suggested by the Guideline.

Conclusion

The Guideline was constructed using the best practices from M&V resources. It indicates how uncertainty should be expressed and suggests bounds that would constitute a reasonable uncertainty level. It also provides methods for data validation, model validation, model prediction validation to provide assurance regarding the model's credibility. The specific tools used for model validation and model prediction validation can be found as add-ins in commonly available software (e.g. MS Excel).

2.2.5 CONCLUSION

This section provided insight into the administrative, technical and legal requirements that a 12L application needs to adhere to. The SANS 50010 standard and the SANAS uncertainty guideline were identified as important resources for EES quantification, hence they were discussed.

The Standard provides technical guidance; it offers the minimum requirements for good M&V practice and uncertainty management and quantification. However, it does not provide practical calculation methods to quantify uncertainty. The Guideline was compiled using industry best practices for addressing M&V uncertainty; it provides calculation techniques for quantifying uncertainty, and additional statistical tests (model validation tests, etc.) which can be used to prove the credibility of the reported EE saving.

To generate a better understanding of the uncertainties associated with an EES, a broader literature investigation is carried out in the following section. In this section the factors which make the largest contribution to EES uncertainty are investigated. Methods to quantify and manage the uncertainty due to the largest contributors are carried out.

2.3 MEASUREMENT AND VERIFICATION UNCERTAINTY

2.3.1 INTRODUCTION

Uncertainty management techniques

Uncertainty management can be subdivided into two sub-categories: quantitative and qualitative techniques. Quantitative techniques are geared towards *statistical techniques*, whereas qualitative techniques include techniques such as *assurance techniques*. Both types of uncertainty management techniques will be investigated in this study.

<u>Statistical techniques</u>
To calculate energy savings M&V teams must deal with large quantities of data. To analyse the data the most useful tool is statistics and its sub-disciplines [21]. Statistical methods often are the sole contributor for the verification of results for a majority of M&V teams [24], [30], [37], [40]. In M&V there is a notable overreliance on statistical methods [21].

Statistical techniques such as Monte-Carlo analysis (or the Mellin Transform Moment Calculation) have been used for quantifying risk management in the retrofit analysis process [49]–[52]. Additionally, Bayesian models have been a growing area for model development while quantifying uncertainty [49]. Both approaches are complex. This study has highlighted the need for a simple approach to uncertainty Q&M, so these approaches will not be considered.

<u>Assurance techniques</u>
Assurance can be provided in a variety of ways as indicated by Table B-1 in Appendix B.2. It provides an indication of assurance mechanisms and the assurance techniques that can be employed. A common assurance method is the use of calibration certificates. The inclusion of multiple models has also been identified as a method of assurance [27].

Sources of uncertainty

Typically, M&V practitioners consider measurement, sampling and modelling uncertainty [5], [53]. Most studies focus on regression models for statistical analysis on uncertainty [26], [45]. As sampling uncertainty does not play a role in every study it will not be considered as a major source of uncertainty in this investigation.

Measurement and modelling uncertainty are usually present in the calculation of savings uncertainty [26]. Additionally, database uncertainty and assessment decision uncertainty will be investigated as they play an important role in EES quantification. Thus, four sources of uncertainty will be investigated in this study as indicated in Figure 2-6.

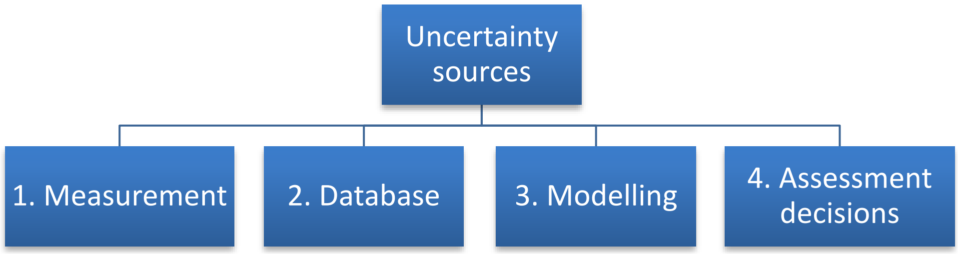


Figure 2-6: Uncertainty sources in EES determination

Measurement uncertainty refers to the accuracy of the measurement. Database uncertainty deals with the accurate transfer and storage of data. Modelling uncertainty is whether the developed model accurately represents the baseline conditions of the system, and correctly predicts the EES. Finally, assessment decisions refer to the decisions an M&V practitioner has to make which effect the reported EES.

Conclusion

Absolute certainty is unachievable. Numerous sources of uncertainty exist; these include instrumentation or measurement error, model error, database uncertainty and errors of assumptions. Not every source of uncertainty lends itself to quantitative uncertainty assessment. [47]

The following sections will detail the investigation into the four sources of uncertainty identified in Figure 2-6. How these sources of uncertainty are quantified and managed will be discussed.

2.3.2 MEASUREMENT UNCERTAINTY

Introduction to measurement uncertainty

Measurement uncertainty is recognised in M&V literature; however, strict guidance on how to manage it is seldom provided [37]. Measurement uncertainty is an important consideration for EES quantification, as the accuracy of the measurand influences the reported saving.

This section will discuss the management strategies available for this source of uncertainty. Specific focus on techniques such as point of measurement allocation and management, and calculation of measurement error will be discussed. Finally, conclusions regarding the techniques identified will be offered.

Random and systematic error

Measurement uncertainty is due to either random errors or systematic errors. Systematic errors originate from imperfect calibration of measurement instruments. Figure 2-7 illustrates a random error model for electricity consumption of an industrial operation.

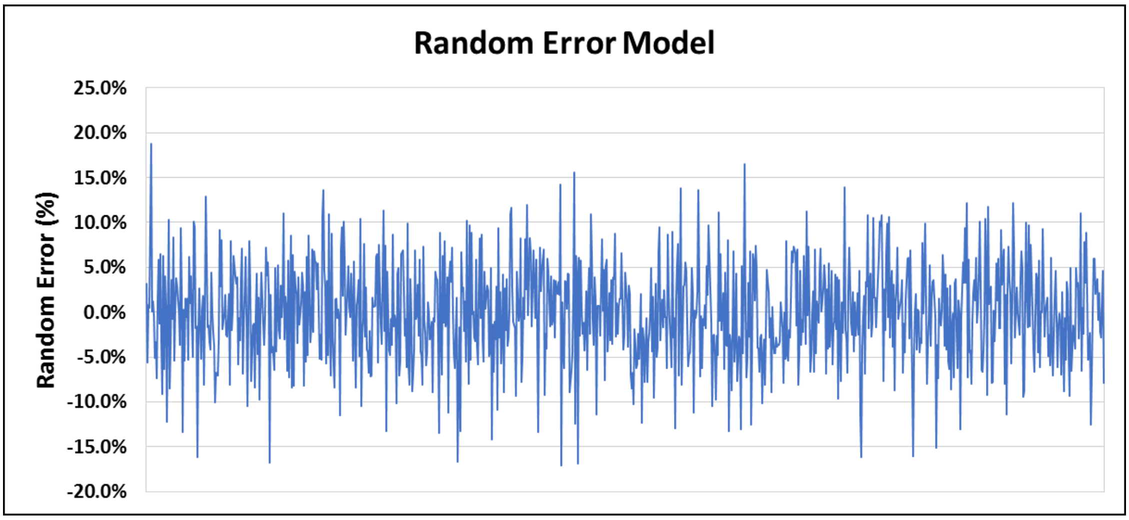


Figure 2-7: Random Error Model

It can be seen from Figure 2-7 that the variance of the error is large (from approximately -17% to 19%). A common method of reducing the random error is by averaging it over many observations[4]. Hence for the case illustrated in Figure 2-7 where there is a large variance, the averaged error value observed is -1.3%, which is small relative to the variance.

Measurement uncertainty management strategies

Measurement uncertainty can be mitigated by using suitable data handling protocols and high-accuracy, calibrated metering equipment [32]. Measurement uncertainty management is often reduced to outlier detection, added to overall uncertainty propagation calculations or is considered negligible [26], [45].

Measurement uncertainty can be considered negligible when using utility grade electricity or natural gas metering equipment, or when metering devices are of high-calibre. Power meters commonly have measurement errors of less than 1%. [32] This is not true if the error refers to the independent variable i.e. the energy governing factor (occupancy, temperature, production, etc.), and this can have a detrimental effect on the reported saving [26], [45].

Mismeasurement of independent variables can invalidate reported results because the confidence interval reported on the saving will be too narrow. Currently the effect of attenuation due to mismeasurement in not well known [37]. Measurement Error Models can also be used to quantify and manage uncertainty. Notable amounts of literature on (MEMs) are available [37]. However, this technique is too technical to be useful to an M&V practitioner without a strong background in statistics.

[4] South Eastern Louisiana University. *"05. Random vs Systematic Error"*. Internet: www.southeastern.edu. June 30, 2002. [Oct 10, 2018].

Further, the accuracy of a measurement can be validated through a check of the difference between check metering values and compliant metering/invoice data. General error estimates such as those found in ASHRAE Guideline 14 [36] may be used for the independent variables (See Appendix B.2). These values should be used with caution as they represent estimates and it is preferable to use actual values where available.

Calculation of instrument measurement error

Equation 2-1 can be used to express the relative measurement error as a percentage when multiple instruments are used, i.e. the overall instrument precision can be calculated. This is only true if the precisions are all expressed at the same confidence limit.

$$RE_{instrument} = \frac{\sqrt{\sum_{n=1}^{c}(RE_{instrument} x\, r_{rating,i})^2}}{\sum_{i=1}^{c}\overline{rt}}$$

Equation 2-1: Relative error of instrument. Extracted from [36]

Where: $RE_{instrument}$ – error of the instrument (tolerance), and r_{rating} – the value relative to which the instrument precision is expressed.

Management of measurement points

In the industrial sector numerous measurements and data points exist [11]. An additional strategy to manage the uncertainty associated with the measurement is through management of the measurement points.

Figure 2-8 depicts a strategy for the management of measurement points, which can be used to identify and classify various data.

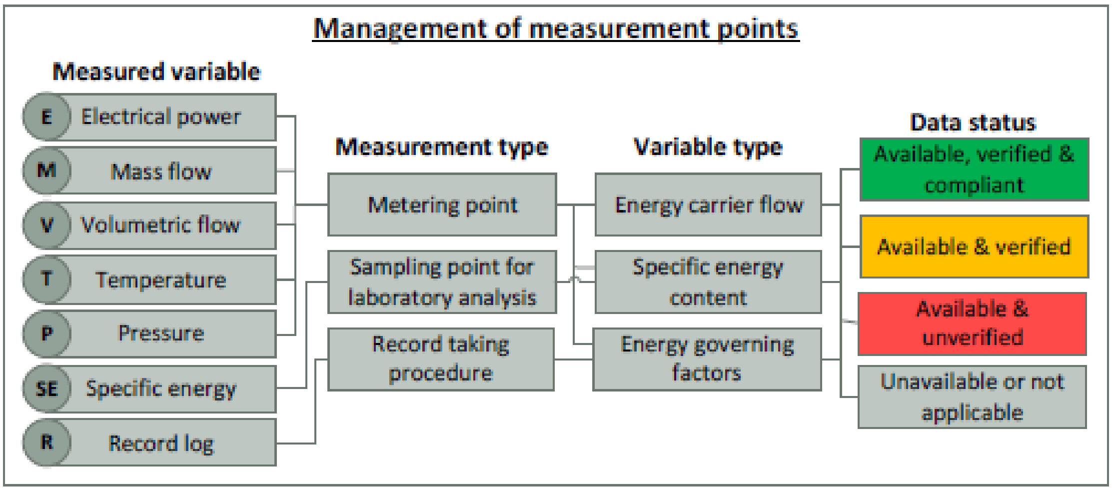


Figure 2-8: Management of measurement points. Extracted from [5]

The measurement points are organised according to the measured variable, measurement type, variable type and the 12L compliance status of the data. Figure 2-8 indicates that the data can be assigned a status. There are four possible options for the status of the data as indicated. The green status indicates the most desirable data; it is available, verified and compliant. This procedure simplifies measurement boundary selection and database management [5]. Figure 2-9 indicates an example of how the measurement point management strategy can be applied to an industrial system.

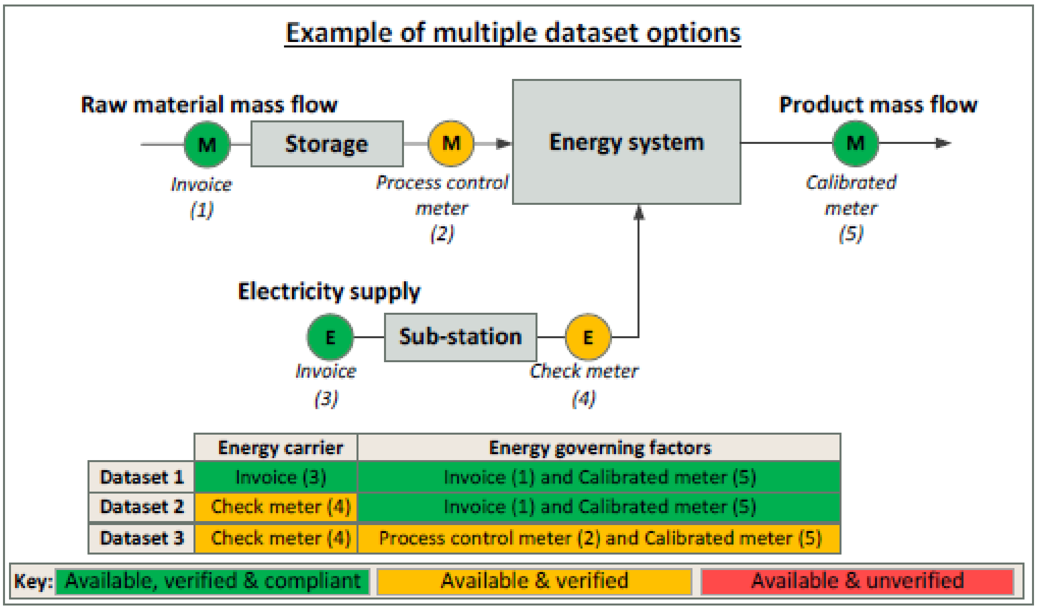


Figure 2-9: Example of measurement point classification procedure. Extracted from [5]

Figure 2-9 illustrates an industrial system which has five measurement points. Measurement points 1, 3 and 5 represent compliant data sources; invoice and calibrated data. These data points would be selected for the M&V of the ESM and make up a single dataset (dataset 1 in Figure 2-9). Figure 2-9 indicates that two other non-compliant datasets (dataset 2 and 3) are possible, that incorporate (measurement points 2 and 4).

Conclusions

After a review of the management techniques for measurement uncertainty, the following observations were made:

- Measurement uncertainty remains an important consideration in energy M&V.
- Complex measurement error calculations exist such as Bayesian methods which represent a growing field in energy research. However, these methods are overly complex.
- Calibrated meters are sufficient for M&V applications, where uncertainties are dominated by other factors such as modelling error.
- The most suitable data handling approach would include the use of better metering devices and improving data collection processes.
- The use of a measurement point management strategy will simplify the M&V process.

Measurement and database uncertainty can often be linked, as both factors contribute to data quality and the accuracy of the reported saving. Hence the next source of uncertainty that will be investigated is database uncertainty.

2.3.3 DATABASE UNCERTAINTY

Introduction

Data quality is a significant contributor to uncertainty as it can bias the outcome and compromise the accuracy of the reported saving [55]. Data is available in different resolutions, compliance, and accuracy. This section discusses the main parameters by which these data sources should be evaluated. Furthermore, it presents simple methodologies that can be used for the dataset evaluation, which can readily be applied.

Database key parameter evaluation

Database evaluation includes various parameters to determine whether the dataset is satisfactory or not. Datasets within the M&V process should conform to the basic principles of accuracy, traceability, relevance and compliance [5], [15]. Figure 2-10 indicates an approach to dataset evaluation.

Figure 2-10 shows how identification of abnormalities can be done, while considering the evaluation parameters. According to the methodology the abnormalities should be logged if they are explainable and undergo uncertainty management if they are unexplainable. A description of each evaluation will be provided below.

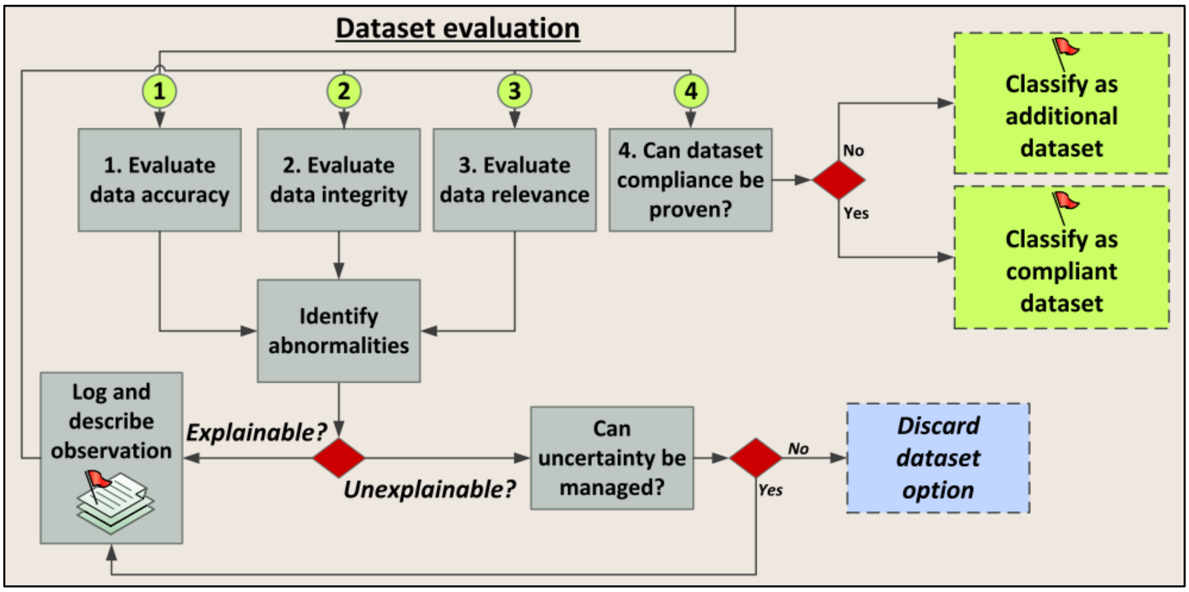


Figure 2-10: Dataset quality evaluation framework. Extracted from [5]

Dataset accuracy

Metered data and supporting documents need to be collected, organised and processed to ensure they are compliant with 12L regulations [23]. It is important to note that data compliance does not denote data integrity or relevance [55]. *Gous et al* [55] developed a method to evaluate data quality, with the steps as follows:

1. Evaluate data source
2. Evaluate dataset quality
3. Select a baseline dataset

Step 1: Evaluate data source

Figure 2-11 below indicates an approach to evaluate the data source. The method has three phases. Phase 1 sees data sources collected, and redundant data sources compared. Phase 2 entails the calculation of the differences between the two data sources. Finally, phase 3 sorts the results based on the magnitude of the differences observed.

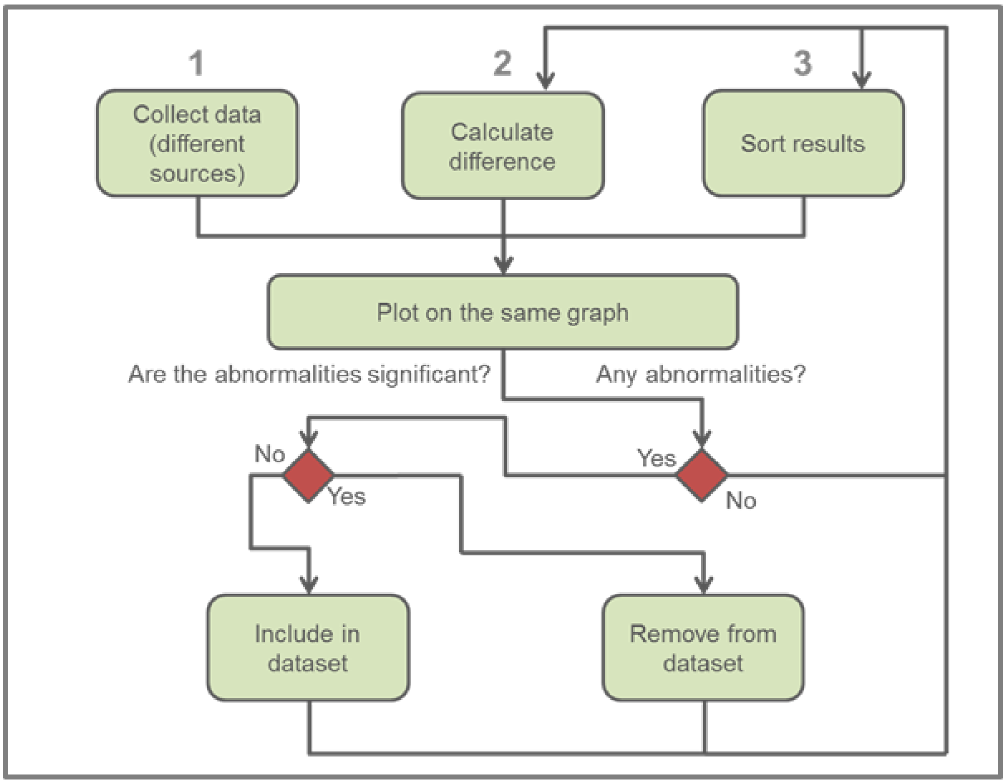


Figure 2-11: Data source evaluation. Extracted from [55]

As can be seen in Figure 2-11 this method uses the visual comparison of data sources as well as calculated differences to sort the results and identify major abnormalities.

An example of how this redundancy check works is indicated in Figure 2-12. The redundant data sources are plotted on the same axis to identify any abnormalities and/or discrepancies.

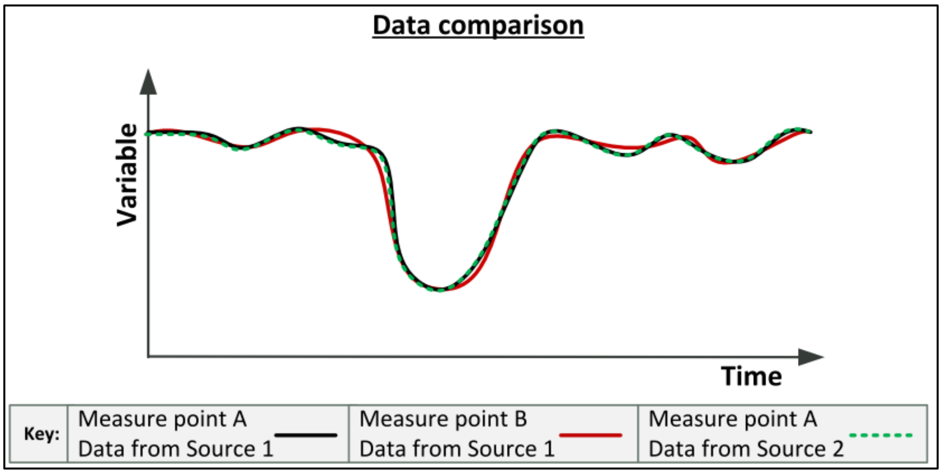


Figure 2-12: Example of visual data comparison. Extracted from [5]

Step 2: Evaluate dataset quality

Abnormalities and missing data are inherently included in a dataset; this creates uncertainty [38], [56]. The purpose of this step is to identify errors and remove abnormalities within the data. Removing error and abnormal data improves the data quality [55]. Figure 2-13 shows the dataset quality evaluation methodology. There are four key parameters investigated: identification of spikes, metering malfunctions, data loss and abnormal operation.

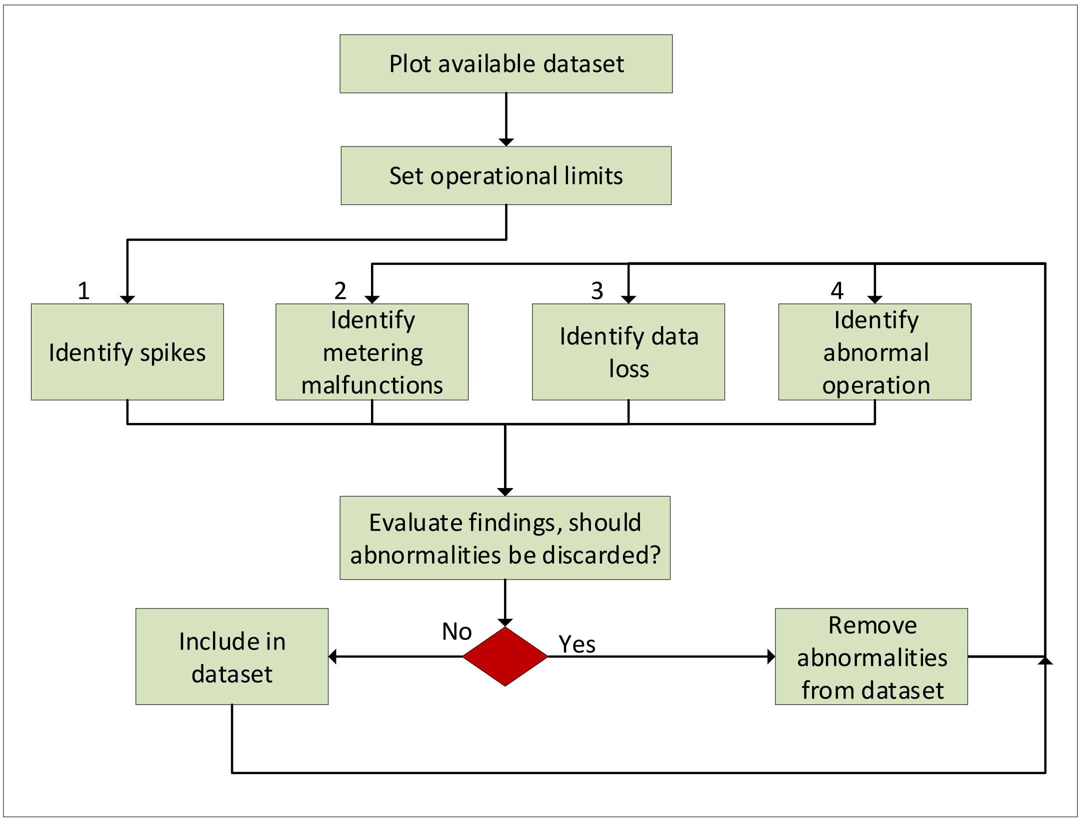


Figure 2-13: Dataset evaluation. Extracted from [55]

A description of the four parameters is investigated in Appendix B.2. By evaluating the dataset, poor data are identified and removed. This delivers a high-quality dataset to be used for EES quantification calculations.

Step 3: Select a baseline dataset

Baseline data must represent a full normal operation cycle [23]. To adhere to the Regulations the baseline period needs to represent a full calendar year preceding the assessment year [14].

Dataset traceability

An aspect of database management is proving the integrity of the dataset. This can be done through the evaluation of the data traceability. The traceability of a data source can be tracked by constructing a traceability pathway. See Figure 2-14 for an illustration of a traceability pathway.

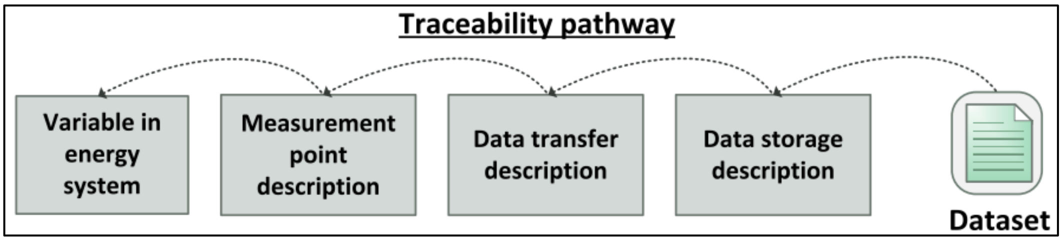


Figure 2-14: Data traceability pathway to test data integrity. Extracted from [5]

Dataset relevance

A simple method to evaluate the relevance of a dataset is to plot the long-term energy intensity (EI) trend. See Figure 2-15 for an example of what this could look like in practice.

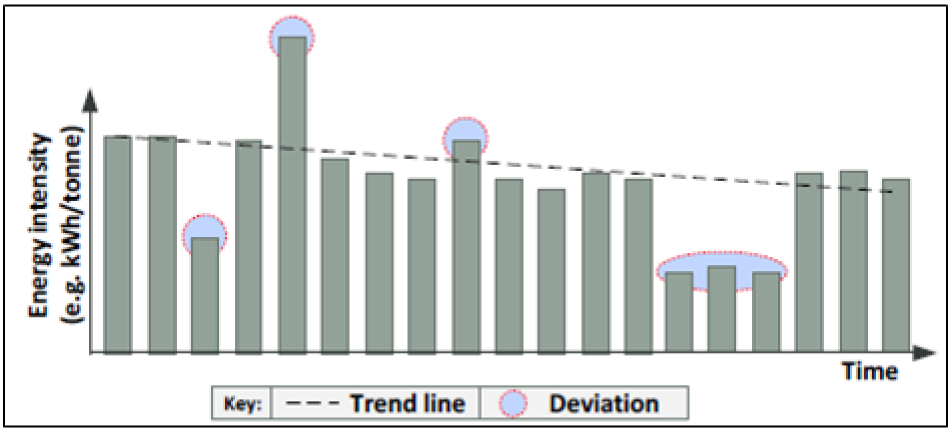


Figure 2-15: Long term intensity trend to evaluate data relevance. Extracted from [5]

The observations made using the energy intensities should be linked to specific operational events, such as scheduled and unscheduled maintenance. An increase or decrease in the EI trend should be linked to change/activity in the system or due to the ESM.

Dataset compliance

A high quality dataset is thus fundamental to the accuracy of the reported energy saving as it prevents the accumulated effect of errors that propagate through the process [15]. There are two data sources that the Standard regards as 'compliant'. The first data source is invoices of measured quantities, and the second is metered data from calibrated equipment. Calibrated measurement equipment is further required to be calibrated by a SANAS accredited calibration laboratory or specialists approved by the original equipment manufacturer.[23]

After evaluating the datasets according to the criteria of accuracy, integrity, relevance and compliance, the dataset will either be rejected or accepted as a usable dataset.

Database management strategies

Besides evaluating the data against specific criteria, other database management strategies exist as follows.

Universal dataset checklist

Gous [15] provides a technique for summarizing the significant information regarding a dataset into a uniform structure. The checklist synthesizes the checks for compliance from multiple resources into a singular reporting structure. See Appendix B.2 for the universal checklist. This checklist is useful as a method for comparing datasets.

Handling data abnormalities

Handling data loss
Missing data may occur for various reasons; the value may not have been recorded, the attributes were not present for that specific instance, or there could have been a technical issue with the storage of the data. Regardless of the cause, missing values/data loss are important as they have an impact on the final model depending on the way in which they are handled.[53]

Strategies for handling missing data include removing instances where there is missing data from the dataset or replacing the data. A common strategy for data with continuous attributes is to replace the missing data with the mean values of the instances where there is no missing data. Also, nominal missing values can be replaced with mode values (the most common value). The strategies for handling data loss/ missing data all have flaws and the method used to handle the data loss/missing data has to be decided case to case. [53]

SANS 50010 [23] states that where data is missing for a period of one month and greater, it can be replaced. The missing data may be replaced provided it is comparable and representative data for the same calendar month(s) from another period. This form of data loss management is used to ensure the baseline data does not underrepresent the operating conditions for the missing months.

Handling Outliers

Detected outliers can be removed, marked or replaced by a representative value [53]. Outliers are values that are significantly different from the normal distribution of an attribute. A common statistical method to check if there are outliers present in a dataset is to model the attribute by fitting it to a Gaussian probability function. [53] There are various complex statistical techniques available to aid in the removal of outliers. However, this study will focus on visual outlier detection, with the outliers being linked to an event to remove them from a dataset.

Conclusion

Evaluation of the database for any abnormalities and to establish the dataset quality is critical. There are four parameters by which the datasets can be investigated: accuracy, traceability, relevance and compliance. Evaluation techniques such as plotting redundant datasets, using universal dataset checklists and interrogating the datasets for specific phenomena (spikes, meter malfunction, data loss and abnormal operation) were discussed.

Measurement and database uncertainty management strategies have been discussed. Once these two considerations have been made the M&V practitioner should have established which data points should be used for the construction of an EES model.

2.3.4 MODELLING UNCERTAINTY

Introduction

Energy saving models are necessary for EES determination [26], [30]. Modelling uncertainty refers to how well the mathematical model describes the variability in the measured data. Reasons for it include: using the wrong model, assuming inappropriate functional forms, including irrelevant information or excluding relevant information. [29] Modelling uncertainty makes the biggest contribution to uncertainty [24]. Hence, it is critical that the modelling uncertainties be well managed.

Baseline model development

Energy savings represent the absence of energy consumption. Thus, a baseline model is developed to predict what the energy usage would have been in the absence of ESM implementation [18], [26]. Any activity has a characteristic energy consumption, which is referred to as the baseline energy consumption. Figure 2-16 indicates a baseline model, which is used to forecast the baseline energy consumption into the performance assessment period (blue line).

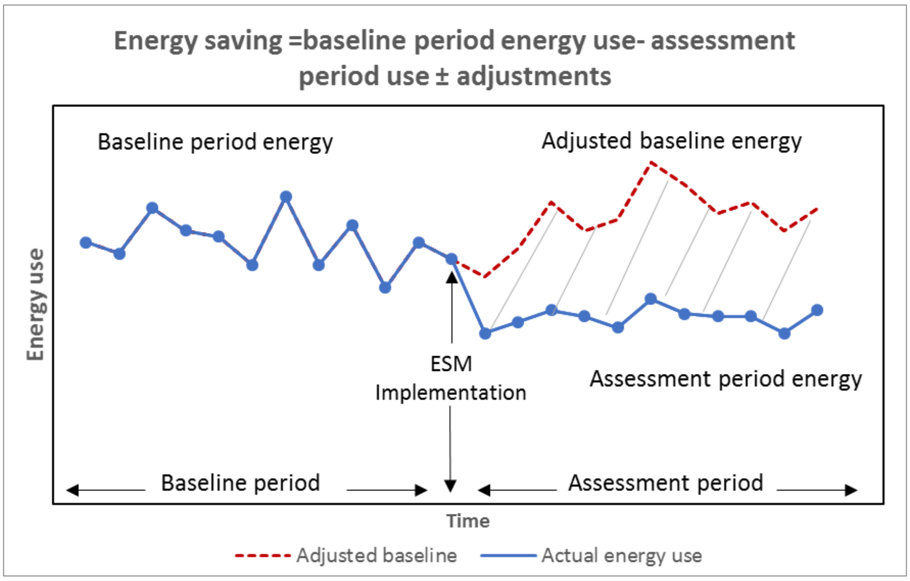


Figure 2-16: Overall approach to EE baseline determination. Extracted from [25]

The performance assessment period represents how the system operated after the ESM has been implemented. Once the ESM is implemented a reduction of the energy consumption by a certain amount is expected if the intervention is successful [26]. In Figure 2-16 the reduced energy consumption should be visible in the performance assessment period. This difference between the adjusted baseline energy (red line) and the assessment period energy (blue line) is the EES.

Metered data is used to construct the baseline energy consumption. Adjustments may be made to the baseline to account for the effect of changes in energy governing factors from the baseline period to the assessment period. The baseline energy equation as given in the Guideline [26] can be seen below:

$$E_B = E_{bp} \pm A_R \pm A_N$$

Equation 2-2: Baseline energy equation

Where: E_B – baseline energy consumption; E_{bp} – baseline period energy consumption; A_R – routine energy adjustments; A_N – non-routine energy adjustments.

If the baseline conditions remain unchanged, there are no adjustments ($A_R = A_N = 0$). Baseline adjustments are only necessary to bring the two time periods under same set of operating conditions if the baseline conditions have changed. [26] The energy savings equation is then provided as follows:

$$E_s = E_B - E_{ap} \pm A_R \pm A_N$$

Equation 2-3: Energy savings equation

Where: E_s – calculated energy saving; E_B – baseline energy consumption; E_{ap} – assessment period energy consumption; A_R – routine energy adjustments; A_N – non-routine energy adjustments.

The Standard allows for various calculation methods to determine the energy efficiency saving [23]. This results in multiple types of models.

Types of energy models

The baseline model calculation methodology is dependent on the nature of the ESM and on the measurement boundary selected. [26] Models have varying degrees of complexity, they can be simple (e.g. estimating the mean) or complicated (e.g. the response to temperature through regression models.) Various baseline models can be developed to represent the baseline period conditions [5]. The five most common model types are:

1. Unadjusted energy reduction,
2. Energy intensity,
3. Linear regression,
4. Calibrated simulation, and
5. Sample based.

See Appendix B.2 for a more detailed description of how the above-mentioned models are constructed. It should be noted that other more complex modelling techniques exist such as: support vector machines, Gaussian modelling, cross-validation and artificial neural networks [34]. Figure 2-17 indicates a visual representation of the concept of multiple model construction.

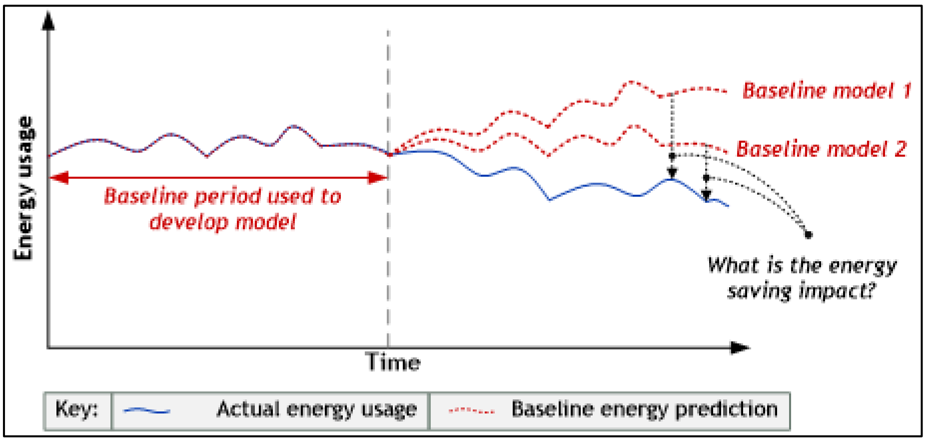


Figure 2-17: Baseline models to predict energy consumption. Extracted from [30]

In Figure 2-17, the energy saving reported is dependent on the baseline model developed. This dependency is what necessitates the management of uncertainty when constructing a model, as the accuracy and reliability of the model have a direct impact on the saving reported.

Model evaluation

<u>*Evaluation of regression models*</u>

Linear regression models are the most commonly used model as they can be validated using statistical analyses. Numerous statistical model validation and model prediction validation tests can be done on a regression model. Various statistical parameters can be used to evaluate the accuracy and reliability of a regression model. The most common statistical parameters evaluated in the M&V field are as indicated [42]:

- Coefficient of determination (R^2) [29], [38], [47], [56],
- Root mean squared error (RMSE) [47], [56],
- Standard error [38], [47],
- F-statistic [2] [38] and t-statistic [47],
- Average error,
- Mean bias error [47],
- Degrees of freedom (df), and
- Absolute and relative precision [45].

The coefficient of determination (R^2) and the root mean squared error are the most common statistical parameters used to validate the model and represent the associated uncertainty. The R^2 indicates how well the regression line fits the relationship between the variables. It can be a value anywhere between zero and one. The closer the value is to one, the better the correlation between the two variables is [42] [18]. A suitable R^2 value is typically bigger than 0.75.

A study done by *Mathews et al* [27] emphasised the overreliance on statistics in the M&V environment, and proposed the use of multiple models as a means of validating the feasible model. The use of multiple models for validation of the claim model is an assurance technique that can be utilised to improve the credibility of the reported EES.

Conclusion

Modelling uncertainty is the dominant uncertainty source. The uncertainty of a model can be mitigated by including model validation statistics and presenting multiple models as an assurance technique.

Various techniques can be employed to manage and quantify measurement, database and modelling uncertainty. However, no resource is available to help one decide on where and when to apply certain techniques. Hence, the following section will investigate assessment decision uncertainty.

2.3.5 ASSESSMENT DECISION UNCERTAINTY

Introduction

There are various decisions which need to be made when constructing the baseline model. These decisions can have a significant effect on the EE saving reported, and if not made properly can lead to incorrect reported savings. The uncertainty associated with assessment decisions cannot be quantified, but assurance techniques can be used to minimise the uncertainty. Three common decisions that need to be made have been highlighted as the most significant, and are indicated below:

1. Measurement boundary selection,
2. Baseline and assessment period selection, and
3. Model selection.

Measurement boundary selection

The measurement boundary construction is of importance. It will determine the points of measurement necessary and which energy governing factors (EGFs) will be of concern. The boundary may be established either for the entire facility or for a portion thereof [23], [36]. The four measurement boundaries are proposed in the Standard: Retrofit isolation, key-parameter measurement; Retrofit isolation, all-parameter measurement; whole facility; and calibrated simulation. Figure B-1 in Appendix B.2 provides a method which can be used to aide in the selection of the measurement boundary.

Baseline and assessment period selection

The selection of the baseline and performance assessment periods needs to align with the implementation of an ESM, and assurance needs to be provided to support the selected periods (e.g. installation documentation or technical reports) [23]. The baseline period is generally immediately before the ESM implementation, since its operations are most likely to represent the post-ESM period [36]. According to the Standard [23] the baseline measurement period shall be constructed to:

1. Represent all operating modes of the facility i.e. represent a full operating cycle.
2. Fairly represent all operating conditions for a normal operating cycle.
3. Only include time periods where all the fixed and variable EGFs are known for the facility.
4. Coincide with the period immediately before the implementation of the ESM.

A facility that operates on an annual cycle in response to the weather should have a full year baseline [36]. Similarly, the assessment measurement period shall be constructed to include at least one normal operating cycle with the baseline period as the point of reference [23].

When more than a continuous 12-month period of data is available, caution should be taken not to overrepresented the time period [36].

Model selection

Due to industrial operations having multiple data sources it is possible to develop multiple baseline models for EES quantification. Constructing multiple alternative models is necessary to evaluate and compare potential M&V models [27]. Comparing multiple models is beneficial as this process can be used as a validation technique. To compare different models a set of criteria needs to be determined. The comparison and selection of models will be further discussed in Section 2.4.3.

Conclusion

The four sources of uncertainty when constructing a 12L application have been discussed. Various qualitative and quantitative strategies to manage these uncertainties has been presented. Table 2-4 provides a summary of uncertainty management techniques available for the given uncertainty sources.

Table 2-4: Summary of available uncertainty management techniques

Source of uncertainty	Statistical Tests	Assurance Techniques	Literature
Measurement	✓	✓	[25], [26], [53], [54]
Database	✓	✓	[11], [25], [26]
Modelling	✓	✓	[15], [25], [26]
Assessment Decisions	✗	✓	[25], [29], [26]

Measurement uncertainty

Table 2-4 indicates that statistical and assurance techniques are available for measurement uncertainty management. A statistical equation for relative equipment is available. Assurance can be provided using calibration certificates.

Database uncertainty

The data base uncertainty has both statistical and assurance techniques available for uncertainty management. In terms of statistical techniques, there are methods to manage the database uncertainty but not to quantify it. These statistical techniques available include outlier removal techniques. Assurance techniques include checking redundant datasets match and compiling universal dataset checklists.

Modelling uncertainty

Statistical techniques for uncertainty management and quantification are in high supply for linear regression models. Constructing multiples models can be used as an assurance technique.

Assessment decision uncertainty

As can be seen in Table 2-4 there are no statistical tests available for this type of uncertainty. This is because it is a more abstract uncertainty form and cannot be quantified statistically. Assurance techniques are the core of this uncertainty management strategy. Assurance includes the use of decision flowcharts, documentation and multiple models as a validation technique.

2.3.6 CONCLUSION

This section provided information regarding the regulations [14], standards [23] and guidelines [24], [29], [36], [43], [47] available to help navigate uncertainty management in M&V, with specific reference to ESM quantification for 12L applications.

The sources of uncertainty identified that needed to be managed were: measurement, database, modelling and assessment decision uncertainty. Methods to manage and quantify these four sources of uncertainty were investigated. A variety of statistical and assurance techniques were discussed. Finally, the SANAS Guideline was investigated, as it provides the best practices available for reporting EES uncertainty and provides model validation techniques.

Although uncertainty management and quantification techniques are well-established in literature, there is no guidance readily available for which techniques of uncertainty management to use under which circumstances. Hence decision support tools will be discussed in the section to follow.

2.4 DECISION SUPPORT TOOLS

2.4.1 INTRODUCTION

Existing uncertainty quantification and management requirements and techniques have been established. A method for making reliable decisions while navigating uncertainty and considering all the different techniques needs to be developed. Thus, this section will discuss available decision support tools. The two support tools that will be discussed are: decision flowchart construction, and multiple criteria decision making.

2.4.2 DECISION FLOWCHART CONSTRUCTION

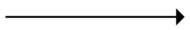
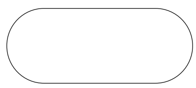
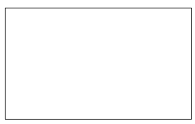
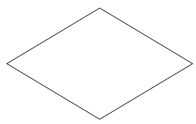
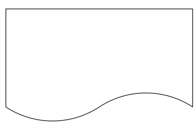
Introduction

Decision flowcharts can be used to navigate the decision-making process in a simple way by associating a criterion to a decision. A flowchart is a visual representation of information that depicts the steps a process must follow to be completed [58]. Common alternative names include: process flowchart, process map and flow diagram.

Flowchart conventions

Flowcharts are constructed using a combination of arrows and shapes. Table 2-5 provides an indication of common flowchart conventions.

Table 2-5: ANSI/ISO Common symbols used for flowchart construction

	**Flowline (Arrowhead)**: indicates the order of operation in the process.		**Terminal**: Indicates the start/end of a process/ sub-process.
	**Process**: indicates any processing function. E.g. An operation that results in the change in value, form or location of information.		**Decision**: represents a decision function, with more than one outcome path e.g. yes/no or true/false
	**Data**: This symbol represents data.		**Document**: Indicates human readable data e.g. printed output, data entry forms.

The American National Standards Institute (ANSI) set standards and symbols for flowcharts [59], and the International Organization for Standards (ISO) adopted the ANSI symbols [60]. The ANSI/ISO standards also provide symbols beyond the basic shapes featured in Table 2-5.

