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AGGREGATED DATASETS – THIRD PARTY DATASETS ANALYSIS

A REPORT FOR WESTERN POWER DISTRIBUTION

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ABBREVIATIONS

ASHP	Air source heat pump	EV	Electric Vehicle
AUF	Accuracy uncertainty factor	NIA	Network Innovation Allowance
CUF	Completeness uncertainty factor	RUF	Resolution uncertainty factor
DQF	Data Quality Factor	UF	Uncertainty factor
DDF	Data Derating Factor		

VERSION HISTORY

A	Initial Draft	20 October 2020
B	Updated draft	23 October 2020
C	Final version	29 October 2020

1. EXECUTIVE SUMMARY

FutureFlex is a joint project delivered by Western Power Distribution (WPD), Everoze and SGC. It is funded by the Network Innovation Allowance (NIA). FutureFlex is trialling a new DSO service suitable for domestic flexibility, called Sustain-H. This service places data optionality at its heart.

The role of the *Aggregated Datasets* workstream is to quantify the impact of lower portfolio data quality for WPD's DSO services. This will ultimately help to inform payment mechanisms for Sustain-H. The methodology is summarised in Figure 1 below: the approach is to independently analyse Resolution, Completeness and Accuracy Uncertainty Factors, and then combine this into a single Data Quality Factor for each technology type. This then informs the Data Derating Factor for Sustain-H remuneration payments in future.

The Aggregated Datasets analysis is conducted in two phases – of which this is the first. Phase 1 is to conduct analysis on third party datasets from two separate trials: Electric Nation (electric vehicles) and Freedom (heat pumps). Phase 2 is then to refine the analysis using data from the Sustain-H service trial. Figure 1 marks which aspects of the Methodology have been completed in this report, and which will be completed at the next stage.

The analysis revealed a series of interesting results, summarised below:

1. **The limitations of available datasets pose a *substantial* challenge for reaching conclusions – emphasising the pressing need for WPD to gather more data in future**. Everoze's analysis was materially affected by the limitations of applying the Freedom and Electric Nation datasets to answer the available datasets. Most notably, key issues included the short duration of the datasets used and the Electric Nation dataset not being a minutely dataset. As such, Everoze strongly advocates seizing future opportunities to secure further domestic flexibility data, to maximise learning.

2. **Data resolution has the biggest impact on demand uncertainty, followed by Completeness, followed by Accuracy.** The standard deviation component of the Data Quality Factor is dominated by the Resolution Uncertainty Factor standard deviation (0.300), which is a magnitude of 10 greater than those calculated from the completeness analysis, and a magnitude of 100 greater than those calculated from the accuracy analysis. In short, lower resolution half-hourly data *substantially* reduces the confidence WPD can have in the ultimate peak demand compared to minutely resolution data. Meanwhile, completeness is of medium importance, and accuracy impacts are negligible.

3. **Results vary significantly by dataset – hinting at a possible need for a technology-specific approach to analysing data resolution:** Consumption profiles vary dramatically between the Freedom data (for heat pumps) and Electric Nation data (for electric vehicles); this applies both across the day and within individual half hour settlement periods. This has implications for the Resolution Uncertainty Factor (UF), suggesting that it may be more appropriate to derive a separate resolution factor per technology. It is further possible that other assets (such as batteries) will show different behaviours again.

4. **For heat pumps at half-hourly resolution, the Data Quality Factor for a complete dataset was 1.43 for a 50% confidence level and 1.92 for a confidence level of 95%.** This means that we are 50% certain the peak demand recorded for a half-hourly metered heat pump portfolio is 1.43 times higher when assuming minutely resolution.

5. **For electric vehicles at half-hourly resolution, the Data Quality Factor for a complete dataset was 1.18 for a confidence level of 50% and 1.53 for a confidence level of 95%.** This means that we are 50% certain the peak demand recorded for a half-hourly metered electric vehicle is 1.18 times higher when assuming minutely resolution. The reason why the impact of resolution is lower for electric vehicles rather than heat pumps is the lower variability of electric vehicle charging requirements over a half hour period which may not vary at all, whereas heat pump demand is more variable.

6. **Analysis to date suggests that portfolio size strongly impacts the half-hourly resolution UF, and consequently the Data Quality Factor**. Everoze repeated the resolution analysis on reduced population samples for both the Electric Nation and Freedom datasets. The smaller population datasets yielded larger Resolution UFs. Interestingly, for a fixed portfolio size, different results were yielded for the two datasets, which indicates that technology type is also a driver of variation in the Data Quality Factor. The impact of portfolio size and technology type on the calculated Data Quality Factor (predominantly driven by the resolution UF), appears to diminish for large portfolios (> 100 assets). This convergence, or asymptotic behaviour, with increasingly large portfolios will have an impact in the design of the DQF/DDF where a simplified approach may be justified. These

sensitivities are to be explored further and the hypotheses tested when more data from the Sustain-H trial is available.

