Chair of Drilling and Completion Engineering

Master's Thesis

Monitoring of Greenhouse Gas Emissions in Well Services Operations

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AFFIDAVIT

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I declare that I have read, understood, and complied with the guidelines of the senate of the Montanuniversität Leoben for "Good Scientific Practice".

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Abstract

Global warming has become a serious topic in the past few years, forcing the European Union to take immediate action to reach net-zero emissions by 2050. According to the US EPA [1]: the warming effect was increased by 45% in the past two decades. As a matter of fact these new regulations will affect all major industries and their future objectives, especially the oil and gas industry. From a personal point of view, the oil market demand will start to decrease drastically, leaving the oil and gas companies in a position where they must rethink investing billions of dollars in meeting the required regulations and developing new oil fields.

Wintershall Dea (WD), the leading European independent gas and oil company with more than 120 years of experience as an operator, is targeting to reduce scope 1 and scope 2 greenhouse gas emissions of its upstream activities (operated and non-operated at equity share basis) to net zero by 2030. Indeed, this is not an easy task; meeting the rising energy demand due to increased population and reducing emissions simultaneously can be quite challenging. However, in 2020 WD has set clear and measurable targets to drive the energy transition.

Based on the research conducted by the WD last year, it was found that an essential part of the solution is in correctly measuring the problem. The correct quantification of the emission is an enabler to correctly plan for net zero. However, a bigger problem arises when the factors contributing to greenhouse gas emissions are being estimated, which leads to a lack of accurate emissions reporting. Utilizing measuring tools and sensors is one approach to reducing these uncertainties, but since the corporation does not control all of the equipment used in the field, installing new measurement devices is practically impossible.

This master's thesis aims at developing a software tool that can document the associated uncertainty by gathering attributes to be associated with the input data from the primary contributors to greenhouse gas (GHG) emissions in well service activities.

The software tool successfully incorporated the designed flowcharts from the previous year's project. New flowcharts were also added to some of the parameters. However, the software tool was only tested with fictitious data since real data collection was not possible due to time constraints.

Zusammenfassung

Die globale Erderwärmung wurde in den letzten Jahren zu einem ernsten Thema und zwang die europäische Union sofortige Maßnahmen zu ergreifen, um bis 2050 die Netto-Null-Emissionen zu erreichen. Laut US EPA: Der Erwärmungseffekt ist in den letzten zwei Jahrzehnten um 45 % gestiegen. Tatsächlich werden diese neuen Vorschriften alle wichtigen Industrien und ihre zukünftigen Ziele betreffen, insbesondere die Öl- und - Gasindustrie. Dort, wo die Nachfrage auf dem Ölmarkt drastisch zurückgehen wird, werden die Öl- und Gasunternehmen in eine Position geraten, in der sie überdenken müssen, Milliarden von Dollar zu investieren, um die erforderlichen Vorschriften zu erfüllen und neue Ölfelder zu erschließen.

Wintershall Dea (WD), das führende europäische unabhängige Gas- und Ölunternehmen mit mehr als 120 Jahren Erfahrung als Betreiber, hat ehrgeizige Nachhaltigkeitsziele für die Reduzierung der Scope-1- und Scope-2-Emissionen auf ein Netto-Null-Ergebnis bis 2030. In der Tat ist es keine leichte Aufgabe, den steigenden Energiebedarf aufgrund der wachsenden Bevölkerung zu decken und gleichzeitig die Emissionen zu reduzieren, kann eine ziemliche Herausforderung sein. Für 2020 hat sich WD jedoch klare und messbare Ziele gesetzt, um die Energiewende voranzutreiben.

Basierend auf den im vergangenen Jahr von der WD durchgeführten Untersuchungen wurde festgestellt, dass ein wesentlicher Schritt zur Erreichung der Nachhaltigkeitsziele darin besteht, dass das Unternehmen genau berichten muss, um die beste und effizienteste Lösung bereitzustellen. Ein größeres Problem entsteht jedoch, wenn die Faktoren geschätzt werden, die zu den Treibhausgasemissionen beitragen, insbesondere für den Kraftstoffverbrauch (FC) (mit den größten Auswirkungen auf die Emissionen), was zu einem Mangel an genauer Emissionsberichterstattung führt. Die Verwendung von Messwerkzeugen und Sensoren ist ein Ansatz zur Verringerung dieser Unsicherheiten, aber da das Unternehmen nicht alle im Feld verwendeten Geräte kontrolliert, kann eine ordnungsgemäße Messung teuer sein.

Ziel dieser Masterarbeit ist die Entwicklung eines Softwaretools, das die damit verbundene Unsicherheit verringern kann, indem Eingabedaten von den Hauptverursachern von Treibhausgasemissionen (THG) bei Bohrlochserviceaktivitäten gesammelt werden.

Das Softwaretool hat die entworfenen Flussdiagramme aus dem Vorjahresprojekt erfolgreich integriert. Einigen Parametern wurden auch neue Flussdiagramme hinzugefügt. Aber das Softwaretool wurde nur mit fiktiven Daten getestet.

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Chapter 1

Introduction

1.1 Overview

Wintershall Dea strongly supports the European Union's 2050 carbon neutrality target. The company has set a challenge for itself and committed to reducing the carbon footprint and Scope 1 and 2 greenhouse gas emissions by 2030 [2]. According to Greenhouse Gases (GHG) protocol, scope 1 emissions are direct emissions from the company-owned and controlled resources, for example, a diesel generator on the well site, whereas scope 2 emissions are indirect emissions, such as emitting purchased energy. Finally, scope 3 are all emissions that are not included in scope 2, such as transporting fuel to the operating facility [3]. WD aims to reduce the scope 1 and 2 greenhouse gas emissions of their upstream activities by 2030 to a net-zero, reduce carbon intensity, maintain zero routine flaring during operations, and reduce the methane intensity below 0.1% by 2025. The energy transition strategy is on four pillars: portfolio optimization, emissions management, innovative technologies, and offsetting [2].

Since Wintershall Dea did commit to a net-zero emissions in upstream activities, the thesis will focus only on well intervention activites at WD operated facilities and understand the factors contributing to emissions. Mr. Clemens (who wrote the first part of this thesis project) defined the following parameters as contributors to the emissions: Fuel consumption, emission factor (EF), density, and fuel grading. Furthermore, the author concluded that fuel consumption is the main parameter that has the most significant impact on the uncertainties since it is the basis of all calculations. It is challenging to estimate fuel consumption during the course of the complete workover activity due to the fact that it is not continuously monitored and can occasionally be quite expensive to measure. The team will have to depend on old databases, mathematical relationships, etc., which makes reporting difficult.

1.2 Challenges and Motivation

The development of a sustainable future is one of the main goals and concerns to be addressed in the next decades. Since the oil and gas sector are the main targets, Wintershall Dea has decided to provide attributes to the main parameters affecting greenhouse gas emissions. Table 1 shows an example of a measured input data structure that can be fed into the company-adopted software "SOFI". By providing additional attributes, the company can defend its input values. As mentioned in the introduction, to reach a Net Zero target, the company need to have accurate measurements or reliable estimations of its emissions. The plan to reach Net Zero will be as credible as the strategy to collect and document the company emissions.

Parameter	**Input Value**	**Units**	**Quality**
Fuel Consumption	1,000	Liters	Measured
Attributes:			
Accuracy	+/- 50 Liters	Device type	Velocity flowmeter
Calibration	Yes		

Table 1: SOFI input + Attributes.

The work aims at the collection of field data (with attributes) to support entries in SOFI with equipment information and accuracies.

1.3 Thesis Objective

The main objective of this work is to develop a software tool (ST) that document the uncertainties associated with the four main parameters in well intervention and well services activities.

To achieve the defined goal of the thesis, the following stepped objectives are developed to be the main focus of the thesis:

- The first part is a review and a deep understanding of what was established in Mr. Clemens Ettinger thesis and being familiar with the suggested workflows and models. This part is crucial since this master thesis work is a continuation of what was achieved previously.
- The second part covers the implementation of the logic behind the estimation and measurement workflows that were introduced in Mr. Clemens Ettinger thesis in a simple software tool. The workflows have never been tested, which makes it exciting to challenge the theory behind Mr. Clemens Ettinger thesis and optimize if required. Generating a software tool from scratch can be quite challenging, for this reason,

research will be conducted on different types of software tool (Excel, MATLAB, Python, etc.). It was found that the tool can designed with Excel built-in coding tool VBA due to its simplicity and ease of adaptation.

- The third and last part will include real-time data collection from one of Wintershall Dea's operating facilities and test the software tool with the collected data. Adjust software tool inputs in case it does not satisfy the field data. However, due to time constraints, data collection was not possible.

1.4 Thesis Structure

This work starts by introducing a methodologies to reduce the uncertainties related to estimation, followed by a second methodology to reduce the uncertainties in measurements. The methodologies are tackling the uncertainties related to well intervention and well services activities in the oil and gas industry. In addition, it includes a thorough overview on the mathematical and statistical models used in estimation. After that, a section was devoted to the 4 main parameters. This includes a literature review and new methodologies to be implemented. Then, the developed Software tool has been introduced in detail, defining its features and applicability. The results provide a representation of the 4 main parameters including attributes to further reduce the uncertainties in estimation and measurement and consolidate the input data before their implementation to the company adopted software. Finally, the thesis work is summarized, the Software tool limitations, and guidelines for optimizing the Software tool are discussed.

Chapter 2

Uncertainty Estimation Tools

2.1 Overview

This section of the thesis will be highlighting on the research made to accomplish the required objective on documenting and potentially reduce the uncertainty associated to estimations and measurements.

After careful consideration of the estimation flowchart (Figure 22) designed by Mr. Clemens in his thesis [4], the below process (Figure 1) has been designed to reduce the estimation uncertainty (the below process is not a replacement of the estimation flowchart designed by Mr. Clemens, but a process designed inside the flowchart after data entry). As easy as it may seem, the first step is to enable data entry. Then, the data will be put through a mathematical and statistical model to reduce the uncertainty and represent the data using fundamental statistics (Mean, Standard deviation, Uncertainty, Confidence Interval). Finally, a value with its associated uncertainty will be generated as an output, and this value will then be incorporated into the company-adopted software "SOFI".

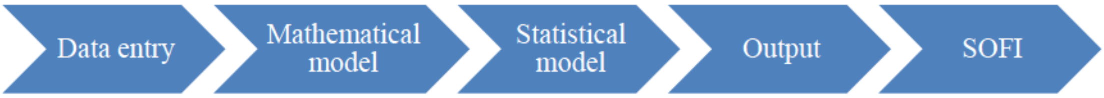


Figure 1: Designed process for estimation uncertainty reduction.

On the other hand, to summarize the flowchart designed by Mr. Clemens in his thesis (Figure 24) for measured parameters, the idea was based on the 3 main points. The first and main criteria was to check for the device calibration, calibration is an important factor since an uncalibrated device can give inaccurate readings. The Scientific Instrument Center (SIC) mentioned that the reliability of the measurements would go down if the equipment is not regularly calibrated, as well as giving inaccurate results [5]. After the calibration check, the device accuracy will be compared against the company's default accuracy limit. Finally, if the device accuracy is lower than the company accuracy limit, the cost criteria will determine which device to proceed with, otherwise, the cost criteria will be skipped. The primary purpose of going through these checks was to provide some attributes to the measured values, ultimately defending the numbers against any uncertainties.

According to the logic behind the measurement workflow the software tool should not ask for another measurement device after the calibration and accuracy criterias have been successfully achieved. Entering the cost evaluation loop should be accessible only when no devices are not achieving the required criterias.

2.2 Statistical Application in Uncertainty Reduction

Heumann et al.[5] described statistics as a collection of methods that interpret a certain sample of data or population. Data statistics play an essential role in our world, as a matter of fact, nobody can speak louder than data (unless data collection is not accurate); speaking of which, these data can be used for medical purposes, monitoring, determination of population growth, risk analysis, stocks growth forecast and much more [6]. In other words, all businesses depend on statistical analysis to help owners respond before it's too late. The following section provides an example of implementing statistical techniques in the oil and gas sectors.