Steps for flowchart development

A decision-making flowchart is a simple tool that can used to make a decision in a uniform manner. There are seven generic steps that can be followed to construct a decision flowchart:

Step 1: Fully analyse the problem and identify the purpose of the decision
Step 2: Collect all relevant information
Step 3: Set up criteria for judging the alternatives
Step 4: Evaluate the alternatives
Step 5: Choose the most suitable among the alternatives
Step 6: Carry out the decision
Step 7: Review the decision and its consequences

Example for flowchart construction

Figure 2-18 provides an example of how a decision flowchart works. There is a starting point, and from there a question is posed. There is more than one possible answer to the question. Depending on the answer to the question an operation can be carried out as indicated by the process block, or the evaluation could end. In the case that the process ends, observations should be made and if possible, a re-evaluation should occur.

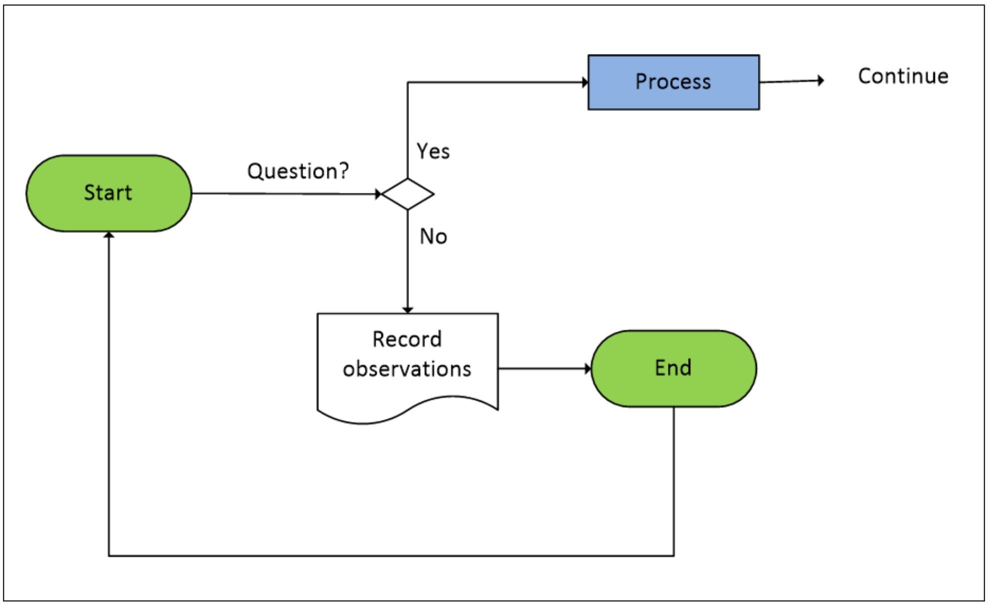


Figure 2-18: Example of decision flowchart construction

As can be seen in Figure 2-18 it is important to understand what the next step would be when a decision is made. Either a re-evaluation of the issue or continuation onto the next operation or question. This method for navigating a problem is valuable, as it links decision making to criteria in a simple, easy to understand technique.

ASHRAE provides decision flowcharts that help navigate the construction of certain models as indicated by Figure B-3 to Figure B-5, and in Appendix B.2. These decision-making flowcharts make use of statistical tests to verify that the assumptions about the model error hold. If the assumptions do not hold, it may be necessary to re-specify the model or to estimate it using a different method.

Conclusion

Decision making flowcharts are encountered in the M&V field. ASHRAE uses decision flowcharts to navigate some key considerations for model development such as model diagnostics, and savings uncertainty quantification. However, no flowchart exists for the full EES quantification process while considering measurement, database, modelling and assessment decision quantification and management of uncertainty.

2.4.3 MULTIPLE CRITERIA DECISION MAKING

Introduction

The Standard allows for multiple modelling techniques, as different measurement boundaries, data sources and quantification methods can be employed to calculate the EES. Hence, various EES models are constructed and there is a need for a method to select the most feasible model.

Multiple-criteria decision making

Making a decision involves making a choice between alternatives as to which is the most suitable option. Decision making is a process that involves the trade-off between various intangibles. To evaluate these intangibles, they must be measured alongside tangibles whose measurements must be evaluated as to how well they fit the objectives of the decision maker.[61]

Multiple criteria decision making (MCDM) refers to a choice that must be made while considering numerous objectives. The result is a compromised solution that takes all the criteria into account, and is acceptable to all stakeholders [62]. A handbook called *'Multi-Criteria Analysis in the Renewable Energy Industry'* [63] indicates the decision-making process primarily consists of five stages, as listed below:

1. Define the problem, generate alternative solutions and establish appropriate criteria,
2. Assign appropriate criteria weights,
3. Evaluation of alternatives,
4. Select the appropriate multi-criteria method to rank alternatives, and
5. Rank the alternatives.

These steps can be followed to effectively apply MCDM. The use of the MCDM process ensures that the decisions made are logical and objective [63].

There are various techniques that can be used to aid the MCDM process. The most common MCDM methods applied in the energy field are listed below:

- Analytical hierarchy process (AHP) [61][62][63],
- Weighted sum and weighted product method (WSM/WPM) [62][63],
- Technique for the order of preference by similarity to the ideal solution (TOPSIS) [62][63] ,
- *Elimination et choix traduisant la realité* (ELECTRE) [62][63], and
- Preference ranking organization method for enrichment evaluation (PROMETHEE) [62][63].

A comparative study was done on the above-mentioned MCDM aid tools by *Kolios et al.* [62]. The study concluded that all the methods supplied results that were in agreement. The more complex methods (TOPSIS and PROMETHEE) showed more accurate results. The study also indicated that the WSM and AHP method showed very similar results. [62]

Botes [20] carried out a study which verified the use of a MCDM technique for model selection. For the purposes of this study the AHP method for MCDM will be discussed, as it is a simple and commonly used decision-making tool [61].

Analytical Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) can be used to compare different EES models. AHP finds the answer that provides the most suitable fit to the objectives of a project, instead of the “correct” answer. AHP uses pairwise comparisons and relies on expert judgement to construct priority scales.

The priority scales measure the intangibles in relative terms. EES model comparison is done using the priority scales which represent how much more one element dominates another relative to a specific attribute. AHP is subjective to the judgement of the evaluator, and the judgements may be inconsistent which is of concern when utilising this tool.[61]

Three Scale Analytic Hierarchy Process

As suggested by the name the AHP consists of a hierarchy. When constructed the hierarchy assists the user to decompose the decision problem into a simplified collection of sub-categories.

Figure 2-19 indicates a generic representation of how a hierarchy is constructed. The pinnacle of the hierarchy represents the goal of the study. The success of the goal is determined by criteria. These criteria can also have sub-criteria which contribute to the element under which it is grouped.

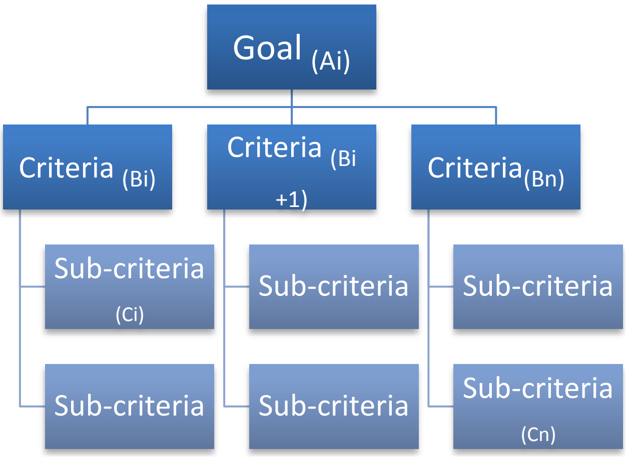


Figure 2-19: Analytic Hierarchy Process pictorial representation

The hierarchy structure is used to carry out pairwise comparisons of elements of the same class. In Figure 2-19, the classes are labelled as A, B and C. The pairwise comparisons are done to determine the impact the criteria have on the element above it. The pairwise comparisons are made using an absolute judgements scale, as indicated in Table 2-6.

Table 2-6: The fundamental scale of absolute numbers

Intensity of Importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
2	Weak or slight	
3	Moderate Importance	Experience and judgement slightly favour one activity over another
4	Moderate plus	
5	Strong Importance	Experience and judgement strongly favour one activity over another
6	Strong plus	
7	Very Strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme Importance	The evidence favouring one activity over another is of the highest possible order of affirmation
Reciprocal of above	If the activity *i* has one of the above non-zero numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared to *i*	A reasonable assumption
1.1 -1.9	If the activities are very close	May be difficult to assign. Indicates the relative importance of the activities.

The scale is used to indicate the degree to which one element dominates over the other. The decisions made are subject to inconsistencies. It should be noted that there are two points of contention when using the AHP method: these are the measurement of inconsistency and how the judgements can be improved.

A judgement matrix is constructed using the pairwise comparison outputs. The priorities of the elements are determined by addition of the rows and dividing by the sum of all the rows. Table 2-7 provides an example of a judgement matrix.

Table 2-7: Hierarchy judgement matrix

A	B1	B2	B3	∑	T
B1	1.00	4.00	4.00	9.00	0.61
B2	0.25	1.00	0.33	1.58	0.11
B3	0.25	3.00	1.00	4.25	0.29
			Cum.	14.83	

The priorities for the criteria (B1 – B3) relative to the goal (A) are indicated in the table by the 'T' value. For instance, the priority of B1 was calculated by: 9.00 / 14. 83 = 0.61. The priorities (weight of different indices) is used in conjunction with a scoring table to determine a final score for each option in a decision-making process.

A goal for this study is to decide on the most suitable model using compliance, uncertainty statistics and the provided assurance. The AHP method can be used to compare the multiple model options available uniformly and objectively.

2.4.4 CONCLUSION

Two decision support tools were investigated: decision flow charts and multiple criteria decision making (MCDM) tools. A decision flowchart can be used to navigate the decisions of EES quantification in a systematic approach. A MCDM support tool called the AHP method can be used for the selection of the most suitable modelling option while considering compliance, uncertainty statistics and provided assurance.

2.5 CONCLUSION

In this chapter the administrative, technical and legal regulations of a 12L application were reviewed. Two supporting documents that provide a critical resource in the EES quantification process were investigated i.e. the SANS 50010 standard and the SANAS uncertainty guideline. The Standard provides technical guidance and the Guideline provides specific methods for addressing M&V uncertainty.

Measurement and verification uncertainty techniques were then investigated. This was done to establish a broader understanding of the available uncertainty quantification and management techniques in industry, and how they differ or agree with the requirements and techniques provided by the Standard and the Guideline.

Four key contributors to uncertainty for EES quantification were identified. These were measurement, database, modelling and assessment decision uncertainty. Uncertainty Q&M techniques for these sources of uncertainty were presented. There was a large variety of methods available. A summary of the techniques available for the four identified sources of uncertainty can be seen in Table 2-8.

Table 2-8: Summary of literature review

Source of uncertainty	Conventional Approach	Alternative Evaluation Techniques
Measurement	• Considered negligible [26] • Universal tolerance value available	• *Assurance technique*: calibration [23] • Measurement error models (MEMs) • Combined uncertainty method available which incorporates measurement error
Database	• Data validation [26] • Outlier removal techniques [26]	• Database management [55] • Universal dataset checklist [55] • Data loss handling technique
Modelling	• Model diagnostics and bias required [23] • Statistical techniques for: 1. Savings uncertainty quantification, 2. Model validation and 3. Model prediction validation.	• *Assurance technique*: Multiple models as validation [27][20]
Assessment Decisions	• Guidance on considerations to make, no support on how to make specific decisions • Decision categories identified: • BL an PA period selection • Measurement boundary selection • Model selection	• Measurement boundary selection options provided [36] [64] • Model selection techniques [20]

In the second column of Table 2-8, ***conventional approaches*** indicate the common approach to quantify and manage the four sources of uncertainty i.e. the techniques provided by the Standard and the Guideline.

Alternative evaluation techniques were also investigated to establish a broader perspective of uncertainty quantification and management techniques available in industry. These are presented in the last column of Table 2-8. Due to the variety of available techniques a need exists for a decision-making method regarding which techniques are most appropriate for different instances. Decision making tools were hence also investigated to address this need.

Two decision support tools specifically were reviewed, namely decision flowcharts and multiple criteria decision-making tools. These two decision making tools were investigated as these methods are found in the industrial M&V sector i.e. decision flowcharts used by ASHRAE G14 [36] and MCDM for EE saving model selection used in a peer reviewed study [20]. Although these decision-making methods have been applied in the field of M&V, they have not yet been developed specifically for uncertainty quantification and management.

It is concluded that a need for an easily implemented, understandable and widely accepted procedure for evaluating and expressing the uncertainty is necessary when quantifying an EES. Chapter 3 will detail the use of methods identified in the literature review for the construction of a methodology.

3 METHODOLOGY

3.1 PREAMBLE

The problem statement from Chapter 1 highlighted the challenges linked to uncertainty quantification and management. In Chapter 2, the main sources of uncertainty were established from a wide range of literature. Also, it provided information on the strategies and methods that are available to manage and quantify these uncertainties. Decision-making tools were also investigated since multiple strategies and methods are available to choose from. Therefore, the aim of this chapter is to utilise these findings from literature to construct a solution that is:

- *Generic*: The solution is reproducible for industrial EES initiative.
- *Simple*: The techniques are non-complex and easy to interpret, so that they can be utilised and interpreted by end users and all stakeholders.
- *Useable*: The solution should aid an end user to navigate the EES quantification process while considering uncertainty.
- *Outcome-based:* The uncertainties associated with the calculation of the EES should be clearly identified, managed and quantified.

The main tool used in the development of the solution is a decision flowchart which is consistent with similar solutions found in M&V literature. The decision flowchart is based on the four key sources of uncertainty reviewed in Chapter 2, namely measurement, database, modelling and assessment uncertainty. The developed decision flowchart needs to provide a quantification and management (Q&M) framework to aid the navigation of the EE saving calculation process while addressing the various uncertainties encountered in a typical M&V process for 12L applications.

The chapter is structured to review the high-level concepts that need to be addressed in the decision flowchart (section 3.2). This is followed by a detailed review of each conceptual element in the decision flowchart (section 3.3). After the detailed review, each element is consolidated to form the developed solution (section 3.4). The solution will be tested on several case studies in Chapter 4 as a measure of verification and validation.

3.2 HIGH LEVEL CONCEPTS: FLOWCHART DEVELOPMENT

Overview of flowchart development

Flowchart development is structured according to specific high-level concepts related to the development of the uncertainty Q&M flowchart. These *'high-level'* concepts refer to the main steps of the flowchart. Figure 3-1 indicates the Five-Step Approach of the uncertainty Q&M flowchart.

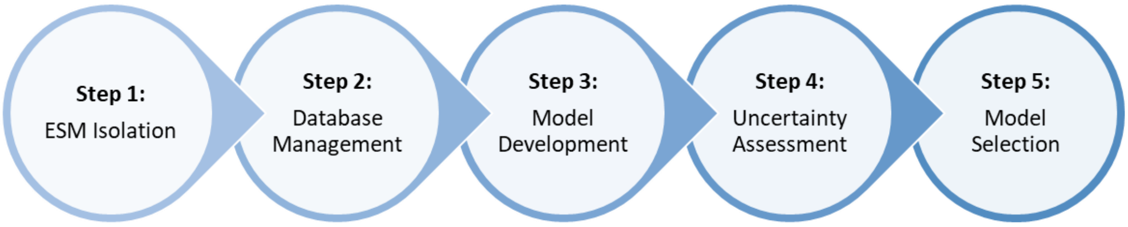


Figure 3-1: High-level overview of uncertainty Q&M flowchart

The five steps indicated in Figure 3-1 were developed through the critical review of literature in Chapter 2. The steps were selected to follow a generic M&V approach to EES determination and address the main sources of uncertainty (presented in section 2.3). The steps are: ESM Isolation, Database Management, Model Development, Uncertainty Assessment and Model Selection. Typically, a model selection step is not included in a standard M&V approach. However, it has been included as the use of multiple models increases the credibility of the claimed value.

Each step includes a high-level conceptual requirement of the standard M&V process, but also includes several outcomes which are required to quantify and manage uncertainty. In this section the high-level concepts are discussed to explain the approach followed. The steps are discussed below:

Step 1: Energy Saving Measure (ESM) Isolation

The Energy Saving Measure (ESM) refers to the specific activities or effort that was implemented to improve energy efficiency. The details of the ESM provide the basis for several decisions that will affect the M&V process. It is therefore important to isolate the ESM in a structured way. This step involves the isolation of the ESM by investigating two operations:

- Baseline and performance assessment period selection, and
- Measurement boundary selection

Once these two operations are determined, the ESM should be isolated to the extent that the required information for uncertainty quantification and management will be made available. This step is used to identify the data sources and measurements available for the selected baseline (BL) and performance assessment (PA) periods. This step incorporates uncertainty management techniques for measurement and assessment decision uncertainty. The details of this step with the associated methods are presented in section 3.3.1.

Step 2: Database Management

Database management refers to the evaluation of the available data sources. This step is important as the data used influences the accuracy of the reported energy saving. The management of the database incorporates many of the techniques mentioned in Chapter 2. This step incorporates three key evaluation analyses:

- Redundant data analysis,
- Dataset interrogation, and
- Universal dataset checklist.

The focus of the redundant dataset analysis is to verify the data, and as a means of considering any interactive effects. The dataset interrogation is used to identify and manage any abnormalities in the data. Lastly, the universal checklist is used to summarize the key information of the datasets evaluated. This step incorporates uncertainty management techniques for database uncertainty. The details of this step with the associated methods are presented in section 3.3.2.

Step 3: Model Development

Model development refers to the generation of a baseline model for calculation of the EES. There are multiple options available when generating a baseline model. The flowchart provides guidance regarding which modelling option should be used in relation to data availability, data resolution and independent variables.

For the purposes of this study, it helps an end user decide between simple modelling options i.e. between linear regression, energy intensity, unadjusted energy reduction, sampling and calibration models. This step focuses on providing guidance for modelling and assessment decision uncertainty. The details of this step are presented in section 3.3.3.

Step 4: Uncertainty Assessment

The uncertainty assessment incorporates the use of statistical techniques for the quantification of the error associated with the reported EES and the validation of the energy model constructed. The aim is to report a final uncertainty value associated with the EE saving. This is important for proving the credibility of the reported saving and abiding by the current requirements for a 12L application. The uncertainty assessment step incorporates three key analyses:

- Model validation
- Savings uncertainty level determination, and
- Combined uncertainty calculation

Model validation refers to the verification that the assumptions of the model hold true. The calculation of an uncertainty level associated with the reported EES is included in the assessment. Combined uncertainty calculation refers to a calculation which incorporates more than one uncertainty source to produce a single uncertainty value. This step incorporates considerations for modelling uncertainty and delivers an EES value that has an associated quantified uncertainty value. The details of this step with the associated methods are presented in section 3.3.4.

Step 5: Model Selection

Multiple modelling options are available. Hence M&V practitioners may choose to develop various models to represent an activity's baseline conditions. Model selection refers to the process of picking the model which represents the baseline most accurately.

From literature it was noted that the model selection step is not typically included in a standard M&V approach. However, it has been included in this methodology since a credible case for using multiple models as a validation technique has been presented [27]. The use of multiple models increases the credibility of the claimed value [27].

The selection process integrates the use of the AHP decision-making tool to rank the models. The model ranked with the highest score is proposed as the feasible claim model, and the following two models with slightly lower scores are suggested as validation models. This step incorporates considerations for assessment decision uncertainty. The details of this step with the associated methods are presented in section 3.3.5.

Summary of high-level concepts

Figure 3-2 indicates the key operations (represented by the blocks) of the uncertainty Q&M flowchart, and how they correspond to the five steps of the uncertainty Q&M flowchart.

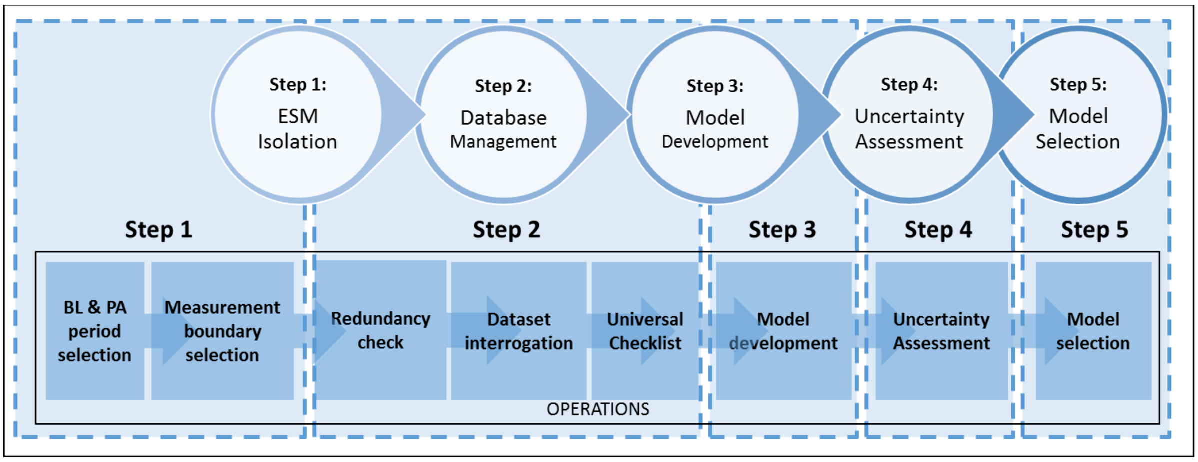


Figure 3-2: Uncertainty Q&M flowchart operations breakdown

A decision flowchart is made up of various components, one of which is referred to as a" process". These process blocks are visually represented as a simple rectangle and indicates an operation. An operation is any process that results in a change of value, form or location of data. In the context of this study the process block will represent the key operations required when constructing an EE saving as seen in Figure 3-2.

Figure 3-2 indicates that step one has two operations, step two is made up of three operations, and steps three to five consist of one major operation. There are eight operations incorporated under the steps altogether. More details of the analyses carried out for each of the operations will be presented in the following section.

Conclusion

In this section, the high-level concepts required to develop the uncertainty Q&M flowchart were discussed as a series of steps. Each of these steps include several methods which are utilised to quantify and manage uncertainty. The detailed review of these methods is presented in the next section.

3.3 DETAILED REVIEW: UNCERTAINTY QUANTIFICATION AND MANAGEMENT STEPS

Preamble to review

This section details the development of the uncertainty Q&M flowchart. The flowchart makes use of yes/no and pass/fail type questions. The symbol convention provided by ANSI/ ISO [60] will be utilised in the development of a flowchart. A detailed flowchart for each of the 5 steps has been constructed to aid users navigate the important considerations of an EES quantification process.

3.3.1 STEP 1: ENERGY SAVING MEASURE (ESM) ISOLATION

Step 1 of the uncertainty Q&M flowchart involves the isolation of the ESM as indicated in Figure 3-3. The ESM is a specific activity or effort that was implemented to improve energy efficiency on specific energy-intensive processes. The ESM will be isolated using two operations: BL and PA period selection, and measurement boundary selection.

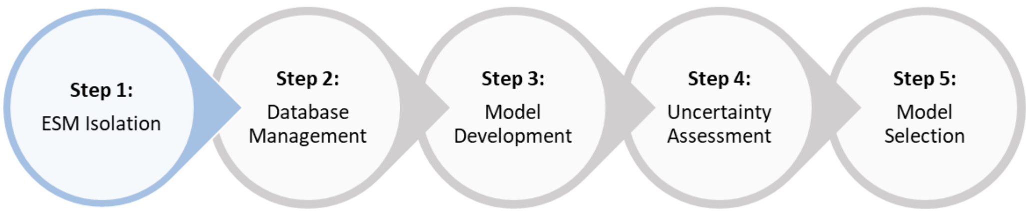


Figure 3-3: Step 1 of detailed uncertainty Q&M flowchart development

Baseline and performance assessment period selection

The BL and PA period selection process can be navigated using the flowchart indicated in Figure 3-4.

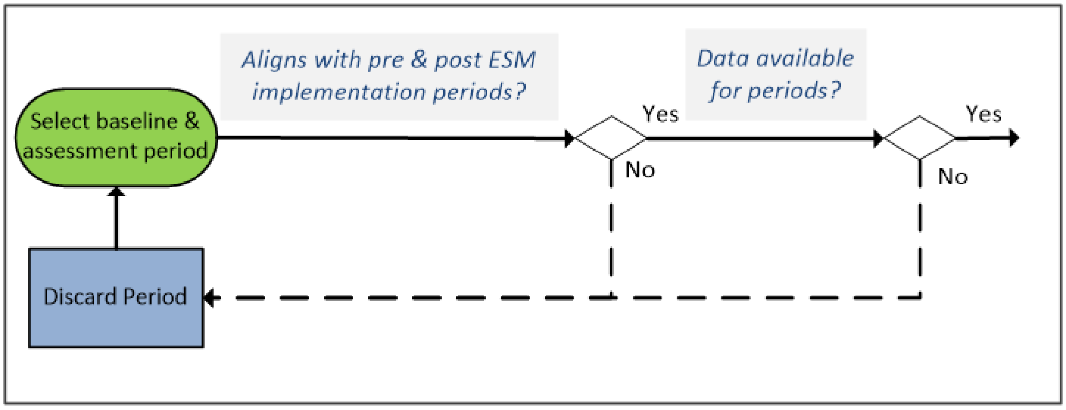


Figure 3-4: Detailed flowchart - baseline and performance assessment period selection

The first question that needs to be asked is when the ESM occurred, as all the results are influenced by the period considered. Hence, the first question asks whether the chosen baseline and performance assessment periods align with the ESM [23]. If the periods chosen do not align with the ESM it should be discarded, and new periods should be selected. This flow is indicated by the dotted line in Figure 3-4, which represents the feedback loop.

The second question posed is whether there is data available for the chosen BL and PA periods. Depending on the data availability for the selected periods, adjustments to the periods may be necessary. Therefore, if there is insubstantial or no data the feedback loop should be followed to select new periods. At this stage the available data should be summarized into a table that can be used for reference for the rest of the EE saving calculation. Table 3-1 indicates the recommended format of this type of table.

Table 3-1: Data availability table

Variable	Measurement	Measuring device	Data source	Data resolution
Coal	E.g. coal quantities	E.g. weigh bins	E.g. batching tonnages	E.g. Daily tonnages

In Table 3-1 an example of how the data availability table should be used is presented. For each listed variable, the measurement, measuring device, data source and resolution of the data should be provided. The ***measurement column*** indicates what is being measured while the ***measuring device column*** represents the equipment used to capture the data. Additionally, the ***data source column*** indicates where the data originated from and the ***resolution column*** details the intervals in which the data is available.

The example provided in Table 3-1 indicates that for the variable which is coal, what is being measured is the coal quantity (measurement). The device used for measurement is weighing bins while the data is provided in batching tonnages reported and is available in a daily resolution.

Once the available data for the chosen periods has been captured in the data availability table, one can continue to the investigation of the next operation, being measurement boundary selection.

Measurement boundary selection

The first part of the flowchart for the measurement boundary selection is indicated in Figure 3-5.

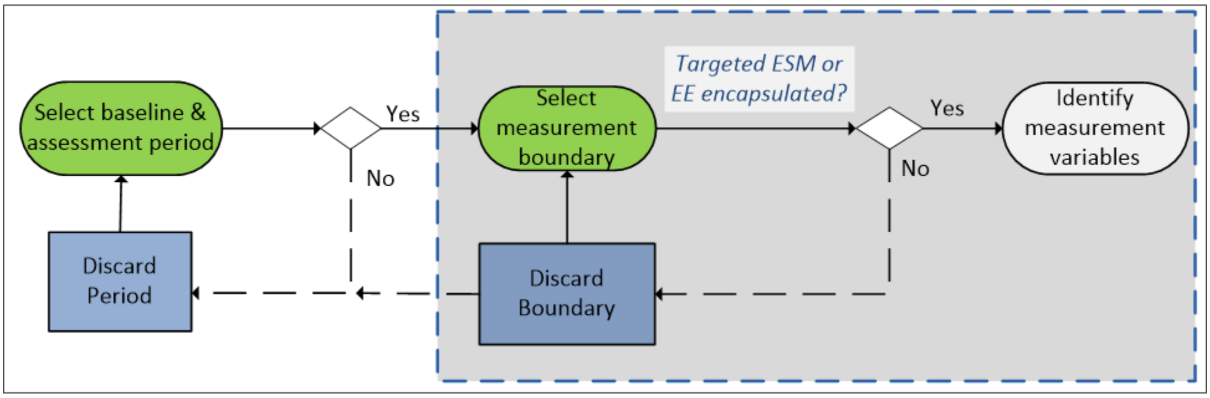


Figure 3-5: Detailed flowchart - measurement boundary selection

Once you have compiled the data availability table (as presented in Table 3-1), it will be easier to decide where to construct the measurement boundary. The main question that needs to be answered when choosing the boundary is whether the ESM/ EE is encapsulated in the boundary (see Figure 3-5). One then needs to consider what data is relevant within the constructed measurement boundary.

There are a couple of standard measurement boundaries for modelling that can be chosen as indicated in the Standard (See Appendix B.2) [64]. These are listed below:

1. Retrofit isolation, key-parameter measurement,
2. Retrofit isolation, all-parameter measurement,
3. Full facility,
4. Calibrated simulation

Based on data availability and relevance to the ESM, the measurement boundary will either be constructed around the whole facility or isolated to the ESM. If there is substantial data loss, a calibrated simulation would be necessary for modelling.

Identify measurement variables

The second part of the measurement consideration of the flowchart is detailed in Figure 3-6. This figure indicates the measurement and database verification process. The measurement and data verification process involves establishing the data traceability and ranking the data according to status i.e. tracking it to its origin e.g. their point of measurement (POM) or to a log sheet. Figure 3-6 indicates how the data can be ranked.

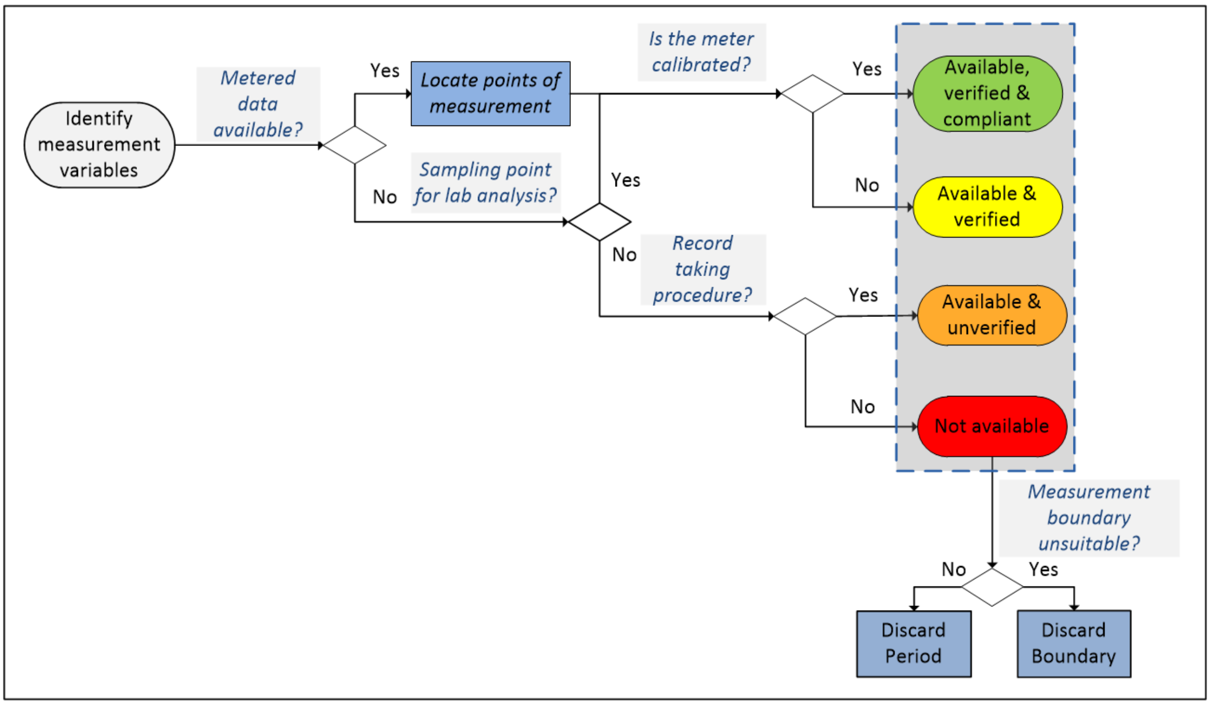


Figure 3-6: Detailed flowchart – measurement and data verification

The data can be assigned status values according to their compliance. This can be done using four categories as indicated in Figure 3-6 by the green, yellow, orange and red ovals. This status depends on the data availability, verification and compliance. It can be observed that where data is not available, one should consider whether the measurement boundary is suitable. If it is unsuitable the measurement boundary should be discarded. If it is suitable, the BL and PA period may need to be reselected.

Next, a point of measurement diagram should be constructed as indicated in Figure 2-9 of Chapter 2. The purpose of the POM diagram is to establish the location of the measured data. This aids in improving the understanding of how the activity works and the variables associated with it. It also plays a role in deciding the most suitable place to construct the measurement boundary.

The status of the data, as well as its compliance, can be added to the data availability table (Table 3-1) such that it looks like Table 3-2 below.

Table 3-2: Complete data availability table

Variable	Measurement	Measuring device	Data source	Data resolution	Compliance	Stream no. on POM diagram	Status of data
Coal	E.g. coal quantities	E.g. weigh bins	E.g. batching tonnages	E.g. Daily tonnages	Calibration	1	Available, verified and compliant

Conclusion from ESM isolation

The main outputs from the ESM isolation step are to select the periods that will be investigated, the data available for that period, the status of that data and the traceability of the data represented through a POM diagram.

3.3.2 STEP 2: DATABASE MANAGEMENT

Overview of database management

Database Management utilises strategies to validate the data and identify and manage any abnormalities. This step of the uncertainty Q&M flowchart is indicated in Figure 3-7 as the second step.

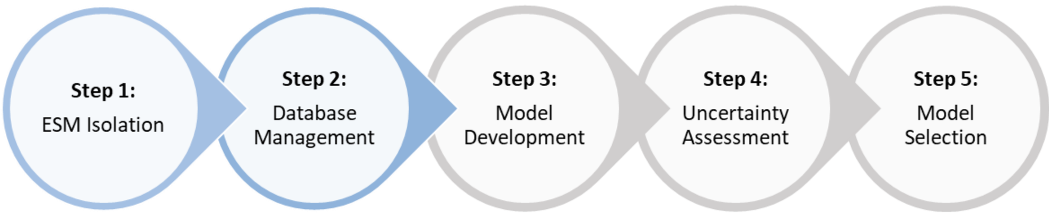


Figure 3-7: Step 2 of detailed uncertainty Q&M flowchart development

Data validation

Data validation refers to the investigation of the accuracy of the data. See Figure 3-8 for the detailed flowchart for Database Management. As can be seen in Figure 3-8, the available dataset needs to be validated. Three key methods were identified from literature to assist with database management, namely redundant data analysis [55], dataset interrogation [55] and the universal dataset checklist [15]. The role of these methods in the developed Q&M flowchart is discussed hereafter.

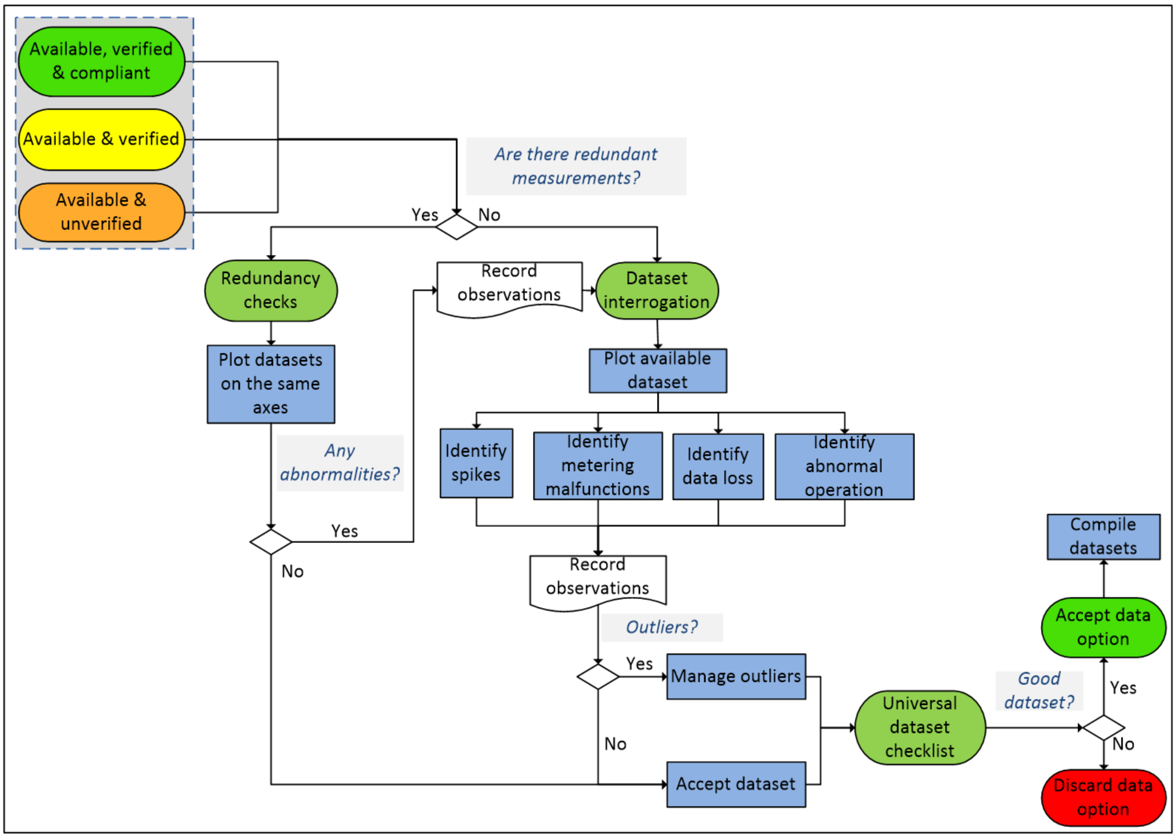


Figure 3-8: Detailed flowchart – Database Management

Redundant data analysis

If there are multiple datasets available, as is usual on full facility level, the datasets will be compared with one another by plotting on the same axes. If there are differences and/or abnormalities, they will be recorded and then the dataset will undergo dataset interrogation. If there are no discrepancies in the datasets, and no irregularities in the values, the datasets will be accepted for model development. A universal checklist will then be constructed to capture the main information regarding the data source.

Dataset interrogation

For the case with no redundant data sources, the user can begin immediately with the dataset interrogation process. As seen in Figure 3-8, the dataset interrogation tests four conditions, namely; if there are any spikes, metering malfunction, data loss or abnormalities in operation. The observations of the dataset interrogation can be recorded in the format indicated in Table 3-3.

Table 3-3: Example of data interrogation results table

Variable	Data source	Spikes	Meter malfunctions	Data loss	Abnormal operation	Comment
Coal	Weigh bins/Sampling and lab analysis	None	None	None	None	

Table 3-3 includes an example for coal as the variable, where the results of the dataset interrogation are displayed. It can be seen in the table that for all the conditions tested, none of them were present. The final column is empty as no additional comments can be made. The comments section should be used to further describe and record the abnormalities seen and indicate when they were observed.

Once the observations of the dataset interrogation have been recorded, outlier removal can be carried out according to the need. It is suggested in this study that instead of using a complex statistical method for outlier removal, outliers should only be removed if they can be linked to a specific event or database malfunction.

Universal dataset checklist

The final operation of this phase of the flowchart is to construct the universal checklists for each data source. The universal checklist is a very helpful tool, as it acts as an easy point of reference when managing the database. It provides valuable information such as data availability, quality, and traceability. Table 3-4 provides the template of the universal dataset checklist, with a filled-in example for the variable coal. This table was adapted for this study and is based on the one constructed by Gous [15].

The checklist is made up of various sub-categories: reporting period, boundary applicability, data availability, applicability to the key performance indicator, internal management, measurement traceability and the transparency of the data. The reporting period indicates the chosen period for the investigation. The boundary applicability indicates the measurement boundary selected, and which part of the section/department it is applicable to. Data availability summarises the resolution and quantity the data is available in.

Table 3-4: Universal dataset checklist

Universal Dataset Checklist				
Details:				
Measurement:	Coal calorific value			
Measurement units:	Energy per coal type tonnage			
ID/Tag name:	lab reported data			
Instrumentation used:	lab analysis			
Criteria of evaluation:				
Reporting Period	Calender year	July - June/ FY	Financial Year	
	Changeable period	Beginning	1	2014
		End	12	2015
Boundary applicability	Full facility		Yes	No
	Section/Department		Furnaces	
	Section/Department		Smelting Operations	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Coal to furnace	
		Environmental	N/A	
		Strategic operations	Production	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Database	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	No	
		Archive records	No	
		Archive period	No	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Available	Yes	No

Conclusion from database management step

The applicability focuses on isolating how the variable relates to the entire operation. Internal management deals with data quality assurance i.e. is the data from a calibrated meter. Traceability accounts for whether the POM can be located, and if there is documentation to support it. Finally, the transparency of data explains the accessibility of the data. The universal checklist is a great tool to summarize the key information of the data source.

Once all these operations have been carried out to validate the data, it can be sorted. It will be sorted into "*acceptable data"* which is data that can be used for modelling or "*discarded data*" which is data that will not be used as it is deemed poor quality. The accepted data sources can then be compiled into datasets.

3.3.3 STEP 3: MODEL DEVELOPMENT

Overview of model development

Multiple methods are available for baseline model development to determine the EES. This step details the guidance provided for making this decision on which simple model type to construct. Details of the Model Development step are provided in this section, as indicated in Figure 3-9.

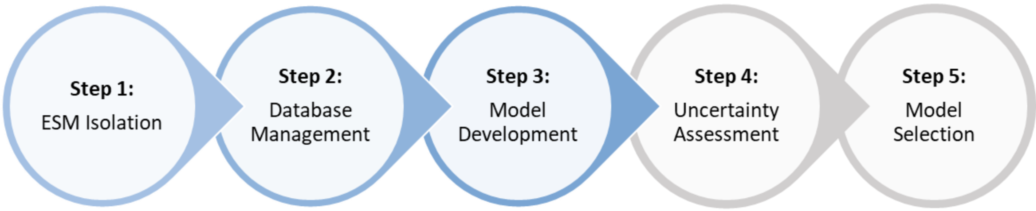


Figure 3-9: Step 3 of detailed uncertainty Q&M flowchart development

Model development options

Figure 3-10 depicts the flowchart that can be used as a guide on which type of model to construct. The figure indicates the most common types of models available as detailed in Chapter 2. Although the most suitable modelling option for specific cases is indicated, it is suggested that not just one type of model be constructed. Multiple models can be constructed and used as validation of the reported EES.

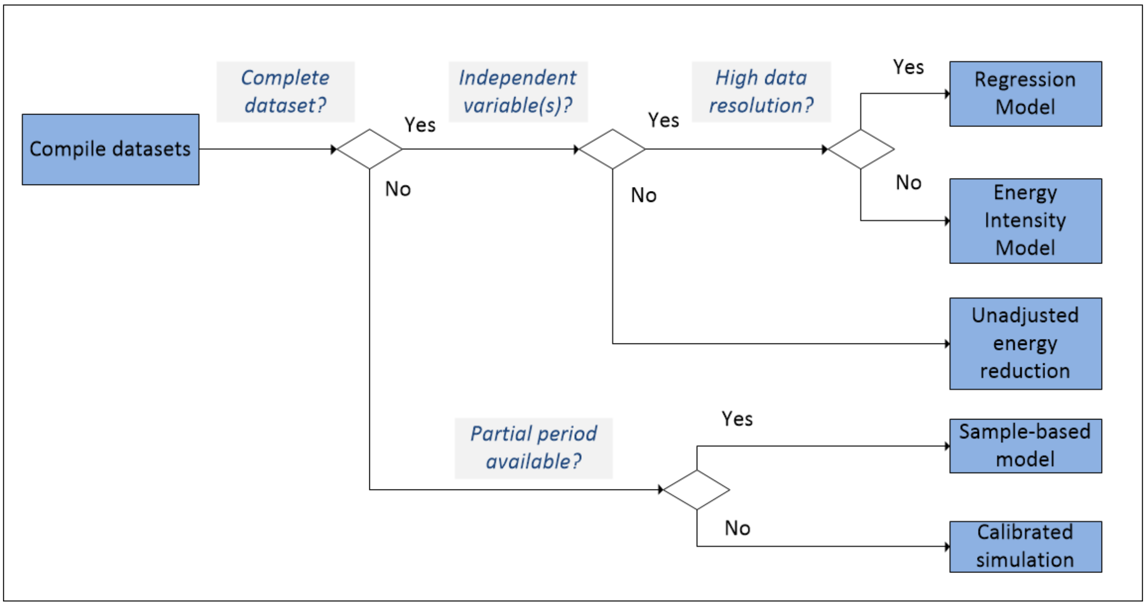


Figure 3-10: Detailed flowchart - Model Development

Returning to the first question posed in Figure 3-10, had the answer been yes, the next question posed would be whether independent variables are available. If no independent variables are available, then an unadjusted energy saving model should be constructed. However, if there are independent variables available, a follow up question is posed to decide whether a linear regression model or an energy intensity model should be used. To determine between the last two models, the resolution of data should be investigated. It is advisable to use regression models where high-resolution data is available instead of energy intensity models.

Conclusion from model development step

This step of the flowchart represents a very simplified case for decision making regarding the type of model that should be constructed. However, once a model is constructed it needs to be validated and the EE saving needs to be reported with an uncertainty value. These two requirements will be addressed in the following section.

3.3.4 STEP 4: UNCERTAINTY ASSESSMENT

Overview of uncertainty assessment

The Uncertainty Assessment step involves the use of statistical techniques for quantification of the uncertainty associated with the reported EES, and for the validation of the model. This section will cover the Uncertainty Assessment as indicated in Figure 3-11.

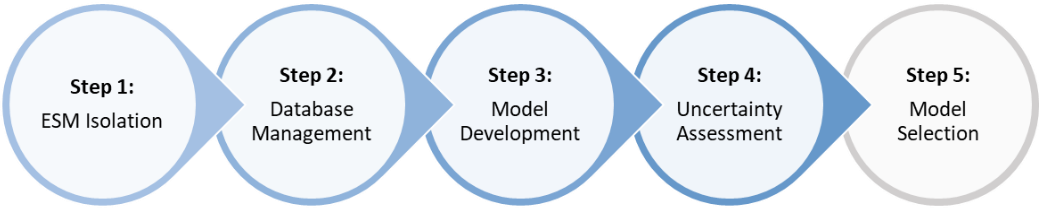


Figure 3-11: Step 4 of detailed uncertainty Q&M flowchart development

The uncertainty assessment step incorporates three key analyses:

- Model validation,
- Savings uncertainty level determination, and
- Combined uncertainty calculation

Description of uncertainty assessment

Figure 3-12 indicates a simplified flowchart for the Uncertainty Assessment step.