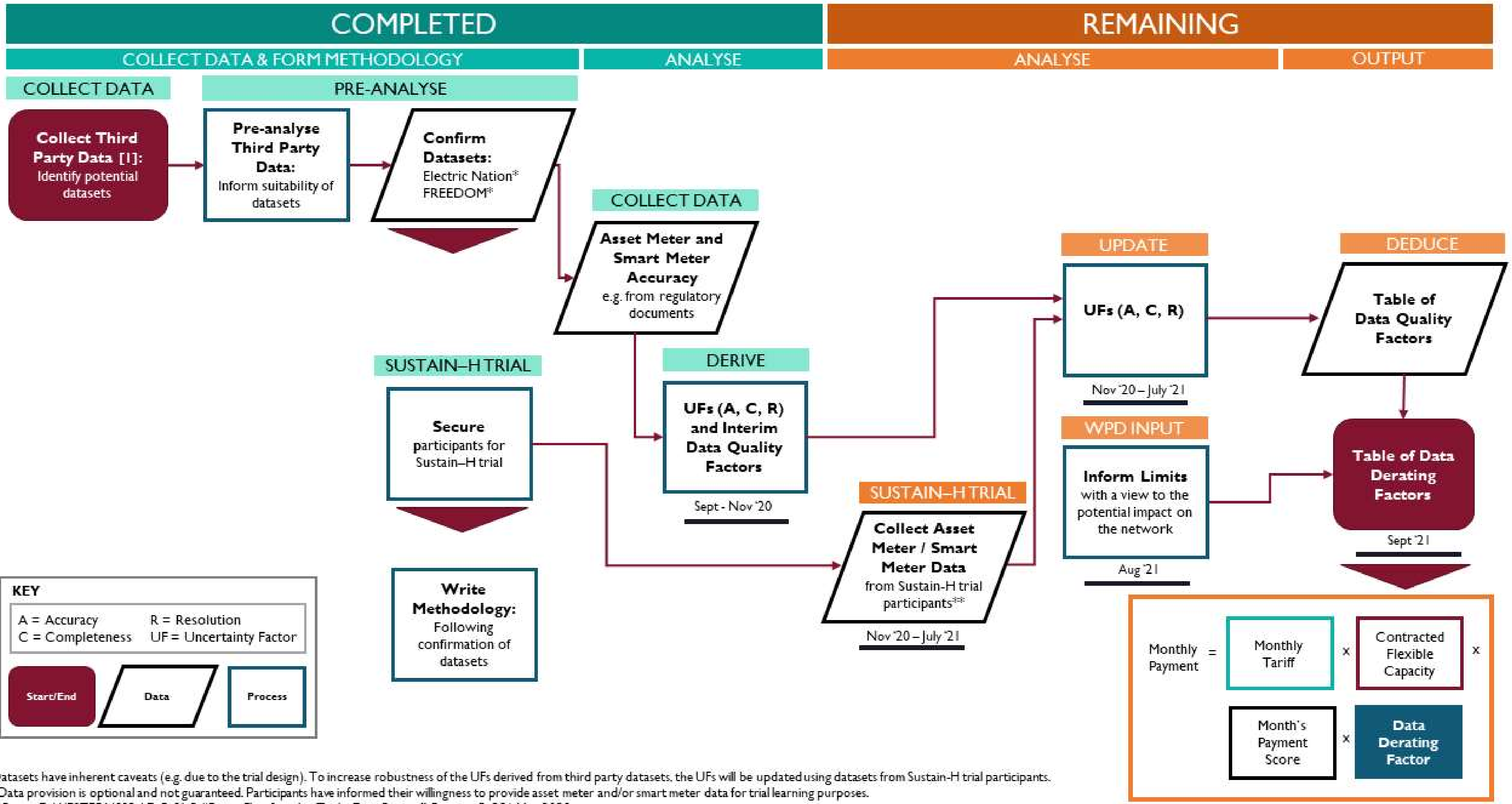
7. **The linear impact of data incompleteness means that WPD can take a pragmatic approach.** In Everoze's analysis, demand uncertainty increased in a broadly linear fashion as the dataset became more incomplete. For instance, an 80% complete dataset led to a 125% increase in demand uncertainty when considering a 50% confidence level. As a result, there is potential for WPD to adopt a pragmatic approach here; for instance, for a 50% confidence level an 80% complete dataset might result in a multiplier of 1.25 within the Data Quality Factor, with corresponding impact on payment. Everoze also investigated the impact portfolio size has on demand uncertainty for an 80% incomplete dataset, and found the impact is independent of portfolio size.

The next step is to update the analyses in 2021, following receipt of Sustain-H trial data. Everoze will prioritise remaining analysis based on:

- Data availability. Sustain-H data is expected to be dominated by electric vehicles; and
- Materiality: Factors demonstrated to be of material significance to data quality.