I. Statistical Analysis in the Geology Sector

The exploration of hydrocarbon resources is a real challenge due to the fact that it is invisible, intangible, and buried deep underground. Understanding the distribution of hydrocarbons underground is impossible to predict future exploration sites. A significant amount of relevant data may only be collected by using several indirect methods of geophysical investigation, drilling, and logging. Right after, statistical analysis can be a key role in predicting hydrocarbons quantity and quality. Main statistical approaches can be conducted like: model formed by oil bearing sands and shales and its statistical analysis, and statistical analysis for predicting reservoir descriptions [7].

II. Statistical Analysis in the Exploration, Development, and Technology

The complexity and difficulty of exploring hydrocarbon resources also encounters high risks. Hydrocarbon reservoirs of industrial development value discovered by various exploration methods may be proved to fail or lack hydrocarbons, leading to lost exploration costs. In general, assuming about 40% of the wells can find hydrocarbons, which is an optimistic case. However, about 60% of wells have been proven to fail resulting in losses. Even for the identified hydrocarbon reservoirs of industrial development value, not all reservoirs typically encounter hydrocarbons when drilling exploration wells. Hydrocarbon exploration and development is highly risky because both technical and economic risks are difficult to predict. The economic benefits of investment also depend on the abundance of hydrocarbon resources, geological conditions and non-recoverable resources during oil extraction. These characteristics have also determined the role of control statistical analysis and forecasting in oil industry production. For example, a statistical analysis of hydrocarbon reserve growth adjusted to an increase in hydrocarbon production, a statistical analysis of simultaneous increases in investment capital. And economic benefits, and the analysis of science and technology to increase oil production and profits [7].

III. Statistical Analysis to Optimize Reservoir Performance

To properly manage the depletion of oil reservoirs, one must understand their physical properties and how they relate to production. In most cases, the difficulty is generally in interpreting the massive amount of data that is available. Mr. Leon et. Al concluded in their paper the benefits of the statistical analysis application to optimize reservoir performance [8]:

- Statistical analysis is extremely useful in tackling complex problems for which large amounts of data are available.
- Statistical analysis of data using statistical methods can spot relationships that appear to influence reservoir performance. This can indicate the importance of various control factors that may not otherwise be accountable.
- Statistical analysis transformed all available data into useful information supporting the challenging decision of terminating a project with great confidence.

2.3 Models implemented in Software Tool for Estimation

The Software tool was built in an Excel based file using the Microsoft programming language Visual Basic for Application (VBA). Since VBA is Excel friendly and easy to adapt, it was decided to proceed with it. Table 2 represents the main two models (Mathematical model, and Statistical model) and the researched methods discussed in this Chapter. The main deliverable of this table is to highlight on the method used for each model, the following points were concluded:

- The weighted arithmetic mean has been implemented for the reason of giving more importance to datasets with higher accuracies.
- Assuming that the data are normally distributed around the mean value, the Gaussian Probability Distribution was found to be the best method in this situation.

Models	Researched methods
Mathematical Model	Weighted Arithmetic Mean
Statistical Model	Gaussian Probability Distribution

Table 2: Visualization of the methods used for estimation.

2.3.1 Probability Distributions

Probability distributions are characterized by the data set itself, normally each data set has a unique probability distribution, for example, the probability of getting the number six while rolling some dice is different than the probability of car accidents per year. Data sets can be classified as discrete or continuous distributions, with the main distinction being that a discrete distribution is a data set made up of counted values (such as the number of employees in a company) and must be an integer. Contrarily, continuous distribution values cannot be completely accurate. In other words, they are essentially measured. For instance, if a person's height is measured, it is unlikely that two people will have the same height [6].

Statistics professionals prefer to work with large data sets because, according to Winters et al., the more data there are, the more likely the output will have a normal distribution [9].

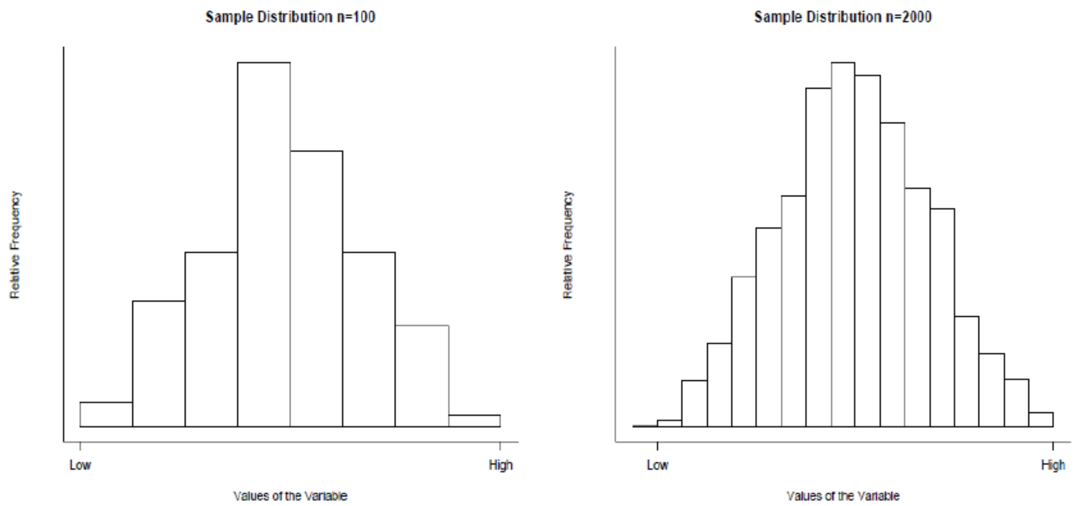


Figure 2: Graphical comparison between small and large sample size [10].

To prove Winters's statement, Figure 2 is a representation of two data set distribution, one can clearly conclude that the higher sample size resulted in a smoother distribution.

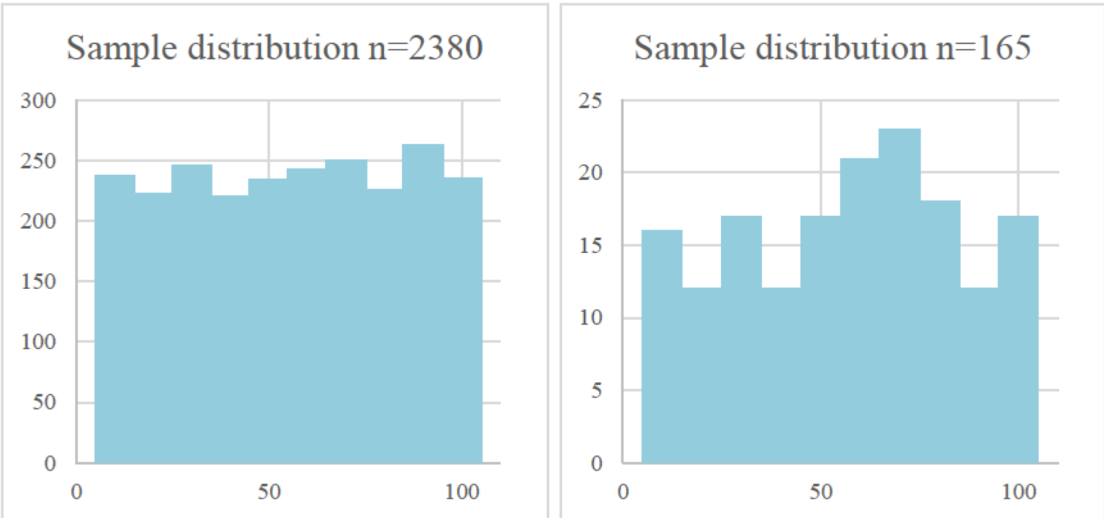


Figure 3: Sample size effect on uniform distribution.

However, Winter's statement is only true if the data set are taken from a normally distributed population. In Figure 3, with the help of Excel, random numbers between 1 and 100 were generated. Since the probability of choosing one random number is uniformly distributed among all integers, the resulting graph should approximately look like a rectangle. The right histogram represents a sample of size 165, whereas the left histogram represents a sample of size 2380. Like the previous case (Figure 2), the larger sample size represented a smoother distribution, which further supports Winter's statement.

2.3.1.1 Gaussian Probability Distribution

The Gaussian probability distribution is the most commonly used distribution in science, also known as the "Bell Shaped Curve" or "Normal Distribution", this theory is a continuous distribution. The Gaussian distribution also assumes a symmetrical distribution around the mean value, which states that values close to the mean occur more frequently than data far from the mean.The mean, median, and mode are equal in a normal distribution representing the highest point of the distribution. Moreover, the standard deviation governs the width of the bell curve [11].

The Gaussian distribution equation

$$\boldsymbol{f(x)} = \frac{\mathbf{1}}{\boldsymbol{\sigma}\sqrt{\mathbf{2\pi}}}\boldsymbol{e}^{-\frac{1}{2}*(\frac{x-\mu}{\sigma})^2} \tag{1}$$

$f(x) = Probability\ function$

$x = Value\ of\ the\ variable$

$\mu = The\ mean$

$\sigma = The\ standard\ deviation$

The Empirical Rule

According to the Gaussian distribution empirical rule, 68% of the observations, 95.4% of the observations, and 99.7% of the observations will be represented by a standard deviation of the mean plus or minus one, two, or three, respectively. The following Figure is an example of a normal distribution curve:

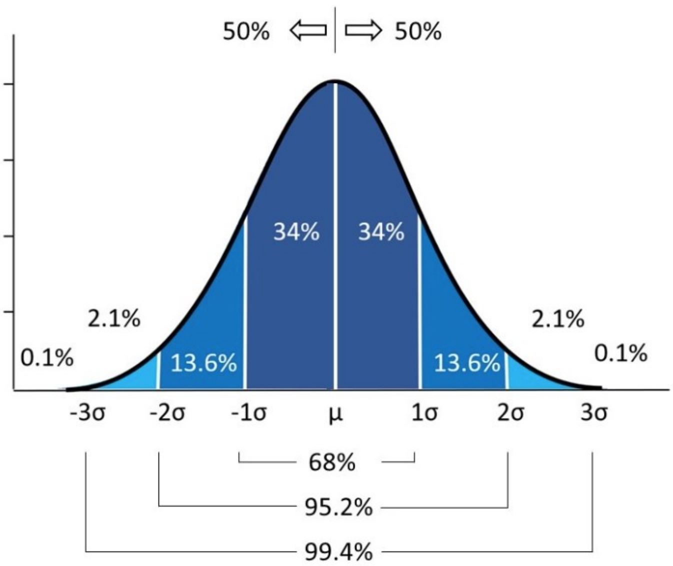


Figure 4: Normal Distribution Curve [12].

Standard Deviation

The standard deviation calculates how widely values vary from the mean. The closer the data are to the mean, the lower the standard deviation, and the more widely distributed the data are, the higher the standard deviation.

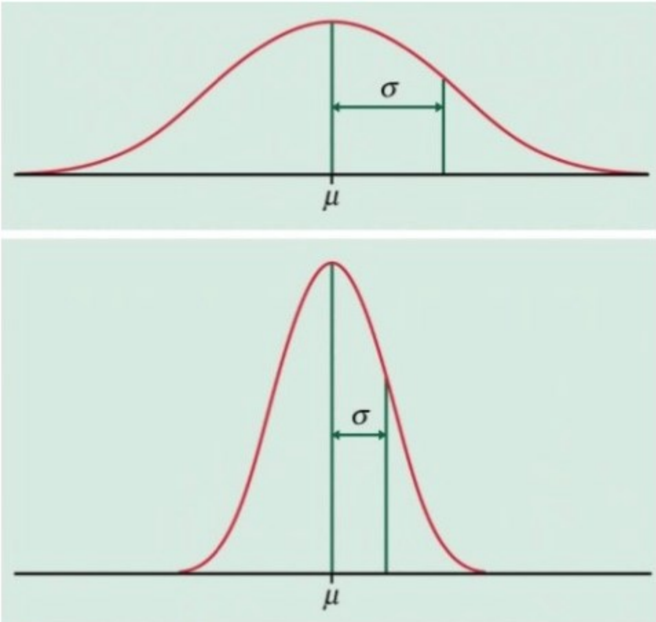


Figure 5: A comparison between high and low standard deviation [13].