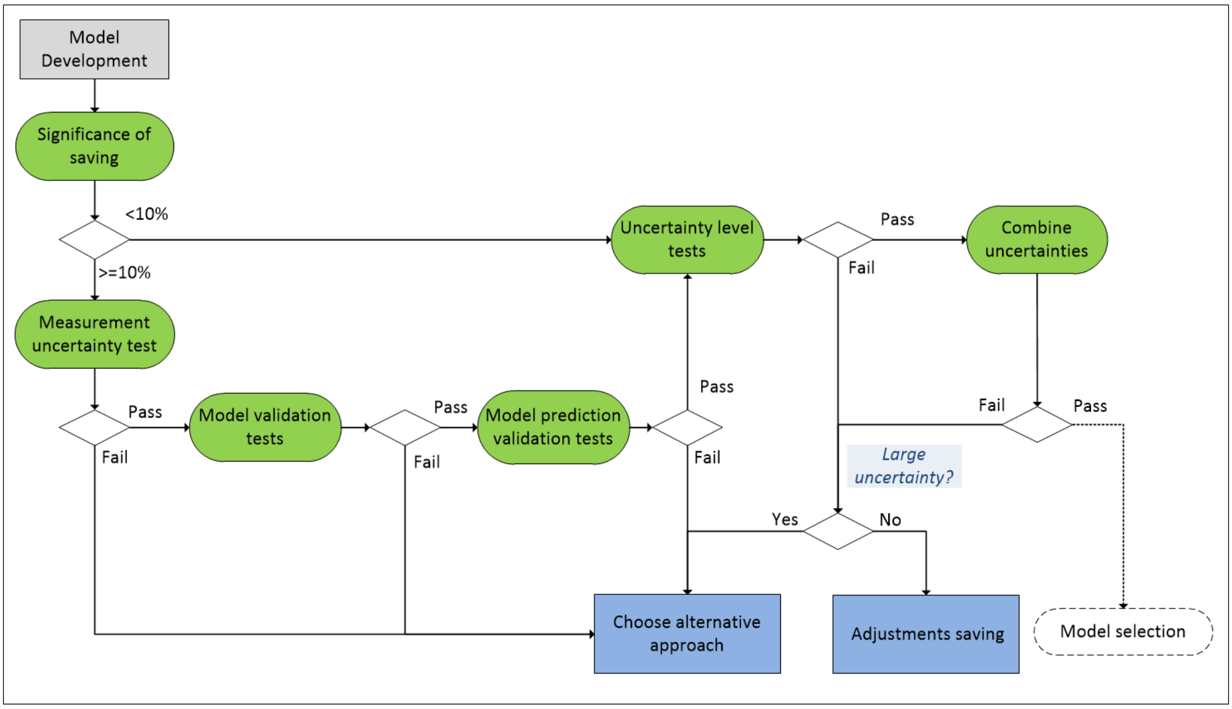


Figure 3-12: Detailed flowchart – Uncertainty Assessment

<u>Significance of savings</u>

The first test indicated in Figure 3-12 is to test the significance of the EES relative to the baseline energy consumption. This is done first because the significance plays an important role in statistical analysis. If the significance is less than 10% then proceed straight to the uncertainty level tests; if not, measurement uncertainty can be quantified.

Measurement uncertainty

The measurement uncertainty test carries a high importance in that the model is deemed untrustworthy if the measurements are not accurate. Hence, if this test is failed an alternative modelling approach using different measurements is suggested. However, if this test is passed model validation tests can be carried out. See Appendix B.2 for measurement uncertainty calculation explanation.

Model validation tests

The model validation tests prove the assumptions of the model have been verified; passing all the model validation tests would constitute moving onto model prediction tests as indicated in Figure 3-12. If any of the model validation tests are failed an alternative modelling strategy should be considered.

The model validation tests include: correlation value (R^2) determination, P-value, and Durbin-Watson and Anderson-Darling (AD) tests where applicable (AD test is only necessary for fifteen or less data points).

Model prediction validation

Model prediction validation tests verify whether the model is a good predictor of the baseline. Model prediction validation tests, once passed for all the tests, constitutes moving to uncertainty level tests, and failing any tests would require the M&V practitioner to consider an alternative modelling option.

The model prediction tests include: testing the model goodness of fit (CV[RMSE]), statistical significance (F-test or SANAS test) and over/under prediction using the Net Determination Bias (NDB) test.

Uncertainty level tests

If the uncertainty level tests are failed, this leads to a question being posed. The question that is posed is whether the observed uncertainty level is large; if it is, an alternative modelling option should be chosen. “Large” uncertainty is defined in this study as an uncertainty level which invalidates the claim. If it is not too large it can be managed i.e. the EES can be adjusted to include the uncertainty. Passing the uncertainty level tests means that the last step which is to combine uncertainties can be carried out. See Appendix B.2 for uncertainty level calculation explanation.

Combined uncertainty

If the combined uncertainty levels are too large, and hence the test is failed, the same question as previously described is posed (is the uncertainty large) and the response options are the same. If the combined uncertainties are passed, one can move on to the next step in the flowchart, which is model selection. See Appendix B.2 for combined uncertainty calculation explanation.

Model specific uncertainty assessment

The uncertainty assessment will differ for each different type of model. Hence, individual decision flowcharts are developed for the main types of models. Figure 3-13 indicates the individual model flowsheets. The first question posed for most of the individual modelling options is whether the baseline spans all operation modes. This is important as the Standard requires that it does [23]. Hence, if this condition is not met, an alternative approach should be considered. A brief explanation of how each of the flowcharts for different model types work is provided in Figure 3-13.

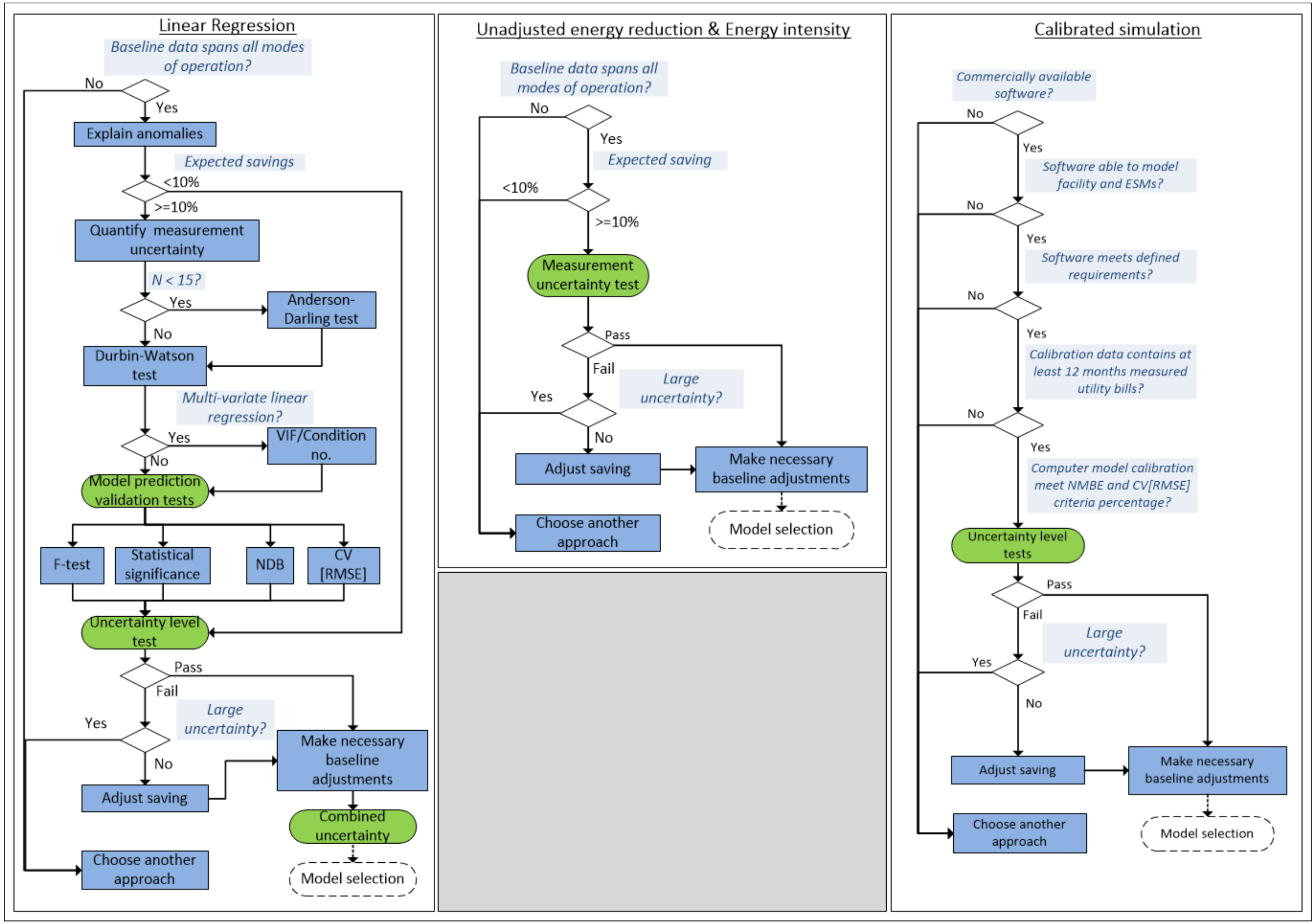


Figure 3-13: Uncertainty assessment flowcharts for individual modelling options

Linear regression uncertainty assessment flowchart:
The first step would be to identify any anomalies in the model and manage them by the removal of data points that can be linked to specific events. Next the significance is determined. If it does not pass this test, it is suggested that the uncertainty levels tests are carried out straight away, to determine whether it is a worthwhile model to continue with.

The significance of the EE saving plays a critical role in uncertainty level calculations for the saving, as small significance (less than 10%) is linked to failed uncertainty level tests. If the significance value is greater than 10%, the normal pathway can be followed. The next operation in the normal pathway is then given as the quantification of measurement uncertainty.

Following that, a question on the size of the sample is posed. If it is smaller than fifteen, the model should be tested with the Anderson-Darling test and then the Durbin-Watson test. However, if the sample size is greater than fifteen, the model only needs to be evaluated with the Durbin-Watson test. The next question posed is whether the model is multivariate or not. if the model has multiple variables, it must undergo an VIF/condition number test, otherwise it does not need to undergo these tests and can move on to the model prediction validation tests.

The model prediction validation tests indicated for this operation include: F-test, statistical significance test, net determination bias (NDB) and the coefficient of variation of the root mean square error.

The next operation that needs to be carried out is the savings uncertainty level tests. The uncertainty levels are tested at 80/20, 90/10 and 68/50 confidence intervals. If the model passes at least one of these tests, it can go straight to the next step of baseline adjustments if necessary. However, if it fails all the uncertainty tests the model should be disposed of and a new approach pursued.

The final operation is the combination of the quantified uncertainties for a final uncertainty value. Once this is completed, one can progress to model selection.

Unadjusted energy reduction/ energy intensity model:
The unadjusted energy reduction model and the energy intensity model have the same flowchart. This is due to the simplicity of the models as well as the fact that they are calculated with just a few data points, which makes it a hard model to statistically analyse.

A discussed in the Linear Regression Model, the significance of the saving must first be calculated. If it is smaller than 10%, a different approach/model may be necessary. If the calculated savings are equal to or more than 10%, the model can undergo the measurement uncertainty test.

The only quantifiable source of uncertainty associated with these models is measurement uncertainty. The measurement uncertainty should hence be quantified by applying the relative instrument error to the baseline energy consumption. If the model passes the test, it can go straight to the next step of baseline adjustments if necessary. However, if it fails all the uncertainty tests, the magnitude of the uncertainty should be considered. In the case of a very large measurement uncertainty, the model should be disposed of, and a new approach pursued. If this is not the case the saving can be adjusted.

<u>Calibrated simulation model:</u>

For the calibrated simulation model, five questions are posed. If the question is answered negatively (i.e. with a “no”) then a new approach needs to be considered. However, if the answer is positive (i.e. a “yes”) then one can follow the flowchart. The five questions posed are:

1 Is there commercially available software to develop the model?
2 Is the software capable of modelling the facility or ESM?
3 Does the calibration data contain at least 12 months of measured utility bills?
4 Does the computer model calibration meet NMBE and CV[RMSE] criteria percentage?
5 Is a large uncertainty value observed?

Once these questions have been answered, the uncertainty level tests at the three confidence intervals (80/20, 90/10 and 68/50) should be tested. Finally, as described for the last two model types, necessary baseline model adjustments should be carried out, or the saving should be adjusted if the model is not discarded.

Conclusion from uncertainty assessment step

The aim of the uncertainty assessment is to validate the models using statistical evaluation, as well as to report a final uncertainty value associated with the EE saving. This uncertainty level can be in the form of a measurement uncertainty for simpler models, or a combined uncertainty value. Once this is achieved, one can move on to the final step.

3.3.5 STEP 5: MODEL SELECTION

Overview of model selection

Model selection refers to the process of choosing the model which represents the baseline most accurately. This can be done using a multiple criteria decision-making (MCDM) technique. Botes [20] tested and verified the use of a MCDM technique for model selection, hence the Analytical Hierarchy Process is used for the ranking of constructed EES models.

Figure 3-14 indicates the final step of the uncertainty Q&M flowsheet, which is the Model Selection step.

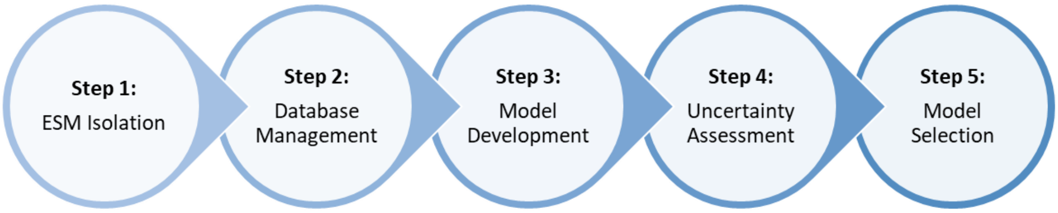


Figure 3-14: Step 5 of detailed uncertainty Q&M flowchart development

Description of model selection

Figure 3-15 indicated the flowchart for the Model Selection step. The AHP method will be used to rank the models, and the top scoring model represents the feasible claim model, and the validation models.

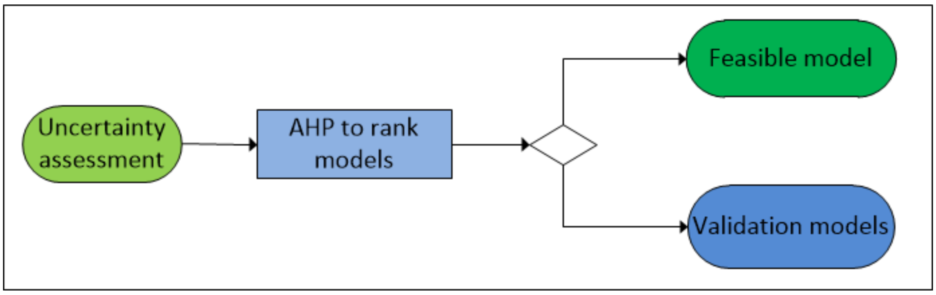


Figure 3-15: Detailed flowchart – Model Selection

The AHP method involves the construction of a hierarchy. The hierarchy constructed for model selection is indicated in Figure 3-16.

The goal of the hierarchy which is presented by the topmost block is to select a feasible claim model (A1). The criteria on which the model feasibility is judged are 12L compliance, economic feasibility, model validation, and statistical uncertainty (B1 – B4). Each criterion has sub-criteria that contribute to it (C11 – C43).

The sub-criteria contribute to the criteria in different weights, and the same can be said for the criteria contributing to the main goal. Some parameters have a bigger importance than others; this is termed the ‘priority’. To determine the priority one parameter has over another, pairwise judgements are carried out (See Appendix B.2).

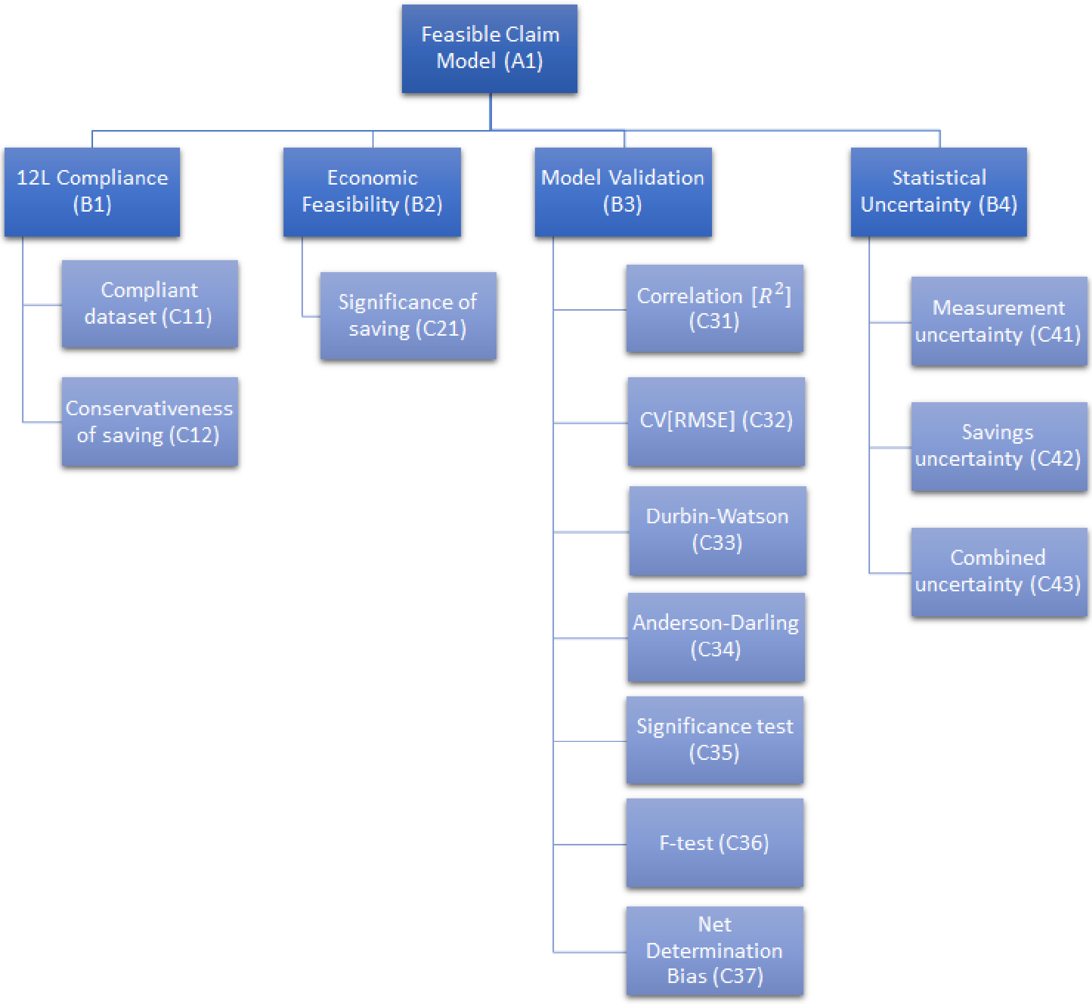


Figure 3-16: AHP for model selection

The priorities for the criteria relative to the goal can be seen in Table 3-5.

Table 3-5: Criteria priority weights

Evaluation Index	B1	B2	B3	B4
Weight	0.49	0.19	0.18	0.14

Table 3-5 indicates that the 12L compliance has the biggest weight of the criteria. The economic feasibility, model validation and statistical uncertainty evaluation all have priorities of similar weight. B2 – B4 have priorities in descending order as one moves from left to right in the table. The priorities for the sub-criteria relative to the goal can be seen in Table 3-6.

Table 3-6: Sub-criteria priority weights

Evaluation Index	C11	C12	C21	C31	C32	C33	C34	C35	C36	C37	C41	C42	C43
Weight	0.25	0.25	0.19	0.05	0.05	0.01	0.01	0.02	0.02	0.02	0.03	0.07	0.05

Scores for each criterion must also be assigned for each model using the *Score Range for Indexes* (Table B-4 - Appendix B.2). The priorities in Table 3-6 along with scores will be used to calculate the final model score. The final scores for the models can be calculated using the table of basic scores (score range of indices) and the table of priority weights (Table 3-6), using the following equation:

$$Final\ Model\ Score\ = \sum[Cii\ score\ x\ Cii\ weight]$$

Equation 3-1: Final model score calculation

Conclusion from model selection

Using the final model scores, the models can be ranked. The model with the highest score will represent the feasible claim model, and those with the second and third highest scores will be included as validation models.

3.4 CONSOLIDATION OF METHODS

Overview of uncertainty quantification and management steps

To meet the objectives of the study, a Five Step Approach to uncertainty quantification and management (Q&M) was developed as indicated in Figure 3-18. The five steps indicate the main operations of a broader uncertainty Q&M flowchart.

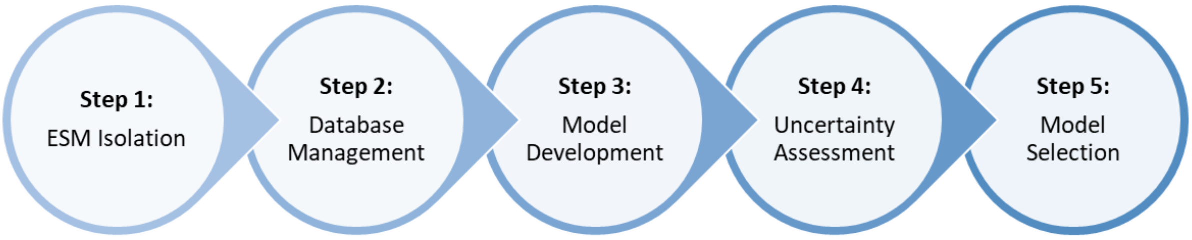


Figure 3-17: Overview of Five Step Approach of uncertainty Q&M flowchart

The steps are: ESM Isolation, Database Management, Model Development, Uncertainty Assessment and Model Selection. These steps were generated using the standard M&V process steps as a guide, while making inclusions for uncertainty Q&M and the selection of the most feasible model amongst multiple model options.

Deliverables of uncertainty quantification and management flowchart

The flowchart incorporates various techniques that help manage the uncertainties, as well as quantify them where applicable. Table 3-7 indicates the deliverables associated with each step.

Table 3-7: Summary of uncertainty Q&M flowchart deliverables

Steps	Deliverables
1	Data availability table
	Point of measurement diagram
	Ranked data by status
2	Redundancy checks
	Dataset interrogation checklist
	Universal dataset checklist
3	Multiple models
4	Significance of saving
	Measurement uncertainty
	Model validation with statistics
	Uncertainty level value for EES
	Combined uncertainty value
5	Ranked models using AHP

These deliverables are what aid in the quantification and management of EES. These deliverables make use of simple, readily-applied methods and statistical techniques that any M&V practitioner is able to use.

Summary of uncertainty quantification and management flowchart analysis

To present the results of the uncertainty Q&M flowchart the structure provided by Table 3-8 is suggested. The table summarises the uncertainty Q&M analysis under the four sources of uncertainty identified in chapter 2, namely measurement, database, modelling and assessment decision uncertainty.

The first column of the table indicates the indices of analysis. The second column is used to indicate the highest ranked model after the application of the AHP method for model selection. The following two columns indicate two validation models. These models and how they meet the criteria are presented in the table. The final column is available for any important comments made for each of the indices of evaluation.

Table 3-8: Summary table for Q&M flowchart analysis

INDICES ANALYSED	Feasible Claim Model	Validation Model A	Validation Model B	COMMENT
	Model 1		Model n	
1. Measurement Uncertainty				
Compliant				
Measurement equipment tolerance				
Measurement uncertainty calculation				
2. Database Uncertainty				
Data traceability				
Redundancy checks				
Dataset interrogation				

INDICES ANALYSED	Feasible Claim Model	Validation Model A	Validation Model B	COMMENT
Outlier investigation				
High quality dataset				
3. Modelling Uncertainty				
Statistical model validation				
Savings uncertainty calculation				
Validation models				
Service delivery consideration				
Combined uncertainty calculation				
4. Assessment Decision Uncertainty				
BL & PA period selection				
IPMVP boundary selection				
AHP model selection				

Conclusion for consolidation of methods

Figure 3-18 indicates the consolidated uncertainty Q&M flowchart. Each of the flowcharts of the Five Step Approach (ESM Isolation, Database Management, Model Development, Uncertainty Assessment, and Model Selection) is combined to produce the consolidated flowchart as indicated.

The uncertainty Q&M flowchart is a tool that incorporates standard M&V procedures, while providing guidance on how best to navigate the quantification of an EE saving. The flowchart is a very simple and readily applied resource.

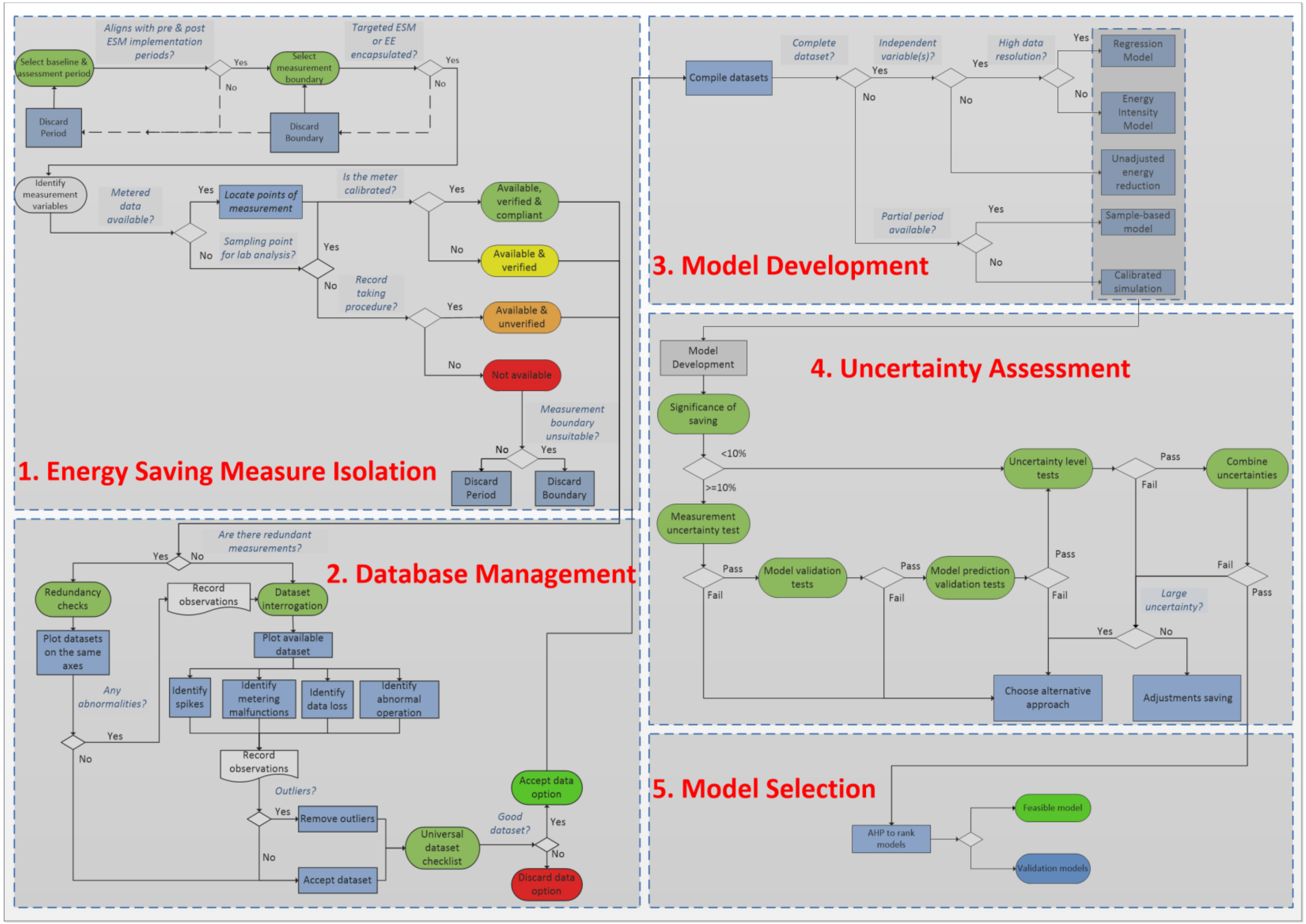


Figure 3-18: Consolidated uncertainty Q&M flowchart

3.5 CONCLUSION

In this chapter, a solution was developed to quantify and manage the uncertainty of EES in the 12L tax incentive landscape. In Chapter 2, flowcharts were recognized as a well-established method used for decision making and navigating model assessment in M&V. For this study, the application of this technique is broadened to include decision making for the 12L EES quantification process with a specific focus on uncertainty evaluation. The tool provided to do this is referred as an uncertainty Q&M flowchart.

The flowchart incorporates a Five Step Approach to EES quantification. These steps are: ESM Isolation, Database Management, Model Development, Uncertainty Assessment, and Model Selection. The solution is developed to be generic, i.e. it can be applied to general industrial case studies with relative ease. This is done by making use of available, simple and standard M&V techniques to enable the general usability of the developed flowchart. These techniques were identified from a wide range of literature that was reviewed in Chapter 2.

The method is also developed to be outcomes-based. This means that each step has specific deliverables that aid in the management and quantification of the four sources of uncertainty identified in Chapter 2 (i.e. measurement, database, modelling and assessment decision uncertainty). Ultimately, the outcomes and the utilised methods are consolidated into a final uncertainty Q&M flowchart.

The next chapter will be used to verify and validate the developed uncertainty Q&M flowchart. This is done to test the viability of the developed method for EES quantification while considering uncertainty by applying it to three different industrial case studies.

4 RESULTS AND DISCUSSION

4.1 PREAMBLE

In Chapter 3, a decision-making flowchart was developed to assist M&V practitioners navigate the energy efficiency savings (EES) quantification process while quantifying and managing uncertainty. This flowchart is called the *'Uncertainty Quantification and Management (Q&M) Flowchart'.* The flowchart uses a Five Step Approach to EES quantification, namely Energy Saving Measure (ESM) Isolation, Database Management, Model Development, Uncertainty Assessment, and Model Selection. Figure 4-1 indicates Five Step Approach of the developed methodology.

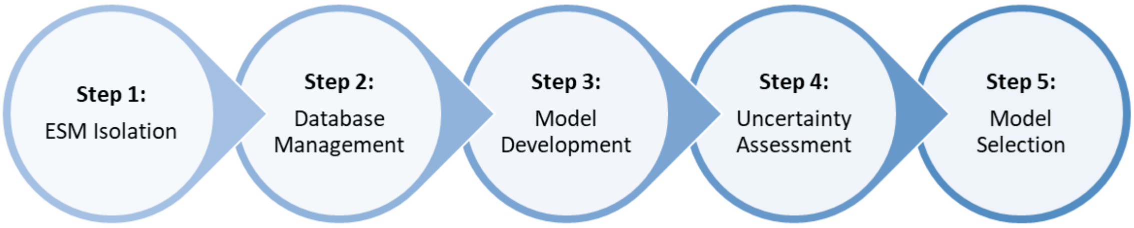


Figure 4-1: Five Step Approach of Uncertainty Q&M Flowchart

In this chapter, the methodology is applied to three industrial case studies to verify the developed methodology. The case studies represent different SA production industries on which energy saving measures were implemented. The data for these case studies were collected from existing M&V reports and correspond to the case studies which were preliminarily investigated in Chapter 1 (refer to Section 1.4).

A detailed application of the developed Q&M flowchart is presented for Case study 1 (Section 4.2). In order to support the readability of the document only key information and observations from Case study 2 and Case study 3 are presented in this chapter (Section 4.3 and Section 4.4). Additional details and supporting information are provided in Appendix C where relevant.

Furthermore, a validation of the results is provided (Section 4.5). The validation is conducted by comparing the outcomes from the case study applications with the requirements of the SANS 50010 standard. Finally, a summary of the key observations from the case study results is also provided to discuss the trends noted from the different case studies (Section 4.6)

4.2 CASE STUDY 1: FURNACE ENERGY INTENSITY REDUCTION

4.2.1 DESCRIPTION OF CASE STUDY

The first case study investigates the energy intensity reduction of a furnace smelting operation. The energy saving measure focussed on the improved use of energy carriers to reduce the quantity of energy required to deliver production volumes. Figure 4-2 indicates the simplified layout of the operation.

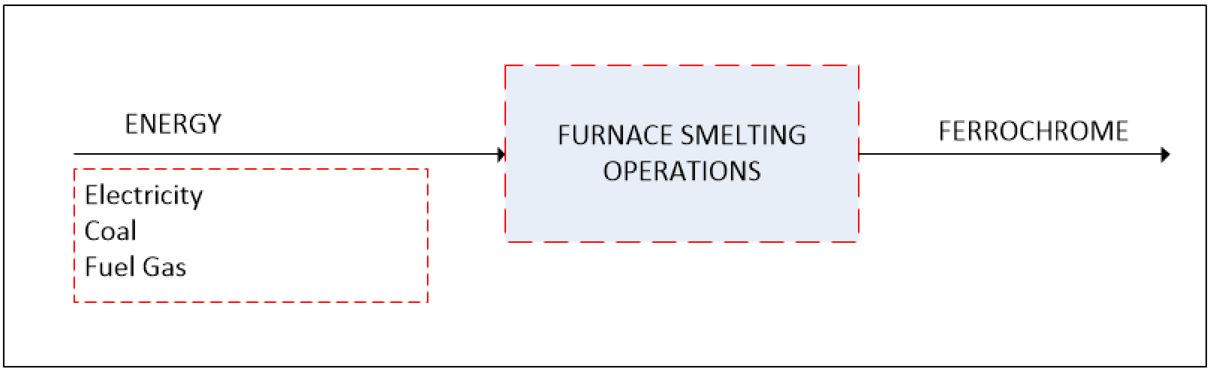


Figure 4-2: Case study 1 – Simplified operational layout

The smelting operation consists of two furnaces which produce ferrochrome. In Figure 4-2 more than one energy source enters the furnace operation boundary. The energy inputs for this operation include electricity, coal and fuel gas. The process output (product) of this operation is the ferrochrome produced by the furnace smelting operations.

4.2.2 APPLICATION OF Q&M FLOWCHART METHODOLOGY

This section details the application of the uncertainty Q&M flowchart to the first case study which entailed the furnace EES quantification process and the results thereof. Additional information in Appendix C.1 is provided where relevant.

Step 1: ESM Isolation

The first step of the Five Step Approach is Energy Saving Measure (ESM) Isolation Step. This step involves the selection of the baseline and performance assessment periods, and measurement boundary. Additionally, the measurement points are identified, managed and classified according to status in this step.

Baseline and performance assessment selection

For this case study, the ESM commenced in 2013. The periods are selected to coincide with the financial year of the entity (from 1 January until 31 December). The selected periods are indicated in Table 4-1 below.

Table 4-1: Case study 1 - Baseline and performance assessment periods

Period	Date
Baseline Period	1 Jan 2014 - 31 Dec 2014
Performance Assessment Period	1 Jan 2015 - 31 Dec 2015

The financial years were selected as baseline and assessment periods, respectively, to align with tax reporting periods as required by the 12L regulations. However, it was determined that these periods also provide a pre-implementation and post-implementation assessment of the ESM. These periods can therefore be used to quantify the effect of the ESM. Next, the data available for the selected time frame is established. Table 4-2 below provides a summary of the available data sources.

Table 4-2: Case study 1 - Data availability table

Variable	Measurement	Measurement device	Data source	Data resolution
Coal	Coal quantities	Weigh bins	Batching tonnages (data stored on database)	Daily tonnages
	Coal analysis	Lab analysis	Lab analysis results (data stored on database)	Daily calorific values
Electricity	Electrical energy	Power metering	Supply invoices	Monthly active energy
			Check metering (data stored on database)	Daily active energy
Fuel Gas	Fuel gas energy quantity	Gas flow metering and heating value analysis	Supply invoices	Monthly gas energy usage
			Check metering (Monthly report)	Monthly gas energy usage
Ferrochrome	Production quantities	Weighbridge	Weighbridge tickets (data stored on database)	Daily tonnages

In Table 4-2 it can be seen that data is available in varying resolutions (monthly, daily) from different data sources. The variables that are measured and available are coal, electricity, fuel gas and ferrochrome. It can be noted that there are also redundant measurements available for the electricity and the fuel gas. As the extent of data availability has been established in this step, the next step is to determine the measurement boundary.

Measurement boundary selection

The measurement boundary is selected as a retrofit isolation, with all-parameter measurement (See Appendix B.2 '*measurement boundary selection*' for definition). This is chosen as the ESM was only carried out on the smelting operations, which represent just a portion of the full operations of the entity. All the parameters are considered pertinent to the operation. Data is available for all the parameters in this selected boundary, hence an all-parameter approach is used to ensure that any possible interactive effects are considered.

As required by Q&M flowchart, a points of measurement (POM) diagram is constructed once the measurement boundary has been established. Figure 4-3 indicates the relevant POMs within the identified measurement boundary.

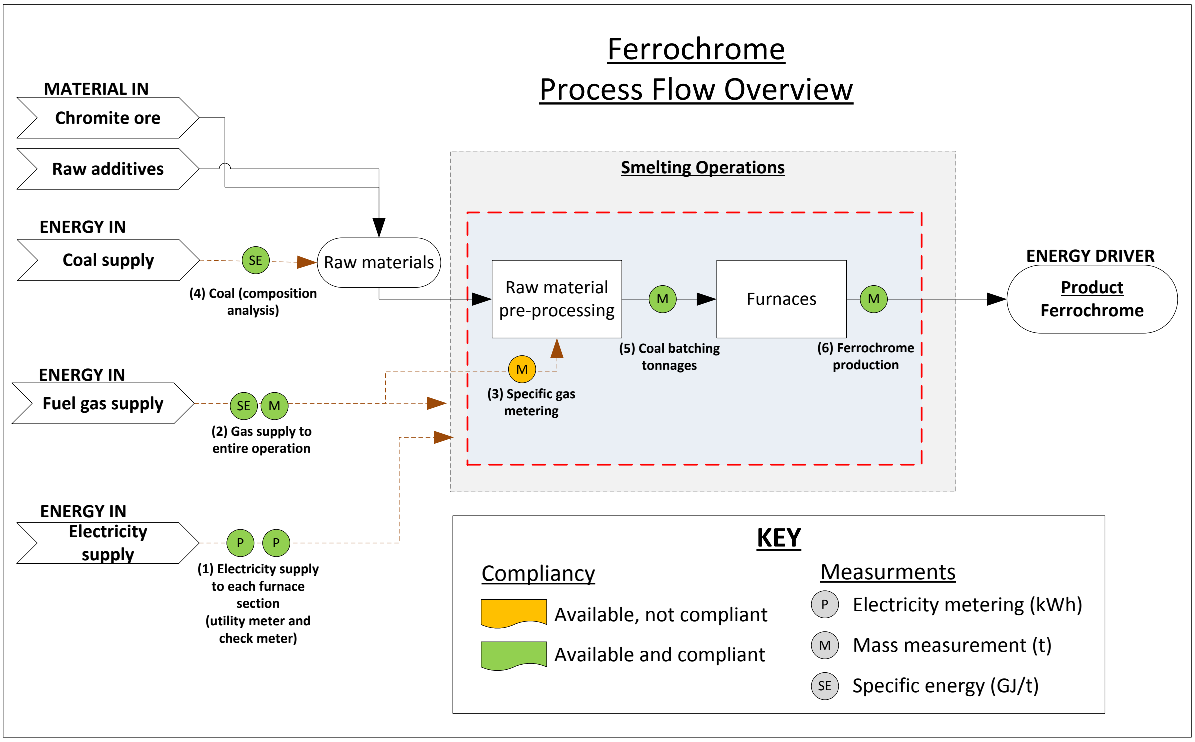


Figure 4-3: Case study 1 - Points of measurement diagram

From Figure 4-3, the red dotted line surrounding the smelting operation indicates the measurement boundary. Measurement points are given by coloured circles. The green circles indicate available and compliant data, and the orange indicates data that is available but not compliant. There are six POMs indicated in Figure 4-3.

Based on the information acquired from the POM diagram an updated data availability table is compiled. Table 4-3 has three columns added to the original data availability table (Table 4-2). These columns provide information on the type of compliance support, and link the measurement number to the POM diagram and the status for the data.

Table 4-3: Case study 1 - Complete data availability table

Variable	Measurement	Measurement device	Compliance	POM No.	Status of data
Coal	Coal quantities	Weigh bins	Calibrated	5	Available, verified and compliant
	Coal analysis	Lab analysis	Certified	4	Available, verified and compliant
Electricity	Electrical energy	Power metering	Invoice	1	Available, verified and compliant
			Calibrated	1	Available, verified and compliant
Fuel Gas	Fuel gas energy quantity	Gas flow metering and heating value analysis	Invoice	2	Available, verified and compliant
			Not compliant	3	Available and not compliant
Ferrochrome	Production quantities	Weighbridge	Calibrated	6	Available, verified and compliant

From Table 4-3 it can be observed that most of the available data is compliant, except POM 3 which represents uncalibrated fuel gas metering. Also, notice that the coal analysis data is compliant, but is different from the other compliant sources in that it is certified. This certification refers to the fact that the coal samples were analysed by a SANAS certified testing laboratory as well as by the suppliers themselves.

Step 2*:* Database Management

Once the ESM has been isolated the Database Management step can be carried out. This part is divided into three key methods which must be applied, namely redundancy checks, dataset interrogation and a universal dataset checklist compilation.

Redundancy checks

Redundant data is available for the electricity and gas consumption data, and a comparison of these data sources was conducted to determine if the different data sources can be reconciled. If the data can be reconciled it provides assurance that data integrity is consistent between different sources. The electricity supply invoices are compared to the site check metering (POM 1) data as can be seen in Figure 4-4.

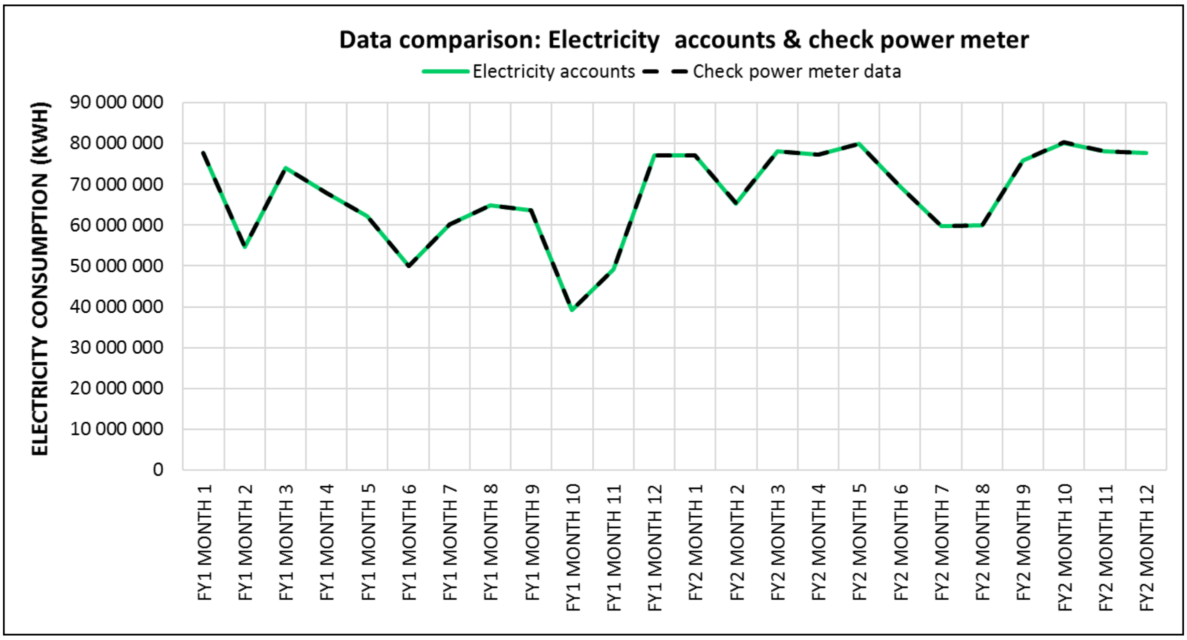


Figure 4-4: Case study 1 - Redundant data comparison: electricity

Little variance is observed between the two datasets in Figure 4-4. The overall difference is calculated to be 0.057%. This produces confidence in the accuracy of the check metering available on site.

The redundant fuel gas data sources are compared i.e. POM 2 and 3 (see Figure C-1 in Appendix C.1), and an overall difference of 16.6% is seen. This difference is significant, and it shows that a data source discrepancy is possible. However, the invoices are the more accurate data source since billing meters need to be maintained according to the custody transfer agreement. In this case, the redundant meters were not calibrated according to manufacturer specifications which made them quantitively unusable.

The next in the *Dataset Management Step* is to interrogate the datasets for abnormalities i.e. for spikes, metering malfunction, data loss and abnormal operation.

Dataset interrogation

The datasets are plotted to identify any irregularities. This was done for all the datasets (coal, electricity, fuel gas and production). An example of this is indicated below, for the dataset interrogation of furnace electricity. See Appendix C.1 for the results of the other datasets.

The results for the dataset interrogation of the electricity data for furnace 1 and 2 can be seen in Figure 4-5 and Figure 4-6. The orange highlighted periods represent periods where planned maintenance occurred. The red highlighted periods indicate where there was a switch in the electricity meters i.e. in this period the meter on furnace 2 collected electricity consumption data for both furnaces. This is evidenced by the fact that the electricity consumption in Figure 4-5 decreased and increased in Figure 4-6 for the highlighted period.