In particular, Everoze proposes to conduct the following steps:

1. Refine resolution analysis: Update the Resolution Uncertainty Factors using electric vehicle data, which is expected to be plentiful from the Sustain-H trial.
2. Probe portfolio effects: Calculate the Resolution Uncertainty Factors for different portfolio sizes.
3. Update Data Quality Factor: Update and the Data Quality Factor using the above, with a focus on delivering a Table of Data Derating Tables which can be of pragmatic use to WPD.
4. Form recommendations: Tease out the implications for future WPD DSO service procurement.



* Datasets have inherent caveats (e.g. due to the trial design). To increase robustness of the UFs derived from third party datasets, the UFs will be updated using datasets from Sustain-H trial participants.
** Data provision is optional and not guaranteed. Participants have informed their willingness to provide asset meter and/or smart meter data for trial learning purposes.
[1] Bacon D, WESTERN002-AD-R-01-B, "FutureFlex: Supplier Trial – Data Review", Revision B, 29th May 2020

FIGURE 1: AGGREGATED DATASETS WORKSTREAM PROCESS

2. INTRODUCTION

2.1 CONTEXT

FutureFlex is a joint project delivered by Western Power Distribution (WPD), Everoze and Smart Grid Consultancy (SGC), funded by the Network Innovation Allowance (NIA). FutureFlex is trialling a new DSO service suitable for domestic flexibility, called Sustain-H. This service places data optionality at its heart.

The role of the *Aggregated Datasets* workstream is to quantify the impact of lower portfolio data quality for WPD's DSO services, which will ultimately help to inform payment mechanisms for Sustain-H.

The first deliverable in Aggregated Datasets, "FutureFlex Supplier Trial – Data Review", examined available datasets to inform Everoze's analyses [1]. The second deliverable, "Aggregated Datasets – Methodology" [2] (the "Methodology"), outlined an approach to quantify the impact lower dataset resolution, completeness and metering accuracy has on demand prediction.

This report follows on from the Methodology, presenting the results from the analysis conducted on third party datasets: data from the Electric Nation [3] and Freedom [4] trials. For the analysis, the Resolution, Completeness and Accuracy Uncertainty Factors (UFs) were analysed independently and then combined into a single Data Quality Factor (DQF). The calculated DQFs will inform the Data Derating Factor (DDF) for Sustain-H remuneration to reflect the commercial impact of the uncertainties quantified.

The UFs and subsequently DQFs calculated and presented in this report will be updated using asset-meter data from Sustain-H trial participants, which will be available from 2021 onwards. The results from this analysis will be presented in a separate report, targeted to be delivered on 31/10/2021.

2.2 OBJECTIVES

The objective of the *Aggregated Datasets* workstream is to help quantify the impact of lower data quality, and thereby inform Sustain-H payments. Specifically, the workstream aims:

- To quantify to what extent aggregation might address data quality challenges at domestic level;
- To establish the implications for DSO service procurement; and
- To provide necessary information to, and integrate with, the Sustain-H service.

The output will be a method to estimate the Data Derating Factor (DDF) within the Sustain-H payment formula.

2.3 REPORT STRUCTURE

The report adopts the following structure:

- **Section 3 – Methodology:** This section recaps the Methodology outlined in [2], including outlining updates.
- **Section 4 – Results & Discussion:** This section presents the results of the analysis.
- **Section 5 – Conclusions:** This section reflects on key findings from the analysis, lists the limitations, and outlines the next steps.

3. METHODOLOGY

This section outlines the methodology that Everoze has used to analyse data from pre-existing datasets as presented in [1]. While analysing the data, a number of refinements to the Methodology were necessary.

This section includes the following:

- Summary of method;
- Method for analysing impact of Resolution on Quality as a flowchart;
- Method for analysing impact of Completeness on Quality as a flowchart;
- Method for analysing impact of Accuracy on Quality as a flow chart; and
- Method for calculating the DQF.

An extensive explanation of the methodology is written in Appendix *2: Updated Methodology*, with any updates or changes to the original methodology highlighted in **red.**

3.1 SUMMARY OF METHOD

The Aggregated Datasets workstream aims to quantify the impact that varying magnitudes of measurement uncertainty have on the measured aggregated portfolio demand. It is hypothesised that this impact will be inversely proportional to portfolio size, or, in other words, that the more the number of assets within the aggregation the more the various sources of uncertainty will tend to cancel out or diminish in terms of their proportional impact.