Figure 6 compares a high standard deviation with wider tails, as seen on top, and a low standard deviation curve with a more compact shape on the bottom.

Central Limit Theorem (CLT)

Assuming that all samples are the same size and regardless of the population's actual distribution shape, the central limit theorem (CLT) of probability theory states that the distribution of a sample variable approaches a normal distribution as the sample size increases [14].

In other words, the mean of 5 random samples from the same population will be approximately the same of the entire population mean. This implies that no matter the sample's distribution, the mean of that sample will be expected to be approximately constant with increasing sample size.

2.3.2 Uncertainty Reduction

Uncertainty, also known as the Standard Deviation, was discussed in detail in Mr. Clemens thesis [4]. He broke down and identified the uncertainties related to estimation and measurement for the four main parameters that are affecting emissions in well intervention activities.

In this part, the estimation uncertainty is reduced by exposing the data to a mathematical and statistical model.

2.3.2.1 Weighted Arithmetic Mean

One of the easiest ways to represent a set of data is by taking the average number of that sample. However, when dealing with uncertainty, it is statistically better to assign more weight to a value with lower uncertainty [15]. For example, one might have a set of data each with different uncertainties, in this case, it makes sense to give more weight to data with lower uncertainty because they are more precise.

The equation below represents the weighted average:

$$X_{wtd} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{2}$$

$X_{wtd} = Weighted\ mean$

$w_i = Weight\ of\ a\ value$

$x_i = Mean\ Value$

The weight is being defined by making each point's weight inversely proportional to the square of its uncertainty. This will result into the following equation:

$$w_i = \frac{1}{\sigma_i^2} \tag{3}$$

$\sigma_i = Uncertainty$

Let's take for example three values with their uncertainties, 6 +/-2, 9 +/-0.5 and 10 +/-1, since 9 has the lowest uncertainty, it would make sense that the weighted mean is around that number. By using equation (15):

$$X_{wtd} = \frac{\frac{6}{2^2} + \frac{9}{0.5^2} + \frac{10}{1^2}}{\frac{1}{2^2} + \frac{1}{0.5^2} + \frac{1}{1^2}} = 9.05 \tag{4}$$

The outcome of this equation leads to the conclusion that data with high levels of uncertainty won't have a significant impact on how the weighted mean is determined. Some might say that it is then better to exclude data with high uncertainty, to some limits it is better to excluded numbers with very high uncertainty because the value itself is not precise, but higher uncertainty doesn't always mean that the number is bad, these numbers can be helpful in finding the true value and reduce its uncertainty range.

<u>Weighted Variance and Standard Deviation Equations</u>

$$VAR = \sigma^2 = \frac{1}{\sum \frac{1}{\sigma_i^2}}$$

(5)

VAR = Variance

$$SD = \sigma = \sqrt{VAR}$$

(6)

SD = Standard Deviation

Chapter 3

Software Tool Input Parameters

3.1 Revised input parameters process

The process of the 4 main parameters has been classified last year by the company as displayed in table 3. All input parameters were part of an estimation and measurement process except for emission factor, which only follows an estimation. Several solutions to mitigate the uncertainties associated with the parameters have been discussed in the previous Master Thesis authored by Mr. Clemens.

Input Parameters	Process	
	Estimation	Measurement
Fuel Consumption	X	X
Density	X	X
Fuel Grading	X	X
Emission Factor	X	

Table 3: Process for input parameters.

A few changes have been made to the input parameter process, though. The only parameters in the company's project from last year that followed the previously discussed workflows was fuel consumption and density due to the nature of its data. It has been determined that the fuel consumption could keep up with the workflows that were produced. On the other hand, the fuel grading won't be included in the estimation; instead, they will only be measured because the bill after each purchase includes fuel specifications. A specific fuel grading workflow has been developed because at the moment there is not a customized format for the analysis of the field data. Additionally, if data are unavailable, a default fuel grading will be provided as input. As the company already implemented a standard density value to be used by default in case the density data are not available for a specific area. Last but not least, emission factor will still be included in estimation, but a different estimation workflow, already developed by EMEP/EEA and IPCC, will be used [16] [17]. Default numbers for fuel consumption and density has not been assigned in the developed software tool but are requested to be added. The updated workflows will be shown later in this chapter.

Input Parameters	**Process**		
	Estimation	Measurement	Default
Fuel Consumption	X	X	X
Density	X	X	X
Fuel Grading		X	X
Emission Factor	X		X

Table 4: Revised process for input parameters.

3.2 Fuel Consumption

Under the assumption of similar fuel type (e.g. diesel petrol), the fuel consumption affects the emissions in linear proportion. Getting accurate fuel consumption is important because of the EU Emissions Trading System, where companies must buy GHG emissions certificates that allow them to emit certain amount of air pollutants, that been said, since every ton of CO2 emitted will increase the cost, the company must be accurate enough to predict their emissions [18].

To accurately report the fuel consumption, the company must use a combination of measurements and estimations to monitor and predict their fuel consumption. As discussed in Mr. Clemens Thesis, there is a large variety of ways to measure fuel consumption from gauge being the least reliable measurement method to flow meter being one of the most accurate methods, of course, each method has its own advantages and drawbacks. All companies are looking forward to improving their measurement accuracies by installing more accurate measurements devices [19].

On the other hand, estimating fuel consumption can be quite challenging. An estimation approach can be either used to predict future fuel consumptions or estimate fuel consumption from well intervention activities that has not been reported. This part will be defining 3 estimation approaches:

- Statistical analysis of fuel consumption from similar jobs
- Specific generator fuel consumption data sheet
- Generic generator fuel consumption data sheet

The statistical analysis represents what was discussed in chapter 2 Figure 1 and the models used to achieve an estimation.

The specific generator data sheet provided by the manufacturer should be the direct alternative approach for estimating fuel consumption if fuel data are not available. In research conducted by Mr. Stuver, fuel consumption was measured from 41 electric rigs and an average of 55 gallons of diesel per hour was recorded, whereas the generators technical sheet provided by the manufacturer estimated a fuel consumption of 69.5 gallons of diesel per hour. The estimated approach was around ~21% higher than the measured result, but still be the best estimate with limited data [20].

The generic generator for diesel fuel consumption can be widely accessible on the internet, for instance, a collection of data from 4 different sources were compared [21] [22] [23] [24].

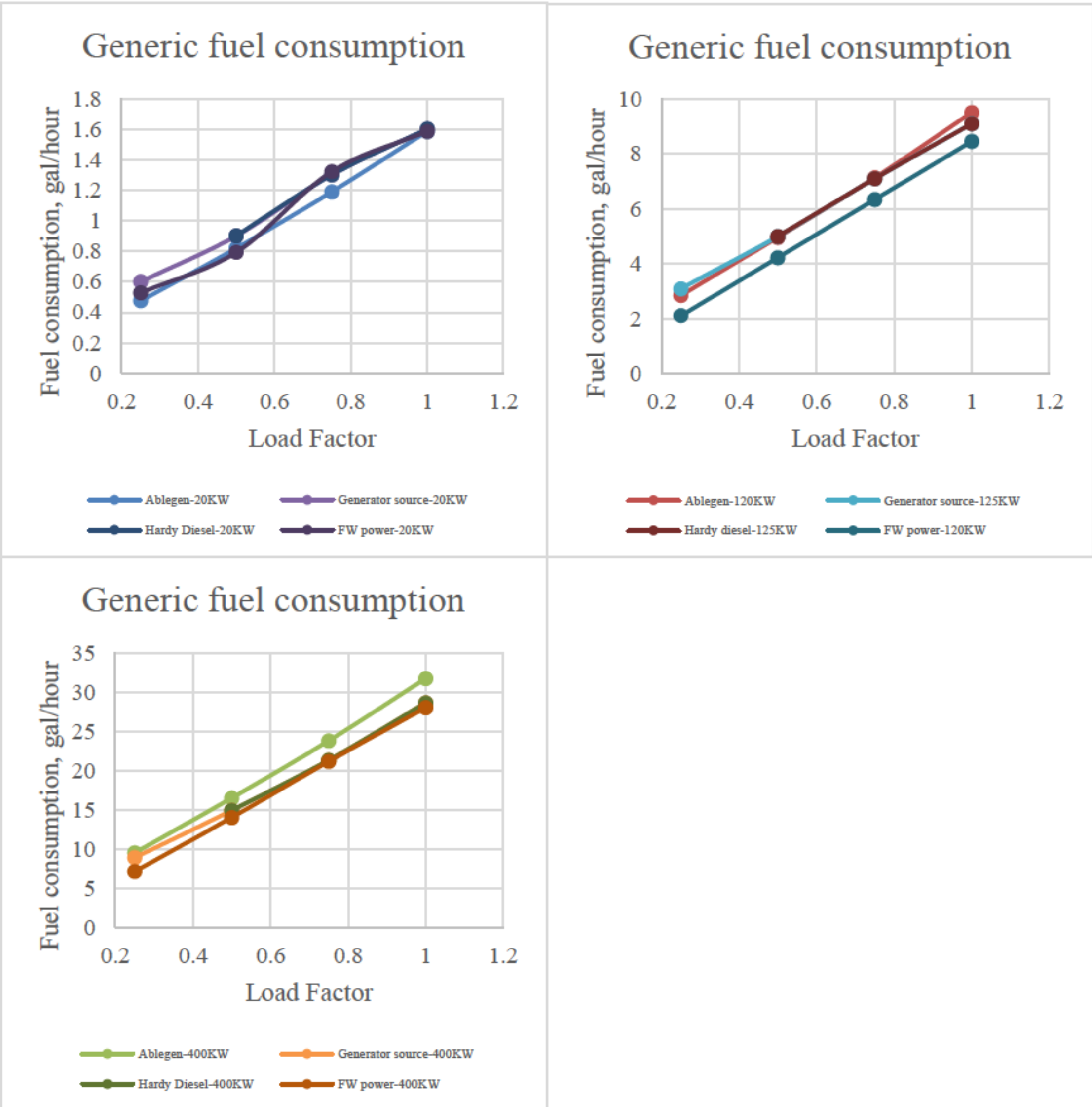


Figure 6: A comparison of generators generic fuel consumption from different sources with respect to their engine sizes (KW).

Figure 6 plots the load factor and fuel consumption of the different generator sizes displaying the generic fuel consumption variability among different web sources. The load factor represents a ratio between the Horsepower provided at the shaft and the maximum Horsepower that could be provided by the engine at max regime. The fuel consumption of three different generator sizes were compared (20KW, ~122.5KW, 400KW) resulting in an average of 15% increase for each set of generators.

3.3 Fuel Density

Diesel fuel density is directly related to Fuel Grading, both parameters follows the EN 590 standard which restricts the density to be between 820 kg/m3 and 845 kg/m3 in normal weather conditions in Europe, and tested by either the EN ISO 3675 or EN ISO 12185 methods [25]. However, in winter times, the fuel grading will change to prevent the blockade of the fluid flow to the engine due to the formation of solid particles under low temperature [26]. According to EN 590 standard, winter fuel has a density between 800 kg/m3 and 845 kg/m3 depending on the climate severity.

Three main problem arises in the reporting of fuel density. The first problem is related to the change in temperature throughout the entire workover activity which will influence the fuel density. As explained by Mr. Clemens, the density and temperature have a linear relationship for a specific range interval (-10 to 30 Degrees Celsius).

The second issue is brought on by mixing fuels with various densities in the same tank. Prior to refuelling, a certain amount of fuel with an unknown density is already in the tank’s bottom. The mixing of these different fuel grades will change the entire fuel specification.

The third issue is the poor fuel quality in some countries where Company operates. Fuel contamination, poor quality of additives... they raise the call for direct measurements as much as possible.

3.4 Fuel Grading

Since SOFI does not yet support fuel grading, a default list of diesel fuel properties has been created to be used instead. The following table represents the input data for default fuel grading:

Default Fuel Grading		
Fuel Properties	**Value**	**Unit**
Carbon Content	86.36	%
Sulfur Content	≤10	mg/kg
Metal Content	≤2	mg/kg
Water Content	≤200	mg/kg
Lower Heating Value	43	MJ/kg
Higher Heating Value	46	MJ/kg

Table 5: Default Fuel Grading properties [27,28].