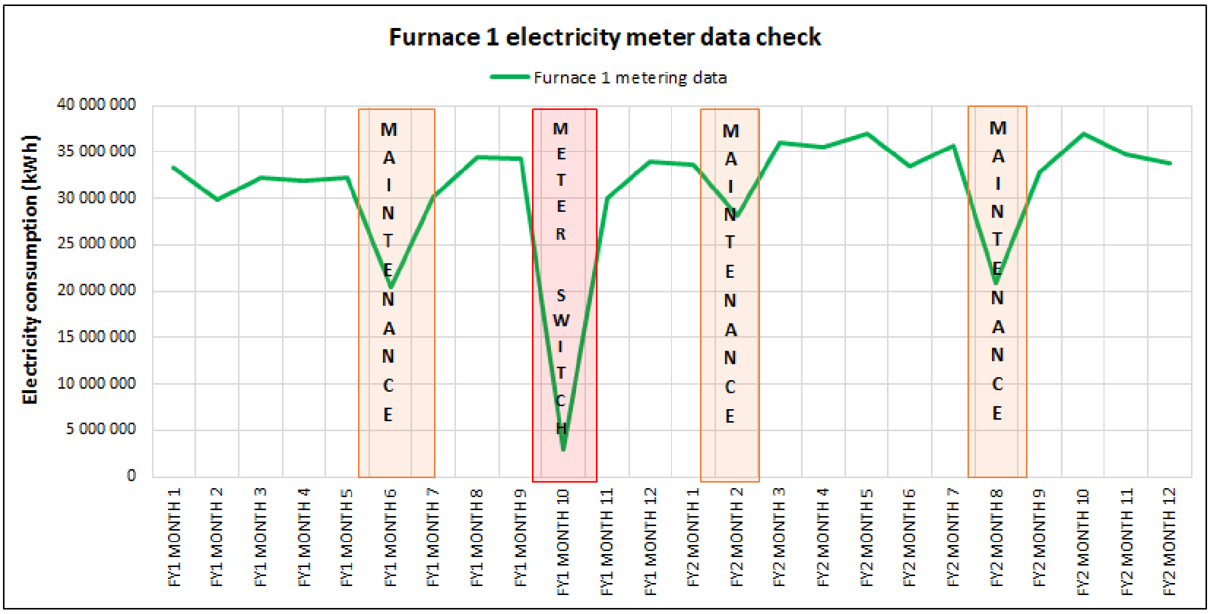


Figure 4-5: Case study 1 - Dataset interrogation of furnace 1 electricity data

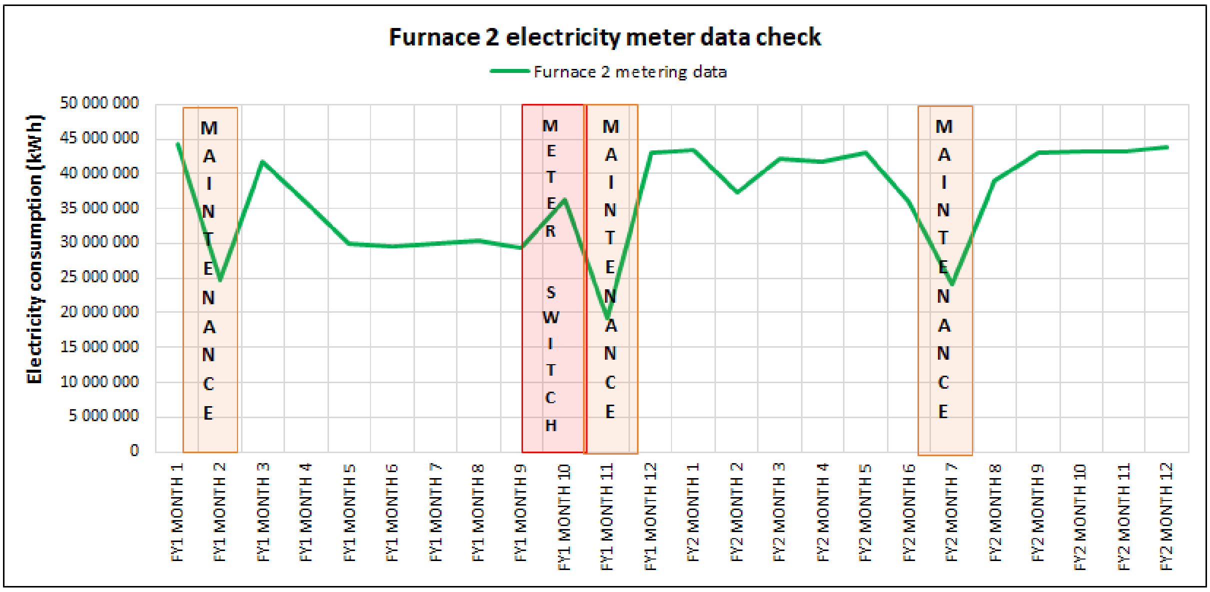


Figure 4-6: Case study 1 - Dataset interrogation of furnace 2 electricity data

The switch in the metering only occurred in this period, after which the metering is done separately for each furnace. This phenomenon does not represent an abnormality in the data, but it should be noted. Observing the above graphs, there are no apparent abnormalities in the data; however, the meter switch is noted.

A summary of the findings for the complete dataset interrogation analysis is provided as a checklist as indicated by Table 4-4.

Table 4-4: Case Study 1 - Dataset interrogation checklist results

Variable	Data source	Spikes	Meter malfunction	Data loss	Abnormal operation	Comment
Coal	Weigh bins	None	None	None	None	-
Electricity	Check metering/Invoices	None	None	None	None	Meter switched
Fuel Gas	Check metering/Invoices	None	None	None	None	-
Production	Calibrated Weighbridge	None	None	None	None	-

In Table 4-4 ‘none’ indicates that the phenomena are not observed. It can be noted that for all the datasets, all the observed irregularities are due to planned maintenance and repairs. Furnace 2 had down time due to maintenance. This maintenance forms part of normal operation.

Next in the database management is the construction of universal dataset checklists for all four of the variables (coal, electricity, gas and production).

Universal dataset checklist

An example of a completed universal checklist can be seen in Table 4-5. The remaining checklists for this case study can be found in Appendix C.1. The checklist provided in Table 4-5 is for metered coal quantities using a weigh bin.

Table 4-5 starts with a description of the reporting period that is being investigated. It then isolates where the data is measured (boundary applicability) i.e. at the furnaces, and the operation it is a part of i.e. smelting operations. The third section gives a breakdown of the data availability that is supplied i.e. daily data, which is available for the full assessment period.

Applicability of the data indicates that the coal is supplied to the furnaces and is part of the production process. Internal management gives more information about the data quality of the coal metering. It highlights the fact that the weigh bins are calibrated, and the data has been stored in a database, with archive records available.

Next the universal checklist provides information regarding the measurements' traceability, which can be traced to the point of origin. The reference documentation available includes a signed piping and instrumentation diagram and a SCADA layout to support the traceability. Finally, the transparency of the data indicates that the coal data is available on request and with permission.

Table 4-5: Case study 1 - Universal dataset checklist for metered coal quantities

Universal Dataset Checklist				
Details:				
Measurement:	Coal quantities			
Measurement units:	Daily tonnages			
ID/Tag name:	Batching tonnages per furnace			
Instrumentation used:	Weigh bins			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	1	2014
		End	12	2015
Boundary applicability	Full facility		Yes	No
	Section/Department		Furnaces	
	Section/Department		Smelting Operations	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Coal to furnace	
		Environmental	N/A	
		Strategic operations	Production	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Database	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No

	Supporting documents	References	SCADA layout and P&ID	
		Archive records	Signed documents	
		Archive period	> 4 years	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Available	Yes	No

The universal dataset checklist summarises the key parameters for the database in a uniform platform that should be used for reference. It can be seen from the dataset checklist that the data adheres to the requirements and criteria listed. Hence, the checklist provides assurance in that it provides independent confirmations that the data are usable for reporting. Once the Database Management Step has been carried out and the datasets have been compiled, model development can begin.

Step 3: Model Development

The datasets available span the full assessment periods and include independent variable datasets. Hence, the modelling options are not limited to unadjusted energy reduction models. All the variables have at least monthly data available and therefore linear regression models can be constructed. Since it has been shown that it can be useful to incorporate multiple models (refer to Section 2.3), not only regression models are developed but also energy intensity (EI) models.

Three models are developed to quantify the EES. These models were developed using the M&V reports gathered for this case study. An (1) all parameter energy intensity model, a (2) total energy regression and a (3) combined energy intensity model were developed. The details of each model will be discussed in the following paragraphs.

Model 1: All parameter energy intensity

The first model developed is an all parameter energy intensity model. This model uses total yearly energy input and ferrochrome production data to compare the energy intensity (Energy input/Production) for FY2015 to that of FY2014. Table 4-6 provides a summary of the yearly data as well as the calculations that are followed to determine the EES of 126.6 GWh.

Table 4-6: Case study 1 - Model 1 results summary

Model 1 : All parameter energy intensity			
Description	**Row**	**Average totals**	
		FY2014	**FY2015**
Ferrochrome (tonnes): ∑Prod	1	213 196	269 056
Total energy (kWh): ∑E	2	1 570 844 546	1 855 860 275

Energy intensity (kWh/ton): ∑E/∑Prod *(Row 2/Row 1)*	3	7 368	6 898
Adjusted energy (kWh) [to account for increased production] *(Row 3 FY2014 x Row 1 FY2015)*	4	1 982 424 360	1 855 860 275
Annual saving (kWh) *(Row 4: FY2014-FY2015)*	**5**	**126 564 085**	

This model is called the all parameter energy intensity model as the energy value is calculated using all the energy entering the system boundary i.e. coal, electricity and fuel gas. Although this model is not complex, it considers all the energy into and out of the selected measurement boundary, hence it accounts for any interactive effects that could affect the system.

Model 2: Total Energy Regression

The second model developed is a linear regression model as indicated in Figure 4-7. The total energy (y-axis) was plotted against the final production (x-axis). The total energy represents the sum of the coal, electricity and fuel gas energy. The data resolution used is weekly because it provides the best overall statistical significance (i.e. R^2, F-value, CVRMSE) of the available data resolutions (daily, weekly and monthly) tested.

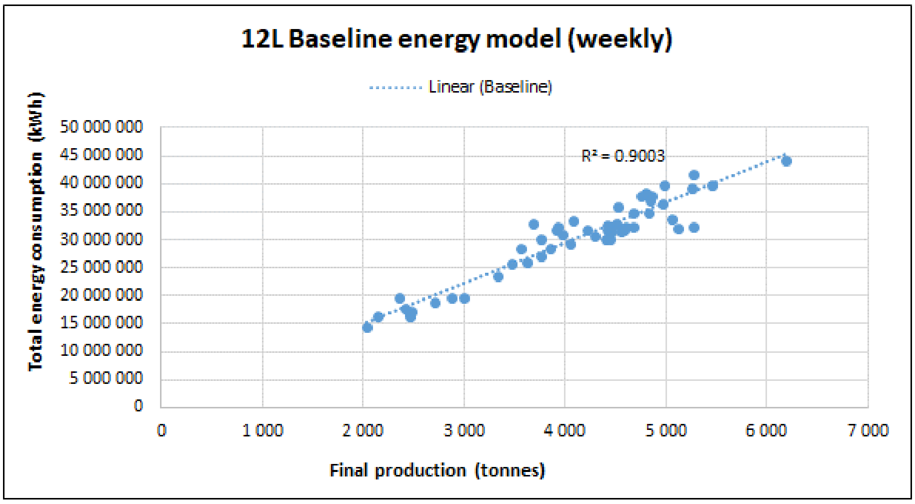


Figure 4-7: Case study 1 - Model 2: Weekly regression model

The linear regression equation of $y = 7\,213x + 634\,562$ represents the relationship and is used to calculate the predicted assessment period energy. The difference between the predicted assessment period energy and the actual assessment period energy gives a saving of 117.9 GWh, as indicated in Table 4-7. It can be noted that a high R^2 value was observed (0.90), i.e. a value close to one.

Table 4-7: Case study 2 - Model 2 results summary

Statistic	Total
Data format	Weekly
Model type	Regression
M	7 213
C	634 562
R^2	90%
F	451
Predicted assessment energy (kWh)a	1 973 778 697
Actual assessment energy (kWh)	1 855 860 275
Actual baseline energy (kWh)	1 570 844 546
Savings from baseline (kWh)	**117 918 422**

Both the first and second model are similar in that they both incorporate all the energy inputs and the production (all parameter analyses). This is an important consideration, as it reduces the need to consider interactive effects as all relevant measurements are included in the modelling technique.

Model 3: Combined Energy Intensity

The final model developed is an energy intensity model. However, unlike the first model, which uses a total energy intensity value, this model calculates the individual energy intensity values for each energy carrier and summates them for a final combined saving value. The individual EI models can be seen in Table 4-8, Table 4-9 and Table 4-10 below.

Table 4-8: Case study 1 - Model 3: Fuel gas energy intensity

Fuel gas Energy Intensity			
Description	**Row**	**Average totals**	
		FY2014	**FY2015**
Production (tonnes): ∑Prod	1	213 196	269 056
Fuel gas energy (kWh): ∑E	2	455 364	533 959
Energy intensity (kWh/ton): ∑E/∑Prod *(Row 2/Row 1)*	3	2	2
Adjusted energy (kWh) [to account for increased production] *(Row 3 FY2014 x Row 1 FY2015)*	4	574 675	533 959
Annual saving (kWh) *(Row 4: FY2014-FY2015)*	**5**	**40 716**	

Table 4-9: Case study 1 - Model 3: Coal energy intensity

Coal Energy Intensity			
Description	**Row**	**Average totals**	
		FY2014	**FY2015**
Production (tonnes): ∑Prod	1	213 196	269 056
Coal energy (kWh): ∑E	2	806 668 355	948 917 023

Energy intensity (kWh/ton): ∑E/∑Prod *(Row 2/Row 1)*	3	3 784	3 527
Adjusted energy (kWh) [to account for increased production] *(Row 3 FY2014 x Row 1 FY2015)*	4	1 018 024 987	948 917 023
Annual saving (kWh) ***(Row 4: FY2014-FY2015)***	**5**	**69 107 964**	

Table 4-10: Case study 1 - Model 3: Electricity energy intensity

Electricity Energy Intensity			
Description	**Row**	**Average totals**	
		FY2014	**FY2015**
Production (tonnes): ∑Prod	1	213 196	269 056
Electrical energy (kWh): ∑E	2	740 497 245	879 177 372
Energy intensity (kWh/ton): ∑E/∑Prod *(Row 2/Row 1)*	3	3 473	3 268
Adjusted energy (kWh) [to account for increased production] *(Row 3 FY2014 x Row 1 FY2015)*	4	934 516 265	879 177 372
Annual saving (kWh) *(Row 4: FY2014-FY2015)*	**5**	**55 338 893**	

Using the three-individual energy intensity models a combined saving of 124.5 GWh is calculated as seen in Table 4-11.

Table 4-11: Case study 1 - Model 3: Combined energy intensity

Model 3: Combined Energy Intensity	
Fuel gas EI Annual saving (kWh)	40 716
Coal EI Annual saving (kWh)	69 107 964
Electricity EI Annual saving (kWh)	55 338 893
Combined EI Annual saving (kWh) *(∑ Row 1 – 3)*	**124 487 573**

This method of calculating the EES is different from the first in that one can observe the individual contribution of each of the energy inputs (carriers) to the energy saving. From Table 4-11 it can be observed that coal contributes the most to the EES while the fuel gas contributes the least. A summary of the three developed models is visually presented in the bar gragh in Figure 4-8.

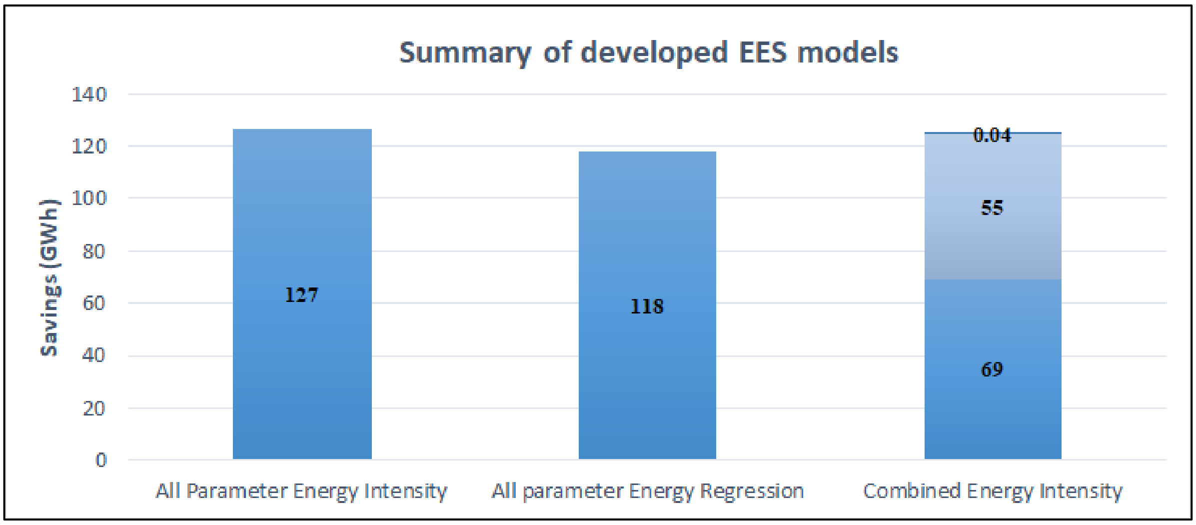


Figure 4-8: Case study 1 – Model development: Summary of models

From Figure 4-8, it is observed that all the models indicate savings within a similar range (±10% variance) despite the different approaches used for three models. This indicates that the observed EES is not strongly influenced by the calculation method. The *All Parameter EI* model (Model 1) indicates the largest EES (127 GWh) and the *All Parameter Regression* model indicates the most conservative value (118 GWh).

Now that multiple models have been developed, they need to be validated and have an associated uncertainty value. Hence, Step 4 of the uncertainty Q&M flowsheet is carried out.

Step 4: Uncertainty Assessment

As discussed in Chapter 3, the Uncertainty Assessment step includes the determination of the significance of the saving, measurement uncertainty, savings uncertainty level and combined uncertainty. Once these uncertainties are determined then model validation and model prediction validation tests need to be conducted.

Significance of saving

The significance of quantified EES values needs to be determined to evaluate the statistical relevance of the savings. The significance of the savings relative to the baseline energy consumption for each model is indicated in Table 4-12.

Table 4-12: Case study 1 - Summary of savings significance values

Model Options	MODEL 1: All Parameter Energy Intensity	MODEL 2: Total Energy Regression	MODEL 3: Combined Energy Intensity
Significance of saving	8.1%	7.5%	7.9%

All the models have a low significance (<10%) relative to the baseline energy consumption of the entity. However, the savings values are large (more than 100 gigawatt hours), so all the statistical tests need to be carried out.

Model validation tests

Model validation tests prove that the assumptions of the model have been verified. Model validation tests need multiple data points. Hence Models 1 and 3 cannot be validated in this way as they use limited data points. Only Model 2 can therefore be assessed using these tests.

The Anderson-Darling test is not done on Model 2 as more than 15 data points are available hence it is not necessary [24]. The results of the R^2, P value and Durbin-Watson (DW) test for Model 2 can be seen in Table 4-14. The model has a good R^2 value, passed p-value test which means the model is meaningful. However, it fails the DW test.

Failing the DW test indicates that there is correlation in the observed errors, and this should not be the case. The errors in a regression model should not follow a pattern [65]. Failing the DW is an indication that the model did not meet one of the assumptions of the model; this reduces the credibility of the model. However, remembering that this is a hindsight investigation on existing M&V report models, this failure highlights the need for a proactive approach to uncertainty quantification and management.

Model prediction validation tests

Model prediction validation tests confirm whether the model is a good predictor of the baseline. Once again, Models 1 and 3 cannot be validated with these tests since they have limited data points. Model 2, however, is tested and it passes all the tests as indicated in Table 4-14. This indicates that Model 2 is a good predictor of the baseline conditions.

Statistical uncertainty calculations

Three statistical uncertainty calculations are carried out, namely measurement, savings and combined uncertainty. The calculations and results of these tests are discussed in the following paragraphs (note that equations from Chapter 2 and Appendix B are used and referenced where applicable).

Measurement uncertainty

The measurement equipment uncertainty is calculated using the relative uncertainty of the measurement equipment as indicated:

$$RE,_{INSTRUMENT} = \frac{\sqrt{\sum_{n=1}^{c}(RE,instrument\ x\ r,rating,i)^2}}{\sum_{i=1}^{c}\overline{rt}} \qquad \text{(Equation 2-1)}$$

$$= \frac{\sqrt{(0.5\ x\ 22\ 708\ 408)^2 + (0.5\ x\ 20\ 816\ 684)^2 + (0.5\ x\ 740\ 736)^2 + (0.5\ x\ 6\ 186)^2}}{\frac{(22\ 708\ 408 + 20\ 816\ 684 + 740\ 736 + 6\ 186)}{4}} = 1.4\%$$

Where the equipment tolerance is 0.5% (RE, instrument) and the rating value can only be assumed by the maximum recorded values logged by the measurement equipment. In the equation the parameters are listed in order: coal, fuel gas, electricity and ferrochrome. The measurement equipment uncertainty (calculated as 1.4%) is the same for all the models, as the same measurements are used for all the models.

Savings uncertainty

The savings uncertainty value is calculated for Model 1 and 3 in the same way. As the models only have measurement uncertainty associated with them, the savings uncertainty will be determined by applying the measurement uncertainty to the baseline energy. Hence for Model 1:

$$Measurement\ error\ on\ saving(\text{kWh}) = RE_{instrument}\ x\ Baseline\ Energy\ consumption \quad \text{(Equation B-11)}$$

$$= 1.4\%\ x\ 1\ 570\ 844\ 546\ kWh = 21\ 867\ 239\ kWh$$

When this error is applied to the EES, the uncertainty on the saving is given as follows:

$$Uncertainty\ level\ on\ saving\ (\%) = 21\ 867\ 239\ kWh\ /\ 126\ 564\ 085 = 17.3$$

Similarly, the savings uncertainty for Model 3 is calculated as 17.6%. The savings uncertainty level for Model 1 and 3 are done at an 80% confidence interval. This means that both models pass the common 80/20 uncertainty level test, as their precision values are both under 20%.

Expanded uncertainty test

For Model 2 an alternative method for calculating the uncertainty level is used, known as the expanded uncertainty test. Using Equation B-13 to Equation B-16 in Appendix B.2 this is done at three different confidence intervals, namely 80/20, 90/10 and 68/50 confidence intervals. A sample calculation for how this is done for the 80/20 confidence interval (CI) is presented below. The CI is calculated by:

$$Confidence\ Interval_{upper/lower} = \bar{X} \pm t\frac{\sigma}{\sqrt{n}} \quad \text{(Equation B-13)}$$

$$Confidence\ Interval_{upper} = (30\ 208\ 549) \pm 1.29\frac{7\ 362\ 542}{\sqrt{52}} = 31\ 522\ 767$$

The precision is then calculated using the calculated confidence interval and the mean, as indicated below:

$$Precision = \frac{CI\ UPPER - \bar{X}}{\bar{X}} \quad \text{(Equation B-14)}$$

$$Precision = \frac{31\ 522\ 767 - 30\ 208\ 549}{30\ 208\ 549} = 4.4\%$$

When this precision is applied to the baseline energy consumption, the savings uncertainty is calculated as follows:

$$Uncertainty\ level\ on\ saving\ (\%) = \frac{Precision\ x\ Baseline\ Energy\ consumption(kWh)}{Quantified\ EE\ Saving(kWh)} \quad \text{(Equation B-16)}$$

$$Uncertainty\ level\ on\ saving\ (\%) = \ (4.4\ \%\ x\ 1\ 570\ 844\ 546(kWh))/(117\ 918\ 422\ (kWh))\ =\ 58.0$$

The result above indicates that at an 80% confidence level the savings precision is 58%. This means Model 2 fails the 80/20 CI test (i.e. 58% is larger than 20% limit). The results for the tests at all three confidence intervals can be seen in Appendix C.1 in Table C-8. A summary of the results is provided in Table 4-13.

Table 4-13: Case study 1 - Model 2 Precision test results

80/20 Precision test		90/10 Precision test		68/50 Precision test	
Saving Precision	58%	Saving Precision	74.1%	Saving Precision	45.0%

It can be seen from Table 4-13 that Model 2 fails the uncertainty tests at the 80/20 and 90/10 CI. This could be linked to the high precision values seen (e.g. 4.4%). Ideally a baseline precision value should be low (<1%). Having a high precision coupled with a small significance (<10%) is the reason the model did not pass the expanded uncertainty tests. However, Model 2 did pass the 68/50 ASHRAE test.

<u>Combined uncertainty</u>

Finally, a combined uncertainty calculation is carried out. Models 1 and 3 only have one source of uncertainty (measurement) hence no combination of uncertainties can occur. However, the analysis could be carried out on Model 2. This is because the CVRMSE and instrument error value is available. Using Equation B-18 (Appendix B.2) the combined relative uncertainty value is calculated to be 1.38%. Equation B-21 is then used to obtain the final combined savings uncertainty value of the saving as 18.4% as indicated in Table 4-14.

Summary of uncertainty assessment

The results of the Uncertainty Assessment step can be seen in Table 4-14 below. The results of the model validation, model prediction validation and statistical uncertainty tests are provided in the table.

It can be seen in Table 4-14 that only Model 2 undergoes model validation and model prediction validation tests. In terms of the statistical analysis for uncertainty quantification the relative measurement uncertainty is displayed, as well as the savings uncertainty calculated using measurement uncertainty for Models 1 and 3 and calculated using expanded uncertainty for Model 2 for an 80/20 CI. Finally, the last row of the table indicates the combined uncertainty value for Model 2 which passes the 68/50 CI test.

Table 4-14: Case study 1 - Uncertainty assessment results

Model Options	MODEL 1	MODEL 2	MODEL 3
Model Validation Tests			
Correlation (R2)	-	0.90	-
P-value	-	$1.1\text{x}10^{-26}$	-
Auto-correlation (Durbin-Watson)	-	0.67	-
Normal distribution (Anderson-Darling)	-	N/A	-
Model Prediction Validation Tests			
Model goodness of fit (CV[RMSE])	-	10.8%	-
Statistical significance (SANAS test)	-	PASS	-
Statistical significance (F-test)	-	PASS	-
Over/under prediction (NDB)	-	PASS	-
Statistical Uncertainty Tests			
Measurement equipment uncertainty	1.4%	1.4%	1.4%
Savings Uncertainty (80/20)	17.3%	58.0%	17.6%
Combined uncertainty (68/50)	-	18.4%	-

From Table 4-14 it can be seen that the complexity of the model plays an important role in the uncertainty assessment that is possible. It can be observed that regression type models can undergo more statistical analysis than energy intensity models. This means regression models provide additional assurance of the credibility of the saving as it includes these statistical analyses.

The last step (Step 5) of the Q&M framework is the Model selection. This step is used to select the most suitable model while considering different criteria such as compliance and the associated uncertainty of the EES. This is explained in the following step.

Step 5: Model Selection

This step consists of the overall comparison between the models and the final scoring of the models using the AHP.

Model comparison

The hierarchy generated in Chapter 3 (Figure 3-16) is used in this step. The four criteria used to evaluate the models against each other are: 12L compliance (B1), economic feasibility (B2), model validation (B3) and statistical uncertainty (B4). These criteria are discussed in the subsections that follows. A summary of the discussion is provided in Table 4-15.

<u>12L Compliance (B1)</u>

The 12L compliance (B1) consists of two sub-criteria: compliant datasets (C11) and the conservativeness of the saving (C12). The investigation conducted in Step 2 (Database Management) indicates that all three models use compliant datasets. The models are also ranked (see Table 4-15) according to their conservativeness by using a zero (0) to one (1) scale. In this scale the zero indicates the least conservative model and one the most conservative. Model 2 is observed to be the most conservative, and Model 1 the least conservative.

Economic Feasibility (B2)

The economic feasibility (B2) is determined by using the significance of the saving. Model 1 has the largest economic feasibility, while Model 2 has the lowest. It can be noted that the conservativeness of the saving (C12) and the economic feasibility of the claim (B2) are essential opposite criteria. However, both are important for this analysis and contribute differently (have different priorities) to the selection of the feasible claim model.

Model Validation (B3)

Table 4-15 indicates the results from Step 3 (Uncertainty Assessment) i.e. the model validation and statistical uncertainty evaluation tests. These results are incorporated as criteria B3 and B4 respectively.

Statistical Uncertainty (B4)

The combined uncertainty precision was calculated as 1.38% for Model 2. When applied to the baseline energy consumption the error observed is 18.44%. This combined value represents the final value that incorporates both instrument and modelling error.

Summary

The discussion of the four criteria evaluated for each chosen model is summarised in Table 4-15.

Table 4-15: Case study 1 - Model selection comparison evaluation

Feasible Claim Model (A1)		MODEL 1: All Parameter Energy Intensity	MODEL 2: Total Energy Regression	MODEL 3: Combined Energy Intensity
12L Compliance **(B1)**				
Compliant dataset **(C11)**		Yes	Yes	Yes
Conservativeness of saving **(C12)**	Value (GWh)	126.6	117.9	124.5
	Rank	0.33	1.00	0.66
Economic Feasibility **(B2)**				
Significance of saving **(C21)**		8.1%	7.5%	7.9%
Model Validation **(B3)**				
Correlation (R2) **(C31)**		-	0.90	-
Model goodness of fit (CV[RMSE]) **(C32)**		-	10.8%	-
Auto-correlation (Durbin-Watson) **(C33)**		-	0.67	-
Normal distribution (Anderson-Darling) **(C34)**		-	Not required (n>15)	-
Statistical significance (SANAS test) **(C35)**		-	PASS	-
Statistical significance (F-test) **(C36)**		-	PASS	-
Over/under prediction (NDB) **(C37)**		-	PASS	-
Statistical Uncertainty **(B4)**				
Measurement uncertainty **(C41)**		1.4%	1.4%	1.4%
Savings Uncertainty (80/20) **(C42)**		17.28%	57.95%	17.6%

Combined uncertainty (68/50) **(C43)**	N/A	18.4%	N//A

Model scoring

Scores of between zero (0) and five (5) were assigned for each sub-criterion, C11 – C43, using the comparisons in Table 4-15. See Appendix B.2 for the conventions of how the scores work. A summary of the scores for each sub-criterion is indicated in Table 4-16.

Table 4-16: Case study 1 - Score table for model comparison

Model Selection	12L Compliance (B1)		Economic Feasibility (B2)	Model Validation (B3)							Statistical Uncertainty (B4)		
Criterion	***C11***	***C12***	***C21***	***C31***	***C32***	***C33***	***C34***	***C35***	***C36***	***C37***	***C41***	***C42***	***C43***
MODEL 1	5	3	5	0	0	0	0	0	0	0	5	5	0
MODEL 2	5	5	3	5	5	0	0	0	5	5	5	0	5
MODEL 3	5	4	4	0	0	0	0	0	0	0	5	4	0

Table 4-16 has sub-criteria with zeros. This indicates that no score was available for this test, due to it not being carried out. Using the scores from Table 4-16 along with the priorities determined in Chapter 3 the final scores for each model are determined. An example of how the final score for Model 1 is calculated is provided as follows:

$$Final\ Model\ Score\ = \sum[Cii\ score\ x\ Cii\ weight] \qquad \text{(Equation 3-1)}$$

$$Final\ Model\ Score = [5\ x\ 0.25] + [3\ x\ 0.25] + [5\ x\ 0.19] + [0\ x\ 0.05] + [0\ x\ 0.05] + [0\ x\ 0.01] + [0\ x\ 0.006] + [0\ x\ 0.02] + [0\ x\ 0.002] + [0\ x\ 0.002] + [5\ x\ 0.03] + [5\ x\ 0.07] + [0\ x\ 0.05] = \mathbf{3.832}$$

A summary of the model scores using the AHP method is provided in Table 4-17.

Table 4-17: Case Study 1 - AHP final model scores

Claim Model	MODEL 1: All Parameter Energy Intensity	MODEL 2: Total Energy Regression	MODEL 5: Combined Energy Intensity
Scores	3.38	4.09	3.37

Table 4-17 indicates that the model with the highest score is Model 2 with a value of 4.09. Models 1 and 3 have similar scores, which is expected as the models have similar approaches. The results from the model selection process indicate that Model 2 be used as the feasible claim model, and Models 1 and 3 be used as validation models.

4.2.3 RESULTS OF Q&M FLOWCHART APPROACH

The results of the uncertainty Q&M flowchart for Case study 1 are condensed and discussed in the subsections that follow. Table 4-18 presents a final summary of the uncertainty Q&M flowchart evaluation.

Measurement uncertainty

The measurement tolerance on the measuring equipment is assumed to be 0.5%. The calculated relative uncertainty (U) of measurement equipment is 1.4%. As model uncertainty is the only source of quantifiable uncertainty that contributes to validation model A and B, the uncertainty level is calculated using the relative uncertainty on the measurement equipment. For validation model A, this is an uncertainty level of 17.3%, and on validation model B is it 17.6%.

Database uncertainty

The datasets for all the models could be traced back to a specific meter on site. This therefore indicates the datasets used to construct all three of the models are traceable. Redundancy checks were also done on the full facility electricity data. Dataset interrogation was carried out on all the datasets, and universal dataset checklists completed for each dataset. No abnormalities were found in the datasets which indicates that the data is of high quality.

Modelling uncertainty

The feasible model (Model 2) has a higher score according to the AHP process than the others. This is because it is the only model that could be validated using statistical analysis. This is the reason the model is chosen as the feasible model. The feasible model passed the savings uncertainty test at 68/50 uncertainty level. The validation models' savings uncertainty is only a function of measurement, and both models passed the 80/20 uncertainty level test.

The validation models are included to provide additional assurance, as the feasible model does not pass the uncertainty level test at 80/20 precision. A service delivery consideration is inherent in all the models, as they incorporate production. Finally, a combined uncertainty value could only be assigned to the feasible model, and that value was calculated to be 18.4%.

Assessment decision uncertainty

In terms of assessment decisions, the baseline and assessment period are chosen according to the financial year instead of when the ESM commenced; however, it aligns with pre- and post-ESM periods. This is done because aligning the application with the financial tax year simplifies the 12L application process. The measurement boundary is chosen as an isolated all parameter boundary and the AHP method was applied to rank the models to determine the most suitable model for the specific case study.

Summary

The discussion of case study 1 results is summarised in Table 4-18. The table indicates the models in order of feasible claim model, validation model A and validation model B. The results are indicated in the form of crosses (X) and ticks (✓). Ticks indicate where the model has met that indices' requirements. Crosses represent where it fails to meet those requirements. Dashes represent where the test could not be carried out. Notice that Table 4-18 is divided to indicate how the four sources of uncertainty were evaluated.

Table 4-18: Case study 1 - Results of Q&M flowchart application

INDICES ANALYSED	**Feasible Claim Model**	**Validation Model A**	**Validation Model B**	**COMMENT**
	MODEL 2: Total Energy Regression	MODEL 1: All parameter Regression	MODEL 3: Combined Energy Intensity	
1. Measurement Uncertainty				
Compliant	✓	✓	✓	Calibration certificates available for all data points
Measurement equipment tolerance	✓	✓	✓	0.5% accuracy on meters assumed
Measurement uncertainty calculation	✓	✓	✓	Relative measurement error of 1.4%.
2. Database Uncertainty				
Data traceability	✓	✓	✓	Power meter data, batching data, weighbridge tickets, and plant specific data
Redundancy checks	✓	✓	✓	Invoices versus check metering - 0.057% difference
Dataset interrogation	✓	✓	✓	Universal checklists constructed for datasets
Outlier investigation	✓	✓	✓	No outliers detected.
High quality dataset	✓	✓	✓	High quality data: available, verified and compliant
3. Modelling Uncertainty				
Statistical model validation	X	-	-	Statistical model validation was only possible for the ***feasible*** model; however, it failed one of the tests i.e. the DW test.

INDICES ANALYSED	Feasible Claim Model	Validation Model A	Validation Model B	COMMENT
Savings uncertainty calculation	✓	✓	✓	Available for all models. Feasible model failed (80/20) test. Validation models passed (80/20) test.
Validation models	✓			Validation models are necessary as feasible model does not pass uncertainty test at 80/20 confidence interval [Passes at 68/50 CI]
Service delivery consideration	✓	✓	✓	Production is included in all these models
Combined uncertainty calculation	✓	-	-	Feasible claim model passed combined uncertainty test at 68/50 confidence level and precision
4. Assessment Decision Uncertainty				
BL & PA period selection	✓	✓	✓	Technical Reports, EEI initiated in 2013
IPMVP boundary selection	✓	✓	✓	Feasible claim model selected with retrofit isolation, all-parameter measurement boundary
AHP model selection	✓	✓	✓	Feasible claim model, and validation models chosen using this decision-making tool

Three models were developed in this case study for an EES implemented on a ferrochrome industry. The Q&M flowchart indicates that Model 2 be used as the feasible claim model. The final reported saving should therefore be indicated as: EES = 117.9 ± 21.7 GWh, if the combined uncertainty value of 18.4 % is applied to the EES.

Interactive active effects such as service delivery are considered by all the models as an isolated all-parameter measurement boundary was selected. The quality of data was shown to be good after application of the assurance methods. The datasets are high quality as the data used in all three models are traceable, compliant and do not have abnormalities.

All the models have compliant data; hence, any could be used as the feasible model. However, Model 2 is indicated as the most suitable as it provides the highest score when evaluated using the AHP method. This was mostly due to the inclusion of statistical model validation tests, whereas the other models could not be validated in this way due to too few data points.

For the feasible model the Durbin-Watson model validation test was failed, and savings precision only passed the 68/50 benchmark. This indicates that additional models could have been helpful to investigate whether these uncertainties could have been managed better. By applying the developed Q&M flowchart these uncertainties can be highlighted and shared with stakeholders. However, since this investigation is applied in hindsight on an existing case study, it cannot be corrected in the scope of this study.

4.3 CASE STUDY 2: WASTE HEAT RECOVERY

4.3.1 DESCRIPTION OF CASE STUDY

The second case study investigates the improved energy efficiency of an industrial gas engine and boiler system. This energy efficiency was achieved by using a heat integration project to recover waste heat from flue gas to generate useable steam. Figure 4-9 provides a simple depiction of the layout of the system.

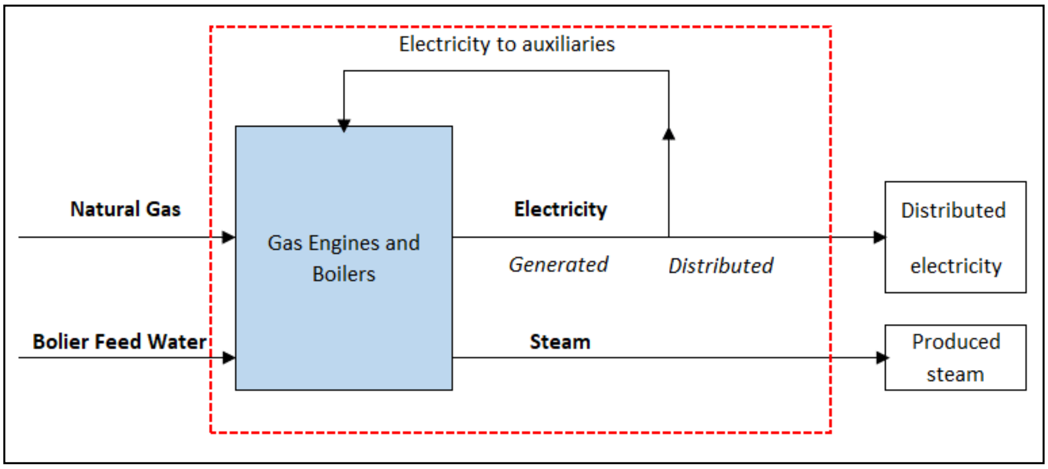


Figure 4-9: Case study 2 – Simplified operational layout

In Figure 4-9 the energy inputs are given as natural gas (NG) and boiler feed water (BFW), with the energy outputs being the steam and electricity generated. Not all the electricity that is generated is supplied to the rest of the operations. A portion of the electricity is recycled back to the auxiliaries of the gas engines and boilers.

The results of the application of the uncertainty Q&M flowchart to this case study can be found in Appendix C.2. Only the end results will be discussed in the section to follow. This is done to improve the readability of this document.

Overview of application of Q&M flowchart

The five-step approach of the uncertainty Q&M flowchart was carried out on case study 2. A brief description is provided of the application of the developed methodology before presenting the results in the next section.

The measurement boundary was constructed as an isolated all parameter boundary around the gas engines and boilers. All the data within the constructed measurement boundary is compliant. However, abnormalities were identified in the datasets during dataset interrogation. These abnormalities were removed as they could be linked to meter malfunctions and logging errors.

Five models were developed using the existing M&V reports. These models included unadjusted energy reduction (model 1 and 2), energy intensity (model 5) and regression type models (model 3 and 4). Model 2 consisted of a multi-year assessment i.e. it made use of two different calculation techniques for two different periods to calculate a final savings values hence the statistics provided in the appendices is for the two different calculation techniques.

Uncertainty assessment is carried out on all five models. Models 1, 2 and 5 have few data points and could not undergo model validation and model prediction validation tests. However, measurement uncertainty values were calculated for these models.

Models 3 and 4 are regression type models and could be validated using statistical tests. Both models failed the Durbin-Watson (DW) test and passed all the other tests. Failing the DW is an indication that the model did not meet one of the assumptions of the model; this reduces the credibility of these models. The models also failed the savings precision tests at 80/20 benchmark. The combined uncertainty value for model 3 and 4 is calculated as 4.4% and 1.9% respectively.

Through the application of the AHP method the model suggested as the most suitable is model 1; the steam energy recovery is calculated using an unadjusted energy reduction model technique. The validation models are model 2 and model 3. The end results of the application of the Q&M flowchart can be seen in the following section.

4.3.2 RESULTS OF Q&M FLOWCHART APPROACH

The results of the application of the Uncertainty Q&M Flowchart Approach for Case study 2 can be seen in Table 4-19. In the table the ticks represent that the requirement or consideration has been met and crosses indicate the opposite. The results in Table 4-19 will be discussed below in the following paragraphs.

Measurement uncertainty

All the constructed models have compliant data as indicated by the ticks in Table 4-19. This means that any of the models are eligible to be feasible models. The measurement tolerance on the measurement equipment is 0.5%; this indicates that the measurements are of high quality as the tolerance is small. Finally, the calculated relative uncertainty is between 0.87% and 1.4%, which is considered small.

Database uncertainty

The datasets for all the models are all traceable. Redundancy checks were done on the NG and electricity generated data POM (2) and POM (3). The redundant datasets agreed well with one another with the highest error still being less than 3% between the different sources.

Dataset interrogation was carried out on all the datasets, and universal dataset checklists were completed for each dataset. Outliers were found in the datasets and were removed in order to have a “clean” dataset (See Appendix C.2). This “clean” dataset was used to develop the models.

Modelling uncertainty

The feasible claim model and validation model A cannot be validated using statistical techniques. Only validation model B underwent model validation statistical tests. It is hence important to include validation model B in the claim, as it includes that additional assurance.

Savings uncertainty values are available for all the models, in varying success in terms of passing the test. A service delivery consideration has been made in all the models by the incorporation of the steam production values. Finally, combined uncertainty values are available for only the validation models since the feasible model only has one quantifiaB source of uncertainty. The use of validation models is an important part of this claim. It provides the assurance by incorporating models that have passed the statistical evaluations.

Assessment decision uncertainty

In terms of assessment decision, the baseline and assessment period are chosen according to the financial year instead of when the ESM was implemented. This is done because aligning the application to the ESM simplifies the application process. The measurement boundary is chosen as an isolated all parameter boundary. Finally, the AHP method is applied to rank the models.

Summary

The discussion of results for Case study 2 is provided in Table 4-19. The results are indicated in the form of crosses (X) and ticks (✓). Ticks indicate where the model has met that index’s requirements. Crosses represent where it fails to meet that requirements.

Table 4-19: Case study 2 - Results of Q&M flowchart application

INDICES ANALYSED	Feasible Claim Model	Validation Model A	Validation Model B	COMMENT
	MODEL 1: Steam energy recovery	MODEL 2: Multi-year assessment	MODEL 3: Different operation modes	
1. Measurement Uncertainty				
Compliant	✓	✓	✓	Calibration certificates available for all data points
Measurement equipment tolerance	✓	✓	✓	0.5% accuracy on meters assumed
Measurement uncertainty calculation	✓	✓	✓	Relative measurement error - 0.87% - 1.4%

INDICES ANALYSED	Feasible Claim Model	Validation Model A	Validation Model B	COMMENT
2. Database Uncertainty				
Data traceability	✓	✓	✓	Power meters, flow meters, Invoices and Log sheets
Redundancy checks	X	X	✓	0.45% difference between official NG invoices versus meters. 2.7% difference between electricity POM (2) and (3)
Dataset interrogation	✓	✓	✓	Universal checklists constructed for datasets
Outlier investigation	✓	✓	✓	Outlier removal for NG, BFW, steam, and electricity datasets
High quality dataset	✓	✓	✓	High quality data: available, verified and compliant
3. Modelling Uncertainty				
Statistical model validation	-	-	X	Passed all of statistical tests except DW test.
Savings uncertainty calculation	✓	✓	✓	Available for all models. Model 1 & 2 passed test, Model 3 failed test.
Validation models	✓			Validation models necessary as feasible model does not include statistical validation
Service delivery consideration	✓	✓	✓	Steam production is included in all these models
Combined uncertainty calculation	X	✓	✓	Passed combined uncertainty test at 68/50 confidence level and precision
4. Assessment Decision Uncertainty				
BL & PA period selection	✓	✓	✓	Monthly Energy Reports
IPMVP boundary selection	✓	✓	✓	Preferred model selected with retrofit isolation, all-parameter measurement boundary
AHP model selection	✓	✓	✓	Preferred model, and validation models chosen using this decision-making tool

The datasets are all compliant. Redundancy checks are carried out on the natural gas and electricity data, with which validation model B is constructed. The feasible model and validation model A did not include data with redundant data sources.

Statistical model validation and model prediction validation test results are only available for validation model B. All the tests were passed except the DW test. As this is a hindsight investigation, this error can be reported to stakeholders but not mitigated. Combined uncertainty values are available for the validation models, and both models pass the 68/50 benchmark. However, no combined uncertainty value is available for the feasible model.

Five models are developed to estimate the EES of a heat recovery project discussed. All the models have compliant data; hence any could be used as the feasible model. However, through the application of the AHP method, Model 1 is ranked as the most feasible claim model. Model 1 did not include any statistical analysis for model validation, hence the use of validation models is critical for that specific assurance. The final reported saving should be quoted as: EES = 56.6 ± 1.17 GWh, if the savings uncertainty value of 2.1% is applied to the EES.

4.4 CASE STUDY 3: COMPRESSED AIR NETWORK ENERGY EFFICIENCY

4.4.1 DESCRIPTION OF CASE STUDY

This case study investigated a compressor EE project. Lower operation of the compressors on a mine due to improvements to the compressor network is the reason energy efficiency was achieved. Improvements included reducing the pressure losses through replacement of piping and adjusting the compressor control philosophy.