The method is based on the following logical sequence:

1. Any 30-minute mean demand value at an aggregate portfolio level, where completeness of the dataset is unknown and where demand is expected to vary over time (and hence within the 30-minute period), can be improved by an understanding of:
    a. Resolution – where correcting from 30-minute resolution (for example) to determine the peak 1-minute resolution demand during that period would increase the perceived demand.
    b. Completeness – where correcting for "incompleteness" would increase the perceived 30-minute average demand; and
    c. Measurement accuracy – where measurements of individual assets or smart meters are independent of each other, and normally distributed.
2. Because these factors are independent of each other, their respective impacts can be treated as such. This means they can be assessed independently, and combined using well-established statistical model(s) or simple arithmetic.
3. Therefore, Everoze has produced a model of independent and 'variable' (therefore probabilistic in nature) Uncertainty Factors (UFs) for: Resolution, Completeness using third party data, and Accuracy using data from asset meter and smart meter data sheets.
4. The Completeness and Resolution UFs consist of a 'multiplier' of the 30 minute average, and the variability is represented by the standard deviation of the multiplier (from the available data).
5. For Accuracy, the multiplier has been set as 1. However, there is a standard deviation which Everoze has defined by accuracy measurement based on available information (e.g. from datasheets and Sustain-H trial participant data, and the number of measurements made).
6. The UFs have been combined into a single DQF for each combination of elements considered, with outputs in a tabulated form:
    a. Dataset (for the pre-trial datasets: Electric Nation and Freedom);
    b. Portfolio size;
    c. Completeness; and
    d. Resolution.
7. The DQFs will be used to establish the DDFs (commercial impact), although this will be undertaken by WPD outside of this sub-workstream.
8. The DQFs will be updated using Sustain-H trial data, anticipated to be received in 2021.

3.2 DATA PRE-PROCESSING

The data was pre-processed following the logical steps captured in Figure 2 including a sample format for the output data files. The output files were fed into the technology-agnostic Completeness and Resolution code for the separate analyses. The pre-processing steps are described in Appendix 1 and a summary of the pre-processing results is set out below.

Freedom: The Freedom trial ran from 1st October 2017 to 30th April 2018. During this period, 53.2% of the 1-minute asset meter data (aggregated from 75 assets) was not flagged as 'null' data. A 61-day period from 1st March to 30th April 2018 displayed the highest consistent participant availability, and so this window was chosen to run the complete analysis and is referred to as the 'High Availability Window'. Everoze removed any whole-asset data if the asset was unavailable for more than 50% of this smaller sampling window. Following pre-processing of the dataset, 49 assets remained. The Resolution and Completeness analyses were performed on this High Availability Window of the full dataset: 49 assets from 1st March to 30th Apr 2018, with only 5.5% of the data being 'null' records.

Electric Nation: The Electric Nation trial ran from January 2017 to December 2018. Trial participants were either in 'Trial 1', 'Trial 2', 'Trial 3' or were not allocated to a particular trial. The different trials were subject to different interventions, therefore Everoze decided, if the impact to the population size used for the analysis was not significant, that the analysis should be performed using data from only one trial for consistency rather than combining the data from all trials. Following pre-processing, Trial 1 displayed the highest population availability (155 assets) over a period of approximately three months (18th April to 15th July 2018) . Therefore, Trial 1 was selected. The Resolution analysis was performed on this portion of the full dataset: 155 assets from Trial 1, from 18th April to 15th July 2018.

It should be noted that the Completeness analysis was only performed on the Freedom dataset, and not the Electric Nation dataset. This was due to the following:

1. **The minutely Electric Nation dataset was relatively incomplete compared to the Freedom dataset.** Following pre-processing, the Electric Nation dataset contained charging events for the cars 5% of the time. On average, 7 out of 155 cars were charging each minute. Therefore, if Everoze were to introduce null data randomly into the existing dataset on a per asset-asset day basis, (which included the times when the null data was 0kW), the probability that the null data would replace datapoints which are already 0kW would be high. Therefore, the impact on electricity demand would be minimal hence limiting the results.
2. **For the completeness analysis, the starting dataset must first be set up to be 100 % complete.** Therefore any null data must be replaced with realistic values based on the available data. However, due to the transactional nature of the Electric Nation dataset, there were no minutely 'null' datapoints, only null data on whole transaction level. The raw Electric Nation data was provided on a per-transaction basis only, displaying the 'Start' and 'End' charge times, battery charger power rating (either 3.6 kW or 7 kW), and the total charging duration for each charging event (termed transaction). To convert the per-transaction data into minutely data, Everoze assumed that the charging rate was constant for each transaction, at 3.6 kW or 7 kW. In reality, charging rate would have varied throughout the charging period.

3.3 RESOLUTION

Figure 3 captures the Methodology steps for the Resolution analysis. There were three key parts to the analysis which Everoze undertook:

- Determining variance of the data at 1-minutely and for 30-minutely average data for the morning and evening Delivery Periods, and whole dataset (all settlement periods);
- Quantifying the impact portfolio size has on uncertainty for the different averaging; and
- Estimating Resolution Uncertainty Factors, or "RUFs", for the derivation of the DQF.