These fuel properties were selected for the main following reasons:

- Since carbon burns produce CO2, its content is a crucial consideration. The German Environment Agency stated that the average carbon content from 13 refineries in Germany for summer diesel fuel is around 86.32 and 86.4 for winter diesel fuel. An average between summer and winter carbon content was chosen as a default number.
- The new regulations for diesel fuel state that the maximum sulfur content should not exceed 10 mg/kg. Like carbon content, sulfur content is another significant pollutant.
- Considered as impurities in the fuel itself, metal and water content are noted. The maximum permitted water content was set at 200 mg/kg, and the maximum permitted metal content was set at 2 mg/kg.
- Since the company emission factors are reported in g/GJ, the lower and higher heating values were finally chosen to convert fuel quantities (tonnes) into a measure of heat.

Figure 7 represents the workflow designed for Fuel Grading, the user can either decide to provide specific data or choose the default values as shown in table 5.

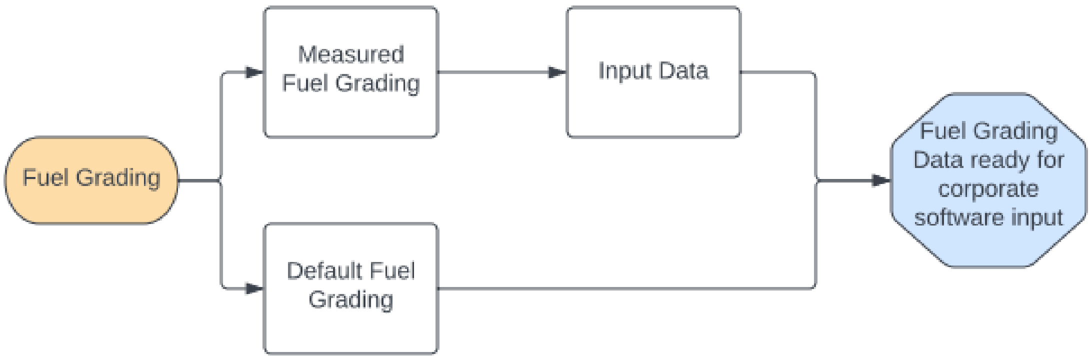


Figure 7: Fuel Grading workflow.

3.5 Emission Factor

Emission factor is the second most important parameter to identify precisely, overestimating or underestimating is a common error. Mr. Stuver mentioned two different methodologies to estimate air pollutants emission factors, the resultant indicated that a gap of approximately 95 lb/hp-hr for NOx can be overestimated if the wrong approach was used [20].

The primary issue associated with emission factors is that emissions are generated by various generators with various engine sizes and technology levels. It can be challenging to provide a single output since EF is directly related to the generator specifications.

According to the EMEP/EEA, the most important air pollutants to take into account are SO2, NOx, CO2, PM, CO and NMVOC. They further mentioned that CO2 and SO2 are fuel-based emissions, which means that they are independent of the engine type and technology [29]. The previous statement is also supported by the IPCC guidelines for national greenhouse gas inventories, which noted that based on the total amount of fuels burned and the average carbon content of the fuels, the CO2 emissions can be estimated fairly accurately [17].

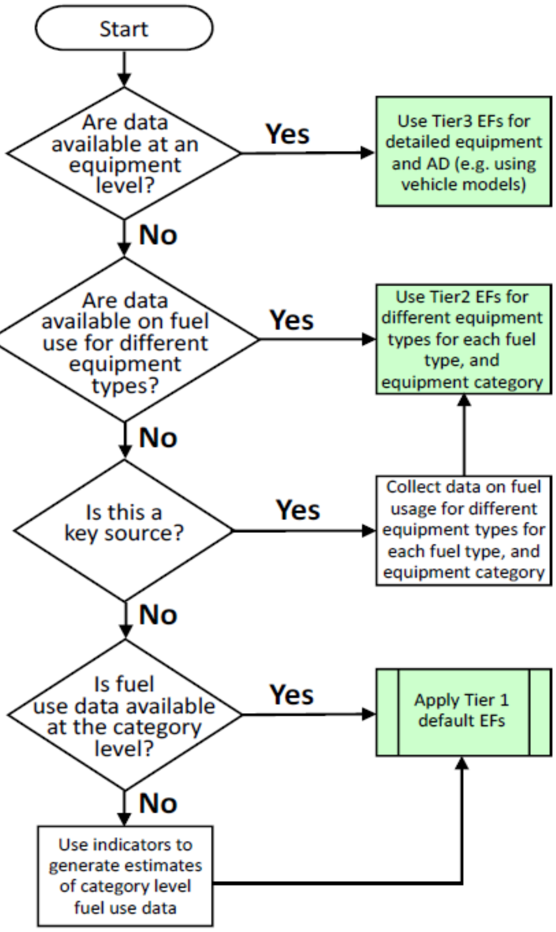


Figure 8: Choice of method [29].

The above flowchart (Figure 8) was designed for users from all nations to select the appropriate emission factors depending on the information available. The emission factors are classified in three different tier levels [29]:

- **Tier 1:** With regard to the broad NFR categories (Agriculture, Forestry, Industrial...), emissions are calculated using a single average EF per pollutant.
- **Tier 2:** Activity data, fuel type, and equipment type are known, the corresponding emission factors are separated into more detailed classifications for estimating emissions.
- **Tier 3:** Data at equipment level are required, hence the equipment technology, operating hours, and engine size must be known. This methodology does not assume fuel consumption to calculate emissions, but rather requires the operating hours which will result in emission per KW hour.

Emission Factors related to diesel fuel off-road machinery have been retrieved from the European Environmental Agency and implemented in the Software tool. This approach is valid for Europe, however it is not clear how appropriate this approach is for operations in the Middle East, Central America and North Africa. Full tables are listed in Appendix A.

Sample Table of a Tier 3 Emission Factor (g/Kwh)

The following table shows a European Environmental Agency tier 3 emission factor table sample. A tier 3 EF is characterized by the engine size and the technology level. The engine sizes are classified in different engine power ranges to reduce the granularity. Moreover, the technology level classifies the engine depending on the year of production, the sophistication of the engine increases with technology level. Finally, the air pollutants are displayed with their corresponding emission factors.

Engine Size	Technology level	NOx	VOC	CH4	CO	N2O	NH3	PM	PM10	PM2.5	BC
8<=P<19	1981-1990	11.5	3.8	0.091	6	0.035	0.002	2.3	2.3	2.3	1.265
37<=P<56	Stage IIIB	3.81	0.28	0.007	2.2	0.035	0.002	0.025	0.025	0.025	0.02
75<=P<130	Stage IV	0.4	0.13	0.003	1.5	0.035	0.002	0.025	0.025	0.025	0.02
130<=P<560	Stage IIIA	3.24	0.3	0.007	1.5	0.035	0.002	0.1	0.1	0.1	0.07
P>560	Stage V	3.5	0.13	0.003	1.5	0.035	0.002	0.045	0.045	0.045	0.002

Table 6: Sample table of a tier 3 emission factor (g/Kwh) [16].

Chapter 4

Methodology Overview of the Developed Software Tool

4.1 Overview

The workflow below represents a general overview of the developed software tool (Figure 9). The tool was designed with Excel built-in coding tool VBA due to its simplicity and ease of adaptation. In addition, it is compatible with the company system.

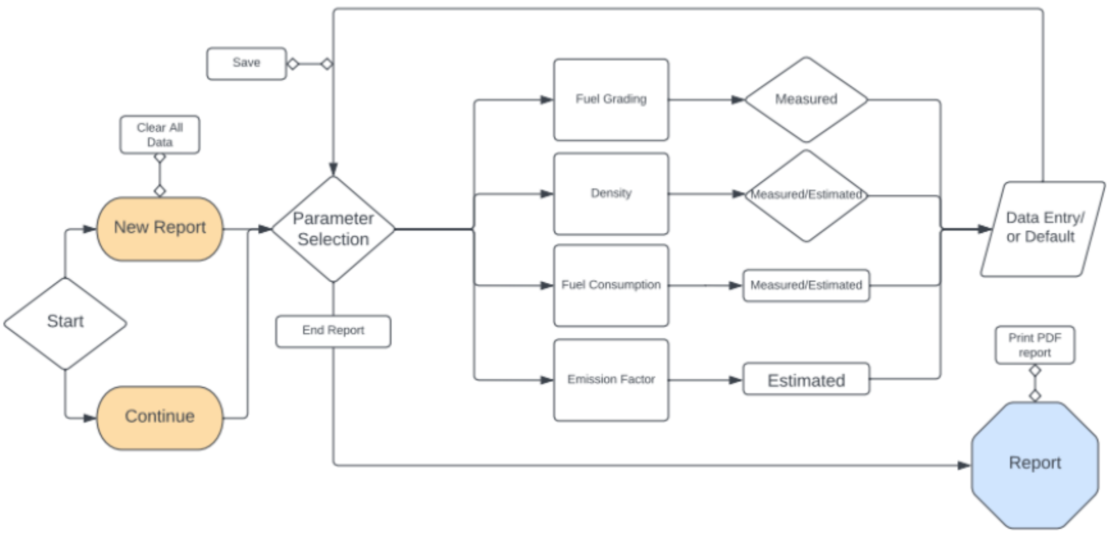


Figure 9: Software tool workflow.

The developed tool aims to provide attributes to the 4 main parameters described earlier in chapter 3 to consolidate the numbers associated with rigless well intervention and well services activities. The user will have the option to start a new report or continue a pre-saved work, starting a new report from pre-saved workbooks will clear all data. The user will then need to choose one of the key parameters for data entry, and depending on the parameter they choose, they will be presented with a series of queries and data entry forms to complete. The user can select up to 4 parameters and generate a report. Finally, the user can convert the report generated into a PDF file.

4.2 Data Entry Source

The user is expected to get data from the following data sources for each parameter as listed in table 7:

Parameter	Data Source		
	Estimation	Measurement	Default
Fuel Consumption	Company /field/ Generator providers Database	Daily fuel consumption	Assigned by student in Software Tool
Density	Company /field/ Database	from bill of lading from refinery	Assigned by student in Software Tool
Fuel Grading		From bill of lading from refinery	Assigned by student in Software Tool
Emission Factor	Equipment data availability		Assigned by student in Software Tool

Table 7: Data entry source.

4.3 Instructions Menu

It is advised to read the first sheet of the tool before moving further (Figure 10). The top left feature allows the user to easily switch between the instruction and the report tab in case additional changes are required. Three different coloured cells have been used to give a smooth visualization to the user, the blue cells represent fixed data that do not change, the pink cells represent data entry, and finally green cells represent automatic output data generated from mathematical formulas. The tool provides detailed instructions on how to use it and what to do in case the user exits in the middle of the workflow (Figure 9). Moreover, additional instructions about the 4 main parameters have been provided so that the user know what to expect. As described earlier, the user can either start a new report or continue a pre-saved workbook by clicking on the green buttons. Finally, the save button is used to preserve the work done where it can be picked up from where it stopped.