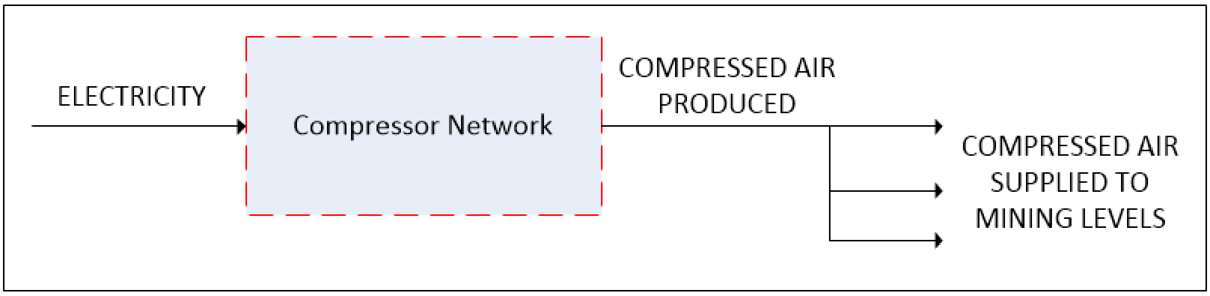


Figure 4-10: Case study 3 – Simplified operational layout

Figure 4-10 indicates electricity to be the energy input for the system, and compressed air to be the energy output. The following section will be used to discuss the results and findings when the Q&M flowchart was applied to the third case study.

The results of the application of the uncertainty Q&M flowchart to this case study can be found in Appendix C.3. Only the end results will be discussed in the section to follow. This is done to improve the readability of this document.

Overview of application of Q&M flowchart

The Five-step approach of the uncertainty Q&M flowchart was carried out on case study 3. A brief description is provided of the application of the developed methodology before presenting the results in the next section.

The measurement boundary is constructed around the compressor air network. It is an isolated all-parameter boundary as with case study 1 and 2. There are five datasets relevant to the measurement boundary selected. These are compressor electricity consumption, compressed air pressure and flow, occupancy and mined ore production. Dataset interrogation revealed abnormalities in the electricity, pressure and airflow datasets. These were due to meter malfunctions and abnormal operation and they were removed from the datasets as outliers were applicable. The electricity data represents the only compliant data source.

Once the datasets were managed, models were generated using the M&V reports. A total of six models were generated. Model 1 is an unadjusted energy reduction model, models 2 – 4 are regression models, and models 5 and 6 are energy intensity models. Model 2 is made up of two models, one for the weekdays and one for Saturdays, hence two sets of statistics are available in the uncertainty assessment.

Only model 2 could be tested for the model validation and prediction validation tests. Although there were three regression models, the correlation coefficient (R^2) on models 3 and 4 were not good, hence carrying out the additional validation tests was deemed undue. Models 1, 5 and 6 could not be tested as they had too few points.

Through the application of the AHP method the model suggested as the most suitable is model 1, using an unadjusted energy reduction model technique. The validation models are model 2 and model 6. The end results of the application of the Q&M flowchart can be seen in the following section.

4.4.2 RESULTS OF Q&M FLOWCHART APPROACH

The results of the application of the Uncertainty Q&M Flowchart Approach for Case study 2 can be seen in Table 4-19. In the table the ticks represent that the requirement or consideration has been met and crosses indicate the opposite. The results of the application of the Uncertainty Q&M Flowchart Approach for Case study 3 can be seen in Table 4-20. In the table the ticks represent that the requirement or consideration has been met and crosses indicate the opposite. The results provided in Table 4-20 will be discussed below.

Measurement uncertainty

Only the first model has compliant data; this means that none of the other models are eligible to be claim models. The measurement tolerance on the measurement equipment is 0.5%; this indicates that the measurements are high quality as the tolerance is small. Finally, the calculated relative equipment uncertainty is between 0.87% and 1.4%.

Database uncertainty

The datasets for all the models are considered traceable since the measured data could be linked back to a specific meter on site. Redundancy checks were done on only the full facility electricity data since this was the only variable with multiple datasets. The data agreed within 1% from one another (Electricity invoices versus the incomer meter and sub-metering data).

Dataset interrogation is carried out on all the datasets and universal dataset checklists are completed for each dataset. Outliers are found in the datasets and are removed. The only high-quality dataset available is for the electricity data.

Modelling uncertainty

The statistical model validation test could not be carried out on the feasible model. However, statistical analysis is possible for validation model A which passed all statistical tests.

A savings uncertainty value is calculated for all the models. Validation model A consists of two models: a weekday model and a Saturday model – the weekday model passed the test, but the Saturday model did not. The Saturday model did not pass the test because the low significance of the saving relative to the baseline Saturday energy consumption demands a very low precision level to pass (< 1%).

Validation models are necessary for assurance, as the feasible model does not include statistical model validation techniques and interactive effects (service delivery) are not considered.

Assessment decisions uncertainty

In terms of assessment decisions, the baseline and assessment period were chosen according to the financial year instead of when the ESM was implemented. This is done because aligning the application to the ESM simplifies the application process. The measurement boundary is chosen as an isolated all parameter boundary. Finally, the AHP method was applied to rank the models.

Summary

The discussion is summarised in Table 4-20. The results are indicated in the form of crosses (X) and ticks (✓). Ticks indicate where the model has met that indices' requirements. Crosses represent where it fails to meet that requirements.

Table 4-20: Case study 3 - Results of Q&M flowchart application

INDICES ANALYSED	Preferred Model	Validation Model A	Validation Model B	COMMENT
	Model 1: unadjusted savings	Model 2: Peak drilling adjusted	Model 6: Occupancy EI	
1. Measurement Uncertainty				
Compliant	✓	X	X	Calibration certificates available for compressor power meters
Measurement equipment tolerance	✓	X	X	0.5% accuracy on compressor power meters
Measurement uncertainty calculation	✓	X	X	Relative measurement error - 1.0%

INDICES ANALYSED	Preferred Model	Validation Model A	Validation Model B	COMMENT
Measurement traceability	✓	✓	✓	Points of measurement diagram
2. Database Uncertainty				
Redundancy checks	✓	✓	✓	<1% difference between official electricity invoices versus sub-meters
Dataset interrogation	✓	✓	✓	Universal checklists constructed for datasets
Outlier investigation	✓	✓	✓	Outlier removal due to data loss for BL & PA periods
High quality dataset	✓	X	X	High quality data: available, verified and compliant
3. Modelling Uncertainty				
Statistical model validation	X	✓	X	Passed all statistical tests
Savings uncertainty calculation	✓	✓	✓	Validation model A: Weekday model passed test, Saturday model failed test (80 CI/20 precision)
Validation models	✓			Validation models necessary as preferred model does not include service delivery consideration or statistical validation
Service delivery consideration	X	✓	✓	Production & occupancy service delivery considered using these two validation models
Combined uncertainty calculation	X	✓	X	Passed combined uncertainty test at 68/50 confidence level and precision
4. Assessment Decision Uncertainty				
BL & PA period selection	✓	✓	✓	Minutes of meetings, and weekly feedback reports available to support selection
IPMVP boundary selection	✓	✓	✓	Retrofit isolation, all-parameter measurement boundary selected
AHP model selection	✓	✓	✓	Preferred model, and validation models chosen using this decision-making tool

Six models are developed. Only the first model has compliant data; this means that none of the other models are eligible to be claim models. Through the application of the AHP method model 1 is ranked as the most feasible claim model. Model 1 did not include statistical analysis for model validation or a service delivery consideration. Hence, the use of validation models is found to be critical in this case study. The final reported saving should be quoted as: EES = 6.00 ± 0.89 GWh, if the savings uncertainty value of 15.0% is applied to the EES.

4.5 VALIDATION OF OUTCOMES

The Standard is used to validate the outcomes of the application of the uncertainty Q&M flowchart. The Standard provides a list of the considerations that should be made when managing uncertainty. The case studies can be checked for the inclusion of these considerations. This validation analysis can be seen in Table 4-21.

Overview of outcomes

In Table 4-21 it can be seen that for the first twelve criteria of the Standard listed, the application of the Q&M flowchart ensures that all these criteria are met for the feasible and validation models. The competency of the M&V practitioner is accounted for in that the models generated were from existing M&V case studies. Discussion on how the last two criteria in the table is met for each case studies is described below.

Case study 1

An estimation of the interactive effects is included in both the feasible and validation models. The feasible model provides model diagnostics and bias statistics; however, it fails to pass all the tests. The Durbin-Watson test is failed. As this is a hindsight approach this failure can be highlighted to stakeholders, but it cannot be managed.

Case study 2

The feasible model does not include considerations for possible interactive effects in the result or model diagnostics and bias. This is due to the fact that the model does not consider all the energy streams entering the measurement boundary. To confirm that all the requirements of the Standard are met, validation models provide the necessary assurance for the criteria not met. The validation model provides considerations for interactive effects and model diagnostic and bias test results. However, it passes all but one of the validation tests. The Durbin-Watson test is failed. As this is a hindsight approach this failure can be highlighted to stakeholders, but it cannot be managed.

Case study 3

The feasible model does not include considerations for possible interactive effects in the result or model diagnostics and bias. To confirm that all the requirements of the Standard are met, validation models provide the necessary assurance for the criteria not met. The validation model provides considerations for interactive effects and model diagnostic and bias test results. It passes all of the validation tests.

Summary

In Table 4-21 the 'FM' refers to the feasible claim model and 'VM' refers to the validation models. The ticks indicate where the case study has included the consideration, and a cross indicates where it has not.

Table 4-21: Validation of uncertainty Q&M flowchart results

SANS 50010	Case Study 1		Case Study 2		Case Study 3	
	FM	VM	FM	VM	FM	VM
M&V Method chosen	✓	✓	✓	✓	✓	✓
Calculation method chosen	✓	✓	✓	✓	✓	✓
M&V boundaries chosen	✓	✓	✓	✓	✓	✓
Significant energy consumption in boundary	✓	✓	✓	✓	✓	✓
Selection of energy governing factors	✓	✓	✓	✓	✓	✓
Frequency of data collection	✓	✓	✓	✓	✓	✓
Data intervals	✓	✓	✓	✓	✓	✓
Measurement methods used	✓	✓	✓	✓	✓	✓
Competency of the M&V practitioner	✓	✓	✓	✓	✓	✓
Sample size/ sample size is representative	✓	✓	✓	✓	✓	✓
Measurement equipment uncertainty	✓	✓	✓	✓	✓	✓
Baseline period energy consumption	✓	✓	✓	✓	✓	✓
An estimation of interactive effects	✓	✓	X	✓	X	✓
Model diagnostics and bias	✓	X	X	✓	X	✓

It can be noted from Table 4-21 that where the feasible claim model did not meet all the requirements of the Standard, validation models provided the additional necessary assurance so that all the criteria of the Standard are met.

Monetary implication of uncertainty assessment

A 2 - 18% uncertainty range is seen in the feasible model's quantified EES. When this uncertainty range is extrapolated country-wide to the R11bn in 12L claims already processed [30], it amounts to a R220m – R1.9bn value. This emphasizes the need for reporting the associated uncertainty with the reported EES. It reaffirms the need for improved uncertainty quantification and management.

The next section provides a discussion of the trends and observations found through the investigation and application of the uncertainty Q&M flowchart on the three industrial case studies.

4.6 DISCUSSION OF RESULTS

In this section discussion of the trends and observations made throughout the investigation and application of the uncertainty Q&M flowchart are summarised.

Complexity of baseline models

The complexity of the baseline model influences the techniques that can be used to quantify and manage uncertainty. The less complex (few data points) the model, the harder to apply statistical techniques for uncertainty quantification. This is because less data points are available, as opposed to more complex models such as linear regression models. Hence, if a less complex model is chosen as the feasible model, more complex validation models are required that have statistical uncertainty assessments included.

Uncertainty levels

Three uncertainty values could possibly be quantified depending on the model, namely measurement, savings and combined uncertainty. Where the model uses few data points (unadjusted energy reduction / energy intensity) the savings uncertainty value is calculated by applying the measurement uncertainty to the baseline energy consumption. However, for the case where more data points are available the savings uncertainty is calculated using the expanded uncertainty value. An uncertainty level must accompany the reported EES value in order to be considered credible.

Measurement uncertainty

Although the SANAS Guideline states that measurement uncertainty is not usually considered as a concern if it is in the dependent variable, the measurement uncertainty is still tested in this study. Where only the measurement uncertainty contributed to the EES uncertainty, it became crucial to quantify the measurement uncertainty. The quantified measurement precision is always small (~ 1%); however, when this is used in Equation B-12 from Appendix B.2 to calculate the error on the reported EES the value impact is significant. The measurement uncertainty level of the quantified EES values in this study ranged from 15% to 26.9%. This indicates that measurement uncertainty is a significant contributor to EES uncertainty.

Expanded uncertainty

Table 4-22 indicates a summary of the expanded uncertainty test results for each of the case studies. It can be observed from the table that none of the uncertainty level requirements (80/20, 90/10 or 68/50) had a 100% pass rate. The 80/20 requirement which is the most popular for M&V [24] had a 66% fail rate, the 90/10 requirement had a 100% fail rate, and the 68/50 requirement had a 33% fail rate. Thus, it can be stated that the 68/50 requirement indicated the most passed expanded uncertainty tests.

Table 4-22: Expanded uncertainty test results for case studies

Indices of evaluation	Case study 1	Case study 2	Case study 3
Model no.	2	3	2
R^2	0.9	0.95	0.71
No. of data points	52	253	141
80/20	FAIL	FAIL	PASS
90/10	FAIL	FAIL	FAIL
68/50	PASS	FAIL	PASS

Where both measurement uncertainty and modelling uncertainty is quantifiable the uncertainties were combined to produce one final value. The use of combined uncertainties is useful as it incorporates the use of various uncertainty contributors, and hence adds to the credibility of the reported EES.

Significance and precision

The failed uncertainty level tests are due to the role the significance of the saving and the precision of the measurement play. Ideally, the significance needs to be big (> 10%) and the precision small (<1%) for the uncertainty levels to be low. This indicates the role of specifying a suitable measurement boundary to ensure that significant results can be observed. For instance, a whole facility approach may be too broad to observe the effect of a single ESM which requires an isolated measurement boundary option.

Validation models

Validation models have been proved to be an important assurance technique. This is seen through the application to the case studies as the validation models covered the pitfalls of the feasibility model i.e. it met the criteria not met by the feasible model (see Table 4-21). This provides assurance that the feasible model is correct.

Compliance

Compliant datasets are crucial for the EES quantification process. This is because the uncertainty can be more easily quantified and managed using these types of datasets. The use of compliant datasets provides assurance that the data is traceable and reliable, and the quantified EES is accurate.

Uniform AHP priorities

The model selection process used the same priority weights for the sub-criteria in every case study. This means that the method for model selection was uniform. This is important for the comparison of the case studies' results.

Hindsight approach

The developed methodology was applied to previous completed M&V case studies. This was done to evaluate the impact the application of the methodology would have on values already reported i.e. to verify that the approach quantifies and manages uncertainty in a manner that provides clarity regarding the pitfalls of previously carried out studies. The implication of this is that errors and pitfalls in the results can only be reported to stakeholders but cannot be managed. This indicates a need for a proactive approach to uncertainty Q&M.

Structured approach

The uncertainty Q&M flowchart uses a structured approach to EES quantification. The yes-no/pass-fail approach of the flowchart is simple to follow and has been used before in the M&V industry. The deliverables of the flowchart include information which is pertinent to a 12L application. Hence the use of this technique provides an easy-to-follow generic procedure that can be utilised by M&V practitioners.

4.7 CONCLUSION

In this chapter the *Uncertainty Quantification and Management (Q&M) Flowchart* developed in chapter 3 was applied to three South African industrial case studies. The Five Step Approach to EES quantification was applied, namely Energy Saving Measure (ESM) Isolation, Database Management, Model Development, Uncertainty Assessment, and Model Selection.

The developed methodology was verified, and the results were presented. The Q&M flowchart allowed a structured approach to identify and evaluate uncertainties. This helps with transparency. It can allow stakeholders to observe the Q&M challenges to help make more informed decisions. An uncertainty value was calculated that could be reported with the EES and the four main sources of uncertainty identified in chapter 2 were all managed and quantified where possible. Finally, a summary of the key observations from the case study results were provided to discuss the trends noted from the different case studies (section 4.6).

Additionally, the methodology was validated. The validation was conducted by comparing the outcomes from the case studies with the requirements of the SANS 50010 standard. It was observed that where the feasible models did not meet all the criteria, the use of validation models ensured that those criteria were met. Final concluding statements regarding the findings of the study as well as recommendations for further development are provided in the next chapter.

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 PREAMBLE

This study was conducted to provide more clarity on how best to navigate the uncertainties encountered in the EES quantification process. The need for the study and the objectives were stated in Chapter 1. A literature study was conducted in Chapter 2. It contains an overview of the 12L regulatory landscape with reference made to supporting resources (SANS 50010 and the SANAS Guideline), a discussion of the measurement and verification uncertainty quantification and management techniques available in industry, and a review of decision-making tools. Chapter 3 provided the developed methodology. This methodology was then verified and validated in Chapter 4 with relevant case studies.

This chapter will conclude this study. It provides a summary of the findings of the study and demonstrates how the study objectives were met. Recommendations for further study are proposed and the document is closed with concluding remarks.

5.2 SUMMARY OF FINDINGS

In the background and relevance of the study a global effort to reduce greenhouse gas (GHG) emissions is noted. South Africa's main strategy to join the global effort is to utilise tax-based incentives (e.g. Section 12L tax incentive) and disincentives (e.g. carbon tax) to motivate industrial GHG emitters to reduce GHG intensities. It is for this purpose that energy efficiency is a key priority for industrial energy users in South Africa.

The accurate quantification of an energy efficiency savings (EES) is critical to assist energy users to utilise the Section 12L tax incentive to fund energy saving measures. In Chapter 1, it was established that a change in the SANS 50010 standard now requires measurement and verification (M&V) bodies not only to manage the uncertainty associated with a reported EES but also to quantify it. This motivates the need for improved uncertainty quantification and management from a regulatory perspective.

It was established that uncertainty evaluation can be burdensome to stakeholders as the statistical techniques used to prove model validity and to quantify uncertainty can be complex, time intensive and require expert knowledge. There can also be confusion on how best to manage and quantify the uncertainties. Hence this study was carried out to investigate how to navigate the uncertainties encountered in the EES quantification process.

Chapter 2 provided information regarding the regulatory structure of the 12L procedure. Important supporting documents which help regulate (SANS 50010) and guide (SANAS Guideline) M&V practitioners in EES quantification were also discussed. The main sources of uncertainty associated with a reported EES were established as measurement, database, modelling and assessment decision uncertainty.

Methods to manage and quantify these uncertainties were presented. It was found that various techniques to quantify and manage these uncertainties were available, and a technique to decide which was the most suitable was needed. Hence, a discussion of decision support tools was provided (refer to section 2.4).

In Chapter 3, the study presented a method which could be used when evaluating the uncertainties associated with a quantified EES. The method made use of various uncertainty quantification and management strategies, as well as decision support tools to navigate the EES calculation process. The use of this method would ensure that the EES quantified have a reported uncertainty value, and due diligence had gone into managing and understanding the uncertainties.

Besides the techniques provided by the SANS 50010 standard and the SANAS Guideline, further research was carried out to ensure the developed strategy incorporates national and international best practices for uncertainty quantification and management. Three different industrial case studies were critically assessed to verify and validate the effectiveness of the proposed methodology.

The results indicated that the *Uncertainty Q&M Flowchart* could be utilised effectively to quantify the EES, while evaluating the four sources of uncertainty identified (measurement, database, modelling and assessment decision uncertainty). The strategy could also provide insight as to which model option would be the most suitable to choose, according to the following criteria: compliance, economic feasibility, model validation and statistical uncertainty.

Meeting the required objectives

To assist industries better understand, manage and quantify the uncertainties associated with calculated EES, the objectives of this study were chosen to:

1. Investigate possible sources of uncertainty associated with the calculation of an EES (refer to section 2.3),
2. Establish the largest contributors to EES uncertainty (refer to section 2.3),
3. Investigate literature for the methods and tools available for the management and quantification of uncertainty (refer to section 2.3),
4. Develop a strategy to manage and quantify uncertainty when calculating an EES (refer to chapter 3),
5. Improve the understanding and interpretation of the results of statistical uncertainty tests (refer to chapter 4),

6. Provide a support tool that assists stakeholders navigate the decisions associated with the calculation of an EES (refer to chapter 3),
7. Report a final EES with an uncertainty value (refer to chapter 4), and
8. Provide a generic solution that can be applied to any industrial EES initiative (refer to chapter 3 and 4).

The following paragraphs will discuss how all the listed objectives were met throughout the study.

Objectives 1 -3

Through an extensive literature review the first three objectives of the study were met. Objective 1 and 2: Four sources of uncertainty were highlighted as key contributors, namely measurement, database, modelling and assessment decision uncertainty. Objective 3: Methods to quantify and manage these identified sources of uncertainty were provided in section 2.3.

Objectives 4 - 8

The uncertainty quantification and management techniques documented in the literature review were used to create a strategy that would meet the latter five objectives.

The criteria for the solution is that it had to be:

- *Generic*: The solution is reproducible for industrial EES initiatives.
- *Simple*: The techniques are non-complex and easy to interpret, so that they can be utilised and interpreted by end users and all stakeholders.
- *Useable*: The solution should aid an end user to navigate the EES quantification process while considering uncertainty.
- *Outcome-based:* The uncertainties associated with the calculation of the EES should be clearly identified, managed and quantified.

Developed solution

The developed solution was an uncertainty Q&M flowchart. Below is a description of how the flowchart met the designated requirements.

Generic

The uncertainty Q&M flowchart was applied to three different EE projects on three different industries. The application of the uncertainty Q&M flowchart shows that the solution could be applied to each case study and deliver consistent results. The flowchart design was therefore found to be generically applicable.

Simple

The Q&M flowchart follows a structured approach that helps guide M&V practitioners in how best to calculate an EES. The decisions made are linked to criteria which makes the flowchart simple to navigate. The methods used to quantify and manage uncertainty represent a structured approach to apply – the specific tools used for model validation and model prediction validation can be found in commonly available software (e.g. MS Excel), and the statistical techniques for uncertainty quantification are in the form of simple equations that can be computed.

Usable

In terms of the usability of the developed methodology it can be noted that although the techniques provided are structured and easy to apply, the use of the methodology can still be time-consuming. It does, however, provide a uniform strategy to approach EES quantification and deliver results that can be easily interpreted by M&V professionals.

Outcome-based

The flowchart incorporates the output of certain deliverables. The deliverables align with the four identified sources of uncertainty. The measurement uncertainty could be managed by the use of deliverables such as point of measurement diagrams and the relative uncertainty calculations (Equation 2.1). For database uncertainty management the deliverables include data redundancy checks and universal dataset checklists.

The modelling uncertainty is managed and quantified using statistical model validation and prediction validation tests which form part of the outcomes. Furthermore, combined uncertainty analyses are carried out where applicable. For assessment decision uncertainty management deliverables were identified to help manage these decisions. An example is the AHP method to rank multiple model options.

The deliverables of the flowchart include information which is pertinent to a 12L application. These deliverables provide the key information necessary to evaluate the credibility of an EES and provide uniform results.

5.3 RECOMMENDATIONS

Further investigation

Recommendations for further studies are provided below. The implementation of these recommendations could improve the results of this study. Five recommendations are listed below.

- Complexity of baseline models,
- Additional case studies,
- Proactive management,
- More complex uncertainty management techniques,
- Wider range of model types developed.

Complexity of baseline models

Where simple models (unadjusted energy reduction/energy intensity) were chosen as the feasible model, more complex models (linear regression models) should be provided for validation. This is to ensure that interactive effects and statistical uncertainty analysis consideration are incorporated. Further study into the use of multiple model options will therefore be useful for uncertainty quantification and management.

Additional case studies

The application of the developed methodology was applied to three case studies to verify and validate the techniques. It would be beneficial to apply the strategy to a larger number of case studies. The use of additional case studies with different complexities may provide more results for evaluation of the Q&M method and more conclusive findings.

Pro-active management

This study used a hindsight approach. In other words, the methodology was applied to case studies that were already completed. It is suggested that the method be applied proactively to case studies as it has been established as a structured methodology that makes use of simple techniques.

More complex uncertainty management techniques

More investigation could go into more complex uncertainty management techniques, and whether they can provide better results or assurance. Sensitivity model analysis and complex outlier removal techniques were not investigated in this study and could be investigated. More consideration towards these two analyses can be further investigated.

Wider range of model types developed

No sample type or calibration models were tested using the uncertainty Q&M flowchart; the inclusion of these types of models could be done in an additional study.

5.4 CONCLUSION

The study introduced a new approach which could be used to quantify and manage the uncertainties associated with a reported EES. This approach provides the M&V practitioner with a strategy to navigate the EES quantification process in a structured manner.

This was done by defining the problem statement and reviewing relevant literature. The knowledge obtained from literature was used to develop a methodology. The developed methodology is called the *Uncertainty Q&M flowchart* and was applied to three industrial SA case studies to test, verify and validate the approach. The outcomes from the methodology were validated against the uncertainty management requirements stated in the SANS 50010 Standard.

The uncertainty Q&M flowchart facilitated a structured approach to identify and evaluate uncertainties. This helps with transparency and can allow stakeholders to observe the Q&M challenges and make more informed decisions. An uncertainty range of 2% - 18% is observed in the quantified EES of the three case studies. When this uncertainty range is extrapolated to the R11bn in 12L claims already processed, this amounts to a R220m – R1.9bn value. This emphasises the need for evaluating and reporting the associated uncertainty with the reported EES.

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APPENDIX A: INITIAL INVESTIGATION INTO SANAS UNCERTAINTY

The SANAS Guideline [24] provides practical methods to quantify uncertainty. Three types of uncertainty tests were carried out in the initial investigation based on the methods found in the Guideline. These tests were:

1. Uncertainty level tests,
2. Model validation tests, and
3. Model prediction validation tests.

The statistical tests with its interpretation and possible outcomes for each of the tests are provided in Table A-1 below.

Table A-1: SANAS Guideline statistical tests

Test Type	Statistical Test	Interpretation	Outcome
1. Uncertainty Level	80/20 Precision	*Uncertainty level test gives two values. The first is the confidence level, and the second is the uncertainty at that confidence level. On the left there are three different test levels that are suggested by different M&V body's*	***Pass**: The uncertainty associated with the energy saving falls within an acceptable range* ***Fail**: The uncertainty associated with the energy saving is too large, and is a cause for concern*
	90/10 Precision		
	68/50 Precision		
2. Model validation tests	Correlation coefficient (R^2 value)	*R squared value indicates whether two variables are linearly related, it is a statistical test to see how close data fit to a fitted regression line. An R squared value of 1 indicates perfect linear correlation of the two variables, or that the data points fit the regression line perfectly.*	***Pass**: The chosen energy governing factor (EGF) is a good indicator for the energy changes in the system/ a direct correlation exists between the EGF and the energy driver.* ***Fail**: The above is not true*
	Regression P-value	*The overall regression significance (regression p value) tests the null hypothesis that the gradient is not different from zero. If the p value is smaller than 0.05 the null hypothesis is*	***Pass**: P<0.05* ***Fail**: The above is not true*

		rejected, and the model is deemed meaningful	
	Anderson-Darling	*Anderson-Darling test is used to test whether the data follows a normal distribution*	***Pass****: The data follows a normal distribution; hence statistical tests are more easily applied.* ***Fail****: The data does not follow a normal distribution*
	Durbin-Watson	*Durbin-Watson is used to test whether auto-correlation of the data is occurring (if sample smaller than 15 – not necessary)*	***Pass****: Autocorrelation does not occur* ***Fail****: Autocorrelation of the data occurs (values of the variables are based on a related object, violation of the assumption of instance independence)*
	Collinearity (VIF/CN)	*VIF/Condition number tests are used to check if collinearity is occurring when multiple variables are used in regression analysis*	*Not evaluated as multiple variable regression analysis is not commonly used.*
3. Model prediction validation tests	Significance/ ANOVA F-test	*This test is used to test whether the regression is a satisfactory predictor*	***Pass****: The model is a good predictor of what happens in the PA period* ***Fail****: The model is not a good predictor of the PA period*
	Net determination bias (NDB)	*Over/under prediction of savings*	***Pass****: The model accurately predicts the savings* ***Fail****: The model is either under or over predicting the energy saving*
	Coefficient of Variation on the Root Mean Square Error (CV[RMSE])	*Model goodness of fit*	***Pass****: The baseline model follows the baseline data well* ***Fail****: The baseline model does not follow the baseline data well*

All the statistical tests listed in Table A-1 were tested in the initial investigation, except the test for collinearity. The collinearity test is not carried out as the models generated were single variate not multivariate, hence the test is not necessary. The results of the application of the statistical tests on three case study models can be seen in Table A-2.

The model tested in case study 1 corresponds with Model 2 in section 4.2. The model tested in case study 2 corresponds with model 4 in section 4.3 and the model tested for case study 3 corresponds with model 2 in section 4.4.

Table A-2: Preliminary investigation results for SANAS statistics application

	Test	Method	Requirement*	Case Study 1			Case Study 2			Case Study 3		
				Case Study 1 *(Weekly)*			Case Study 2 *(Daily)*			Case Study 3 *(Weekday)*		
				Result	Baseline Retro-fit	Saving	Result	Baseline Retro-fit	Numerical	Result	Baseline Retro-fit	Saving
1	Uncertainty levels	80/20 CI/precision test	20%	FAIL	4.4%	58.1%	FAIL	1.5%	23.6%	PASS	1.2%	12.8%
		90/10 CI/precision test	10%	FAIL	5.6%	74.1%	FAIL	1.9%	30.1%	FAIL	1.5%	16.3%
		68/50 CI/precision test	50%	PASS	3.4%	45.0%	PASS	1.2%	18.3%	PASS	0.9%	9.9%
2	Normality of residuals	Anderson-Darling	*see AD limit table in SANAS Guideline*									
	Auto-correlation	Durbin-Watson	1<d<4	FAIL	0.7		FAIL	0.34		PASS	1.45	
	Collinearity	Variance inflation factor	Minintab									
		Condition number	Python									
	Correlation	R squared value	>0.7	0.90			0.88			0.71		
	Regression significance	P value	<0.05	1.10E-26			8.10E-162			1.90E-39		
3	Useful Regression (satisfactory predictor)	F-test (ANOVA)	Fobs>4 x Fcrit	PASS			PASS			PASS		
		$\left(\frac{Max\ \hat{Y}_i - Min\hat{Y}_i}{\sqrt{p\times\frac{s^2}{n}}}\right) \geq 4$	>4	PASS	65.1		PASS	214		PASS	103.6	
	Over/under prediction of savings	Net Determination Bias (NBD)	NDB<=0.005%	PASS	0.0%		PASS	0.00%		PASS	0.00%	
	Model goodness of fit	Coefficient of Variatioin on the Root Mean Square Error [CV(RMSE)]	25%	PASS	7.77%		PASS	10.5%		PASS	5.92%	

Case study 1 – Initial investigation results

The expanded uncertainty tests were tested for three confidence limits (80/20, 90/10 and 68/50). Only one of the tests were passed, this being the 68/50 confidence interval test. For the model validation tests, only the Durbin-Watson (DW), R^2 and p value test is necessary. The DW test is failed which indicates an issue with the errors in the model. The R^2 and p value test is passed, with the value observed being good (0.90) i.e. close to 1. All the model prediction validation tests were carried out and all the tests were passed, indicating that the model is a good predictor of baseline conditions.

Case study 2 – Initial investigation results

The expanded uncertainty tests were tested for three confidence limits (80/20, 90/10 and 68/50). Only one of the tests were passed, this being the 68/50 confidence interval test. For the model validation tests, only the Durbin-Watson (DW), R^2 and p value test is necessary. The DW test is failed which indicates an issue with the errors in the model. The DW test is failed which indicates an issue with the errors in the model. The R^2 and p value test is passed with the value observed being good (0.88) i.e. close to 1. All the model prediction validation tests were carried out and all the tests were passed, indicating that the model is a good predictor of baseline conditions.

Case study 3 – Initial investigation results

The expanded uncertainty tests were tested for three confidence limits (80/20, 90/10 and 68/50). Two of the tests were passed, this being the 80/20 and 68/50 confidence interval tests. For the model validation tests, only the Durbin-Watson (DW), R^2 and p value test is necessary. The DW test is failed which indicates an issue with the errors in the model. The DW test is passed and the R^2 and p value test is passed with the value observed being good (0.71) i.e. close to 1. All the model prediction validation tests were carried out and all the tests were passed, indicating that the model is a good predictor of baseline conditions.

APPENDIX B: SUPPORTING RESOURCES AND UNCERTAINTY Q&M TECHNIQUES

APPENDIX B.1 : 12L REGULATIONS AND SUPPORTING RESOURCES

12L REGULATIONS

The Regulations in Section 12L of the Income Tax Act (1962) as published on 9 December 2013 [14] is presented in this Appendix. Furthermore, the Regulations include the amendments as published on 6 March 2015 which came into operation on 1 April 2015 [35].

SCHEDULE

PREAMBLE

SINCE it has become necessary to promote the efficient utilisation of energy to safeguard the continued supply of energy and to combat the adverse effects of greenhouse gas emissions related to fossil fuel based energy use on climate change;

AND SINCE energy efficiency saving may be considered as a potentially successful method to guarantee the efficient utilisation of energy;

AND SINCE the intended purpose of a carbon tax is to mitigate greenhouse gas emissions and also to utilise (recycle) some of the revenue to be generated from such a tax to finance incentives to advance the further efficient utilisation of energy;

THEREFORE a tax incentive as contained in section 12L of the Income Tax Act, 1962, and these Regulations is devised to encourage the efficient utilisation of energy.

BE IT THEREFORE ENACTED by Regulation as follows:—

Definitions

1. In these Regulations, any word or expression to which a meaning has been assigned in the National Energy Act, or the Income Tax Act bears the meaning so assigned, and—

"accreditation number" means an accreditation number contained in a certificate of accreditation issued by the South African National Accreditation System under section 22(2)*(b)* of the Accreditation for Conformity Assessment, Calibration and Good Laboratory Practice Act, 2006 (Act No. 19 of 2006), to a measurement and verification body for the inspection, measurement, reporting and verification of energy efficiency savings;

"allowance" means the amount allowed to be deducted in respect of energy efficiency savings as contemplated in section 12L of the Income Tax Act;

"baseline" means baseline as defined in the standard;

"captive power plant" means where generation of energy takes place for the purposes of the use of that energy solely by the person generating that energy;

"certificate" means an energy efficiency savings certificate contemplated in section 12L(3) of the Income Tax Act that is issued by SANEDI, comprising the content set out in regulation 4;

"certificate number" means a unique traceable number allocated to a certificate by SANEDI;

"energy efficiency" means energy efficiency as defined in the standard;

"energy efficiency savings" means the difference between the actual amount of energy used in the carrying out of any activity or trade, in a specific period and the amount of energy that would have been used in the carrying out of the same activity or trade during the same period under the same conditions if the energy savings measure was not implemented;

"Income Tax Act" means the Income Tax Act, 1962 (Act No. 58 of 1962);

"measurement and verification" means measurement and verification as defined in the standard;

"measurement and verification body" means a body that is accredited by the South African National Accreditation System in terms of section 22 of the Accreditation for Conformity Assessment, Calibration and Good Laboratory Practice Act, 2006 (Act No. 19 of 2006), for the purposes of inspection, measurement, reporting and verification of energy efficiency savings;

"measurement and verification professional" means a natural person who performs measurement and verification of energy efficiency savings under the auspices of a measurement and verification body;

"National Energy Act" means the National Energy Act, 2008 (Act No. 34 of 2008);

"report" means a measurement and verification report that—

(a) contains a computation of energy efficiency savings in respect of a person for a year of assessment; and

(b) is compiled by a measurement and verification professional in accordance with the criteria and methodology contained in the standard;

"reporting period energy use" means reporting period energy use as defined in the standard;

"SANEDI" means the South African National Energy Development Institute established in terms of section 7 of the National Energy Act; and

"standard" means the South African National Standard 50010 (SANS 50010, Measurement and Verification of Energy Savings), issued by the South African Bureau of Standards in terms of the Standards Act, 2008 (Act No. 8 of 2008).

Procedure for claiming allowance

2. A person that claims the allowance must, in respect of each year of assessment for which the allowance is claimed—

(a) register with SANEDI in the form and manner and at the place that SANEDI may determine;

(b) appoint a measurement and verification professional to compile a report containing a computation of the energy efficiency savings in respect of that person for that year of assessment;

(c) submit the report to SANEDI; and

(d) obtain a certificate from SANEDI.

Responsibilities of SANEDI

3. (1) SANEDI must appoint suitably qualified persons to consider reports submitted by a person claiming the allowance.

(2) If after consideration of a report SANEDI is satisfied that the information contained in a report—

(a) complies with the standard;

(b) is an accurate reflection of the energy efficiency savings of the person claiming the allowance in respect of the year of assessment for which the allowance is claimed; and

(c) complies with these Regulations,

SANEDI must issue a certificate containing the information set out in regulation 4 to the person claiming the allowance.

(3) SANEDI may investigate or cause to be investigated any energy efficiency savings of a person contained in a report to be satisfied that the information contained in the report is an accurate reflection of the energy efficiency savings of the person submitting the report.

(4) SANEDI must—

(a) keep and maintain all reports submitted for consideration;

(b) create and maintain a database of all certificates issued by SANEDI in accordance with these Regulations; and

(c) at all times provide the Minister of Finance and the Commissioner for the South African Revenue Service with ready access to—

  (i) the reports contemplated in paragraph *(a)*; and

  (ii) the database contemplated in paragraph *(b)*.

Content of certificate

4. The certificate issued by SANEDI as contemplated in regulation 3(2) must contain—

(a) the baseline at the beginning of the year of assessment for which the allowance is claimed, derived and adjusted in accordance with regulation 5 and determined in accordance with the standard;

(b) the reporting period energy use at the end of the year of assessment for which the allowance is claimed, determined in accordance with the standard;

(c) (i) the annual energy efficiency savings expressed in kilowatt hours or the equivalent of kilowatt hours for the year of assessment for which the allowance is claimed, determined in accordance with the standard; and

(ii) in case of a captive power plant, the difference between the kilowatt hours equivalent of energy input and the kilowatt hours equivalent of energy output during the year of assessment in accordance with the standard;

(d) the initials and surname of the measurement and verification professional who compiled the report;

(e) the name and accreditation number of the measurement and verification body under whose auspices the measurement and verification professional compiled the report;

(f) the name and tax registration number of the person to whom the certificate is issued;

(g) the date on which the certificate is issued; and

(h) the certificate number.

Baseline calculation

5. (1) For the purpose of this regulation **"greenfield project"** means a project that represents a wholly new project which does not utilise any assets other than wholly new and unused assets.

(2) The baseline—

(a) for the first year of assessment for which the allowance is claimed must—

(i) in the case of a greenfield project, be constructed from comparable data in the relevant sector; or

(ii) in any other case, be derived from data gathered during the year of assessment preceding the first year of assessment for which the allowance is claimed; and

(b) must be adjusted for every year of assessment for which the allowance is claimed—

(i) in accordance with the methodology in the standard; and

(ii) by taking into account the reporting period energy use at the end of the immediately preceding year of assessment for which the allowance was claimed to compute the baseline for the beginning of the subsequent year of assessment for which the allowance is claimed.

Limitation of allowance

6. (1) For the purpose of this regulation—

"co-generation" means combined heat and power;;

"combined heat and power" means the production of electricity and useful heat from a fuel or energy source which is a co-product, by-product, waste product or residual product of an underlying industrial process;

"energy from waste" means waste or under-utilised energy in the form of process furnace off-gas from an industrial process;

"renewable sources" means—

(a) biomass;

(b) geothermal;

(c) hydro;

(d) ocean currents;

(e) solar;

(f) tidal waves; or

(g) wind;

"waste heat" means heat that is—

(a) produced directly by an industrial process or machines or equipment utilised in that industrial process; and

(b) regarded as a waste by-product that is not utilised for any useful application; and

"waste heat recovery" means utilising waste heat or underutilised energy generated during an industrial process.

(2) A person may not receive the allowance in respect of energy generated from renewable sources or co-generation other than energy generated from waste heat recovery.

(3) A person generating energy through a captive power plant may not receive the allowance unless the kilowatt hours or the equivalent kilowatt hours of energy output of that captive power plant in respect of a year of assessment is more than 35 per cent of the kilowatt hours or the equivalent kilowatt hours of energy input in respect of that year of assessment.

Concurrent benefits

7. For the purposes of section 12L(4) of the Income Tax Act any credit, allowance, grant or other similar benefit granted by—

(a) any sphere of government; or

(b) any public entity that is listed in Schedule 2 or 3 to the Public Finance Management Act, 1999 (Act No. 1 of 1999),

for any energy efficiency savings constitutes a concurrent benefit.

Short title and commencement

8. These regulations are called the Regulations in terms of section 12L of the Income Tax Act, 1962, on the allowance for energy efficiency savings and come into operation on 1 November 2013.

SANS 50010 UNCERTAINTY Q&M REQUIREMENTS

SANS 50010:2017
Edition 2

Management of uncertainty shall include, but are not limited to the following:

a) M&V method chosen;

b) calculation method chosen;

c) M&V boundaries chosen;

d) selection/choice of significant energy consumption within the boundary;

e) selection/choice of energy governing factors;

f) frequency of data collection;

g) data intervals;

h) measurement method(s) used;

i) competency of the M&V practitioner;

j) sample size and whether the sample size is considered representative;

k) measurement equipment uncertainty;

l) possible consequential effects not included in the M&V result;

m) the baseline period energy consumption;

n) the assessment period energy consumption;

o) an estimation of interactive effects; and,

p) model diagnostics and bias.

NOTE 1 Uncertainty from some of these sources can be quantified through common diagnostics such as histograms, standard deviation, coefficient of variation, consideration of maximum and minimum values, t-statistics, R^2 values, p-values, confidence levels, model prediction bounds, or other goodness of fit measures. Where engineering calculations or simulations are used, uncertainty can be described based on the methods employed, using common rules from handbooks or through sensitivity analysis.

NOTE 2 Frequency of backups shall be set to reduce the risk of information loss to an acceptable level.

NOTE 3 There is a trade-off between uncertainty levels and the cost of doing M&V. The cost may be lowered by doing fewer measurements, which would result in lower confidence levels and reported savings, but with savings still being reported conservatively as required.

APPENDIX B.2 : UNCERTAINTY QUANTIFICATION AND MANAGEMENT TECHNIQUES

ASSURANCE TECHNIQUES

Table B-1: Generic assurance mechanisms and the provided assurance techniques [15].

Assurance mechanism	Mechanism description	Provided assurance
Archived records	Storage of records for an extended period for revaluation.	Traceability: Historic results traceable to the original source document. Transparency: Information on process used during previous time periods.
Availability of information	Ease of accessing information used during an evaluation. Ease of recreating the results from available information.	Transparency: Information is available within a predetermined domain and can be used to recreate results.
Certified monitoring	Measurements and monitoring are certified to conform to technical requirements by an external party.	Accuracy and validation of results: Obtained information adheres to a set of technical requirements. Independent assurance: Certification is provided by external party.
Defined reporting structures	Designated platforms available for reporting information to stakeholders.	Transparency: Stakeholders obtain necessary information from an established platform.
Disclosure of methods and processes	Assumptions, methods and process used within to obtain the results are stated.	Transparency: Information used is known to stakeholders. Traceability: Information can be traced to the origin, be it an assumption or process.
Disclosure of uncertainty	Statements of known uncertainties with the potential to change the results.	Addressing uncertainties: Impact of uncertainty is known to stakeholders. Transparency: Uncertainties affecting the results are known for decision making.
Documented procedures	Documents that describe the procedure that is followed for a set activity or process.	Traceability: Outcomes can be traced to the source by evaluating the descriptions. Transparency: The descriptions provide insight into what is included or not.
Expert judgement	Opinion and/or recommendations from an individual or a team with specific technical knowledge or expertise.	Accuracy and validation of results: Assumptions and processes are based on information received from an expert in a specific field.
External evaluation	Evaluations performed on an activity by an entity which is not responsible for the operation thereof.	Accuracy and validation of results: Results are validated through additional evaluations and operational bias is reduced. Independent assurance: Evaluation by an external entity provides confidence in the results and lessens any bias.
Historic-predictive analysis	Using historic analyses to predict and evaluate current assessments.	Accuracy and validation of results: Validation of results through the comparison between expected and actual results.
Independent M&V	Measurement and verification of activities performed by an independent entity.	Independent assurance: Independent confirmation that outcomes are correct and trustworthy.
Management of uncertainty	Processes or structures to mitigate and/or eliminate uncertainties.	Addressing uncertainties: Known uncertainties are addressed and the impact thereof is reduced.
Supporting documentation	A document that presents and confirms given information.	Traceability: Source documentation confirms stated information.
Trend analysis based on key indicators	Using operational key indicators to trend and analyse outcomes.	Accuracy and validation of results: Outcomes are validated against trends of key operational indicators.
Uncertainty quantification	Quantified value of the potential impact that uncertainty may have on the outcome.	Addressing uncertainty: A quantified value that indicates the trustworthiness and potential risks of the results. Accuracy and validation of results: A quantified margin of accuracy of the results.

MEASUREMENT BOUNDARY SELECTION

<u>SANS 50010 Measurement boundary options:</u>

Type 1: Retrofit isolation, key-parameter measurement

The ESM is isolated from the rest of the facility. Only the key EGFs that are pertinent to the activity or the energy consumption (or both) are measured. Other variables that influence the energy usage may be estimated using historical data, engineering judgement, laboratory tests and equipment manufacturing specifications.

Type 2: Retrofit isolation, all-parameter measurement

The ESM is isolated from the rest of the facility. All EGFs pertinent to the activity or the energy consumption (or both) must be measured, and not estimated. This option has a greater level of certainty in the savings calculation than option 1, as all the points are measured [11].

Type 3: Whole facility

The measurement boundary is constructed around the whole facility. The energy performance of the entire facility and all relevant EGFs shall be considered to assess the potential energy savings. Energy invoice billed consumption can be used with this option [11].

Type 4: Calibrated simulations

Missing energy data is simulated using calibrated simulation models. The simulated data may replace the missing data. The accuracy of the simulation models is determined by comparing the simulation model output with the relevant calibrated measured data. This may be done for part or for all of the facility, and the measurement boundary shall be drawn accordingly. This method is not restricted to cases where there are data problems. This method could be used for baseline or assessment period data where the data is unreliable or unavailable.