3.4 COMPLETENESS

Figure 4 captures the Methodology steps for the Completeness analysis. There were three components to the Completeness analysis:

- Quantifying the 'completeness' of the datasets for the portfolios considered;
- Determining the impact of different levels of data completeness on the uncertainty of measured portfolio demand representing the 'real' portfolio demand;
- Quantifying the impact portfolio size has on uncertainty for a given completeness percentage; and
- Estimating Completeness Uncertainty Factors, or "CUFs", for the DQF equation.

3.5 ACCURACY

Figure 5 captures the Methodology steps for the Accuracy analysis. There were three components to the analysis:

- Quantifying the 'Accuracy' of different meter types;
- Calculating the standard deviation of this uncertainty; and
- Estimating Accuracy Uncertainty Factors, or "AUFs", for the DQF equation.

3.6 DATA QUALITY FACTOR

The DQF has been calculated by combining the outputs from the independent Resolution, Completeness and Accuracy analyses. The independent analyses have produced a series of 'Multipliers' and 'Standard Deviations' for different scenarios considered. Everoze has calculated the DQF for different levels of confidence, 50% and 95%, using Equation 1 and Equation 2 respectively. In these equations, M represents the 'Multiplier' and SD the standard deviation. Subscripts R, C and A denote Resolution, Completeness and Accuracy, respectively.

The DQFs have been calculated for each dataset independently, using data across all settlement periods rather than just the individual Delivery Periods. The DQF will be updated when data from the Sustain-H trial are received and the range of factors calculated will span across different population sizes, delivery periods, and technologies.

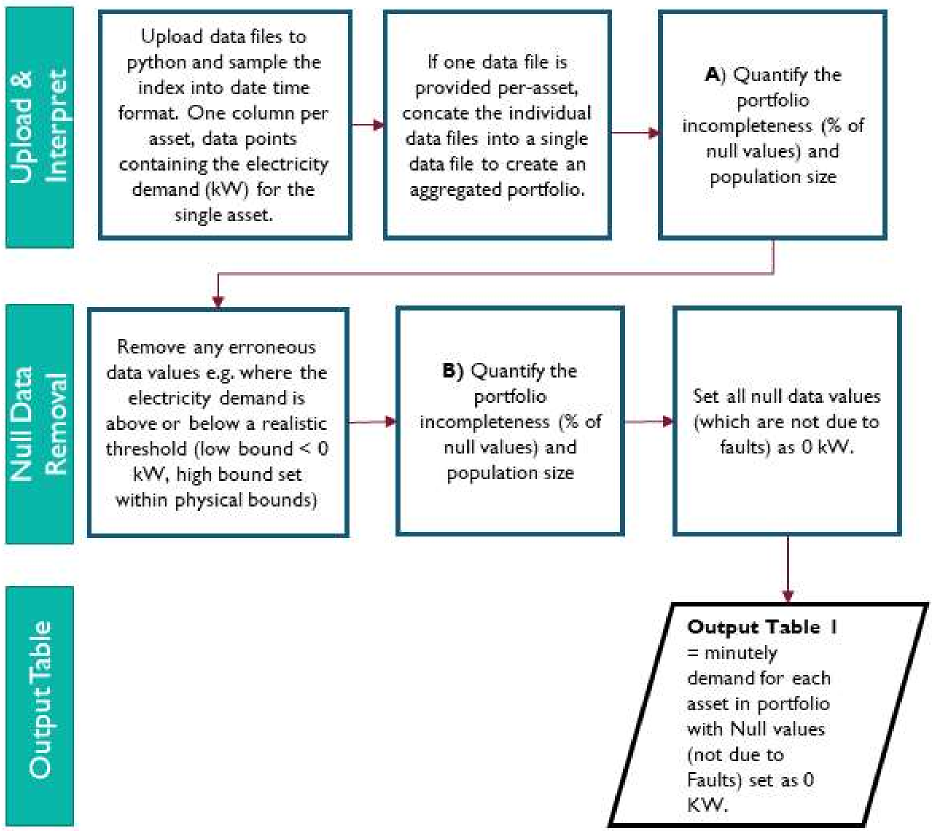
$$DQF = M_R \, x \, M_C \, x \, M_A$$

EQUATION 1 – DQF FOR A 50% CONFIDENCE LEVEL

$$DQF = M_R \, x \, M_C \, x \, M_A + (1.645 \, x \sqrt{(SD_R)^2 + (SD_C)^2 + (SD_A)^2})$$