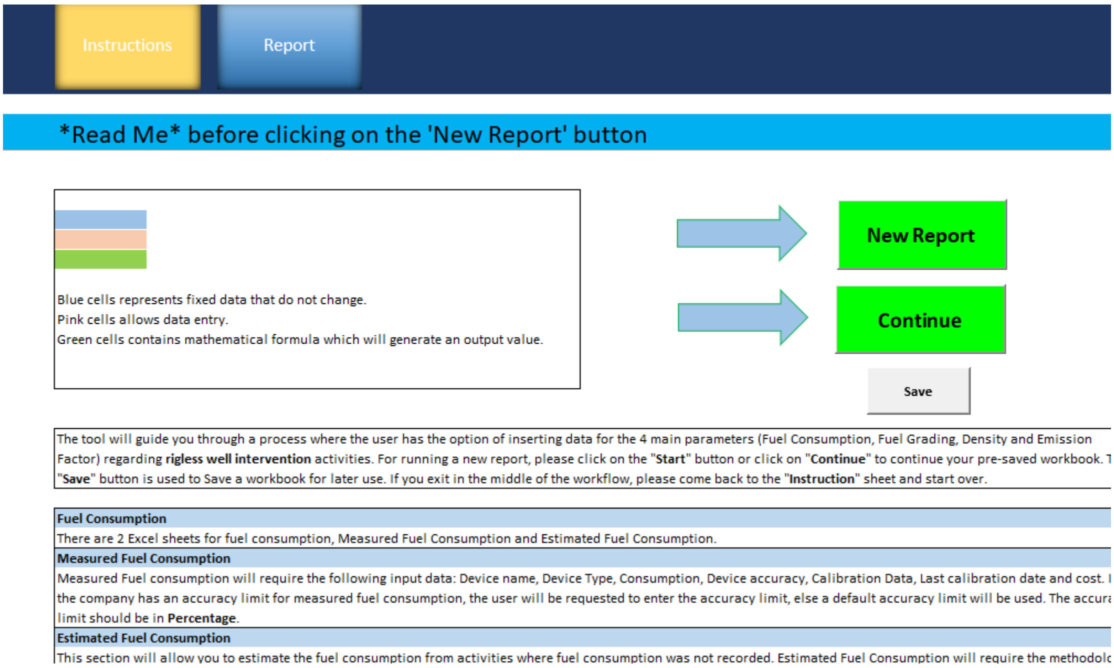


Figure 10: Instructions menu.

4.4 Parameter Selection

As a next step, the user must select the parameter which will be considered for the subsequent steps. The main parameters are listed as follow:

- Fuel Consumption
- Density
- Fuel Grading
- Emission Factor

The user will be directed to the respective worksheet depending on the parameter selected.

4.4.1 Fuel Consumption

Fuel consumption from rigless well intervention can be either estimated or measured. The tool provides the option of going through an estimation or measurement approach as shown in Figure 11.

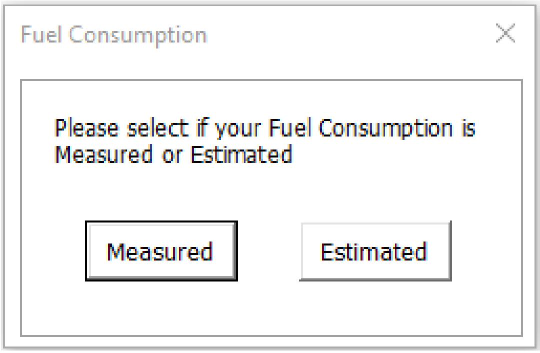


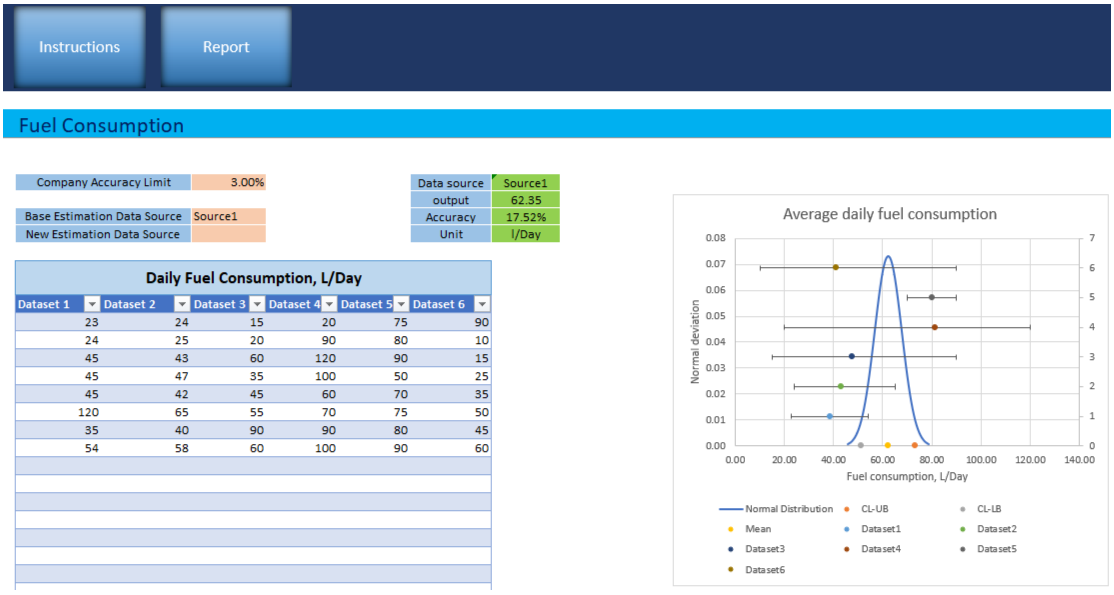
Figure 11: Measured or Estimated.

4.4.1.1 Estimated

For estimation, the tool will request 2 main data entry forms, the first form is to define the source of data used for estimation. The tool only accepts data imported from TXT or CSV files in the second form, which is connected to rigless well intervention daily fuel consumption which will be displayed in the table (Figure 12). Additionally, a default accuracy limit for estimated fuel consumption will be shown automatically; in this case, the company accuracy limit has been set to 3%, but the user has the option of providing a different accuracy limit in accordance with the company policy. More data can be seen in green cells, these are related to the output values from the mathematical model.

In addition, a Gaussian probability distribution curve, as well as the mean, confidence interval (upper and lower bound), and datasets have been displayed for better visualization of the provided data (Figure 12). the Gaussian distribution curve is the resultant from the mathematical and statistical models (Weighted arithmetic mean and Central Limit Theorem) described in chapter 2.

The data provided in Figure 12 are synthetic data.



Daily Fuel Consumption, L/Day

Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5	Dataset 6
23	24	15	20	75	90
24	25	20	90	80	10
45	43	60	120	90	15
45	47	35	100	50	25
45	42	45	60	70	35
120	65	55	70	75	50
35	40	90	90	80	45
54	58	60	100	90	60

Figure 12: Estimated fuel consumption worksheet.

It is obvious that the "Source 1" accuracy is way higher than the company accuracy limit, this is mainly due to the spread of data and the small sample sizes. The software tool will keep on asking the user for "new estimation data sources" until the accuracy has been achieved or no more data sources are available. If the accuracy has not been achieved, the software tool will choose the data source with the highest accuracy. Moreover, if the cost associated with a direct measurement is acceptable, the user will be directed to the measurement workflow.

4.4.1.2 Fuel Consumption Data Analysis Worksheet

This section of the thesis represents the data processing for estimated fuel consumption. As discussed previously the data will be subjected to:

1. A mathematical model ➔ Weighted arithmetic mean.
2. A statistical model ➔ Gaussian Probability Distribution.

Step 1: Mathematical Model

The mathematical model process is described as follow:

1. Calculate the Mean of each dataset.
2. Calculate the Standard Deviation (SD) of each dataset.
3. Calculate the Weight of each dataset (Equation 16).
4. Multiply the Mean by its associated Weight.
5. Apply Equation 15 to calculate the final Mean.
6. Apply Equation 18 and 19 to calculate the final Variance and Standard Deviation, respectively.

	Mathematical Model			
	Mean (x)	SD	Weight (w)	x(i)*w(i)
Dataset 1	38.7	11.76	0.01	0.28
Dataset 2	43.0	14.24	0.00	0.21
Dataset 3	47.5	24.35	0.00	0.08
Dataset 4	81.3	30.91	0.00	0.09
Dataset 5	80.0	7.64	0.02	1.37
Dataset 6	41.3	26.15	0.00	0.06

Figure 13: Mathematical Model Process.

Step 2: Statistical Model

Figure 14 shows the basic statistics of the corresponding datasets, the mean, variance, standard deviation, confidence interval (95%), CL-UB, CL-LB, and the uncertainty have been calculated to generate a Gaussian probability distribution curve as shown in Figure 15.

By applying the empirical rule of the Gaussian distribution, a 95% confidence level was calculated by simply multiplying the standard deviation by 2.

The confidence level-upper bound and confidence level-lower bound were calculated by adding and subtracting the confidence interval from the mean.

Finally, the overall uncertainty is being calculated by dividing the confidence interval by the mean value.

Mean	62.35
Varience	29.85
StDev	5.46
Confidence interval	10.93
Confidence Level-Upper bound	73.28
Confidence Level-Lower bound	51.43
Uncertainty	17.52%

Figure 14: Basic Statistics.

Figure 15 represents the final Gaussian distribution curve. Although one would expect the overall mean value to be around the 4 data points (datasets 1, 2, 3, and 6) which shares approximately the same mean value, the overall mean value was shifted to the right since dataset 5 mean value has higher accuracy.

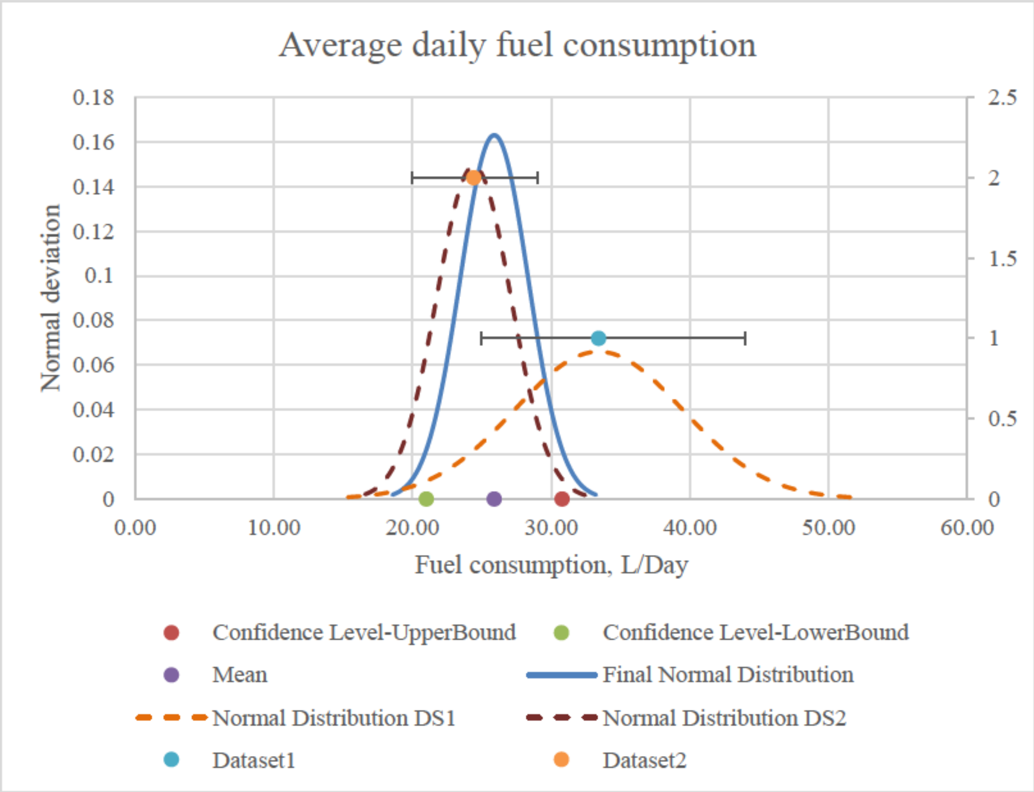


Figure 15: Gaussian Probability Distribution.

4.4.1.3 Measured

The first data entry form will ask for information from a base device (the initial device from which the measurements were taken); the user should provide the device name, type, value (recorded fuel consumption), accuracy, calibration, and the date of the most recent calibration (Figure 16). The accuracy check will be determined by comparing the accuracy of the device against the company accuracy limit. In this case, the default company accuracy limit is set to 3%. The Calibration check will be determined by comparing how often the device should be calibrated and the last calibration date of the device. A small comment will be generated by the software tool on the device status regarding the accuracy and calibration.