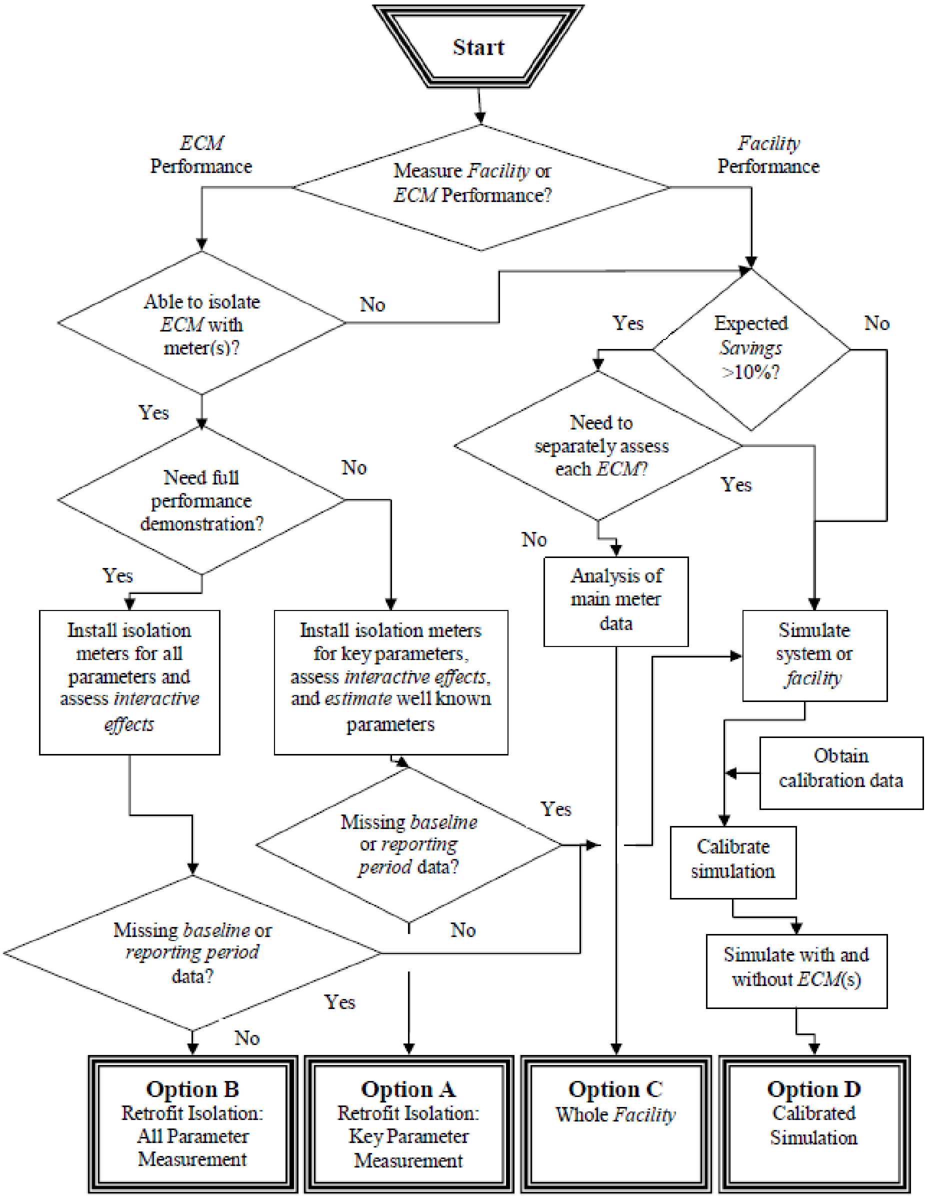

Figure B-1: M&V option decision flow chart. Extracted from IPMVP Vol 1 [60]

ANALYTIC HIERARCHY PROCESS

The pairwise comparisons for the sub-criteria and criteria of the AHP developed in chapter 3 can be seen in Table B-2. An explanation on how the comparisons is done is provided in Table B-3 below. The 'T' value in Table B-2 represents the priority of the criterion in relation to the other criteria.

Table B-2: AHP pairwise comparisons

A	B1	B2	B3	B4	∑	T			
B1	1.00	0.50	5.00	5.00	11.50	0.49			
B2	2.00	1.00	0.50	1.00	4.5	0.19			
B3	0.20	2.00	1.00	1.00	4.20	0.18			
B4	0.20	1.00	1.00	1.00	3.20	0.14			
				Cum.	23.4				
B1	**C11**	**C12**	**∑**	**T**					
C11	1.00	1.00	2.00	0.50					
C12	1.00	1.00	2.00	0.50					
		Cum.	4.00						
B2	**C21**								
C21	1.00								
B3	**C31**	**C32**	**C33**	**C34**	**C35**	**C36**	**C37**	**∑**	**T**
C31	1.00	1.00	4.00	4.00	4.00	4.00	4.00	22.0	0.27
C32	1.00	1.00	4.00	4.00	4.00	4.00	4.00	22.0	0.27
C33	0.25	0.25	1.00	3.00	0.33	0.33	0.50	5.67	0.07
C34	0.25	0.25	0.33	1.00	0.25	0.25	0.25	2.58	0.03
C35	0.25	0.25	3.00	4.00	1.00	1.00	1.00	10.5	0.13
C36	0.25	0.25	3.00	4.00	1.00	1.00	1.00	10.5	0.13
C37	0.25	0.25	2.00	4.00	1.00	1.00	1.00	9.50	0.11
							Cum.	82.8	
B4	**C41**	**C42**	**C43**	**∑**	**T**				
C41	1.00	0.50	0.50	2.00	0.19				
C42	2.00	1.00	2.00	5.00	0.48				
C43	2.00	0.50	1.00	3.50	0.33				
			Cum.	10.50					

The goal of the hierarchy process (A1) is to determine the feasible model. B1-B4 is the criteria on which this will be decided. Sub-criteria (C11 – C43) contributes to the criteria. Table B-3 below provides reasons for why one criterion is favoured over another.

Table B-3: Explanation of pairwise comparison scores

B2>B1	Economic feasibility (B2) is more significant than compliance (B1) as it won't matter if compliant data is available if the saving is too small to warrant a claim.
B2>B4	Economic feasibility is more significant than the statistical uncertainty. Carrying out statistical uncertainty tests where economic feasibility is not established is not useful. Also, bigger savings is linked to lower uncertainty --> (uncertainty = precision x BL energy / EES)
B2>B3	Economic feasibility is more significant than proving model validity. Model validity

	won't matter if saving too small.
B1>B4	Compliance is more significant than statistical uncertainty. Less uncertainty if you use good datasets, as the quantified EES is deemed more accurate, as the measurements are from calibrated equipment/ compliant data sources.
B1>B3	Compliance is more significant than model validation. Non-compliant model can't be used as claim model only as validating model even if the assumptions of the model is validated. Hence, the use of compliant data is imperative.
B3=B4	Validating model is a form of uncertainty management --> reduces uncertainty in the given result, while providing statistical uncertainty results gives a quantitative value to the uncertainty. Both functions are equally important in the process.
C11:C12	Of equal importance.
C31:C32	Of equal importance - both relate to how well the model fits the data.
C31:C33	R^2 (correlation) is more significant than auto correlation.
C31:C34	Anderson darling only necessary for small datasets <15. Not very important test as rarely necessary.
C31:C35	R^2 more significant than statistical significance test.
C31:C36	R^2 more significant than F-test.
C31:C37	R^2 more significant then over/underpredicting --> good fit hopefully negates over/undershooting.
C41:C42	Savings uncertainty more significant than measurement uncertainty as it is considered the more dominant uncertainty source, whereas measurement uncertainty is often considered negligible.
C41:C43	Savings uncertainty more important than combined uncertainty, as combined uncertainty calculation may not be possible for every model, whereas savings uncertainty calculation is.

The score range table used for the allocation of scores for each criterion is indicated by Table B-4.

Table B-4: Score Range for Indexes

Score	Definition
0	No Benefit/ No information available
1	Very Low Benefit
2	Low Benefit
3	Moderate Benefit
4	Moderate Plus
5	Strong Benefit

ASHRAE INSTRUMENT UNCERTAINTIES

Table B-5: ASHRAE Instrument uncertainties for M&V Applications. Extracted from [54]

Quantity	Type	Guideline 14
Temperature	Ambient outdoor portable electronic	2–5%
	Domestic water portable electronic	2%
	Air ducts	5%
	Pipes and ducts	2–5%
Air velocity	Indoor: non-mechanical or blower door	5%
	Handheld anemometer	10%
	Recording anemometer	5%
	Meteorological grade anemometer	2%
	Air ducts: array	2–5%
Pressure	Gauge	0.25–2%
	Ducts	1–5%
	Pressurization/ depressurization	3–5%
Energy	Electrical Energy meter	1%
	Current Transformer	2–3%
	Portable Watt meter	1–5%
	Current: low cost home energy	
	Stick-on Meter	
	Plug-through meter	
	Relative humidity	2–5%
	Energy meter (gas)	1%
Flow rate	Bucket and stopwatch, portable meter/probe	5%
	Domestic, accumulating	1–2%
	HVAC inline or insertion meters	2%
	Ultrasonic, flare	
	Smokestack gas	
Run-time	Permanent	1–5%
	Portable	2–5%
Light	Sensor / logger	
Other	Pyranometer	2–5%
	Door position	2%
	RPM	1%
	CO_2	
	Combustion	2%

DATASET MANAGEMENT

Definition of dataset phenomena:

Step 1: Spikes can indicate equipment malfunction. These malfunctions can include temporary communication loss over short periods. Spikes usually occur over short intervals, but the amplitude of such values may affect the accuracy of the dataset.

Step 2: Identifying meter malfunctions guarantees that the recorded values are of a high quality. Errors such as hanging data (constant value) will cause subsequent values to remain within present boundaries. This errored data and calculations "look right" and propagate through future calculations affecting the results.

Step 3: Data loss within a dataset would change how the system is represented by the data. It is important that there is a distinction between data loss and when the system is not running. Data loss can either be represented by the absence of or flagged values. Previous steps would have removed outliers if it were outside the boundary limits. Excluding the data loss values should be considered carefully and consulted with the stakeholders.

Step 4: The final step in the dataset evaluation identifies abnormal system operations.

UNIVERSAL DATASET CHECKLIST

Table B-6: Universal Dataset Checklist. Adapted from [15]

Data compliance evaluation				
Details:				
Measurement:				
Measurement units:				
ID/Tag name:				
Instrumentation used:				
Criteria of evaluation:				
Reporting Period	Calendar year	July - June	Year	
	Changeable period	Beginning	Month	Year
		End	Month	Year
Boundary applicability	Full facility		Yes	No
	Section/Department		Unit	
	Section/Department		Unit	
Data availability	Resolution	Highest available	Year	
	Available period	Full assessment	Yes	No
		Periodically	Period	
	Historic data	Archive records	Type	
		Archive period	Specify	
Applicability to key performance indicator	Focus area	Production	Specify	
		Energy	Specify	
		Environmental	Specify	
		Strategic operations	Specify	
		Human resources	Specify	
		Other	Specify	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Specify	
		Frequency	Specify	
		Archive records	Type	
		Archive period	Specify	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Specify	
		Archive records	Type	
		Archive period	Specify	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Available	Yes	No

DEVELOPMENT OF DIFFERENT MODEL TYPES

Unadjusted energy reduction

This type of model provides the simplist approach to energy saving quatification. This technique requires calibrated power metering or invoice data for the pre and post – ESM implementation periods. The difference between the unadjusted baseline period energy consumption and that of the performance assessment period is used to calculated the saving. This simple year-on year energy reduction equation as given by [21] is indicated:

$$E_s = E_B - E_{ap}$$

Equation B-1: Unadjusted energy reduction equation

Where: E_s – calculated energy saving; E_B – unadjusted baseline energy consumption; E_{ap} – unadjusted assessment period energy consumption.

The uncertainty associated with this method is limited to annual extrapolation, except for minor meter measurement error. Energy savings can be precisely and accurately calculated using this technique, however, this model is resource intensive.

Energy Intensity

Another simple method for the energy savings determination is energy intensity calculations. The energy intensity is calculated using the energy consumption and a service delivery parameter (e.g. production). See Table B-7 for energy saving determination by intensity calculation.

Table B-7: Intensity calculations of energy savings. Extracted from [18]

Description of value to be calculated	Baseline period (BL)	Performance assessment period (PA)
Total energy consumption *(kWh)*	E_{BL}	E_{PA}
Total production *(e.g. tonnes)*	P_{BL}	P_{PA}
Energy Intensity *(e.g. kWh/tonnes)*	I_{BL}	I_{PA}
Adjusted BL energy consumption *(kWh)*	E_{BL}	-
Annual energy savings *(kWh)*	$E_{SAVINGS}$	

The first step is to calculate the energy intensity values for both the baseline and PA periods. Energy intensity is the ratio of the energy consumption (E_i) over the production (P_i). This can be done using:

$$I_i = \frac{E_i}{P_i}$$

Equation B-2: Energy intensity equation

The next step would be to determine the predicted baseline energy consumption using the performance assessment production and the baseline intensity. See equation:

$$E_{BL(adjusted)} = P_{AP} \times I_{BL}$$

Equation B-3: Predicted baseline energy consumption equation

The energy savings can then be determined using Equation B-4. The difference between the adjusted baseline energy consumption $(E_{BL(adjusted)})$ and the actual performance assessment period energy consumption (E_{PA}) gives the energy saving.

$$E_{savings} = E_{BL(adjusted)} - E_{AP}$$

Equation B-4: Energy saving equation

The selling points of this type of model is that it is simple, and incorporates a service delivery consideration, unlike the unadjusted energy reduction calculation.

Linear regression

Linear regression models are a slightly more complicated than the previous two models. This method is the most prevalent method used for the quantification of energy savings [15], [22], [26], [40], [43]. This method is recommended for more accurate results and where a high-resolution dataset is available [51].

Regression models establish the relationship between the energy carrier (dependent variable) and one or more energy drivers (independent variable e.g. energy governing factors). This type of model is useful for statistical analysis and prediction purposes. The first step for regression model construction is to develop a scatter plot for the data as indicated in Figure B-2.

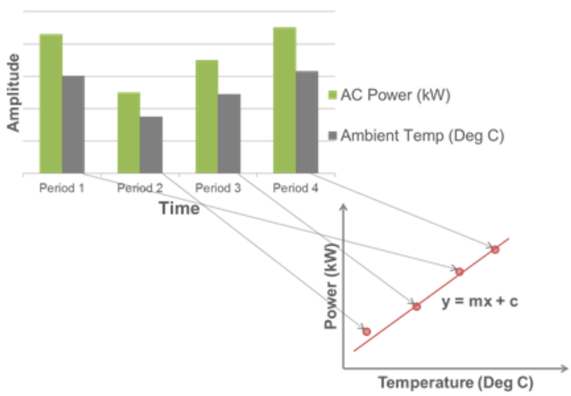

Figure B-2: Regression model development

Figure B-2 indicates how two data sources (power being the dependent variable, and temperature the independent variable) with the same time can be plotted on a scatter graph. A line is subsequently fitted to through the data points to produce a regression equation by means of the least squares method. The equation is given by the general linear form of:

$$y = mx + c$$

Equation B-5: Linear regression equation

In Equation B-5, y denotes the dependent variable, x the independent variable, m the gradient and c the intercept of the line with the y-axis. The regression equation can be used to predict the PA period energy consumption by substituting the actual independent variable values (x values) into the equation. The y calculated will hence represent the predicted energy for the PA period. The energy saving for each data point can then be calculated using the difference between the predicted energy consumption and the actual energy consumption in the assessment period.[18]

Regression models often need to be adjusted to capture non-linear behaviour caused by interactive effects. Multivariate interactions between variables such as ambient conditions, occupancy levels and operating conditions can be of concern. Regression models are also very sensitive to data availability, so it is necessary to adjust uncertainty estimates accordingly.[49]

Calibrated simulation

Calibrated simulations represent a complex model which is used when a full dataset is not available i.e. there is missing data. This missing data can be replaced with simulated data from a calibrated model, for part or all the facility. This method is not limited to situations with data problems, it can also be used where baseline or PA period data is unreliable or unavailable in the case of a Greenfields ESM.[23]

Sample-based

Statistically valid samples can be used as valid measurements of the total parameter[23]. The Guideline provides three different sample size methods, to determined what is a reasonable sample size to characterize the baseline adequately [26]. Generally, one must exercise caution when using sample sizes smaller than 15. If n< 15 there are significant implications that need to be tested for a regression model.

STATISTICAL TESTS

This annex provides information regarding specific statistical tests for uncertainty quantification and model validation.

Coefficient of correlation calculation:

R^2 can be calculated using the equation below [66]:

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

Equation B-6: Correlation coefficient

Where: *SSResid* – the residual sum of squares, and *SSTo* – the total sum of squares.

The ***residual sum of squares*** can be calculated using the equation:

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

Equation B-7: Sum of squared residuals

Where: y_i – the ith y-value. The ***total sum of squares*** can be calculated using the equation [66]:

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

Equation B-8: Total sum of squared residuals

Where $\bar{y}$ denotes ***the mean*** y-value and can be calculated as follows [66]:

$$\bar{y} = \frac{y_1 + y_2 + \cdots + y_n}{n}$$

Equation B-9: Mean value calculation

Root mean squared error calculation:

The RMSE characterizes the error between the predicted and actual values. The RMSE should be below 15% [42]. It can be calculated using the equation[66]:

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

Equation B-10: Root mean squared error

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

<u>Measurement uncertainty calculation:</u>

The relative error of the measurement equipment is given as:

$$RE_{instrument} = \frac{\sqrt{\sum_{n=1}^{c}(RE_{instrument} x\, r_{rating,i})^2}}{\sum_{i=1}^{c}\overline{rt}} \qquad \text{(Equation 2-1)}$$

Where: $RE_{instrument}$ – error of the instrument (tolerance), and r_{rating} – the value relative to which the instrument precision is expressed.

If the precision due to the measurement error is applied to the baseline energy consumption the error on the saving is expressed as:

$$Measurement\ error\ on\ saving(\text{kWh}) = RE_{instrument}\ x\ Baseline\ Energy\ consumption$$

Equation B-11: Measurement uncertainty level on saving (kWh)

The percentage uncertainty on the savings due to measurement uncertainty is hence given as:

$$Measurement\ error\ on\ saving(\%) = \frac{RE_{instrument} x\ Baseline\ Energy\ consumption\ (kWh)}{Quantified\ EE\ Saving(kWh)}$$

Equation B-12: Measurement uncertainty level on saving (%)

<u>Uncertainty level test:</u>

The uncertainty level expressed as and expanded uncertainty value is calculated using precision at a specific confidence interval (CI). Below the equation used to calculate the upper and lower CI is indicated:

$$Confidence\ Interval_{upper/lower} = \overline{X}\ \pm t\frac{\sigma}{\sqrt{n}}\ or\ \overline{X}\ \pm z\frac{\sigma}{\sqrt{n}}$$

Equation B-13: Confidence interval

Where $\overline{X}$ – mean, σ – standard deviation, n – sample size and t/z – from t-table (relates to CI) [68/50 has z= 1]. Depending on confidence interval (80/90/10) chosen the t/z value varies. The equation used to calculate the precision at a chosen confidence interval is indicated below.

$$Precision = \frac{CI\ UPPER - \overline{X}}{\overline{X}}$$

Equation B-14: Precision of measurement

Using the precision, the uncertainty level on the saving is calculated as follows.

$$Uncertainty\ level\ on\ saving\ (kWh) = Precision\ x\ Baseline\ Energy\ consumption$$

Equation B-15: Uncertainty level on saving (kWh)

$$Uncertainty\ level\ on\ saving\ (\%) = \frac{Precision\ x\ Baseline\ Energy\ consumption(kWh)}{Quantified\ EE\ Saving(kWh)}$$

Equation B-16: Uncertainty level on saving (%)

Combined uncertainty:

The equation below is used for cases where baseline energy consumption or demand is constant for all periods. It is unaffected by any known independent variables [36].

$$U = \frac{t}{F}\sqrt{\frac{CVSTD^2}{m} + U_S^2 + RE_{instrument}^2}$$

Equation B-17: Combined uncertainty equation 1

The following equation is used where the baseline energy consumption or demand varies from period to period in response to the known independent variables (common for mining applications) [36].

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

Equation B-18: Combined uncertainty equation 2

The above simplifies to the following, where no sampling is done (q=Q) and utility bills are the sole source of energy consumption data.

$$U = t \times \frac{1.26 \times CVRMSE}{F} \times \sqrt{\frac{n+2}{n \times m}}$$

Equation B-19: Combined uncertainty equation 3

It should be noted that U decreases as the period (m) lengthens. The ‘t’ value above indicates the t value from the t-table. The maximum level of uncertainty of 50% is prescribed at a confidence level of 68% according to the ASHRAE guidelines.

$$Combined\ uncertainty\ (kWh) = \text{U}\ x\ Baseline\ Energy\ consumption$$

Equation B-20: Combined uncertainty level on saving (kWh)

$$\text{Combined uncertainty (\%)} = \frac{\text{U}\ x\ Baseline\ Energy\ consumption(kWh)}{Quantified\ EE\ Saving(kWh)}$$

Equation B-21: Combined uncertainty level on saving (%)

SANAS GUIDELINE

SANAS Guideline Example 1 - 4 [24]:

Symmetrical savings distribution:Adjustment of saving

Example 1: Symmetrical savings distribution, uncertainty higher than threshold

Suppose a project saves 200MWh with a 48MWh precision at the 80% confidence level. The relative precision on the savings is then only 24%, not the required 20%. Therefore, the creditable savings are reported as:

200 – (0.24-0.2)×200 = 192MWh. Example 2: Symmetrical savings distribution, uncertainty within threshold

Suppose a project saves 200MWh with a 10MWh precision at the 80% confidence level. The relative precision is then 5%, which is better than the required 20%. Therefore the creditable savings are reported as the mean: 200MWh.

Skewed savings distribution: Adjustment of saving

Example 3: Skewed savings distribution, uncertainty higher than threshold

If the mode of the savings is 200MWh, and the 10th percentile of the savings distribution is at 140MWh, the precision is 30%. If the reporting precision requirement is 20%, it means that the precision is 10% higher than the allowable percentage for reporting the mode of the savings. Therefore the creditable savings are reported as

200 – (0.3-0.2)×200 = 180MWh.

Example 4: Skewed savings distribution, uncertainty within threshold

If the mode of the savings 200MWh, and the 10th percentile of the savings distribution are at 190MWh, the precision is 5%. Therefore the creditable savings are reported as 200MWh.

SANAS Guideline Unquantifiable uncertainties [24]:

Factors vary by project, but could include the following:

- Differences in weather between meteorological station and facility;
- Human errors for data entry, survey response, operations etc.;
- Poor instrument selection, placement, and installation;
- Misestimation of key energy governing factors for any chosen Measurement option;
- Missing data;
- Uncertainty arising from incorrect model form;
- Model extrapolation uncertainty, if the baseline period values do not cover the whole input range;
- Human behaviour in certain kinds of projects, e.g. the size of the non-participant population for spill-over or free ridership calculation in so-called net-to-gross evaluations;
- Self-selection (rather than random selection) and other survey biases;
- Assumptions about the distribution of the data: assuming normality when data is non-normally distributed, for example; and
- Multicollinearity of energy governing factors.

Expressing uncertainty*[33]:*

Below an example of how to express uncertainty is provided:

100 MWh of EES is determined at a 68/50 uncertainty level. It means that the saving should be reported as 100MWh ± 50 MWh, i.e. there is a 50% precision on the saving which is true 68% of the time.

It is important to note that the expanded uncertainty needs to be applied to the energy saving and not the baseline energy consumption. For example, if an 80% confidence interval is chosen, and the baseline data has a 1% precision. Then the energy use is presented as 100MWh ± 1MWh. Hence, the saving is given by 10 MWh ± 1MWh, which translates to a 10% precision relative to the savings and not a 1% precision relative to the baseline energy consumption. [33]

ASHRAE DECISION FLOWCHARTS

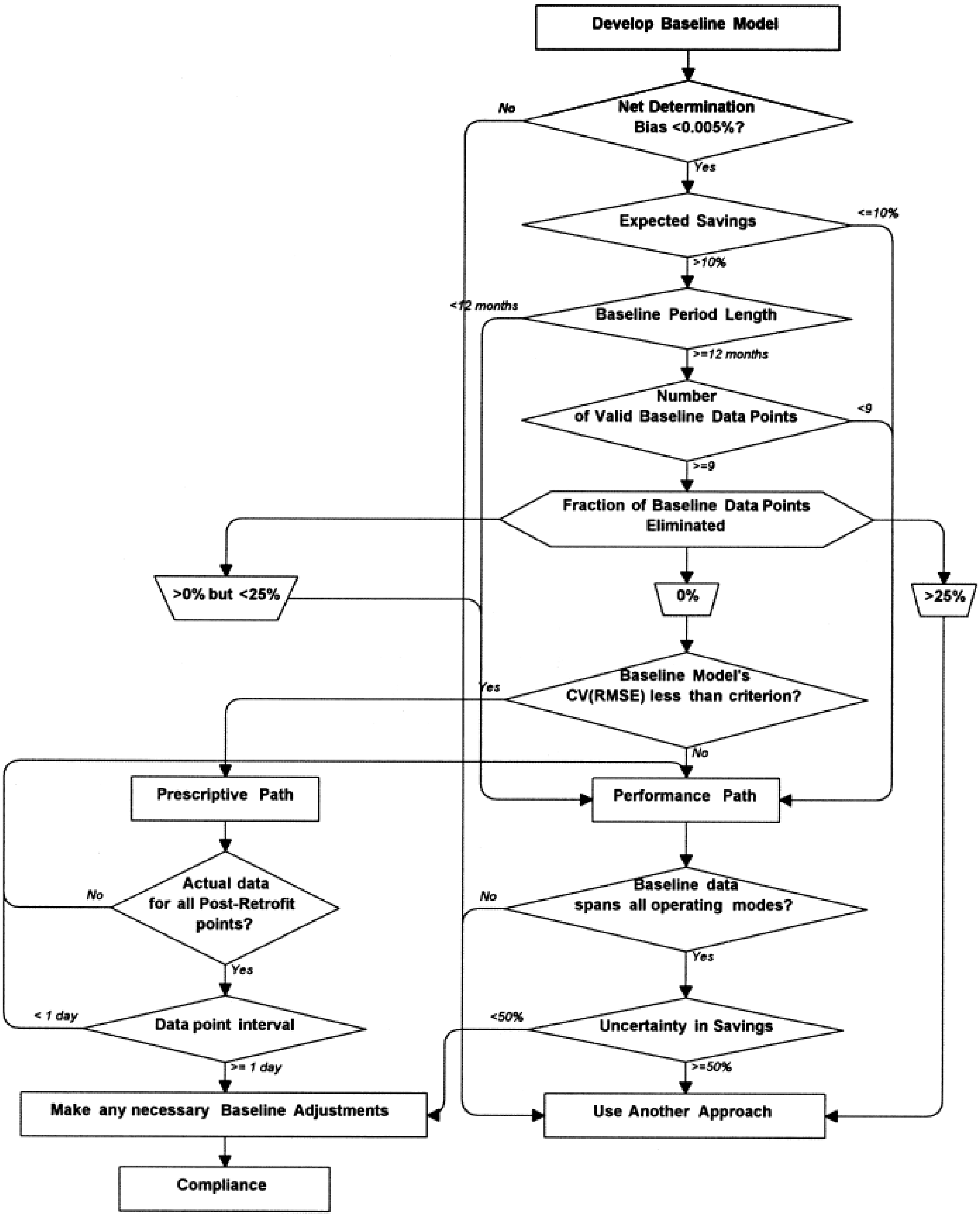

Figure B-3 : ASHRAE G14 –whole facility retrofit approach

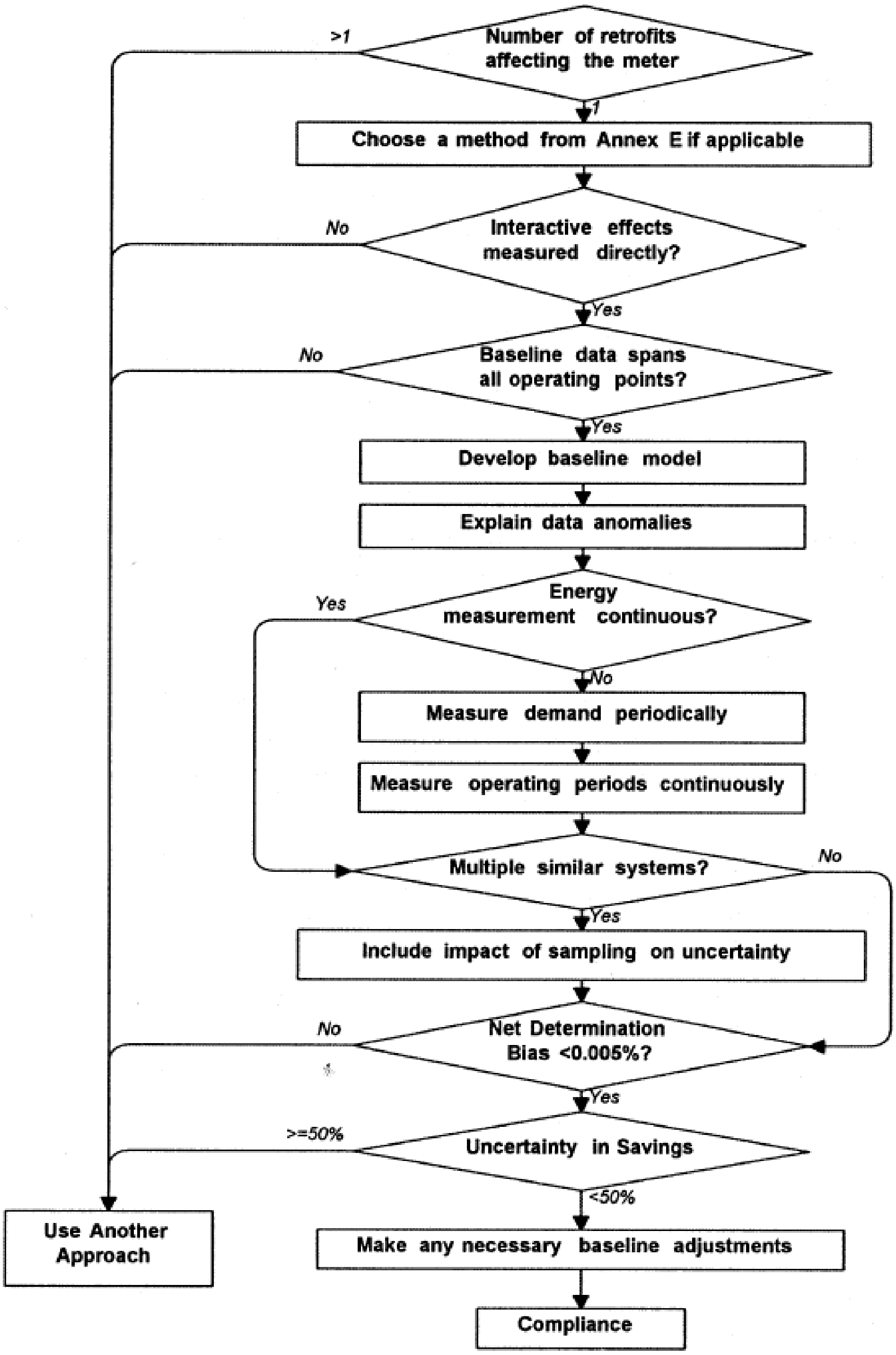

Figure B-4: ASHRAE G14 - retrofit isolation approach

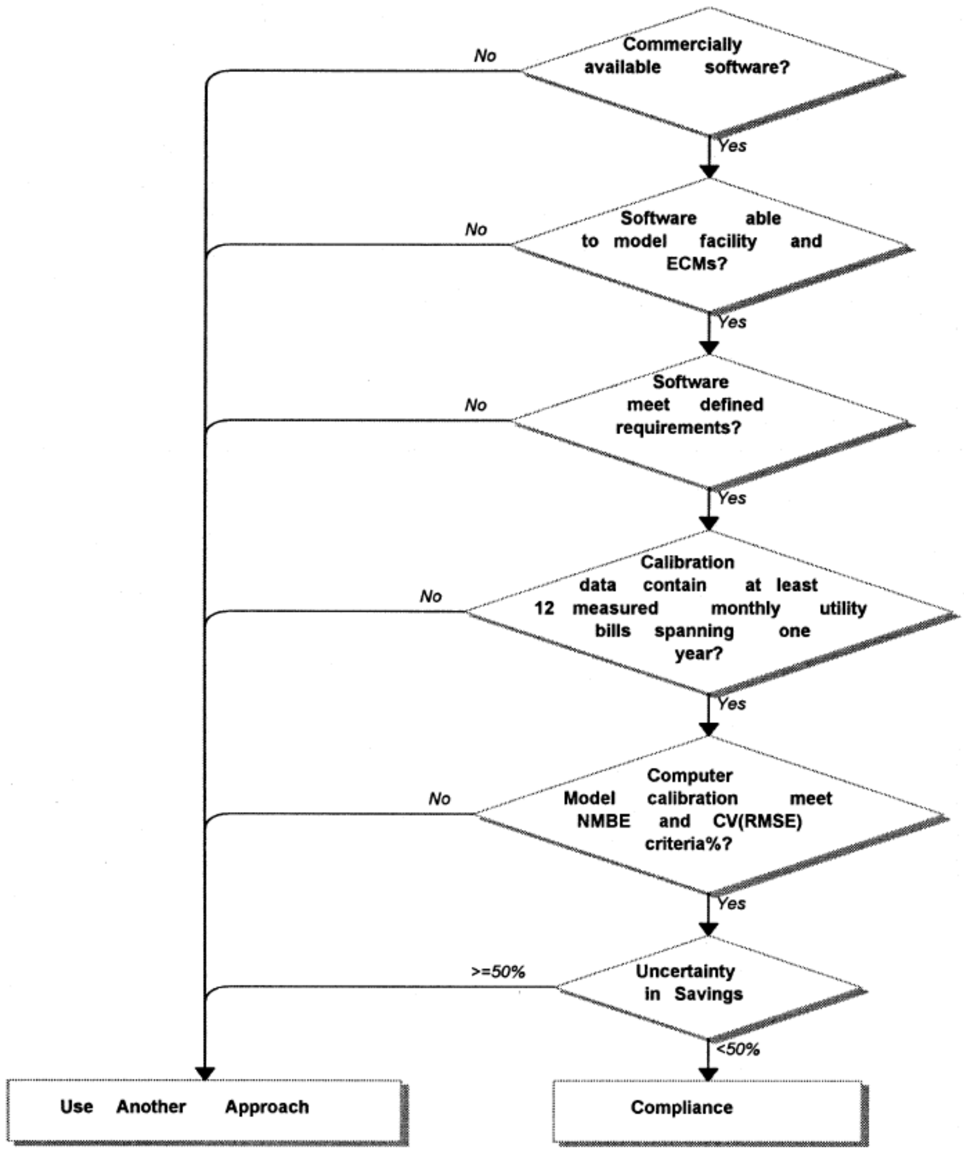

Figure B-5: ASHRAE G14 flowchart for calibrated simulation approach

APPENDIX C: CASE STUDIES

APPENDIX C.1 : CASE STUDY 1 APPENDIX

Case study 1 is discussed in detail in the document, this annex provides information regarding the results for step 1 (database management) and step 4 (uncertainty assessment) of the uncertainty Q&M flowchart analysis which is not included in-text.

APPLICATION OF Q&M FLOWCHART METHODOLOGY

Step 2: Database management

Redundant Dataset Analysis

Redundant datasets were available for electricity and fuel gas. The redundancy comparison for electricity can be seen in section 4.2.2. The visual representation of the fuel gas redundancy check can be seen in Figure C-1 below. The discrepancy (16.6%) between the two data sources is evident in the figure.

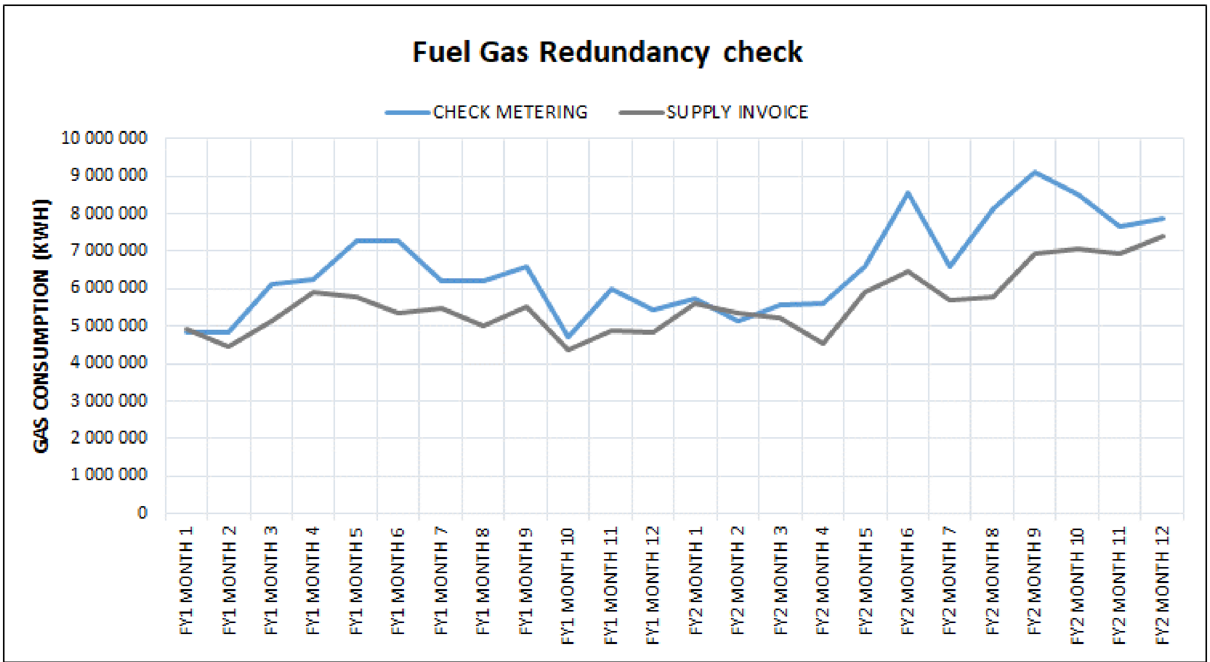

Figure C-1: Case study 1 – Redundant data comparison: fuel gas

Dataset Interrogation Results

Dataset interrogation is carried out on the four data sources; electricity, coal, fuel gas and production. The results are indicated below.

<u>Electricity Dataset Interrogation:</u>

The profiles generate to interrogate the electricity data can be found in section 4.2.2. The dips in the profile can be linked to maintenance done on the furnaces. Table C-1 indicates the periods when the furnaces underwent maintenance. The periods correspond to the areas highlighted in orange in the figures found in section 4.2.2.

Table C-1: Case study 1 - Furnace maintenance periods

Furnace	Year	Start	End
1	FY1	Month 6	Month 6
	FY2	Month 2	Month 2
	FY2	Month 8	Month 8
2	FY1	Month 2	Month 2
	FY1	Month 9	Month 10
	FY1	Month 11	Month 11
	FY2	Month 6	Month 6
	FY2	Month 7	Month 7
	FY2	Month 8	Month 8

Coal Dataset Interrogation

Similar to the profiles for electricity, the coal supply to furnace 1 and 2 follows the same trend with reduction seen where maintenance occurs. The dips in the coal quantity profiles (Figure C-2 and Figure C-3) correspond to the maintenance period indicated in Table C-1 above.

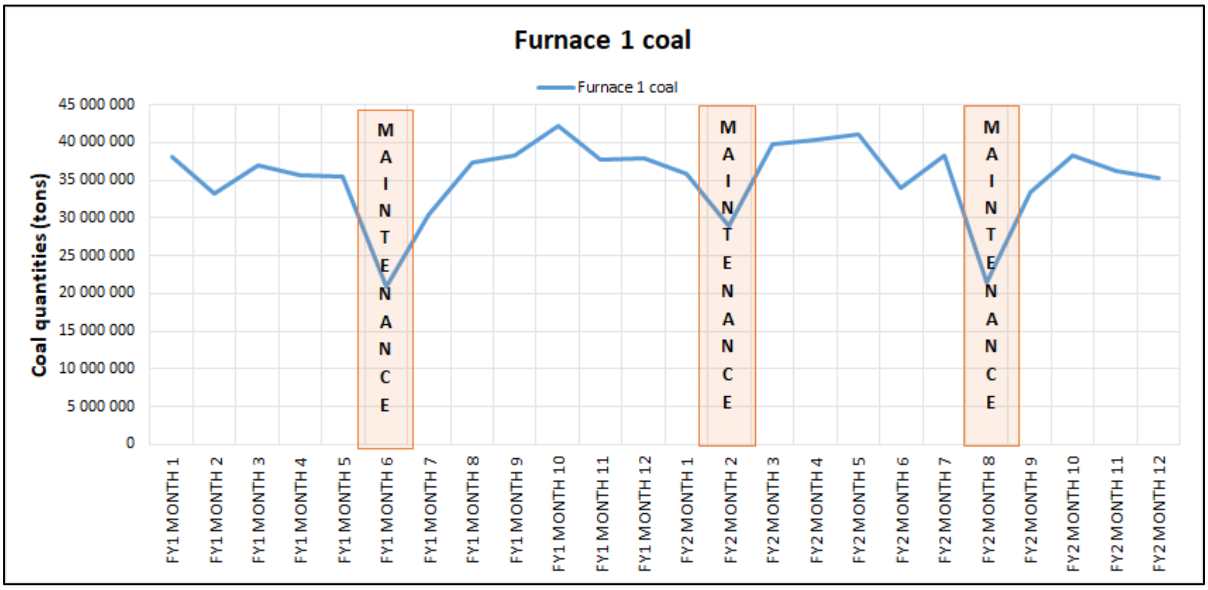

Figure C-2: Case study 1 - Dataset interrogation for coal quantity to furnace 1

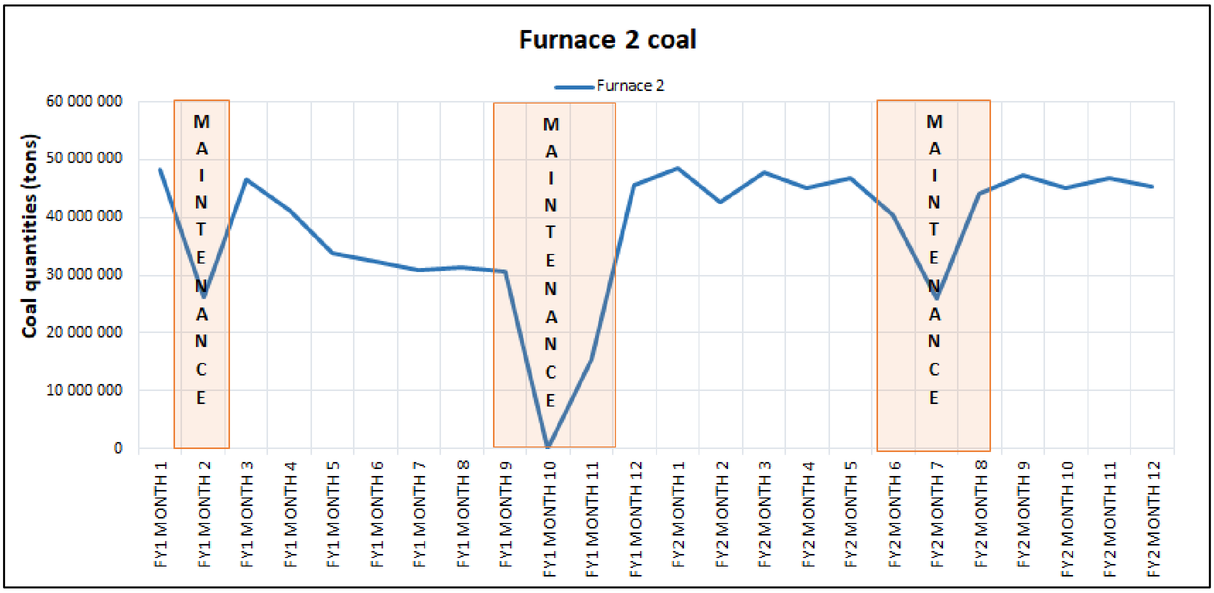

Figure C-3: Case study 1 - Dataset interrogation for coal quantity to furnace 2

<u>Fuel Gas Dataset Interrogation</u>

The profile for fuel gas invoices for furnace 1 and 2 are indicated in Figure C-4. Furnace 2 is offline in financial year 1 between month nine to month eleven, as is indicated by the period highlighted in orange. This is scheduled maintenance for the relining of the furnace.

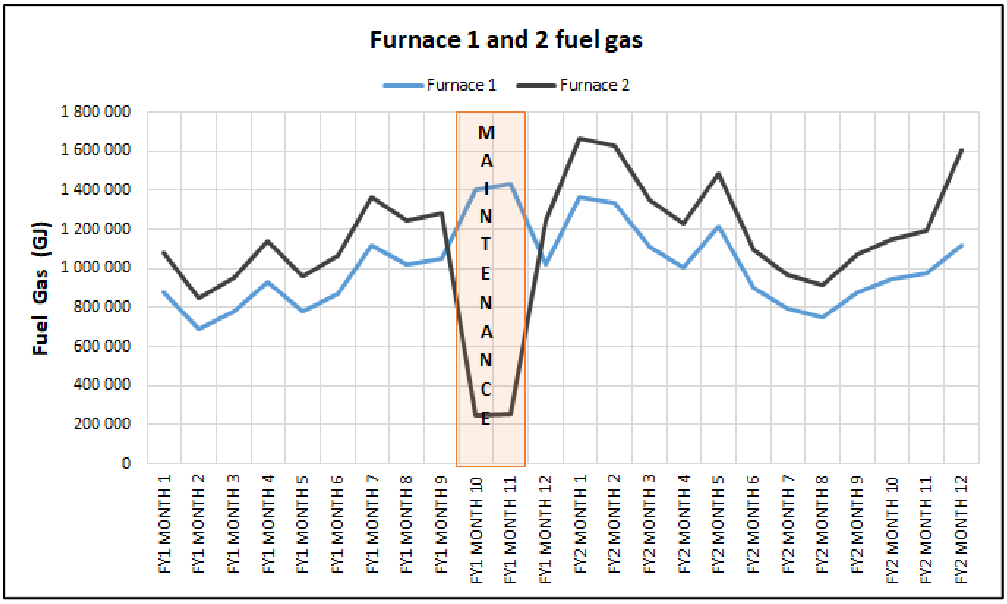

Figure C-4: Case study 1 – Gas invoice dataset interrogation

<u>Ferrochrome Production Dataset Interrogation</u>

The ferrochrome production profiles for furnace 1 and 2 can be seen in Figure C-5 and Figure C-6. The periods highlighted in orange on the graphs indicate the routine, scheduled maintenance shutdowns. As with before the maintenance periods align with those indicated in Table C-1.