EQUATION 2 – DQF FOR A 95% CONFIDENCE LEVEL

Pre-Processing

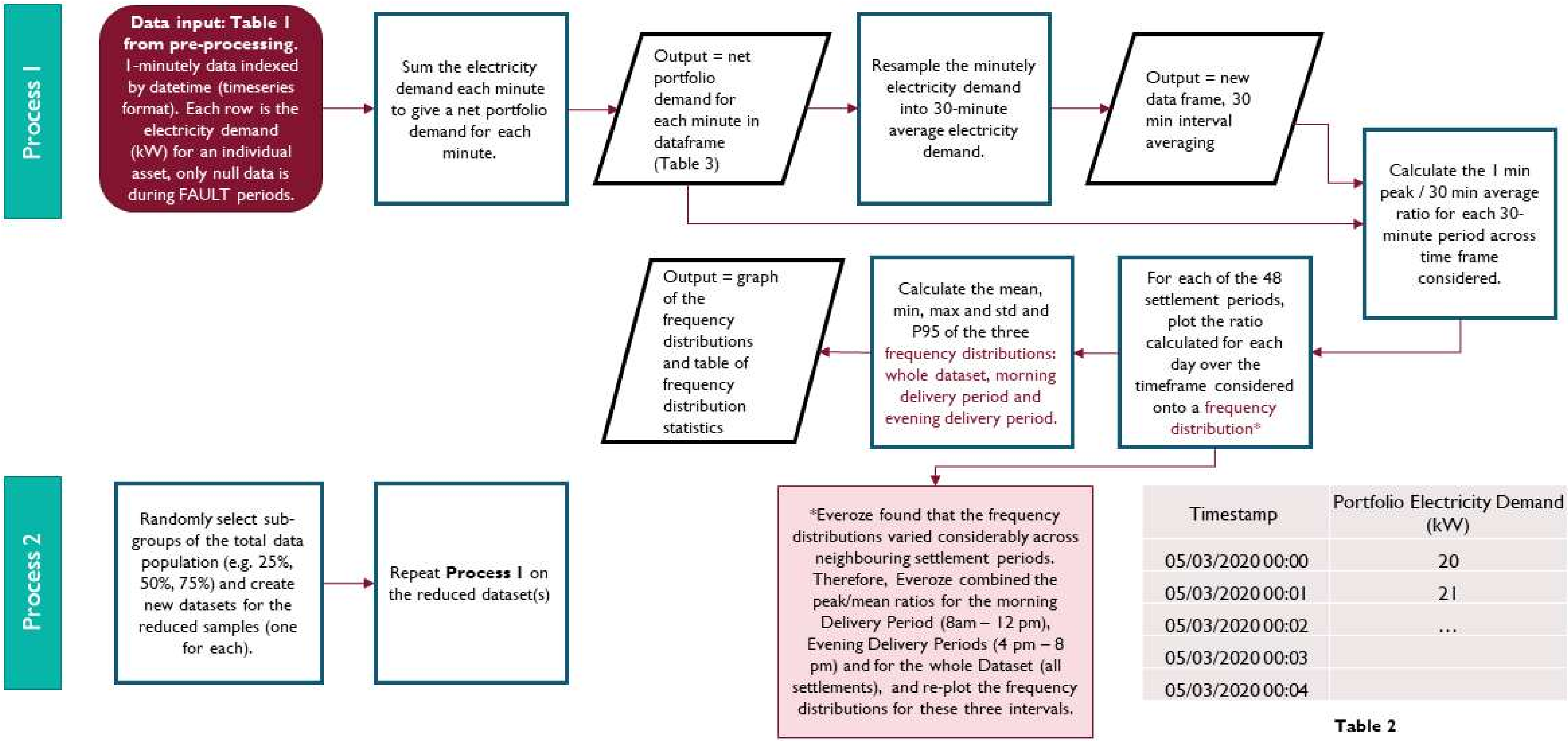


	Electricty Demand (kW)					
DateTime	Asset 1	Asset 2	Asset 3	Asset 4	Asset 5	Asset 6
05/03/2020 00:00	0.1	0	0.2	…		
05/03/2020 00:01	0.5	0.3	0			
05/03/2020 00:02	…					
05/03/2020 00:03						
05/03/2020 00:04						