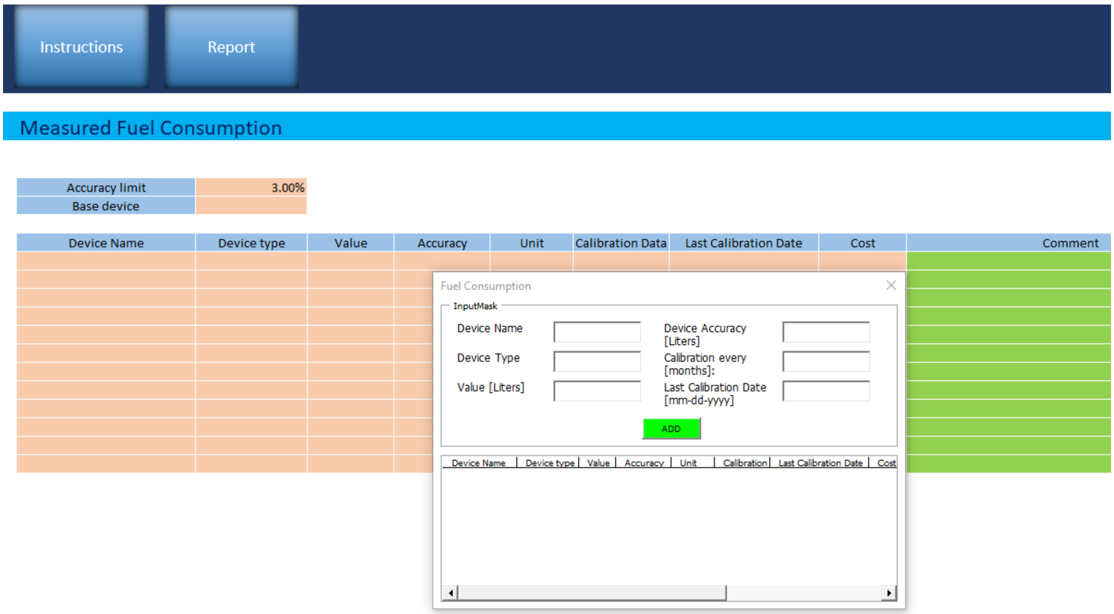


Figure 16: Measured fuel consumption worksheet.

In case another device that is achieving the accuracy and calibration checks must be added, the cost of the previous device should be provided by the user, as shown in Figure 17.

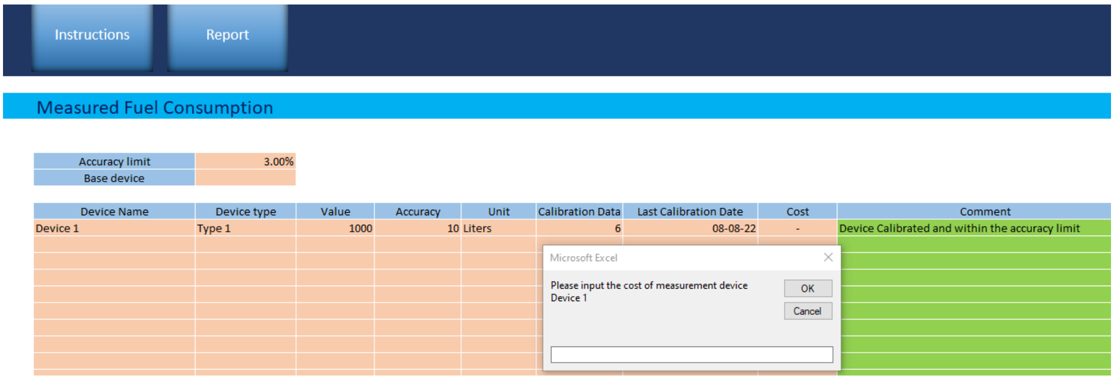


Figure 17: Device cost.

After adding the cost, another data entry form will pop out as shown in Figure 18 to add the second device. The tool will compare the costs and accuracies of both devices and choose the most efficient one.

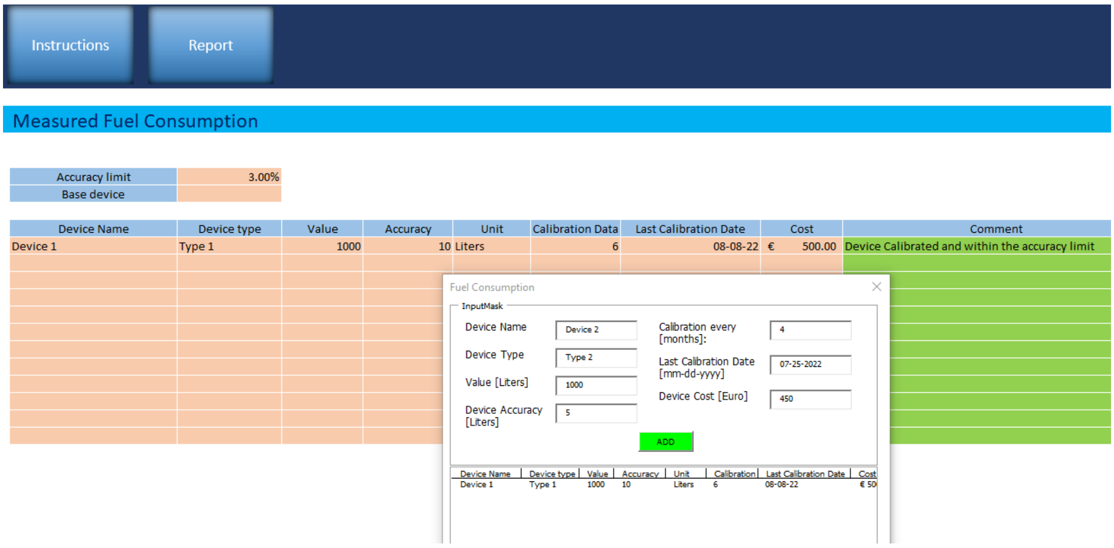


Figure 18: Comparison of both devices.

4.4.2 Density

Density will be following the estimation and measurement workflow, for the main reason that energy providers measure the density before dispatch, however, in countries were the density is not measured, an estimation approach should be followed. The company will receive the billing documents with the density included. Density and fuel consumption follow exactly the same process. However, only the data entry form will change, as shown in Figure 19. In this case, the user must provide the provider's name. Similarly, a default company accuracy limit has been set to +/- 0.005 kg/l.

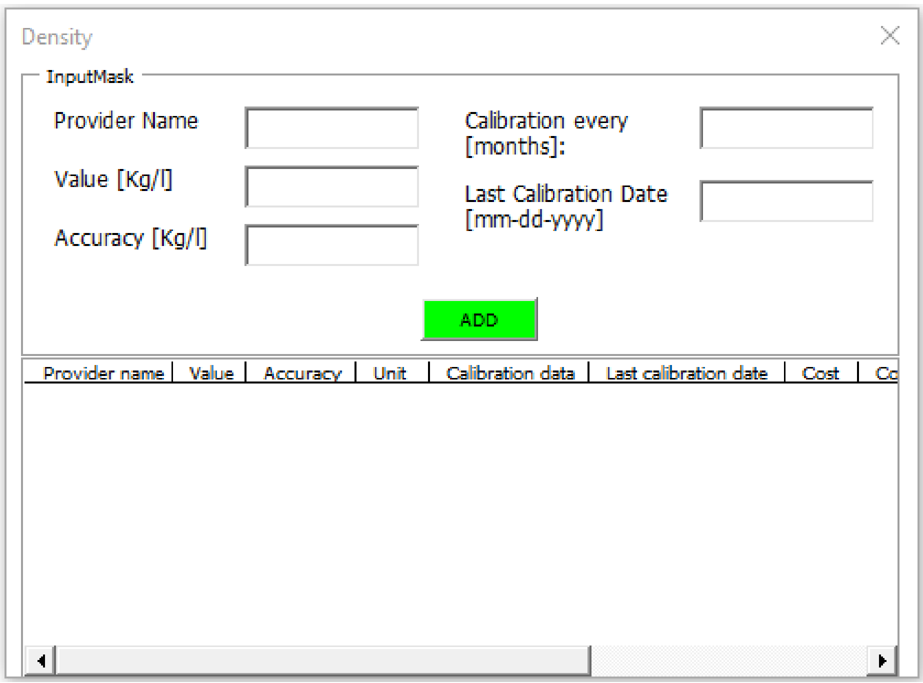


Figure 19: Density data entry form (before cost comparison).

4.4.3 Fuel Grading

By applying the workflow designed in this thesis (Figure 20) for fuel grading into the software tool, a pop out tab will appear asking the user to choose between default or specific fuel grading.

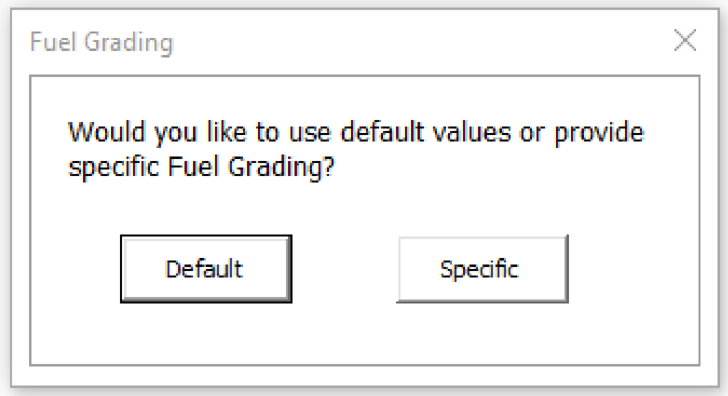


Figure 20: Default or Specific Fuel Grading.

4.4.3.1 Default

In case of default fuel grading, the data provided by the software as shown in table 5 will be transferred to the final report.

4.4.3.2 Specific

In contrast, the software tool will ask for specific input data from the user for the corresponding fuel properties, as shown in Figure 21.

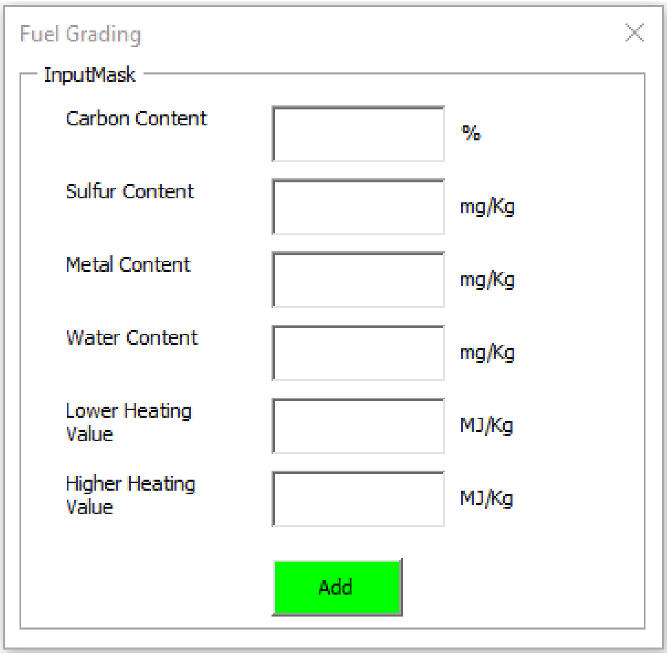


Figure 21: Specific Fuel Grading.

4.4.4 Emission Factor

The Software tool will guide the user through the flowchart (Figure 8) to find the best emission factor estimate. The units used by EMEP/EEA are in g/tonne fuel for tier 1 and 2, and g/Kwh for tier 3, however, data have been converted to g/GJ to satisfy Wintershall Dea adopted Software needs (Figure 22).

Note: data for tiers 2 and 3 are not visible since the engine size and technology level are empty.

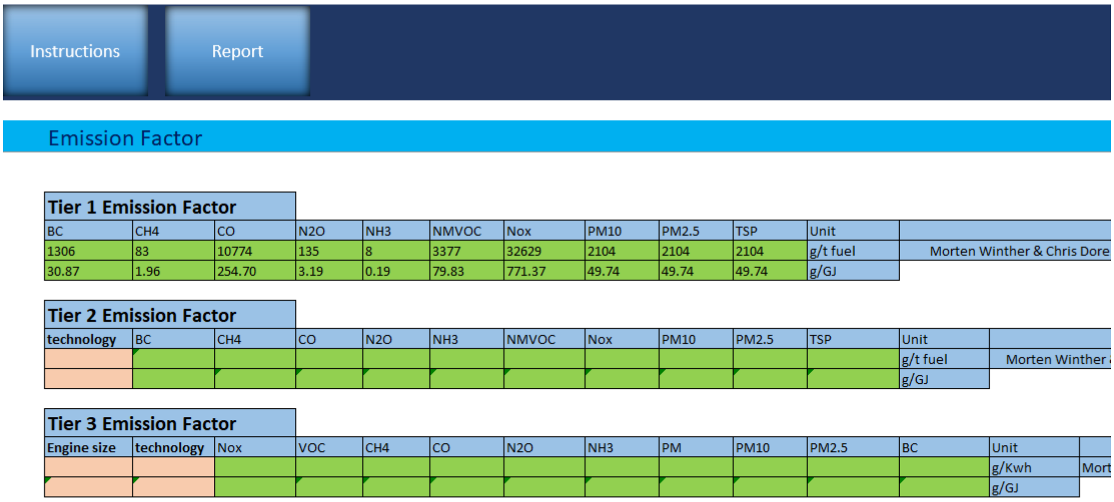


Figure 22: Emission Factor worksheet.