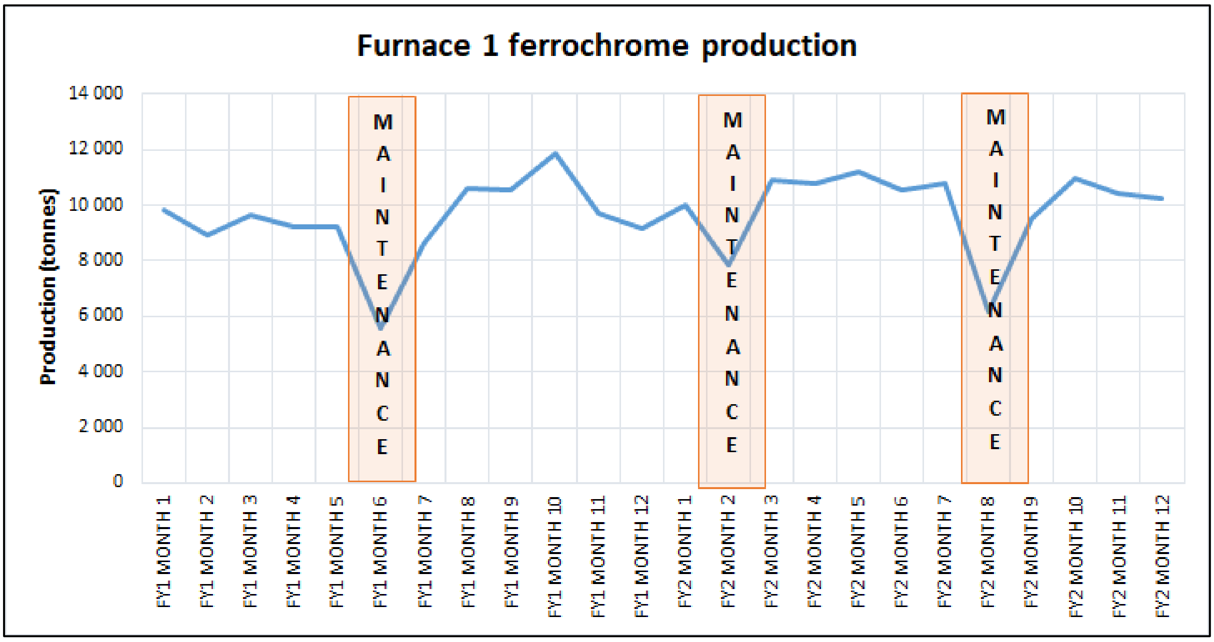

Figure C-5: Case study 1 – Furnace 1 production dips

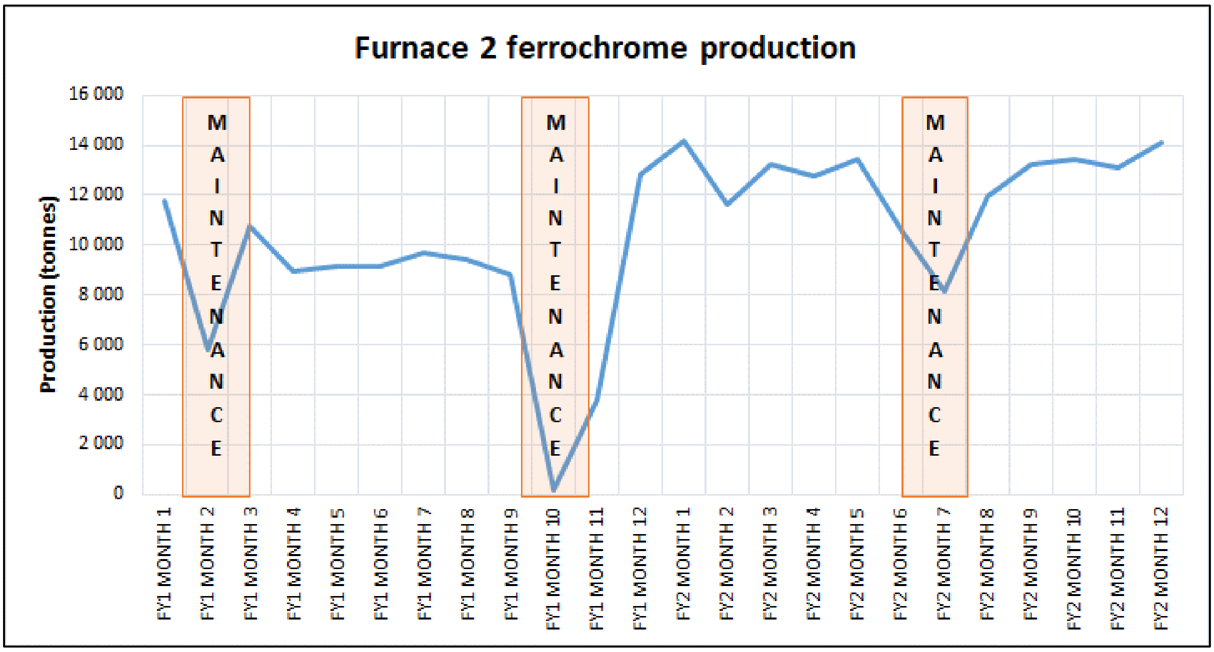

Figure C-6: Case study 1 – Furnace 2 production dips

Universal Dataset Checklists

The universal datasets generated for the available datasets can be found below.

Table C-2: Case study 1 – Coal Weigh-bin Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Coal quantities			
Measurement units:	Daily tonnages			
ID/Tag name:	Batching tonnages per furnace			
Instrumentation used:	Weigh bins			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	1	2014
		End	12	2015
Boundary applicability	Full facility		Yes	No
	Section/Department		Furnaces	
	Section/Department		Smelting Operations	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Coal to furnace	
		Environmental	N/A	
		Strategic operations	Production	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Database	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-3: Case study 1 – Electricity power meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Electricity			
Measurement units:	kWh			
ID/Tag name:	Monthly active energy			
Instrumentation used:	Power meter			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	1	2014
		End	12	2015
Boundary applicability	Full facility		Yes	No
	Section/Department		Furnaces	
	Section/Department		Smelting Operations	
Data availability	Resolution	Highest available	Half hourly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Electricity to furnace	
		Environmental	N/A	
		Strategic operations	Production	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Database	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-4: Case study 1 – Electricity invoice Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Electricity			
Measurement units:	kWh			
ID/Tag name:	Monthly active energy			
Instrumentation used:	Invoices			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	1	2014
		End	12	2015
Boundary applicability	Full facility		Yes	No
	Section/Department		Furnaces	
	Section/Department		Smelting Operations	
Data availability	Resolution	Highest available	Half hourly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Electricity to furnace	
		Environmental	N/A	
		Strategic operations	Production	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Database	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Invoices	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-5: Case study 1 – Fuel Gas power meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Fuel Gas			
Measurement units:	GJ			
ID/Tag name:	Monthly gas energy usage			
Instrumentation used:	Power meter			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	1	2014
		End	12	2015
Boundary applicability	Full facility		Yes	No
	Section/Department		Furnaces	
	Section/Department		Smelting Operations	
Data availability	Resolution	Highest available	Half hourly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Gas to furnace	
		Environmental	N/A	
		Strategic operations	Production	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Database	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-6: Case study 1 – Fuel Gas Invoice Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Fuel Gas			
Measurement units:	GJ			
ID/Tag name:	Monthly gas energy usage			
Instrumentation used:	Invoices			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	1	2014
		End	12	2015
Boundary applicability	Full facility		Yes	No
	Section/Department		Furnaces	
	Section/Department		Smelting Operations	
Data availability	Resolution	Highest available	Half hourly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Gas to furnace	
		Environmental	N/A	
		Strategic operations	Production	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Database	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Invoices	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-7: Case study 1 – Product Weighbridge Universal Dataset Checklist

<table>
<tr><th colspan="5">Universal Dataset Checklist</th></tr>
<tr><td colspan="5">Details:</td></tr>
<tr><td>Measurement:</td><td colspan="4">Ferrochrome Product</td></tr>
<tr><td>Measurement units:</td><td colspan="4">Daily tonnages</td></tr>
<tr><td>ID/Tag name:</td><td colspan="4">Weighbridge</td></tr>
<tr><td>Instrumentation used:</td><td colspan="4">Weighbridge tickets</td></tr>
<tr><td colspan="5">Criteria of evaluation:</td></tr>
<tr><td rowspan="3">Reporting Period</td><td>Calendar year</td><td>July - June/ FY</td><td colspan="2">Financial Year</td></tr>
<tr><td rowspan="2">Changeable period</td><td>Beginning</td><td>1</td><td>2014</td></tr>
<tr><td>End</td><td>12</td><td>2015</td></tr>
<tr><td rowspan="3">Boundary applicability</td><td colspan="2">Full facility</td><td>Yes</td><td>No</td></tr>
<tr><td colspan="2">Section/Department</td><td colspan="2">Furnaces</td></tr>
<tr><td colspan="2">Section/Department</td><td colspan="2">Smelting Operations</td></tr>
<tr><td rowspan="5">Data availability</td><td>Resolution</td><td>Highest available</td><td colspan="2">Half hourly</td></tr>
<tr><td rowspan="2">Available period</td><td>Full assessment</td><td>Yes</td><td>No</td></tr>
<tr><td>Periodically</td><td colspan="2">N/A</td></tr>
<tr><td rowspan="2">Historic data</td><td>Archive records</td><td colspan="2">Database</td></tr>
<tr><td>Archive period</td><td colspan="2">> 4 years</td></tr>
<tr><td rowspan="6">Applicability to key performance indicator</td><td rowspan="6">Focus area</td><td>Production</td><td colspan="2">N/A</td></tr>
<tr><td>Energy</td><td colspan="2">Product from furnace</td></tr>
<tr><td>Environmental</td><td colspan="2">N/A</td></tr>
<tr><td>Strategic operations</td><td colspan="2">Production</td></tr>
<tr><td>Human resources</td><td colspan="2">N/A</td></tr>
<tr><td>Other</td><td colspan="2">N/A</td></tr>
<tr><td rowspan="5">Internal Management</td><td rowspan="5">Data quality assurance</td><td>Procedure</td><td>Yes</td><td>No</td></tr>
<tr><td>Type</td><td colspan="2">Calibrated</td></tr>
<tr><td>Frequency</td><td colspan="2">At installation</td></tr>
<tr><td>Archive records</td><td colspan="2">Database</td></tr>
<tr><td>Archive period</td><td colspan="2">>10 years</td></tr>
<tr><td rowspan="4">Measurement traceability</td><td>Traceability description</td><td>Origin to end point</td><td>Yes</td><td>No</td></tr>
<tr><td rowspan="3">Supporting documents</td><td>References</td><td colspan="2">Weigh bridge tickets</td></tr>
<tr><td>Archive records</td><td colspan="2">N/A</td></tr>
<tr><td>Archive period</td><td colspan="2">N/A</td></tr>
<tr><td rowspan="4">Transparency of data</td><td rowspan="4">Data acquisition</td><td>Public domain</td><td>Yes</td><td>No</td></tr>
<tr><td>On request</td><td>Yes</td><td>No</td></tr>
<tr><td>With permission</td><td>Yes</td><td>No</td></tr>
<tr><td>Not available</td><td>Yes</td><td>No</td></tr>
</table>

Step 4: Uncertainty assessment

The uncertainty assessment results not included for case study 1 in section 4.2.2 can be found below.

Expanded uncertainty test

The results of the expanded uncertainty tests on model 2 for three different confidence limits is indicated below. Model 2 only passes the 68/50 confidence limit test.

Table C-8: Case study 1 – Model 2 expanded uncertainty test results

80/20 Precision test		90/10 Precision test		68/50 Precision test	
Mean (X)	30 208 549	Mean (X)	30 208 549	Mean (X)	30 208 549
Sample size	52	Sample size	52	Sample size	52
Degrees of freedom	51	Degrees of freedom	51	Degrees of freedom	51
Confidence level	1	Confidence level	0.90	Confidence level	0.68
Alpha (α)	0	Alpha (α)	0.05	Alpha (α)	0.16
t	1.29	Z	1.65	Z	1.00
σ	7 362 542	σ	7 362 542	σ	7 362 542
CI upper	31 522 767	CI upper	31 888 095	CI upper	31 229 550
CI lower	28 894 331	CI lower	2 8529 003	CI lower	29 187 548
Baseline Precision	4.4%	Baseline Precision	5.6%	Baseline Precision	3.4%
Baseline Energy	1 570 844 546	Baseline Energy	1 570 844 546	Baseline Energy	1 570 844 546
Energy Saving	117 918 422	Energy Saving	117 918 422	Energy Saving	117 918 422
Saving Precision	58%	Saving Precision	74.1%	Saving Precision	45.0%

APPENDIX C.2 : CASE STUDY 2 APPENDIX

Case study 2 is not discussed in detail in the document. This annex provides information regarding the detailed results of each step of the uncertainty Q&M flowchart which is not included in-text.

APPLICATION OF Q&M FLOWCHART METHODOLOGY

The uncertainty Q&M is applied to quantify the waste heat recovery EES. As in Case study 1, the Five-Step Approach is carried out. Only the main results for each step will be discussed in this section since the methodology is explained in detail in the first case study.

Step 1: ESM Isolation

Baseline and performance assessment selection

The baseline and assessment period selected for the investigation is indicated in Table C-9. The ESM is implemented in October 2015. However, the periods are chosen to coincide with the financial year of the entity (from 1 July until 30 June). The financial years were selected to align with tax reporting periods as required by the 12L regulations. However, it is determined that these periods also provide a pre-implementation and post-implementation assessment of the ESM. These periods can therefore be used to quantify the effect of the ESM.

Table C-9: Case study 2 – baseline and performance assessment periods

Period	Date
Baseline Period	1 July 2015 - 30 June 2016
Performance Assessment Period	1 July 2016 - 30 June 2017

The data availability is established for the periods mentioned above. A data availability table is constructed and can be seen below as Table C-10.

Table C-10: Case study 2 – Data availability for boiler operations

Measurement	Measurement device	Data source	Data resolution
Natural gas (NG)	Mass flow metering	Database/ invoices	Daily volumes/ monthly volumes
	Natural gas analysis (heating values)	Database/ invoices	Daily volumes/ monthly volumes
Electricity	Electricity metering	Database	Daily
Steam produced	Mass flow manual logging system	Boiler log sheet	Daily tonnages
	Temperature metering	Database	Daily

	Pressure metering	Database	Daily
Boiler feed water (BFW)	Mass flow metering	Database /invoices	Daily
	Temperature metering	Database / invoices	Daily

A summary with the necessary POM streams will be indicated in the following section of the first step.

Measurement Boundary Selection

The measurement boundary is constructed around the gas engines and the boilers. It is an isolated all-parameter boundary as with Case study 1. A POM diagram is constructed with the status of the data as indicated in Figure C-7.

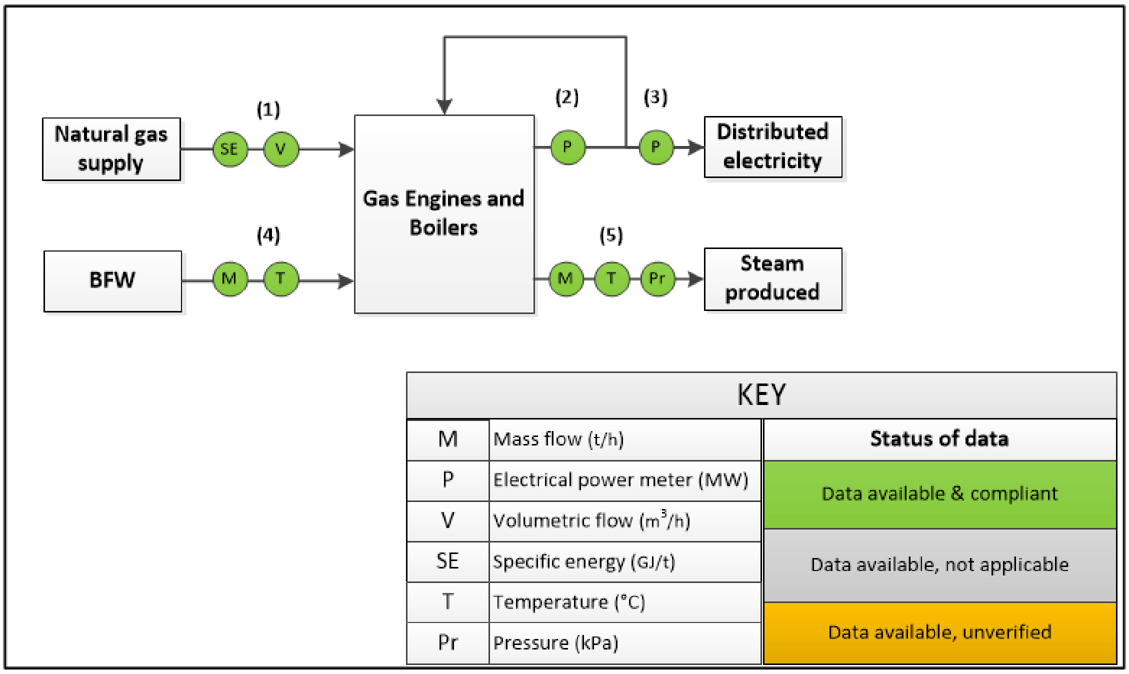

Figure C-7: Case study 2 – Points of measurement diagram

A complete data availability is then constructed using the POM diagram and initial data availability table. It can be noted from Table C-11 that all the data points represent compliant (calibrated or invoice data) data points (indicated as green).

Table C-11: Case study 2 – Complete data availability table

Measurement	Measurement device	Data source	Data resolution	Compliance	Number	Status of data
	Mass flow metering	Database	Daily volumes/ monthly			Available, verified and compliant

(NG)		*Monthly invoices*	volumes	/ invoices		Available, verified and compliant
	Natural gas analysis (heating values)	Database	Daily volumes/ monthly volumes			Available, verified and compliant
		Monthly invoices				Available, verified and compliant
Electricity	Electricity metering	Database	Daily	Calibration	2 & 3	Available, verified and compliant
Steam produced	Mass flow manual logging system	Boiler log sheet	Daily tonnages	Calibration and official documents	5	Available, verified and compliant
	Temperature metering	Database	Daily		5 & 6	Available, verified and compliant
	Pressure metering	Database	Daily		5 & 6	Available, verified and compliant
Boiler feed water (BFW)	Mass flow metering	Database/ invoices	Daily	Calibration	4	Available, verified and compliant
	Temperature metering	Database/ invoices	Daily		4	Available, verified and compliant

Having established the ESM boundaries, the next step in the process is to manage the database.

Step 2: Database Management

Redundancy Dataset Analysis

Redundant datasets were available for electricity and natural gas. Redundancy checks are done on the electricity production data and the natural gas supplied data. A difference of 0.45% is noted in the data sources for natural gas – see Figure C-8. For the electricity redundancy check, POM (2) and POM (3) are compared – see Figure C-9 and a 2.71% difference is observed. This difference can be linked to the electricity routed to the auxiliaries.

<u>Natural gas redundancy check</u>

A comparison between the two redundant data sources for natural gas is indicated in Figure C-8. The overall natural gas energy figures for the entire period are indicated in Table C-12.

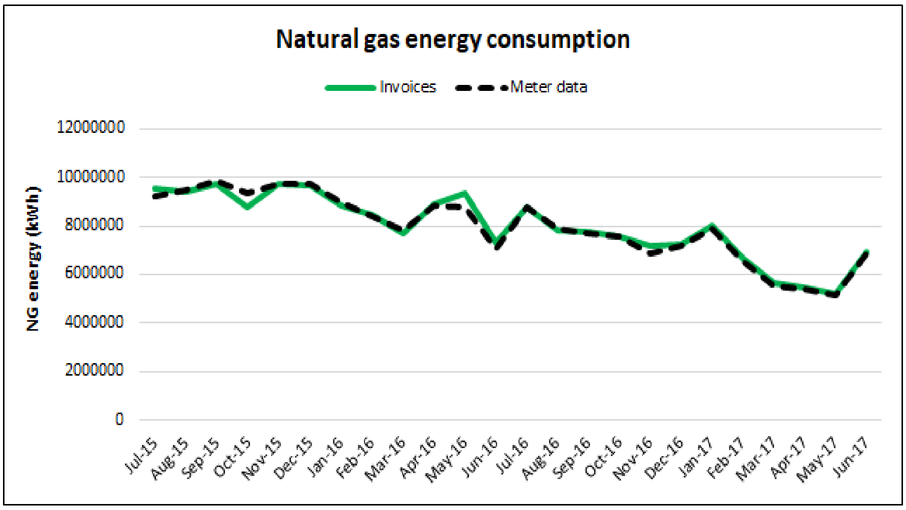

Figure C-8: Case study 2 – Natural Gas Redundancy check

Table C-12: Case study 2 – Natural Gas Redundancy Check

Natural Gas Redundancy Check	
Invoices (kWh)	191 439 622
Check Metering (kWh)	190 580 121
Difference	0.45%

<u>Electricity redundancy check</u>

A comparison between the two redundant data sources for electricity is indicated in Figure C-9. The overall electricity figures for the entire period are indicated in Table C-13.

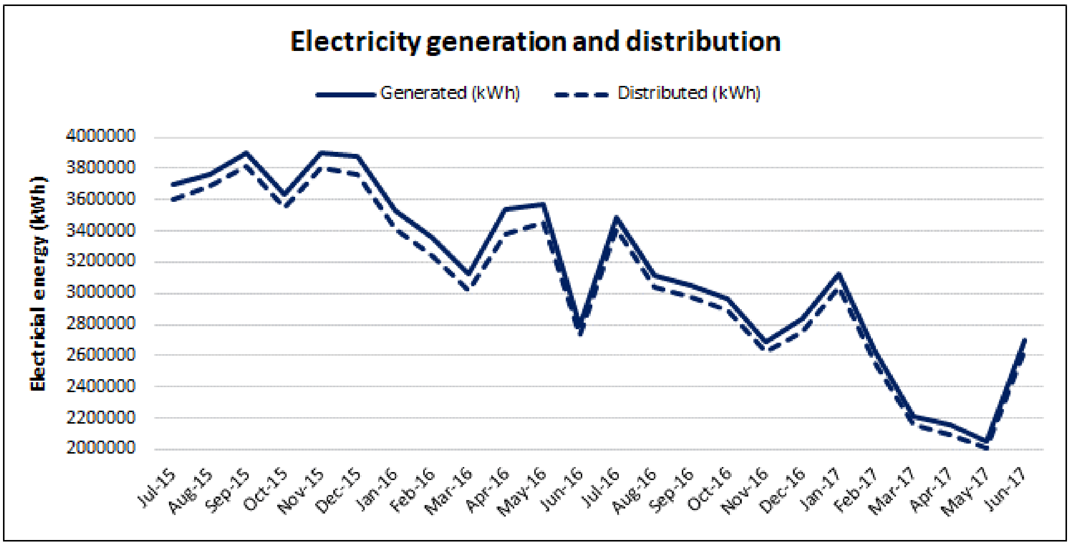

Figure C-9: Case study 2 – Electricity Redundancy Check

Table C-13: Case study 2 – Electricity Redundancy Check

Electricity Redundancy Check	
Electricity generated (POM 2) (kWh)	75 685 419

Electricity distributed (POM 3) (kWh)	73 630 917
Difference	2.71%

The next evaluation for Database Management is to interrogate the data for any abnormalities.

Dataset Interrogation Results

As discussed in Case study 1, the datasets were thoroughly investigated for any abnormalities such as spikes, meter malfunction, data loss and any other abnormal operation. The results for the dataset interrogation for case study 2 is presented in Table C-14.

Table C-14: Case Study 2 – Dataset interrogation checklist results

Variable	Data source	Spikes	Meter malfunctions	Data loss	Abnormal operation	Comment
Natural gas (NG)	Mass metering & Heating value	None	Present	None	None	Abnormal data –faulty metering. Incorrect heating value.
Electricity	Power metering	None	Present	None	None	Abnormal data –faulty metering.
Steam produced	Manual logging system	Present	None	None	None	Logging error on boiler log sheets
Boiler feed water (BFW)	Mass metering	None	None	None	None	-

The dataset interrogation is carried out on the four variables indicated in Table C-11. 'None' in the table represents the absence of the mentioned phenomena, and 'present' indicates that the phenomena occurred.

For the NG and electricity data, some abnormal data is observed. These are due to meter malfunction. Table C-14 also indicates that there are some errors on the logged values for the steam produced.

All the abnormalities are removed from the datasets, as they could be linked to meter-malfunctions and logging error. Graphs for the dataset interrogation, and information regarding the outlier removal can be found below.

Boiler Feed Water and Steam Dataset Interrogation

In Figure C-10 the red circles indicate periods where an abnormality is observed in the data. Table C-15 indicates the dates where these abnormalities occur and the reason therefore. All the abnormalities are removed from the dataset.

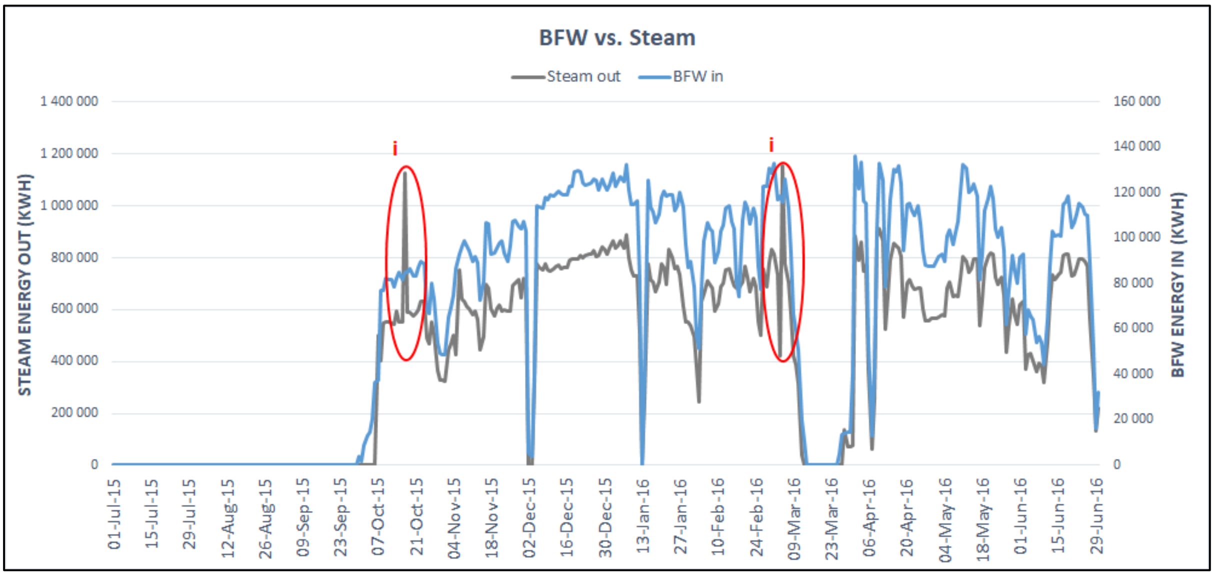

Figure C-10: Case study 2 - BFW and steam dataset interrogation

Table C-15: Case study 2 – BFW and steam dataset interrogation abnormalities

Baseline (FY16)								
Group	**Period**	**No.**	**Occurrence**	**Variance with average FY16 values**			**Explanation**	**Outlier**
				Variable	**Value for specified period**	**Variance (%)**		
i	Oct '15	**18**	Logging error on boiler log sheets	Steam generated (t/h)	48	105%	Abnormal data - data discrepancy	Yes
	Mar '16	**17**						
	Mar '16	**19**						

Natural Gas and Electricity Dataset Interrogation

In Figure C-11 the circles (and letters) indicate periods where an abnormality is observed in the data. Table C-16 indicates the dates where these abnormalities occur and the reason therefore. All the abnormalities are removed from the dataset.

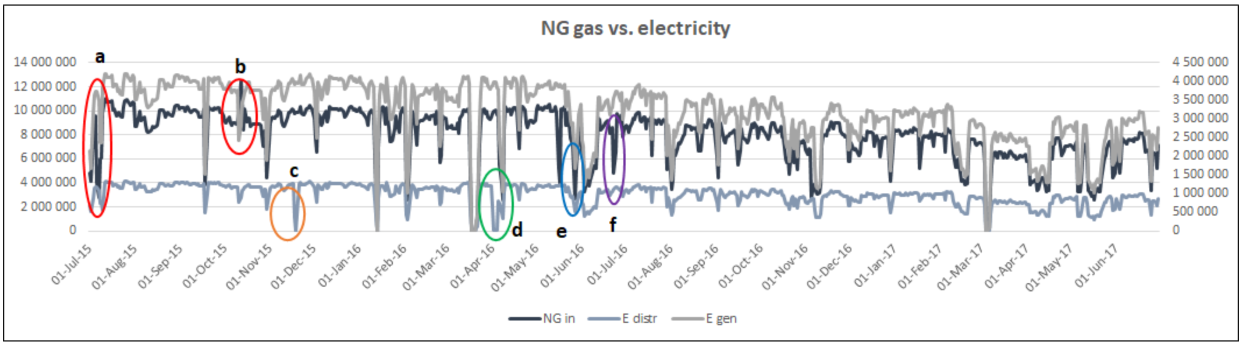

Figure C-11: Case study 2 – NG and electricity dataset interrogation

Table C-16: Case study 2 – NG and electricity dataset interrogation abnormalities

Baseline (FY16)							
Group	Period	Occurrence	Variance with average FY16 values			Explanation	Outlier
			Variable	Value for specified period	Variance (%)		
a	Jul '15 7 Jul '15	NG decreased significantly; electricity generated and distributed stayed constant	NG HV (MJ/m3n)	15	-63%	Incorrect heating value	Yes
b	10 Jul '15	Electricity distributed decreased significantly; NG and electricity generated stayed constant	Electricity distributed (MW)	72	-49%	Abnormal data – possible faulty metering	Yes
c	11 Oct '15 12 Oct '15	NG increased significantly; electricity generated and distributed decreased	Natural gas (m3n/h)	42 522	31%	Abnormal data – possible faulty metering	Yes
d	18 Nov '15 19 Nov '15 20 Nov '15	Electricity distributed decreased significantly; NG and electricity generated stayed constant	Electricity distributed (MW)	54	-62%	Abnormal data – possible faulty metering	Yes
e	1 Apr '16 2 Apr '16 3 Apr '16 4 Apr '16 5 Apr '16	Electricity distributed decreased significantly; NG and electricity generated stayed constant	Electricity distributed (MW)	38	-73%	Abnormal data – possible faulty metering	Yes
f	16 May '16 17 May '16 24 Jun '16	NG decreased significantly; electricity generated and distributed stayed constant	Natural gas (m3n/h) (MJ/m3n)	16 059	-51%	Abnormal data – possible faulty metering	Yes

Hence all the identified outliers for steam, gas and electricity were removed. Once the dataset interrogation had been carried out, universal dataset checklists are compiled. These can be found below for all the variables investigated.

Universal Dataset Checklists

Table C-17: Case study 2 – Natural gas meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	NATURAL GAS (NG) CONSUMPTION			
Measurement units:	m^3n/h			
ID/Tag name:	Meter			
Instrumentation used:	Check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	7	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Monthly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	NG to Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Filed documentation	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-18: Case study 2 – Natural Gas Invoice Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	NATURAL GAS (NG) CONSUMPTION			
Measurement units:	m^3n/h			
ID/Tag name:	Monthly invoice data			
Instrumentation used:	Invoices			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	7	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Monthly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Documentation	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	NG to Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Filed documentation	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-19: Case study 2 – NG heating value meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	NATURAL GAS (NG) HEATING VALUE			
Measurement units:	MJ/m^3n			
ID/Tag name:	Metered heating value			
Instrumentation used:	Check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	7	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	NG to Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Filed documentation	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No

		With permission	Yes	No
		Not available	Yes	No

Table C-20: Case study 2 – NG heating value invoice Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	NATURAL GAS (NG) HEATING VALUE			
Measurement units:	MJ/m^{3}n			
ID/Tag name:	Daily Invoice			
Instrumentation used:	Invoices			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	7	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Documentation	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	NG to Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Filed documentation	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-21: Case study 2 –Electricity meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	ELECTRICITY GENERATED			
Measurement units:	MW			
ID/Tag name:	Metering			
Instrumentation used:	Check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	7	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Electricity from Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Filed documentation	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-22: Case study 2 – Supplied electricity meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	ELECTRICITY SUPPLIED/ DISTRIBUTED			
Measurement units:	MW			
ID/Tag name:	Metering			
Instrumentation used:	Check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	7	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	> 4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Electricity from Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Filed documentation	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-23: Case study 2 – BFW meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	BOILER FEED WATER (BFW) MASS FLOW			
Measurement units:	m³/h			
ID/Tag name:	Metering			
Instrumentation used:	Check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	10	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	None	
		Archive period	0 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	BFW to Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	None	
		Archive period	0 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-24: Case study 2 – BFW temperature meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	BOILER FEED WATER (BFW) TEMPERATURE			
Measurement units:	°C			
ID/Tag name:	Temperature metering			
Instrumentation used:	Check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	10	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	None	
		Archive period	0 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	BFW to Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	None	
		Archive period	0 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-25: Case study 2 –Steam log sheets Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	STEAM MASS FLOW			
Measurement units:	ton/h			
ID/Tag name:	Boiler log sheets			
Instrumentation used:	Check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	10	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	None	
		Archive period	0 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Steam from Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Documentation	
		Archive period	> 1 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Boiler log sheets	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No

		With permission	Yes	No
		Not available	Yes	No

Table C-26: Case study 2 –Steam pressure meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	STEAM PRESSURE			
Measurement units:	kPa			
ID/Tag name:	Pressure metering			
Instrumentation used:	Check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	10	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	None	
		Archive period	0 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Steam from Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Documentation	
		Archive period	> 1 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No

		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Table C-27: Case study 2 – Steam temperature meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	STEAM TEMPERATURE			
Measurement units:	°C			
ID/Tag name:	Temperature metering			
Instrumentation used:	Check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June/ FY	Financial Year	
	Changeable period	Beginning	10	2015
		End	6	2017
Boundary applicability	Full facility		Yes	No
	Section/Department		Boilers	
	Section/Department		Heat Integration	
Data availability	Resolution	Highest available	Daily	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	None	
		Archive period	0 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Steam from Boilers	
		Environmental	N/A	
		Strategic operations	Steam generation	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Documentation	
		Archive period	> 1 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	

Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Not available	Yes	No

Step 3: Model Development

In this step, five models are developed to quantify the EES using the existing M&V reports. The first model is based an unadjusted energy model, where 57 GWh of extra steam energy is seen to be recovered year on year. The second model is a multi-year assessment where the dark blue portion of the bar graph indicates the saving due to the heat integration project and the light blue portion represents the saving due to increased efficiency (steam production).

The third model incorporated different operational modes where the effect of improved waste heat recovery due to increased boiler utilisation is determined. The fourth model is an all parameter linear regression model i.e. it considers all the energy streams entering and exiting the system boundary. The final model is similarly, an all parameter energy intensity model. A summary of these five models is provided below.

Model 1: Steam energy recovery

The first model is an unadjusted energy reduction type model. It makes use of the total energy in (BFW energy) and the total energy out (steam energy) y-o-y to calculate a EES.

Table C-28: Case Study 2 – Model 1: Steam energy recovery

Description		Steam E calculation	Baseline (FY16)	Assessment (FY17)	Net to steam savings
IN	Row 1	Total BFW energy (tonnes)	232 031	345 853	113 822
	Row 2	Total BFW energy (kWh)	24 521 829	36 971 715	12 449 886
OUT	Row 3	Total steam energy (tonnes)	207 242	292 912	85 671
	Row 4	Total steam energy (kWh)	158 038 750	227 150 780	69 112 030
(Row 4 - Row 2)	Row 5	Net to steam energy (kWh)	**133 516 921**	**190 179 065**	**56 662 144**

Row 5 indicates the steam energy recovered for the baseline and assessment period. From Table C-28 it is observed that the recovered steam energy increased by approximately 57GWh y-o-y.

Model 2: Multi-year assessment

Model 2 is made up of two calculations. The calculations are done for EE initiatives for different periods, hence the name multi-year assessment. The first saving is calculated for the heat integration project (HIP) initiative, and the second is calculated for the increased efficiency due to steam production. The results can be seen in Table C-29 below.

Table C-29: Case Study 2 – Model 2: Multi-year assessment

FY16 savings (HIP)		***Increased efficiency (steam production)***		
136 218 803	**kWh**	FY16	276 827	*tonnes*
Unclaimed days in FY16	*274*	FY17	293 715	*tonnes*
Actual days in FY16	*366*	Additional	**16 888**	*tonnes*
Actual energy in FY16	**181 956 503**	*Enthalpy*	2 791	*kJ/kg*
Unclaimed savings in FY16		Savings from increased efficiency		
45 737 700	kWh	**13 091 956**		kWh
Overall energy savings			**58 829 656**	kWh

The HIP initiative has a savings value of 45GWh, and the savings from steam efficiency is 13 GWh. The overall quantified is hence energy saving given by Model 2 is 58 GWh.

Model 3: Different operation modes

This model is a regression type model. Average energy consumption is regressed against average energy production. A good correlation coefficient is observed (~1). The model is called a different operation modes model because the baseline period is made up of less days than the performance assessment period. Hence, the saving is adjusted by multiplying by the baseline days divided by the assessment period number of days i.e. 253/363 ≈ 0.7.

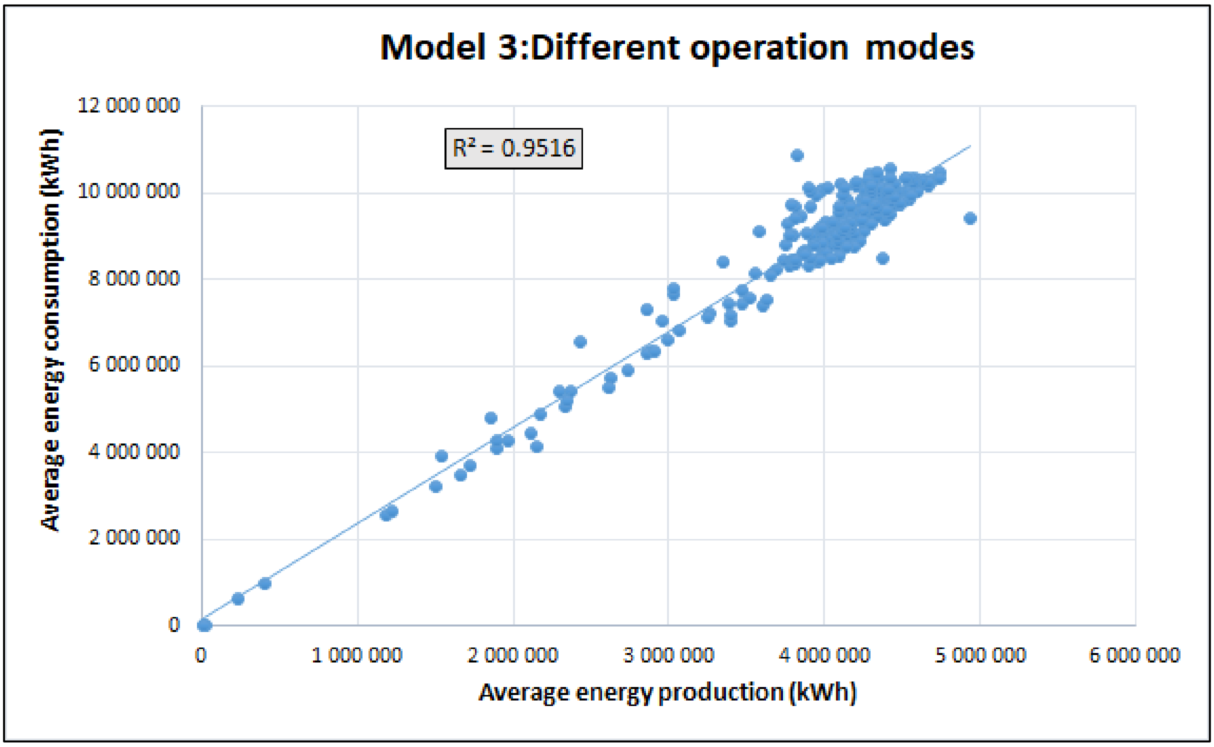

Figure C-12: Case Study 2 – Model 3: Different operation modes linear regression model

The quantified EES for this model can be seen in Table C-30, the initial saving is 86GWh and is adjusted (using 0.7 previously mentioned) to get a final saving of 60 GWh.

Table C-30: Case Study 2 – Model 3: Different operation modes

Different operation modes			
BL	PA	**Savings (kWh)**	
FY16_2	*FY17*	**86 281 509**	**60 135 597**

<u>Model 4: All parameter regression</u>

The fourth model is an all parameter linear regression model. It is called 'all-parameter' as it considers all the energy streams entering and exiting the system boundary.

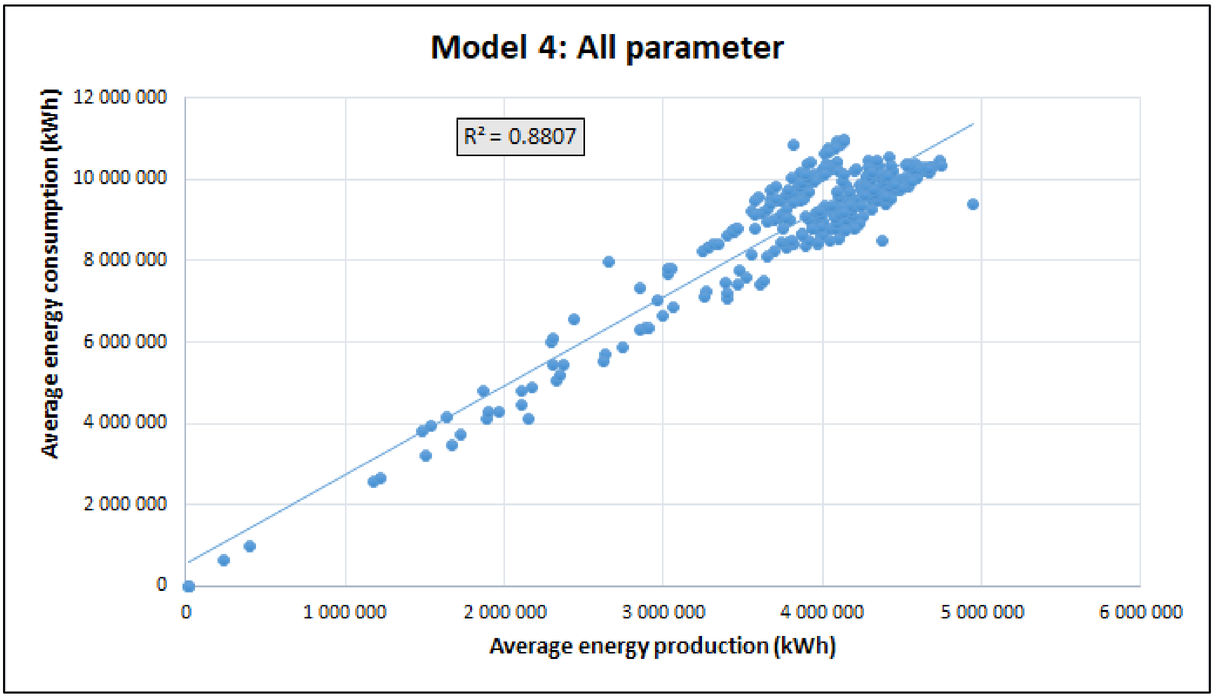

Figure C-13: Case Study 2 – Model 4: All parameter linear regression

A good correlation coefficient is observed (~1). The calculated saving of 196 GWh can be seen in Table C-31 below. This saving is much bigger than the other energy savings values, this is due to total value of all the energy streams being considered.

Table C-31: Case Study 2 – Model 4 Energy saving

Savings (kWh)	**196 025 004**

<u>Model 5: Daily energy intensity model</u>

Model 5 is an energy intensity model which makes use of the total energy consumption and total annual production. Table C-32 indicates the energy saving of 166 GWh. The energy saving is calculated by taking the difference between the actual total energy consumption in FY17 and the predicted total energy (indicated by shaded blocks.)

Table C-32: Case Study 2 – Model 5: Daily Energy Intensity

Daily Energy Intensity		
	FY16	**FY17**
Total annual energy consumption (kWh)	3 110 820 460	*2 547 493 561*
Total annual production (kWh)	1 330 488 660	1 163 485 240
Intensity	2.3	2.2
Predicted Total annual energy consumption (kWh)		*2 720 349 144*
Savings (kWh)	172 855 582	
Adjusted Savings after outlier removal(kWh)	165 712 790	
Savings (GWh)	**165.7**	

A summary of the models developed can be seen in Figure C-8. It can be noted that the last two models which use the total energy consumption indicate a bigger saving.

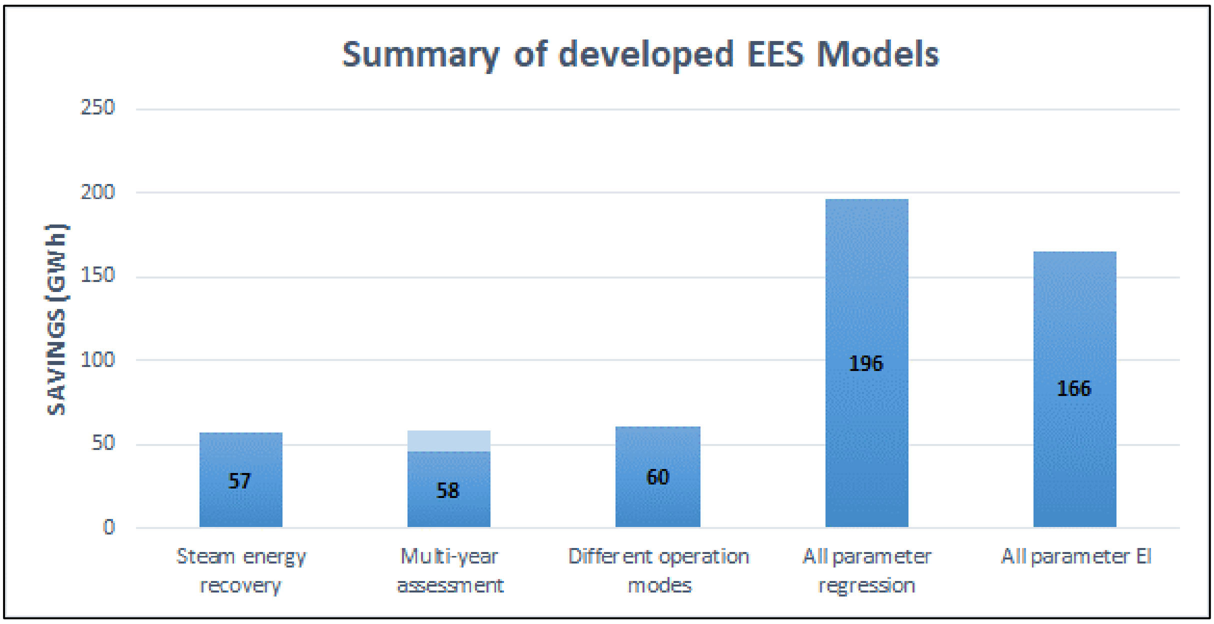

Figure C-14: Case study 2 – Model development - Summary of models

Once the models were constructed the next step is carried out which i.e. the Uncertainty Assessment step.