Table 1

FIGURE 2: DATASET-AGNOSTIC PRE-PROCESSING STEPS

Resolution

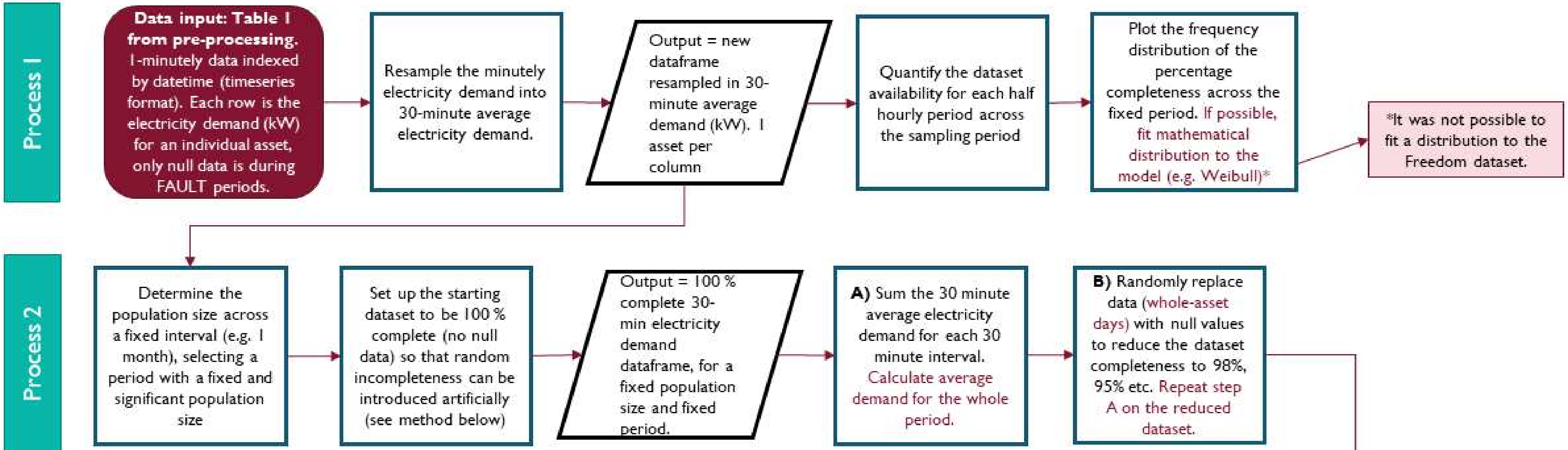


Timestamp	Portfolio Electricity Demand (kW)
05/03/2020 00:00	20
05/03/2020 00:01	21
05/03/2020 00:02	...
05/03/2020 00:03	
05/03/2020 00:04	

Table 2

FIGURE 3: DATASET-AGNOSTIC METHODOLOGY STEPS FOR THE RESOLUTION ANALYSIS

Completeness



% COMP.	Std	P95	Maximum	Minimum	Mean
98	Average demand 100 % C / average demand 98 % C	…	…	…	…
95	…				
90					
80					

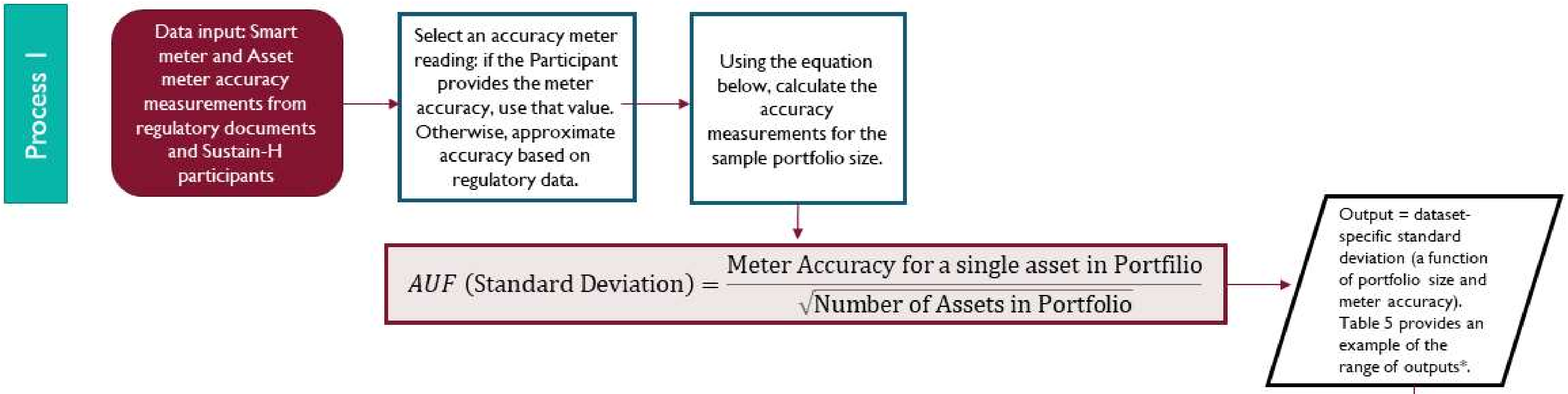
Table 3

Method to make dataset 100 % complete, In order of priority:

a. Take the average for asset with identified invalid data across the same hour across the duration of the dataset, split between weekdays and weekends.
b. If the data available to perform the averaging process in item 1 is < 75%, then: take a through day average for that asset, split between weekdays and weekends
c. If the data available to perform the averaging process in item 2 is <75%, then either delete that asset all together, or take an average across all assets for that time of day.