4.4.4.1 Tier 1 Emission Factor

Tier 1 emission factors will be directly applied if the engine size and technology level data are not available, as shown in Figure 22.

4.4.4.2 Tier 2 Emission Factor

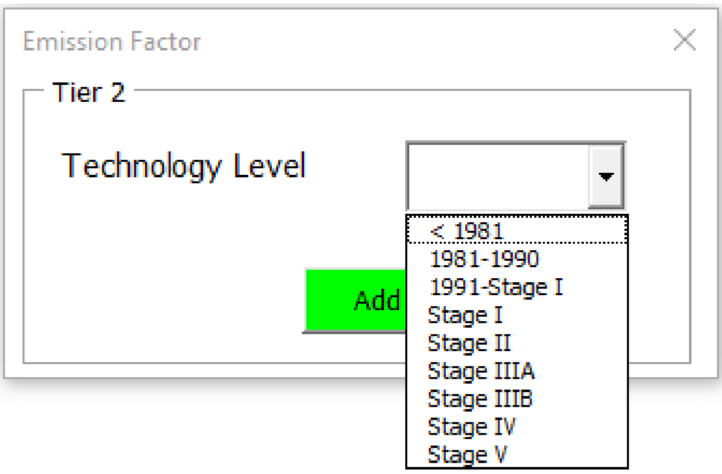


Figure 23: Input data for a tier 2 emission factor.

A tier 2 approach, also known as technology dependent approach [29], is mainly focusing on the technology level of the equipment. The technology level is a representation of the equipment's standards and norms [30]. However, by choosing one of the technology levels, the Software will provide the appropriate emission factors as shown in Figure 24.

Tier 2 Emission Factor											
technology	BC	CH4	CO	N2O	NH3	NMVOC	Nox	PM10	PM2.5	TSP	Unit
Stage II	825	39	7135	136	8	1587	22101	1034	1034	1034	g/t fuel
Stage II	19.5	0.92	168.68	3.22	0.19	37.52	522.48	24.44	24.44	24.44	g/GJ

Figure 24: Stage II emission factors.

4.4.4.3 Tier 3 Emission Factor

In case of having data at equipment level, the user will have the option of selecting one of the following generator sizes (Figure 25).

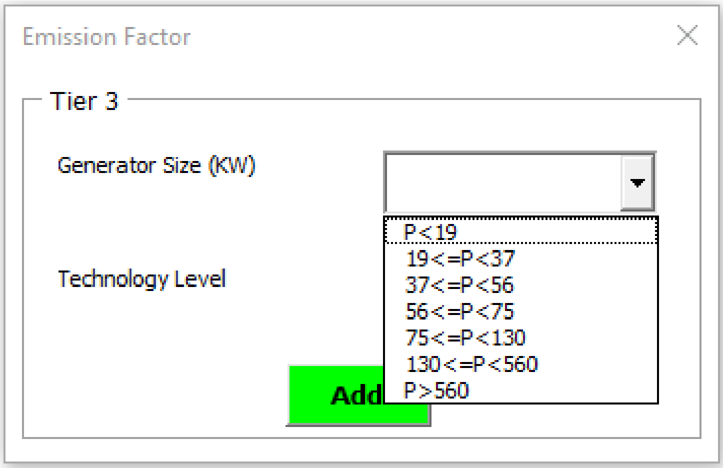


Figure 25: Engine size selection.

However, technology levels will differ according to the engine size (check for Appendix A Tier 3 emission factor table), the developed Software tool is able to recognize the technology levels associated with the engine size.

The following figure shows the different technology levels:

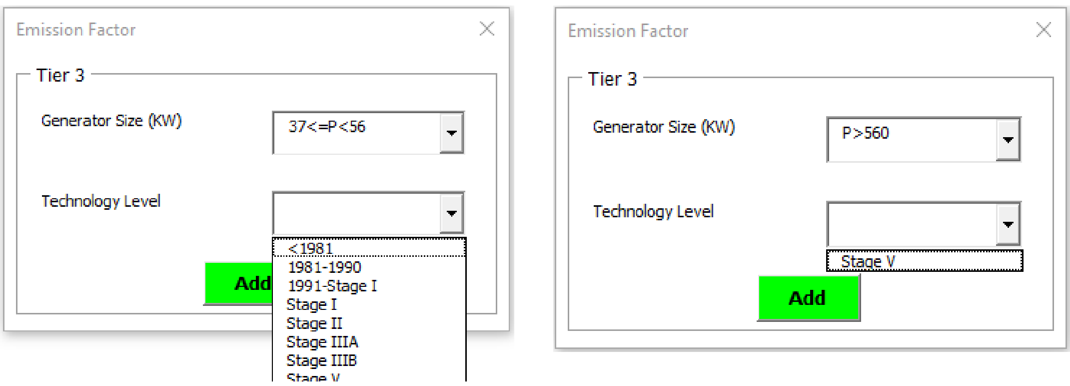


Figure 26: A comparison between technology levels selection depending on the engine size.

Tier 3 Emission Factor												
Engine size	technology	Nox	VOC	CH4	CO	N2O	NH3	PM	PM10	PM2.5	BC	Unit
37<=P<56	Stage IIIA	3.81	0.4	0.01	2.2	0.035	0.002	0.2	0.2	0.2	0.16	g/Kwh
37<=P<56	Stage IIIA	1058.33	111.11	2.78	611.11	9.72	0.56	55.56	55.56	55.56	44.44	g/GJ

Figure 27: 37<=P<56 (KW) and Stage IIIA emission factors.

4.5 Final Report

Coming to the last step, the user will be directed to the Report worksheet where all the parameters will be displayed with attributes. Attributes are important features for the values itself, since they give more confidence and reduces the uncertainties related to its respective parameter. In addition, the user can extract the final report generated by the developed software tool as a PDF file and save it for future work.

Figure 28 is an example of a final report, the data are completely random for visual purposes.

The top left section includes the actual date the report was generated, the “year” reflects the year in which the well intervention or well service activity was performed. Finally, the job type was included to specify the job performed.

The 2nd section shows the measured light oil consumption, in this example, it was assigned by the user that 1,000 liters of fuel has been consumed for this job. Moreover, the Software Tool displays additional attributes to further consolidate the claim. The device name and type represent the measurement device used to measure the fuel consumption. The calibration was analyzed by the Software Tool by comparing the last calibration date and how often the device must be calibrated combined with the current date. The accuracy was compared with the company accuracy limit and show how accurate the measurement device is. And finally, the cost was found empty since no new measurement devices were implemented.

The 3rd section shows the estimated light oil consumption, no data were available since the fuel consumption was measured in this particular job.

The 4th section represents the light oil density, similarly to the measured fuel consumption, however, instead the provider’s name (refinery) must be provided by the user.

The 5th section shows the estimated emission factor, 10 different emission factors were provided by the Software Tool in g/tons of fuel and g/GJ. Both units of measurement were displayed to give the user more flexibility of choosing the best suitable unit for his case. In addition, the generator size, technology level, and tier level have been displayed to support the data provided by the Software Tool.

Finally, the last section shows an example of a Measured (specific) fuel grading. The carbon and sulfur content are important fuel properties since they will convert into greenhouse gases after combustion. Metal and water content are considered as impurities in the fuel. And finally, the lower and higher heating value can be used to convert fuel quantities into a measure of heat.

Report Date:	12-01-23
Year:	2023
Job Type:	Rigless Well Intervention

Light oil consumption "Measured"				
Consumption	1000	Unit	Liters	
Attributes:				
Type of Job	Device Type	Calibration	Accuracy	Cost
Wireline	Velocity Flowmeter	Yes	+/- 10	-

Light oil consumption "Estimated"			
Consumption		Unit	
Attributes:			
Data source	Accuracy		

Light oil Density			
Density		Unit	
Attributes:			
Provider Name	Calibration	Accuracy	Cost

Emission Factor "Estimated"										
Nox	VOC	CH4	CO	N2O	NH3	PM	PM10	PM2.5	BC	Unit
3.24	0.3	0.007	1.5	0.035	0.002	0.1	0.1	0.1	0.07	g/Kwh
900	83.33	1.94	416.67	9.72	0.56	27.78	27.78	27.78	19.44	g/GJ
Attributes:										
Generator size, KW				Technology Level				Tier Level		
130<=P<560				Stage IIIA				Tier 3		

Fuel Grading "Measured"		
Fuel Properties	Value	Units
Carbon Content	86.36	%
Sulfur Content	≤10	mg/Kg
Metal Content	≤2	mg/Kg
Water Content	≤200	mg/Kg
Lower Heating Value	43	MJ/Kg
Higher Heating Value	46	MJ/Kg

Figure 28: Software tool final report.

4.6 A Correlation between SOFI and Software tool Final Report

The following figures show the input mask from SOFI with the three factors that are relevant for the software and the processing of data: value, unit, and quality. The input data, whether measured or estimated, are reflected in the quality. The primary necessary data are shown in relation to the developed software tool's final report (Figure 31). Then come the attributes that the software tool will offer to minimize the uncertainties associated with measurement and estimation.

Light Oil mass input ⓘ ⇐Light Oil units

Details	Value	Unit	Not Applicable	Quality	Released
⋮					■

Figure 29: SOFI input mask for Fuel Consumption.

Light Oil density ⓘ

Details	Value	Unit	Quality	Released
⋮				■

Figure 30: SOFI input mask for Density.

Natural Gas - CH4 per Energy of Fuel ⇐Emission factor basis selection - Natural Gas

Details	Value	Unit	Not Applicable	Environmental Dete...	Quality	Released
⋮						■

Figure 31: SOFI input mask for Emission Factor.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

This thesis presented the development of a Software tool to reduce the uncertainties related to well services activities, which can provide attributes to the four main parameters (Fuel consumption, Fuel grading, Density, and Emission factor). This Software tool was not tested with real data. However, the designed flowcharts related to the four parameters were successfully implemented.

The first step of this thesis was to review the flowcharts designed by Mr. Clemens. The following points were concluded from the literature review:

- The weighted arithmetic mean works best at giving more importance to data with higher accuracies. This approach was implemented because data with higher accuracies are more likely to be cleaner and closer to the actual value.
- After examining different probability distribution models, the Gaussian probability distribution which follows the Central Limit Theorem was implemented to govern input data because statisticians found that datasets will more likely reach a Gaussian distribution "Bell Curve" with increasing data.
- The measurement process designed by Mr. Clemens should be reviewed. If the calibration and accuracy have been successfully achieved, the software tool should not ask for another device.
- The cost loop should be accessible only when the devices are not achieving the calibration and accuracy criteria defined by the company. Only then a cost evaluation process should be taken into account.

After reviewing the estimation and measurement workflows, the parameters contributing to GHG have been reviewed. The main findings are:

- A default number was added to the input parameters process. The default number should only be used if data are not available.
- The first approach to estimate fuel consumption should be the statistical analysis of fuel consumption from similar jobs. If that data is unavailable, the alternative should be a specific generator fuel consumption data sheet. A generic fuel consumption data sheet should be used if neither of these methods is available.
- The default fuel grading table was extracted from the European database; hence it can only be used in Europe.
- It was concluded that assigning different tier levels to emission factors is the right approach for estimation. Therefore, a new flowchart from the Environmental European Agency has been adopted.