Step 4: Uncertainty Assessment

The results of the model validation and uncertainty tests can be found in Table C-33.

Table C-33: Case study 2 – Uncertainty assessment results

Model Options	MODEL 1	MODEL 2		MODEL 3	MODEL 4	MODEL 5
Model Validation						
Correlation (R^2)	-	-	-	0.95	0.88	-
P-value	-	-	-	4.2×10^{-167}	8.1×10^{-162}	-

Auto-correlation (Durbin-Watson)	-	-	-	0.77	0.34	-
Normal distribution (Anderson-Darling)	-	-	-	-	-	-
Model Prediction Validation Tests						
Model goodness of fit (CV[RMSE])	-	-	-	7.4%	10.5%	-
Statistical significance	-	-	-	PASS	PASS	-
Statistical significance (F-test)	-	-	-	PASS	PASS	-
Over/under prediction (NDB)	-	-	-	PASS	PASS	-
Statistical Uncertainty Tests						
Measurement uncertainty	0.87%	0.87%	0.98%	1.4%	1.4%	1.4%
Savings uncertainty (80/20)	2.06%	3.48%	16.0%	70.6%	23.6%	26.9%
Combined uncertainty (68/50)	-	3.13%		4.40%	1.90%	-

It can be seen in Table C-33 that only Models 3 and 4 could undergo model validation tests. Both models passed all the model validation and model prediction tests except the Durbin-Watson test. Failing the DW test indicates that auto-correlation could be present.

The measurement uncertainty refers to the calculated relative measurement error. All the measurement uncertainty values are low (less than 1.5%), which indicates low tolerance values on the measurement equipment.

Models 1 and 2 passed the savings uncertainty 80/20 test, whereas Models 3 to 5 failed these tests. The last three models failed the test due to a small saving significance when compared to the baseline energy consumption.

Finally, where applicable the uncertainties where combined. All the models had very low combined uncertainty values and passed the test at the prescribed 68/50 uncertainty interval.

The last step is then carried out (Model Selection) where the AHP method is used to rank the models.

Step 5: Model Selection

The models were scored according to the prescribed criteria. The model comparative analysis results can be seen in Table C-54 and the allocated scores can be seen in Table C-35.

Table C-34: Case study 2 – Model selection comparison evaluation

<table>
<tr><th colspan="2">Feasible Claim Model (A1)</th><th>MODEL 1: Steam energy recovery</th><th colspan="2">MODEL 2: Multi-year assessment</th><th>MODEL 3: Different operation modes</th><th>MODEL 4: All parameter</th><th>MODEL 5: Daily Intensity</th></tr>
<tr><td colspan="8">12L Compliance (B1)</td></tr>
<tr><td colspan="2">Compliant dataset (C11)</td><td>Yes</td><td colspan="2">Yes</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td rowspan="2">Conservativeness of saving (C12)</td><td>Value (GWh)</td><td>56.7</td><td colspan="2">58.8</td><td>60.1</td><td>196.0</td><td>165.7</td></tr>
<tr><td>Rank</td><td>1.00</td><td colspan="2">0.75</td><td>0.50</td><td>0.00</td><td>0.25</td></tr>
<tr><td colspan="8">Economic Feasibility (B2)</td></tr>
<tr><td colspan="2">Significance of saving (C21)</td><td>42.4%</td><td colspan="2">31.2%</td><td>2.7%</td><td>6.3%</td><td>5.3%</td></tr>
<tr><td colspan="8">Model Validation (B3)</td></tr>
<tr><td colspan="2">Correlation (R2) (C31)</td><td>N/A</td><td>N/A</td><td>N/A</td><td>0.95</td><td>0.88</td><td>N//A</td></tr>
<tr><td colspan="2">Model goodness of fit (CV[RMSE]) (C32)</td><td>N/A</td><td>N/A</td><td>N/A</td><td>7.4%</td><td>10.5%</td><td>N//A</td></tr>
<tr><td colspan="2">Auto-correlation (Durbin-Watson) (C33)</td><td>N/A</td><td>N/A</td><td>N/A</td><td>0.77</td><td>0.34</td><td>N//A</td></tr>
<tr><td colspan="2">Normal distribution (Anderson-Darling)(C34)</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td><td>N/A</td></tr>
<tr><td colspan="2">Statistical significance (SANAS test) (C35)</td><td>N/A</td><td>N/A</td><td>N/A</td><td>PASS</td><td>PASS</td><td>N//A</td></tr>
<tr><td colspan="2">Statistical significance (F-test) (C36)</td><td>N/A</td><td>N/A</td><td>N/A</td><td>PASS</td><td>PASS</td><td>N//A</td></tr>
<tr><td colspan="2">Over/under prediction (NDB) (C37)</td><td>N/A</td><td>N/A</td><td>N/A</td><td>PASS</td><td>PASS</td><td>N//A</td></tr>
<tr><td colspan="8">Statistical Uncertainty (B4)</td></tr>
<tr><td colspan="2">Measurement uncertainty (C41)</td><td>0.87%</td><td>0.87%</td><td>0.98%</td><td>1.4%</td><td>1.4%</td><td>1.4%</td></tr>
<tr><td colspan="2">Savings uncertainty (80/20) (C42)</td><td>2.06%</td><td>3.48%</td><td>16.0%</td><td>70.6%</td><td>23.6%</td><td>26.9%</td></tr>
<tr><td colspan="2">Combined uncertainty (68/50) (C43)</td><td>N/A</td><td colspan="2">3.13%</td><td>4.40%</td><td>1.90%</td><td>N//A</td></tr>
</table>

Table C-35: Case study 2 – Score table for model comparison

<table>
<tr><th>Model Selection</th><th colspan="2">12L Compliance (B1)</th><th>Economic Feasibility (B2)</th><th colspan="7">Model Validation (B3)</th><th colspan="3">Statistical Uncertainty (B4)</th></tr>
<tr><td>Criterion</td><td>C11</td><td>C12</td><td>C21</td><td>C31</td><td>C32</td><td>C33</td><td>C34</td><td>C35</td><td>C36</td><td>C37</td><td>C41</td><td>C42</td><td>C43</td></tr>
<tr><td>Model 1</td><td>5</td><td>5</td><td>5</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>5</td><td>5</td><td>0</td></tr>
<tr><td>Model 2</td><td>5</td><td>4</td><td>4</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>5</td><td>4</td><td>4</td></tr>
</table>

Model 3	5	3	1	5	5	1	0	0	5	5	4	1	4
Model 4	5	1	2	4	4	1	0	0	5	5	4	2	5
Model 5	5	2	1	0	0	0	0	0	0	0	4	2	0

The scores from the table above, along with the priorities determined in Chapter 3 (Table 3-6) were used to determine the final model scores. The final scores can be seen in Table C-36.

Table C-36: Case Study 2 – AHP final model scores

Claim Model	MODEL 1: Steam energy recovery	MODEL 2: Multi-year assessment	MODEL 3: Different operation modes	MODEL 4: All parameter	MODEL 5: Daily Intensity
Scores	3.87	3.55	3.22	2.93	2.15

In Table C-36 Model 1 is indicated to be the highest ranked model with a score of 3.87. Hence, Model 1 is the most eligible model to be claimed. Although this model didn't include any statistical analysis, it is rank the highest as it has high scores in the other categories. Models 2 and 3 are the next highest ranked models and can be used as validation models.

APPENDIX C.3 : CASE STUDY 3 APPENDIX

Case study 3 is not discussed in detail in the document. This annex provides information regarding the detailed results of each step of the uncertainty Q&M flowchart which is not included in-text.

APPLICATION OF Q&M FLOWCHART METHODOLOGY

As with the other case studies, the Five-Step Approach of the uncertainty Q&M flowchart is carried out.

Step 1: ESM Isolation

Baseline and performance assessment selection

Once again, the ESM assessment periods are chosen to align with the financial years. The assessment periods can be seen in Table C-37.

Table C-37: Case study 3 - Baseline and performance assessment periods

Period	Date
Baseline Period	1 July 2014 - 30 June 2015
Performance Assessment Period	1 July 2015 - 30 June 2016

The data availability is constructed and can below in Table C-38.

Table C-38: Case study 3 - Data availability for compressor network

Measurement	Measurement device	Data source	Data resolution
Electricity	Power metering	Electricity supply invoices	Monthly
	Power metering	Check metering database	Half hourly
Compressed air flow	Flow metering (volumetric/mass)	Check metering database	2-minute interval
Compressed air pressure	Pressure metering	Check metering database	2-minute interval
Production	Mass flow metering	Gold processing plant figures	Monthly
Occupancy	Personnel clock system	Personnel occupancy figures	Monthly

Measurement Boundary Selection

The measurement boundary is constructed around the compressor air network. It is an isolated all-parameter boundary as with case study 1 and 2. A POM diagram is constructed with the status of the data as indicated in Figure C-15 .

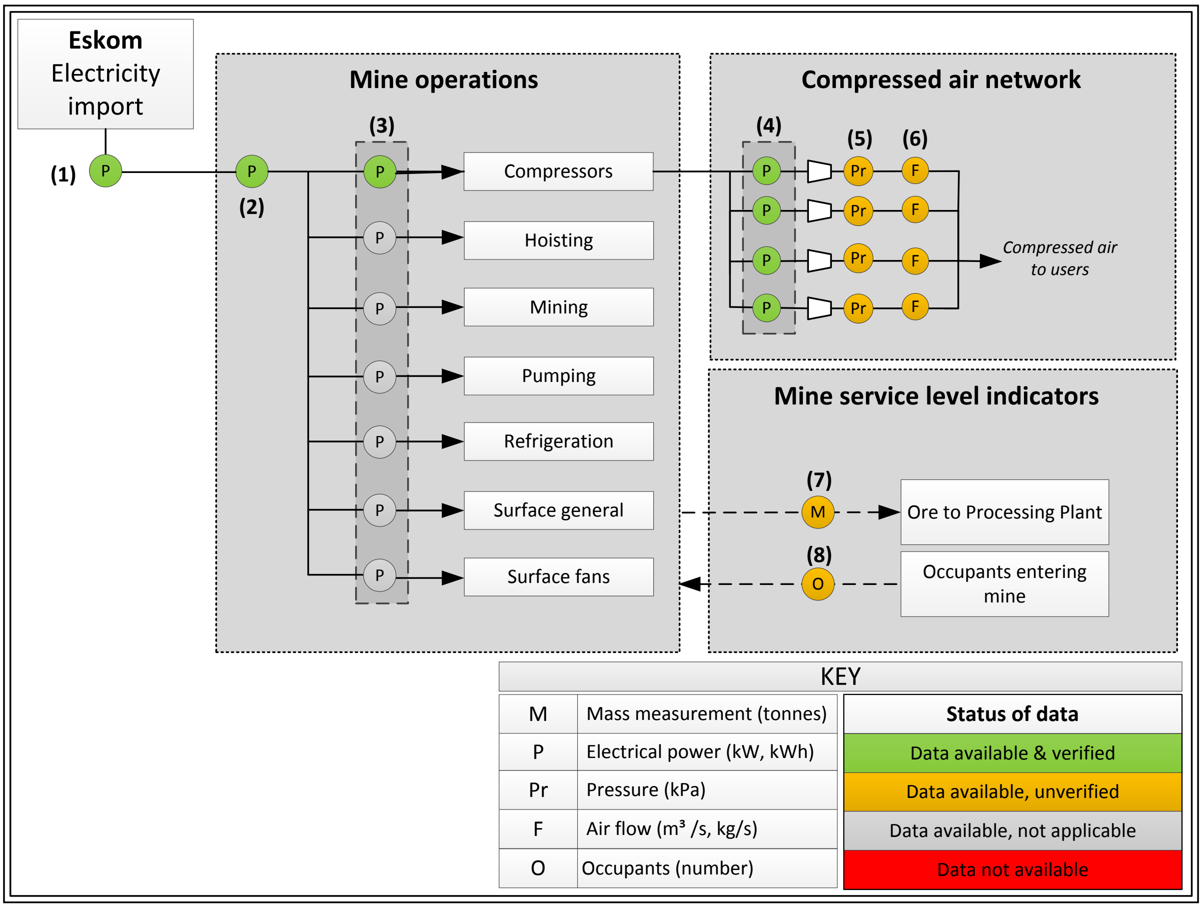

Figure C-15: Case study 3 - Points of measurement diagram

A complete data availability is then constructed using the POM diagram and initial data availability table as seen by Table C-39.

Table C-39: Case study 3 - Complete data availability table

Measurement	Measurement device	Data source	Data resolution	No.	Status of data
Electricity	Power metering	Electricity supply invoices	Monthly	1	Available, verified and compliant
	Power metering	Check metering database	Half hourly	2, 3 & 4	Available, verified and compliant
Compressed air flow	Flow metering (volumetric/mass)	Check metering database	2-minute interval	6	Available and verified

Compressed air pressure	Pressure metering	Check metering database	2-minute interval	5	Available and verified
Production	Mass flow metering	Gold processing plant figures	Monthly	7	Available and verified
Occupancy	Personnel clock system	Personnel occupancy figures	Monthly	8	Available and verified

It can be noted from Figure C-15 that the power data points represent compliant (calibrated) data. However, the other data points, compressed air pressure and flow as well as the tonnes of ore being sent to the processing plant and the amount if occupants entering the mine, are not compliant. The next step in the process is Database Management.

Step 2: Database Management

Redundancy Dataset Analysis

The redundant data points identified are for the full facility electricity data. The Electricity supply invoices, incomer data and sub-metering check meter data are compared (See Figure C-16). A 0.29% difference is observed between the Electricity invoice data and incomer check meter data, and a 0.71% difference between Electricity invoice data and sub-metering data.

These differences are all under 1%, which indicates that all three the datasets agree well. This also means that the check metering data is trustworthy, as it agrees so closely with the Electricity invoice data.

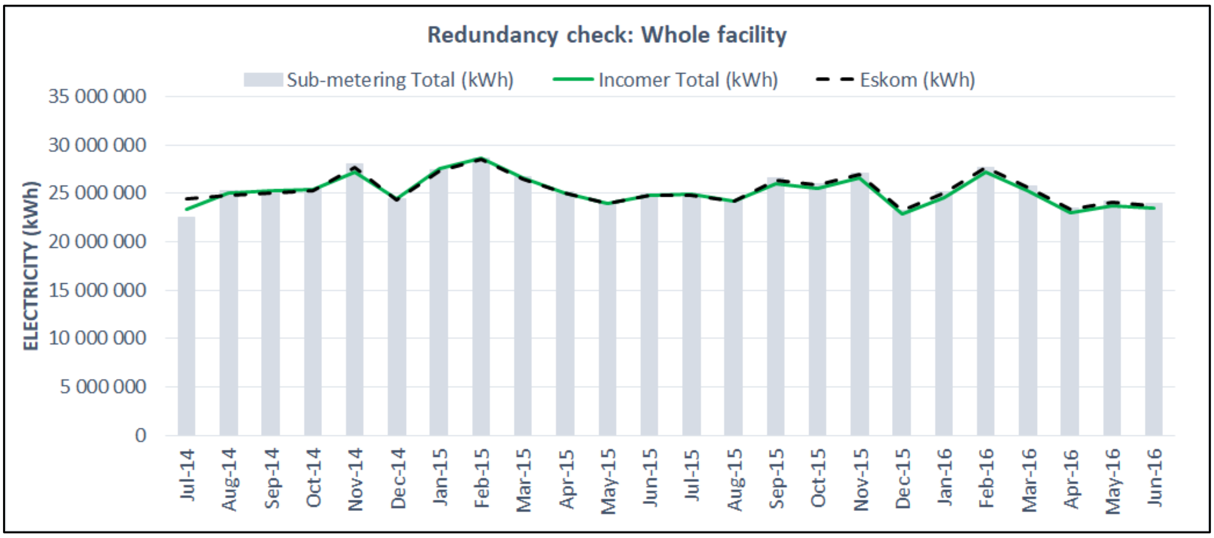

Figure C-16: Case study 3 - Redundancy check

Dataset Interrogation Results

The results for the dataset interrogation can be seen in Table C-40. Dataset interrogation is carried out on the four variables indicated in Table C-40. The individual graphs for each of the variables can be seen below.

<u>Compressed air</u>

The profile for compressed airflow can be seen in Figure C-17 below. The first five months of the profile indicates data loss/ no data is recorded.

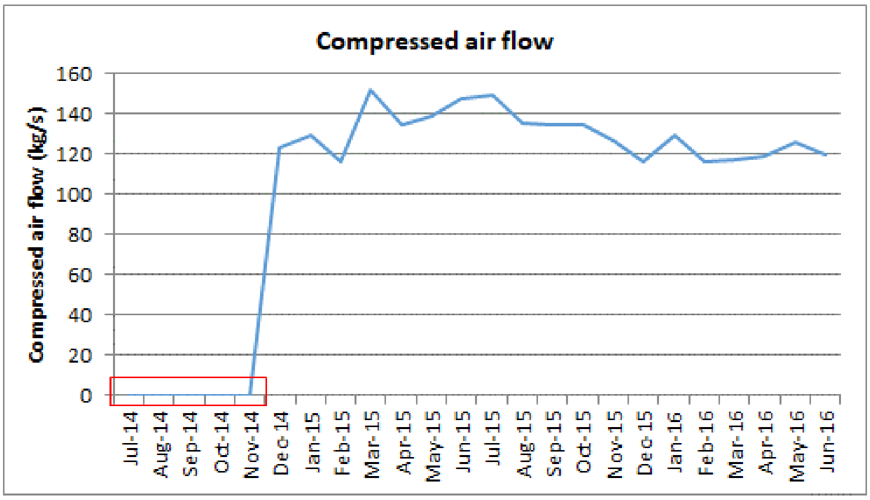

Figure C-17: Case study 3 - Compressed airflow dataset interrogation

<u>Compressor electricity</u>

The profile for compressor electricity can be seen in Figure C-18 below. No abnormalities are observed in the profile.

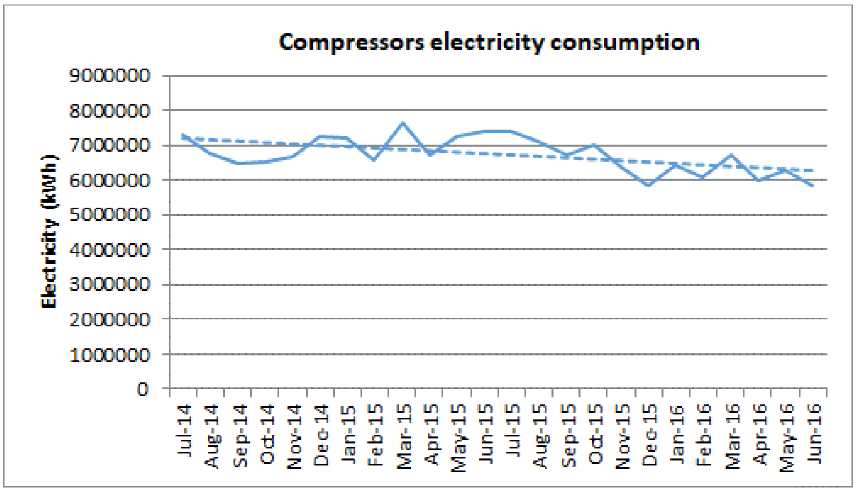

Figure C-18: Case study 3 – Compressor electricity dataset interrogation

Mine occupancy and production

The profiles for occupancy and production can be seen in Figure C-19 below. No abnormalities are observed in the profile.

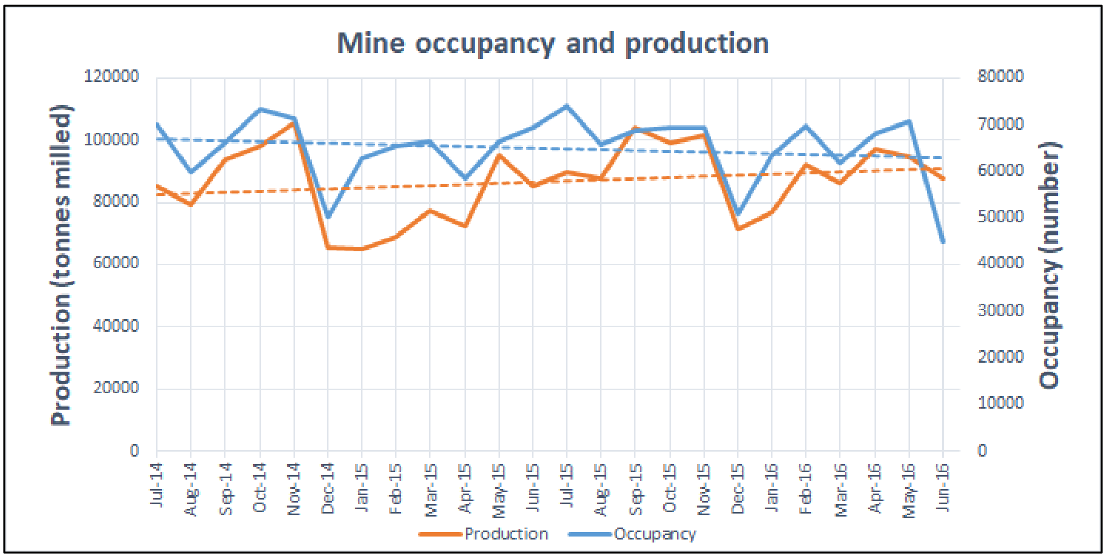

Figure C-19: Case study 3 – Occupancy and production dataset interrogation

A summary of the dataset interrogation results is provided in Table C-40 below.

Table C-40: Case Study 3 - Dataset interrogation checklist results

Variable	Data source	Spikes	Meter malfunctions	Data loss	Abnormal operation	Comment
Compressor electricity consumption	Check metering	None	None	None	Present	Compressor no. 3 not running from 13th Dec 2015 – June 2016
Airflow	Flow metering	None	None	Present	Present	Data loss first five months of the baseline period.
Production	Mass metering	None	None	None	None	-
Occupancy	Clock sheets	None	None	None	None	-

Abnormal operation is seen in the electricity data. This is due to a compressor (Compressor 3) being offline for the period indicated in Table C-40. The pressure data has data loss. The airflow data also displays two types of irregularities. The first being data loss, there is no data logged for the airflow in the first five months of the baseline period. No irregularities are seen for the production or occupancy data.

Universal Database Checklists

Having carried out dataset interrogation the universal dataset checklists are compiled for all the variables. These can be found below.

Table C-41: Case study 3 – Electricity invoice Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Electricity			
Measurement units:	kilowatt (kW)			
ID/Tag name(s):	Monthly Invoice			
Instrumentation used:	Invoice			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June /FY	Financial Year	
	Changeable period	Beginning	7	2014
		End	6	2016
Boundary applicability	Full facility		Yes	No
	Section/Department		Full facility	
	Section/Department		Mine Operations	
Data availability	Resolution	Highest available	Monthly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	>4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Electricity to mine	
		Environmental	N/A	
		Strategic operations	Mine Operations	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Filed documents	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Invoices	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Available	Yes	No

Table C-42: Case study 3 – Electricity meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Compressor Electricity			
Measurement units:	kilowatt (kW)			
ID/Tag name(s):	Tag data from database			
Instrumentation used:	Individual check metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June /FY	Financial Year	
	Changeable period	Beginning	7	2014
		End	6	2016
Boundary applicability	Full facility		Yes	No
	Section/Department		Compressors	
	Section/Department		Mine Operations	
Data availability	Resolution	Highest available	Half-hourly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	>4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	Electricity to compressors	
		Environmental	N/A	
		Strategic operations	Mine Operations	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	Calibrated	
		Frequency	At installation	
		Archive records	Filed documents	
		Archive period	>10 years	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Mine electricity reticulation diagrams	
		Archive records	Signed documents	
		Archive period	>2 years	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Available	Yes	No

Table C-43: Case study 3 – Air pressure Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Compressed air delivery pressure			
Measurement units:	kPa			
ID/Tag name(s):	Tag data from database			
Instrumentation used:	Individual pressure metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June /FY	Financial Year	
	Changeable period	Beginning	7	2014
		End	6	2016
Boundary applicability	Full facility		Yes	No
	Section/Department		Compressors	
	Section/Department		Mine Operations	
Data availability	Resolution	Highest available	Half-hourly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	>4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	N/A	
		Environmental	N/A	
		Strategic operations	Mine Operations	
		Human resources	N/A	
		Other	Compressed air to mines	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	N/A	
		Frequency	N/A	
		Archive records	N/A	
		Archive period	N/A	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Available	Yes	No

Table C-44: Case study 3 – Air flowrate Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Compressed air delivery flowrate			
Measurement units:	m3/s			
ID/Tag name(s):	Tag data from database			
Instrumentation used:	Volumetric flow metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June /FY	Financial Year	
	Changeable period	Beginning	12	2014
		End	6	2016
Boundary applicability	Full facility		Yes	No
	Section/Department		Compressors	
	Section/Department		Mine Operations	
Data availability	Resolution	Highest available	Half-hourly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	>4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	N/A	
		Environmental	N/A	
		Strategic operations	Mine Operations	
		Human resources	N/A	
		Other	Compressed air to mines	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	N/A	
		Frequency	N/A	
		Archive records	N/A	
		Archive period	N/A	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No

		With permission	Yes	No
		Available	Yes	No

Table C-45: Case study 3 – Production mass meter Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Mined ore production			
Measurement units:	Tonnes milled			
ID/Tag name(s):	N/A			
Instrumentation used:	Mass flow metering			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June /FY	Financial Year	
	Changeable period	Beginning	7	2014
		End	6	2016
Boundary applicability	Full facility		Yes	No
	Section/Department		N/A	
	Section/Department		N/A	
Data availability	Resolution	Highest available	Monthly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	>4 years	
Applicability to key performance indicator	Focus area	Production	Ore mined	
		Energy	N/A	
		Environmental	N/A	
		Strategic operations	Mine operations	
		Human resources	N/A	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	N/A	
		Frequency	N/A	
		Archive records	N/A	
		Archive period	N/A	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Not available	
		Archive records	N/A	
		Archive period	N/A	
Transparency of data	Data acquisition	Public domain	Yes	No

		On request	Yes	No
		With permission	Yes	No
		Available	Yes	No

Table C-46: Case study 3 – Occupancy Universal Dataset Checklist

Universal Dataset Checklist				
Details:				
Measurement:	Occupancy			
Measurement units:	No of people underground			
ID/Tag name(s):	N/A			
Instrumentation used:	Personnel clock system			
Criteria of evaluation:				
Reporting Period	Calendar year	July - June /FY	Financial Year	
	Changeable period	Beginning	7	2014
		End	6	2016
Boundary applicability	Full facility		Yes	No
	Section/Department		N/A	
	Section/Department		N/A	
Data availability	Resolution	Highest available	Monthly	
	Available period	Full assessment	Yes	No
		Periodically	N/A	
	Historic data	Archive records	Database	
		Archive period	>4 years	
Applicability to key performance indicator	Focus area	Production	N/A	
		Energy	N/A	
		Environmental	N/A	
		Strategic operations	N/A	
		Human resources	Workers entering mine	
		Other	N/A	
Internal Management	Data quality assurance	Procedure	Yes	No
		Type	N/A	
		Frequency	N/A	
		Archive records	N/A	
		Archive period	N/A	
Measurement traceability	Traceability description	Origin to end point	Yes	No
	Supporting documents	References	Logs for clocking system	
		Archive records	N/A	
		Archive period	N/A	

Transparency of data	Data acquisition	Public domain	Yes	No
		On request	Yes	No
		With permission	Yes	No
		Available	Yes	No

Step 3: Model Development

In this step six models were developed to quantify the EES using existing M&V reports. A summary of these models is provided in Figure C-24.

The first model developed is an unadjusted energy reduction model. Models 2 to 4 are regression type models, where the independent variable are the peak period airflow, production and occupancy, respectively. The final two models are energy intensity models, with production and occupancy as the independent variable. More information on how these models is provided below.

Model 1: Unadjusted energy reduction

The first model generated is an unadjusted energy reduction. This model uses the y-o-y difference in energy consumption of the compressors to calculate the EES.

Table C-47: Case study 3 – Model 1: Unadjusted energy reduction

FY15 Electricity consumption (kWh)	83 812 993
FY16 Electricity consumption (kWh)	77 810 562
Unadjusted energy reduction (kWh)	**6 002 430.76**

As can in Table C-47 the energy saving is calculated as 6.0 GWh.

Model 2: Peak drilling period regression

Model 2 calculates the EES using two models; one for the weekdays (Figure C-20) and one for the Saturdays (Figure C-21). As can be seen below.

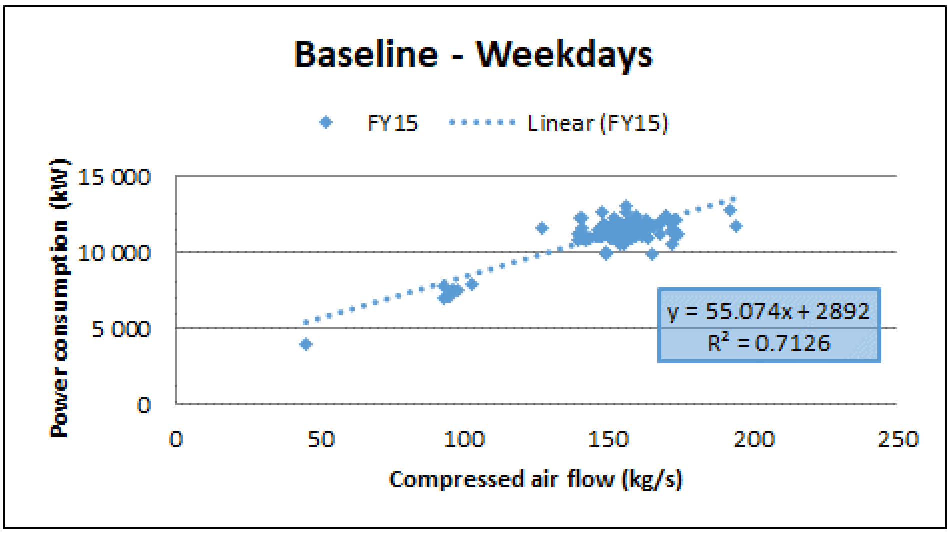

Figure C-20: Case study 3 – Model 2: Weekdays peak drilling period regression

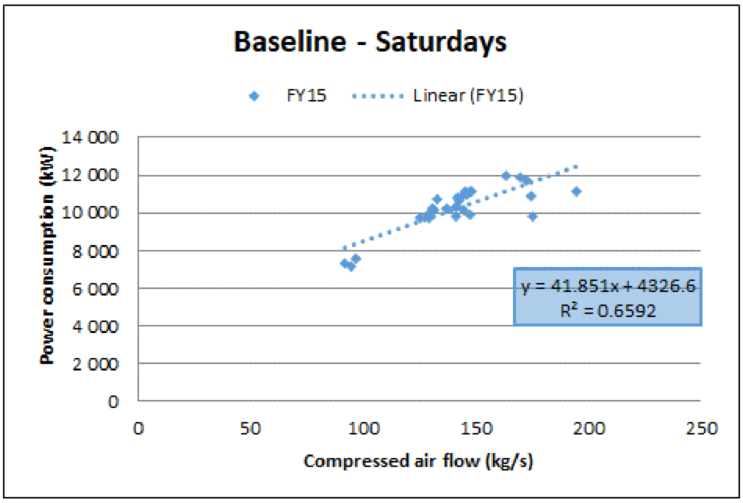

Figure C-21: Case study 3 – Model 2: Saturdays peak drilling period regression

The EES value quantified by this model is 7.5GWh as can be seen in Table C-48.

Table C-48: Case study 3 - Model 2 Energy savings

SUMMARY		Full year result (MWh)
Baseline energy consumption	82 915 631	84 064
Adjusted baseline energy consumption	84 094 294	85 259
Assessment period energy consumption	76 733 701	77 796
Savings	7 360 593	**7 463**

Model 3: Production

The third model developed is a regression model. Production is regressed against electricity consumption. A very poor coefficient of correlation is observed (~0). This indicates that there is no correlation between the power consumption and production. See Figure C-22 below for the model.

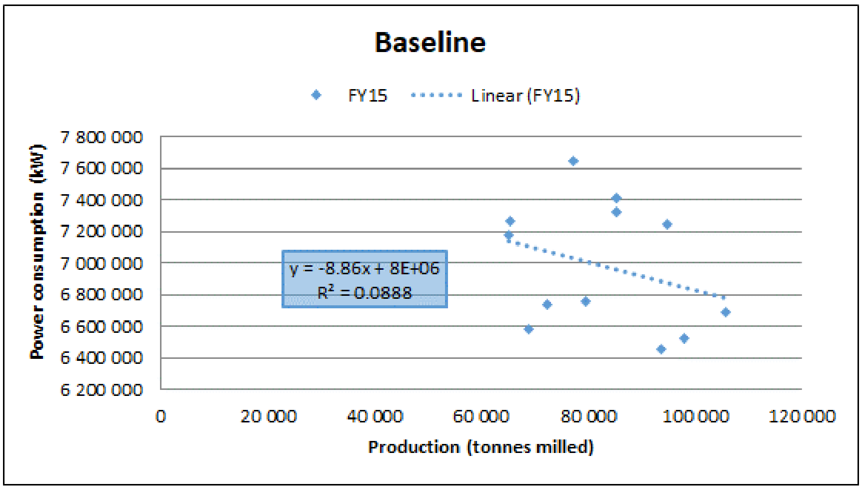

Figure C-22: Case study 3 – Model 3: Production regression

The EES is quantified as 5.2 GWh as indicated in Table C-49.

Table C-49: Case study 3 – Model 3 Energy saving

Electricity (FY15)	83 812 993
Electricity (FY16)	77 810 562
Predicted Electricity (FY16)	82 961 364
Energy Saving (GWh)	**5 150 802.41**

Model 4: Occupancy regression

The fourth model developed is a regression model. Occupancy is regressed against electricity consumption. A very poor coefficient of correlation is observed (~0). This indicates that there is no correlation between the power consumption and occupancy. See Figure C-23 below for the model.

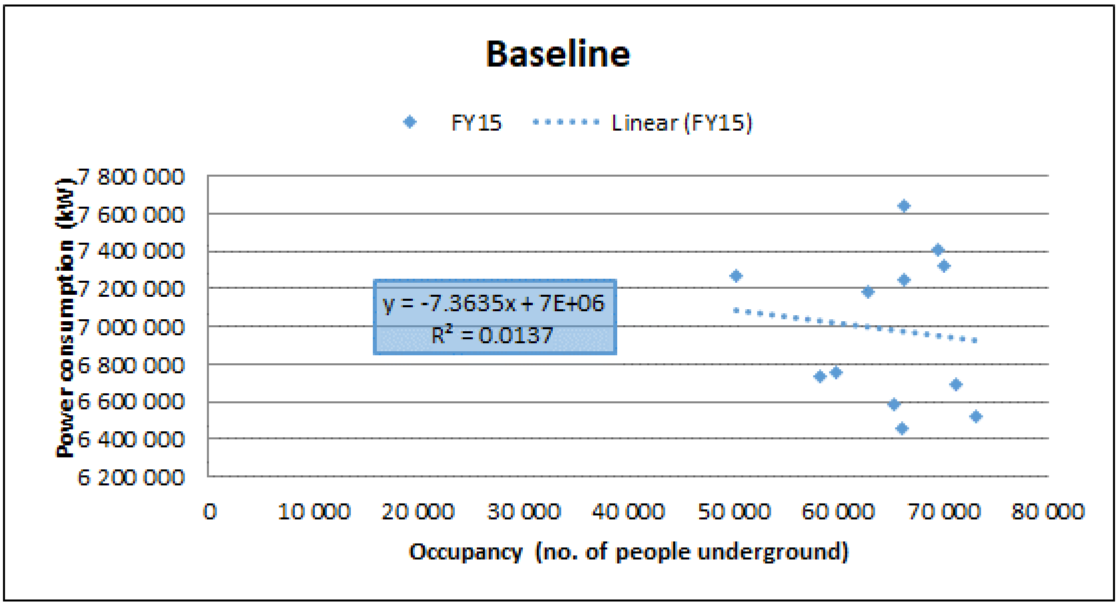

Figure C-23: Case study 3 – Model 4: Occupancy regression

The EES is quantified as 6.0 GWh as indicated in Table C-50.

Table C-50: Case study 3 – Model 4 Energy saving

Electricity (FY15)	83 812 993
Electricity (FY16)	77 810 562
Predicted Electricity (FY16)	83 834 317
Energy Saving (GWh)	**6 023 755**

Model 5: Production Energy Intensity

Model 5 is a production energy intensity model. The saving is calculated by taking the difference between the actual electricity consumption and the predicted electricity. The savings is as quantified as 14 GWh and can be seen in Table C-51.

Table C-51: Case study 3 – Model 5 Energy saving

MODEL 5: **Production Energy Intensity**	
Production (FY15)	991 429
Electricity (FY15)	83 812 993
E/P (FY15)	85
Production (FY16)	1 087 550
Actual electricity consumption (FY16)	77 810 562
Predicted Electricity (FY16)	91 938 828
Energy Saving (kWh)	**14 128 265**

Model 6: Occupancy Energy Intensity

Model 6 is an occupancy energy intensity model. The saving is calculated by taking the difference between the actual electricity consumption and the predicted electricity. The savings is as quantified as 5.7 GWh and can be seen in Table C-52.

Table C-52: Case study 3 – Model 6 Energy saving

MODEL 6: **Occupancy Energy Intensity**	
Production (FY15)	779 313
Electricity (FY15)	83 812 993
E/P (FY15)	108
Production (FY16)	776 417
Actual electricity consumption (FY16)	77 810 562
Predicted Electricity (FY16)	83 501 536
Energy Saving	**5 690 973**

A summary of the models developed can be seen in Figure C-24. All the models have values in a similar range except Model 5, which displays a big saving compared to the other models.

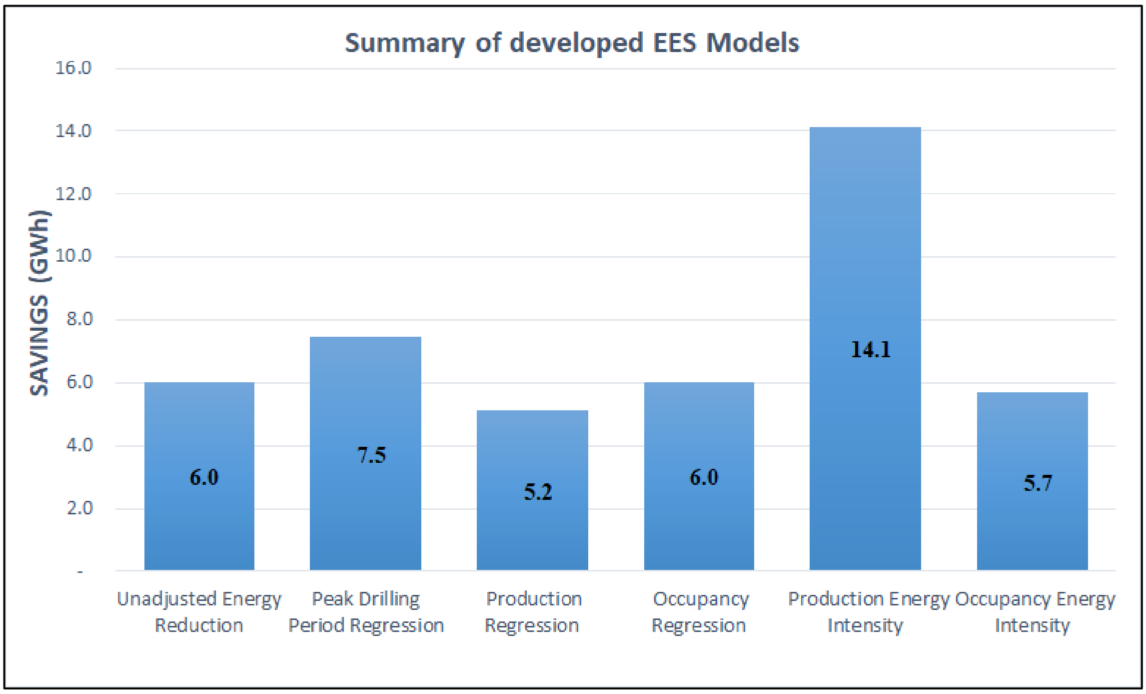

Figure C-24: Case study 3: Model development - Summary of models

Having generated the models, the uncertainty assessment can be carried out.

Step 4: Uncertainty Assessment

The results of the model validation and uncertainty tests can be found in Table C-53.

Table C-53: Case study 3 - Uncertainty assessment results

Model Options	Model 1	Model 2		Model 3	Model 4	Model 5	Model 6
Model Validation Tests							
Correlation (R2)	-	0.71	0.66	0.09	0.01	-	-
P-value	-	1.9×10^{-39}	1.6×10^{-7}	-	-	-	-
Auto-correlation (Durbin-Watson)	-	1.45	2.46	-	-	-	-
Normal distribution (Anderson-Darling)	-	-	-	-	-	-	-
Model Prediction Validation Tests							
Model goodness of fit (CV[RMSE])	-	5.92%	8.92%	-	-	-	-
Statistical significance (SANAS test)	-	PASS	PASS	-	-	-	-
Statistical significance (F-test)	-	PASS	PASS	-	-	-	-
Over/under prediction (NDB)	-	PASS	PASS	-	-	-	-
Statistical Uncertainty Tests							
Measurement uncertainty (C41)	1.00%	1.00%		-	-	-	-
Savings uncertainty (80/20) (C42)	15.0%	12.8%	32.1%	36.7%	31.4%	-	-
Combined uncertainty (68/50) (C43)	-	5.23%		-	-	-	-

In Table C-53 above the results of the uncertainty assessment can be seen. Model 1, 5 and 6 could not undergo model validation and model prediction validation tests.

Model 1 can only undergo the last type of test, which is the statistical uncertainty test. The only quantifiable uncertainty for model 1 is due to model uncertainty. This uncertainty is hence directly applied to the baseline to determine its possible effect. It is observed that with an equipment measurement uncertainty of 1.00%. this translates to a 15% uncertainty on the savings.

Model 2 – 4 are regression type models. Hence, they are tested for the correlation coefficient (R^2) to determine if the model indicates a relationship between the regressed variables. Model 2 indicates a good R^2 values, however models 3 and 4 do not. Due to model 3 and 4 not displaying good R^2 they do not go further model validation tests, as they have proven to be bad models. As can be seen in Table C-53 model 2 passes the rest of the model validation and model prediction validation tests. Models 5 and 6 did not undergo statistical uncertainty tests, this is because model 5 shows a high savings value in comparison to the other models, and model 6 uses occupancy data which does not use a meter – hence calculation of measurement uncertainty would not reflect all relevant instrument error.

Finally, where applicable the uncertainties where combined. The models had lowed combined uncertainty values and passed the test at the prescribed 68/50 uncertainty interval. The last step of the uncertainty Q&M flowchart is then carried out. The AHP method is used to rank the models.

Step 5: Model Selection

The models were scored according to the prescribed criteria. The model comparative analysis results can be seen in Table C-54. The scores can be seen in

Table C-55.

Table C-54: Case study 3 – Model selection comparison evaluation

Feasible Claim Model (A1)		Model 1	Model 2		Model 3	Model 4	Model 5	Model 6
12L Compliance (B1)								
Compliant dataset **(C11)**		Yes	No		No	No	No	No
Conservativeness of saving **(C12)**	Value (GWh)	6.00	7.46		5.15	6.02	14.1	5.69
	Rank	0.60	0.20		1.00	0.40	0.00	0.80
Economic Feasibility (B2)								
Significance of saving **(C21)**		7.16%	8.87%		6.15%	7.19%	16.9%	6.79%
Model Validation (B3)								
Correlation (R2) **(C31)**		N/A	0.71	0.66	0.09	0.01	N//A	N//A
Model goodness of fit (CV[RMSE]) **(C32)**		N/A	5.92%	8.92%	N//A	N//A	N//A	N//A
Auto-correlation (Durbin-Watson) **(C33)**		N/A	1.45	2.46	N//A	N//A	N//A	N//A
Normal distribution (Anderson-Darling) **(C34)**		N/A	N/A	N/A	N/A	N/A	N//A	N//A
Collinearity (VIF/Condition No.)		N/A	N/A	N/A	N/A	N/A	N//A	N//A
Statistical significance (SANAS test) **(C35)**		N/A	Pass	PASS	N//A	N//A	N//A	N//A
Statistical significance (F-test) **(C36)**		N/A	PASS	PASS	N//A	N//A	N//A	N//A
Over/under prediction (NDB) **(C37)**		N/A	PASS	PASS	N//A	N//A	N//A	N//A
Statistical Uncertainty (B4)								
Measurement uncertainty **(C41)**		1.00%	1.00%		N//A	N//A	N//A	N//A
Savings uncertainty (80/20) **(C42)**		15%	12.8%	32.1%	36.7%	31.4%	N//A	N//A
Combined uncertainty (68/50) **(C43)**		N/A	48.9%		N//A	N//A	N//A	N//A

Table C-55: Case study 3 - Score table for model comparison

Model Selection	12L Compliance (B1)		Economic Feasibility (B2)	Model Validation (B3)							Statistical Uncertainty (B4)		
Criterion	C11	C12	C21	C31	C32	C33	C34	C35	C36	C37	C41	C42	C43
Model 1	5	4	3	0	0	0	0	0	0	0	5	0	0
Model 2	1	2	4	5	5	5	0	5	5	5	2	3	2
Model 3	1	5	1	0	0	0	0	0	0	0	0	0	0
Model 4	1	3	3	0	0	0	0	0	0	0	0	0	0
Model 5	1	0	5	0	0	0	0	0	0	0	0	0	0
Model 6	1	5	2	0	0	0	0	0	0	0	0	0	0

The scores from the table above, along with the priorities determined in Chapter 3 (Table 3-6) are used to determine the final model scores. The final scores can be seen in Table C-56.

Table C-56: Case Study 3 - AHP final model scores

Feasible Claim Model	Model 1: Unadjusted Saving	Model 2: Peak Drilling Model	Model 3: Production Regression	Model 4: Occupancy Regression	Model 5: Production EI	Model 6: Occupancy EI
Scores	2.92	2.71	1.67	1.56	1.21	1.86

Table C-56 indicates that model 1 has the highest ranking. In other word, it meets the goals of the AHP the closest and should be used as the feasible claim model. Models 2 and 6 are the next highest ranked models and should accompany the feasible model as validation models.