The main conclusions and limitations of the developed software tool are as follows:

- The data entry source (table 7) is not limited to the sources given for estimation, measurement, and default. The suggested data source is from literature review and expert opinion, it is advised to test the suggested data source and investigate potential new data sources to be added in the table.
- The software tool output was designed to match the interface of the company's adopted software Sofi for practical transfer of data.
- The software tool documents' the origin of data associated with measurement and estimation.
- The Software tool is sensitive to data input, for instance, the user is advised to perform a data quality check that matches the parameters units of measurements before importing them. For example, density values should be consistant in Kg/l; importing data of different units will result in misleading values.
- The user can only save his work after completing a full parameter data entry (as shown in Figure 9).
- For estimated fuel consumption, data can only be imported from a TXT or CSV file with a maximum of 6 datasets. The datasets must be separated by a "Space" delimiter.
- Daily fuel consumption TXT or CSV files is currently limited to 320 data points per dataset.
- Density values are not restricted. For example, if the user input 825 kg/l which is wrong (0.825 kg/l is a realistic density for diesel), the software tool will not restrict this input.
- Specific Fuel Grading data are not restricted. Unrealistic values will be accepted.

- The default fuel grading properties are taken from multiple sources. Thus, it does not assume a specific diesel fuel type and cannot be used outside Europe. For example, the company should not use the same Default Fuel grading for assets in Latin America or Africa.
- The Software tool was not tested with real data.

5.2 Future Work

In the future, more work can be done to improve the software tool's applicability and promote its effectiveness:

- Update the measurement workflow, so the software tool does not ask for another measurement device if the calibration and accuracy criteria are met.
- A weighting factor can be added to the cost loop in the measurement workflow (Mr. Clemens Thesis figure 24) to assign weights to the cost and the device's accuracy. For example, if a device has an accuracy of +/-10 Liters and cost of 1000 €, while another device has an accuracy of +/-2 Liters and cost of 1100 €, it can be decided that the second device is better even though the cost is higher.
- A default number should be assigned to the following parameters: fuel consumption and density.
- Create a library for all the estimations performed with the tool.
- An average loading factor for each type of operation can be taken into account to calculate the fuel consumption; the generator loading varies depending on the operating conditions for different jobs. For instance, assuming an average load factor for wireline operations is assigned at 50%, while the average load factor for a pumping unit is 80%, the loading factor can be used to estimate fuel consumption if the generator engine size is known.
- Mixing fuels with different densities in the same tank can change the fuel specification after each refuelling. The company can understand the difference in fuel density inside the tanks with the aid of sufficient on-site data. The data gathered can be utilized to calculate an average value that can be used for estimation.
- As a suggestion, a more accurate fuel density can be calculated by installing a device directly before the generator intake line. The data can be used as blueprints to other well intervention jobs in the same region.

- The implemented emission factors were extracted from the European Environmental Agency; additional search could be performed to find emission factors for fuels that suits the regulations in South America or Africa.
- Allow the user to choose a specific business unit (Mexico, Germany, Egypt…) before starting the process of the software loop. This option will allow the classification of different default numbers according to each country's regulations. For example, if the user chooses Mexico, the default density value is automatically adjusted according to the diesel used in Mexico.
- Create a coding algorithm for implementing a "Back" button whenever the user needs to correct any mistakes. In addition, it allow the user to save his work at any time and continue from where he stopped.
- Create a coding algorithm for importing daily fuel consumption and density data from any type of file without any restrictions.
- Gather enough density and fuel grading data from various the company business units to limit input data to the appropriate country. As an example, in Europe, the density values from refineries can vary between 0.82 and 0.86 kg/l, however in Latin America, the densities might vary between 0.80 and 0.85 kg/l.
- Assign a suitable "Company accuracy limit" for estimated and measured fuel consumption and Density.
- As a suggestion, measurement devices should be installed in every workover activity to reduce uncertainties and provide better emission reduction techniques.
- Test the software tool with actual data.

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Appendix A

Emission Factors

BC	CH4	CO	N2O	NH3	NMVOC	Nox	PM10	PM2.5	TSP
1306	83	10774	135	8	3377	32629	2104	2104	2104

Table 8: Diesel Fuel tier 1 emission factors.

Technology Level	BC	CH4	CO	N2O	NH3	NMVOC	NOx	PM10	PM2.5	TSP
< 1981	3414	199	20690	121	7	8077	26552	6207	6207	6207
1981-1990	2369	171	18890	128	7	6962	33942	4308	4308	4308
1991-Stage I	2001	144	16258	135	8	5851	43552	3642	3642	3642
Stage I	800	42	6639	137	8	1725	31077	1005	1005	1005
Stage II	825	39	7135	136	8	1587	22101	1034	1034	1034
Stage IIIA	758	36	6826	136	8	1470	15653	950	950	950
Stage IIIB	78	15	6445	137	8	625	11933	98	98	98
Stage IV	78	13	6019	137	8	536	1570	98	98	98
Stage V	56	23	7352	136	8	930	7663	116	116	116

Table 9: Diesel Fuel tier 2 emission factors.

Engine Power (kW)	Technology Level	Nox	VOC	CH4	CO	N2O	NH3	PM	PM10	PM2.5	BC
P<8	<1981	12	5	0.12	7	0.035	0.002	2.8	2.8	2.8	1.54
P<8	1981-1990	11.5	3.8	0.091	6	0.035	0.002	2.3	2.3	2.3	1.265

P<8	1991-Stage I	11.2	2.5	0.06	5	0.035	0.002	1.6	1.6	1.6	0.88
P<8	Stage V	6.08	0.68	0.016	4.8	0.035	0.002	0.4	0.4	0.4	0.32
8<=P<19	<1981	12	5	0.12	7	0.035	0.002	2.8	2.8	2.8	1.54
8<=P<19	1981-1990	11.5	3.8	0.091	6	0.035	0.002	2.3	2.3	2.3	1.265
8<=P<19	1991-Stage I	11.2	2.5	0.06	5	0.035	0.002	1.6	1.6	1.6	0.88
8<=P<19	Stage V	6.08	0.68	0.016	3.96	0.035	0.002	0.4	0.4	0.4	0.32
19<=P<37	<1981	18	2.5	0.06	6.5	0.035	0.002	2	2	2	1.1
19<=P<37	1981-1990	18	2.2	0.053	5.5	0.035	0.002	1.4	1.4	1.4	0.77
19<=P<37	1991-Stage I	9.8	1.8	0.043	4.5	0.035	0.002	1.4	1.4	1.4	0.77
19<=P<37	Stage II	6.5	0.6	0.014	2.2	0.035	0.002	0.4	0.4	0.4	0.32
19<=P<37	Stage IIIA	6.08	0.6	0.014	2.2	0.035	0.002	0.4	0.4	0.4	0.32
19<=P<37	Stage V	3.81	0.42	0.01	2.2	0.035	0.002	0.015	0.015	0.015	0.002
37<=P<56	<1981	7.7	2.4	0.058	6	0.035	0.002	1.8	1.8	1.8	0.99
37<=P<56	1981-1990	8.6	2	0.048	5.3	0.035	0.002	1.2	1.2	1.2	0.66
37<=P<56	1991-Stage I	11.5	1.5	0.036	4.5	0.035	0.002	0.8	0.8	0.8	0.44
37<=P<56	Stage I	7.7	0.6	0.014	2.2	0.035	0.002	0.4	0.4	0.4	0.32
37<=P<56	Stage II	5.5	0.4	0.01	2.2	0.035	0.002	0.2	0.2	0.2	0.16
37<=P<56	Stage IIIA	3.81	0.4	0.01	2.2	0.035	0.002	0.2	0.2	0.2	0.16
37<=P<56	Stage IIIB	3.81	0.28	0.007	2.2	0.035	0.002	0.025	0.025	0.025	0.02
37<=P<56	Stage V	3.81	0.28	0.007	2.2	0.035	0.002	0.015	0.015	0.015	0.002
56<=P<75	<1981	7.7	2.4	0.058	6	0.035	0.002	1.8	1.8	1.8	0.99
56<=P<75	1981-1990	8.6	2	0.048	5.3	0.035	0.002	1.2	1.2	1.2	0.66
56<=P<75	1991-Stage I	11.5	1.5	0.036	4.5	0.035	0.002	0.8	0.8	0.8	0.44
56<=P<75	Stage I	7.7	0.6	0.014	2.2	0.035	0.002	0.4	0.4	0.4	0.32
56<=P<75	Stage II	5.5	0.4	0.01	2.2	0.035	0.002	0.2	0.2	0.2	0.16
56<=P<75	Stage IIIA	3.81	0.4	0.01	2.2	0.035	0.002	0.2	0.2	0.2	0.16
56<=P<75	Stage IIIB	2.97	0.28	0.007	2.2	0.035	0.002	0.025	0.025	0.025	0.02
56<=P<75	Stage IV	0.4	0.28	0.007	2.2	0.035	0.002	0.025	0.025	0.025	0.02
56<=P<75	Stage V	0.4	0.13	0.003	2.2	0.035	0.002	0.015	0.015	0.015	0.002

75<=P<130	<1981	10.5	2	0.048	5	0.035	0.002	1.4	1.4	1.4	0.77
75<=P<130	1981-1990	11.8	1.6	0.038	4.3	0.035	0.002	1	1	1	0.55
75<=P<130	1991-Stage I	13.3	1.2	0.029	3.5	0.035	0.002	0.4	0.4	0.4	0.22
75<=P<130	Stage I	8.1	0.4	0.01	1.5	0.035	0.002	0.2	0.2	0.2	0.16
75<=P<130	Stage II	5.2	0.3	0.007	1.5	0.035	0.002	0.2	0.2	0.2	0.16
75<=P<130	Stage IIIA	3.24	0.3	0.007	1.5	0.035	0.002	0.2	0.2	0.2	0.16
75<=P<130	Stage IIIB	2.97	0.13	0.003	1.5	0.035	0.002	0.025	0.025	0.025	0.02
75<=P<130	Stage IV	0.4	0.13	0.003	1.5	0.035	0.002	0.025	0.025	0.025	0.02
75<=P<130	Stage V	0.4	0.13	0.003	1.5	0.035	0.002	0.015	0.015	0.015	0.002
130<=P<560	<1981	17.8	1.5	0.036	2.5	0.035	0.002	0.9	0.9	0.9	0.45
130<=P<560	1981-1990	12.4	1	0.024	2.5	0.035	0.002	0.8	0.8	0.8	0.4
130<=P<560	1991-Stage I	11.2	0.5	0.012	2.5	0.035	0.002	0.4	0.4	0.4	0.2
130<=P<560	Stage I	7.6	0.3	0.007	1.5	0.035	0.002	0.2	0.2	0.2	0.14
130<=P<560	Stage II	5.2	0.3	0.007	1.5	0.035	0.002	0.1	0.1	0.1	0.07
130<=P<560	Stage IIIA	3.24	0.3	0.007	1.5	0.035	0.002	0.1	0.1	0.1	0.07
130<=P<560	Stage IIIB	1.8	0.13	0.003	1.5	0.035	0.002	0.025	0.025	0.025	0.018
130<=P<560	Stage IV	0.4	0.13	0.003	1.5	0.035	0.002	0.025	0.025	0.025	0.018
130<=P<560	Stage V	0.4	0.13	0.003	1.5	0.035	0.002	0.015	0.015	0.015	0.002
P>560	Stage V	3.5	0.13	0.003	1.5	0.035	0.002	0.045	0.045	0.045	0.002

Table 10: Equipment level tier 3 emission factors.

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Nomenclature

μ	Mean
σ	Standard deviation / Uncertainty
n	Sample size
X_i	Value
X_m	Mean
δ_i	Absolute value
w_i	Weight of a value
X_{wtd}	Weighted mean
σ^2	Variance

Abbreviations

WD	Wintershall Dea
ST	Software Tool
GHG	Greenhouse Gases
FC	Fuel Consumption
EF	Emission Factor
CLT	Central Limit Theorem
VBA	Visual Basic for Application
SD	Standard Deviation
CL-UB	Confidence Level-Upper Bound
CL-LB	Confidence Level-Lower Bound
Erfc	Error Function
EEA	European Environment Agency
IPCC	Intergovernmental Panel on Climate Change