FIGURE 4: DATASET-AGNOSTIC METHODOLOGY STEPS FOR THE COMPLETENESS ANALYSIS

Accuracy



Population Size	Standard Deviation [%] for 1 % accuracy
1	1.000
5	0.447
25	0.200

Table 4

*It had been concluded that the multiplier for Accuracy is 1.0 as there is no expected bias in meter readings, only uncertainty from the meter accuracy

FIGURE 5: DATASET-AGNOSTIC METHODOLOGY STEPS FOR THE ACCURACY ANALYSIS

4. RESULTS & DISCUSSION

4.1 RESOLUTION

4.1.1 Determine the variance of the data at 1-minutely intervals and when averaged into half hourly intervals for a portfolio.

The intention of this exercise is to understand how much greater the demand can be on a short term (minutely) resolution when compared to a half-hourly resolution. This will enable WPD to understand how large the minutely peak demand might be in a given half hourly period when provided with only half hourly data.

To do this, Everoze has determined the ‘peak/mean’ ratio for both the Electric Nation and Freedom datasets following the analysis described in Section 3.3 and Appendix 1. Everoze has produced the following outputs:

1. Bar chart – peak/mean ratio: A bar chart comparing the peak/mean ratio for the two datasets (and consequently technology) for each settlement period, Figure 6.
2. Daily consumption profile: To review the variation of the peak over mean ratio it is useful to also understand the daily variation in the power consumption of the two datasets, as shown in Figure 7.
3. Frequency distribution – peak/mean ratio: Frequency distribution plots of the peak/mean ratio for the Morning and Evening delivery periods, and all Settlement Periods, Figure 8, Figure 9 and Figure 10, and a table showing the Mean, Minimum, Maximum, Standard Deviation and P95 of those plots, Table 1.
4. Scatter plots – peak/mean ratio: Scatter plots capturing the variation of peak/mean ratio to the half hourly demand average (mean) across all settlement periods, Figure 11 and Figure 12.

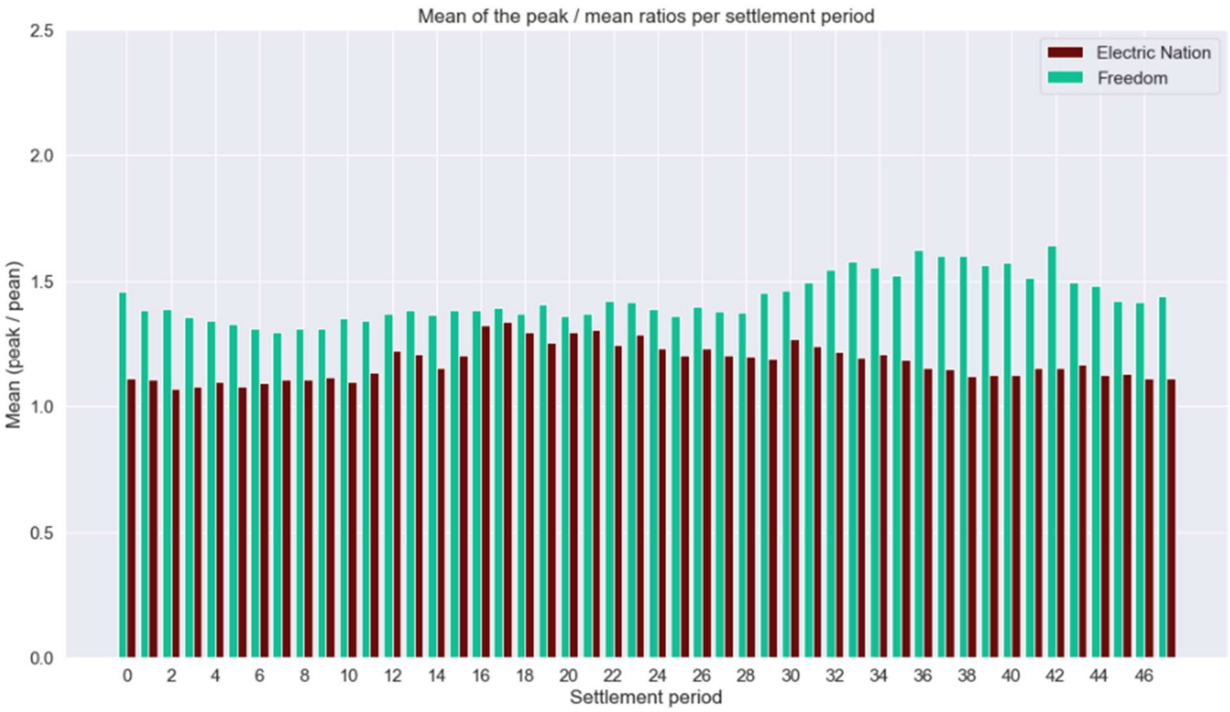


FIGURE 6: MEAN OF THE PEAK / MEAN RATIOS PER SETTLEMENT PERIOD

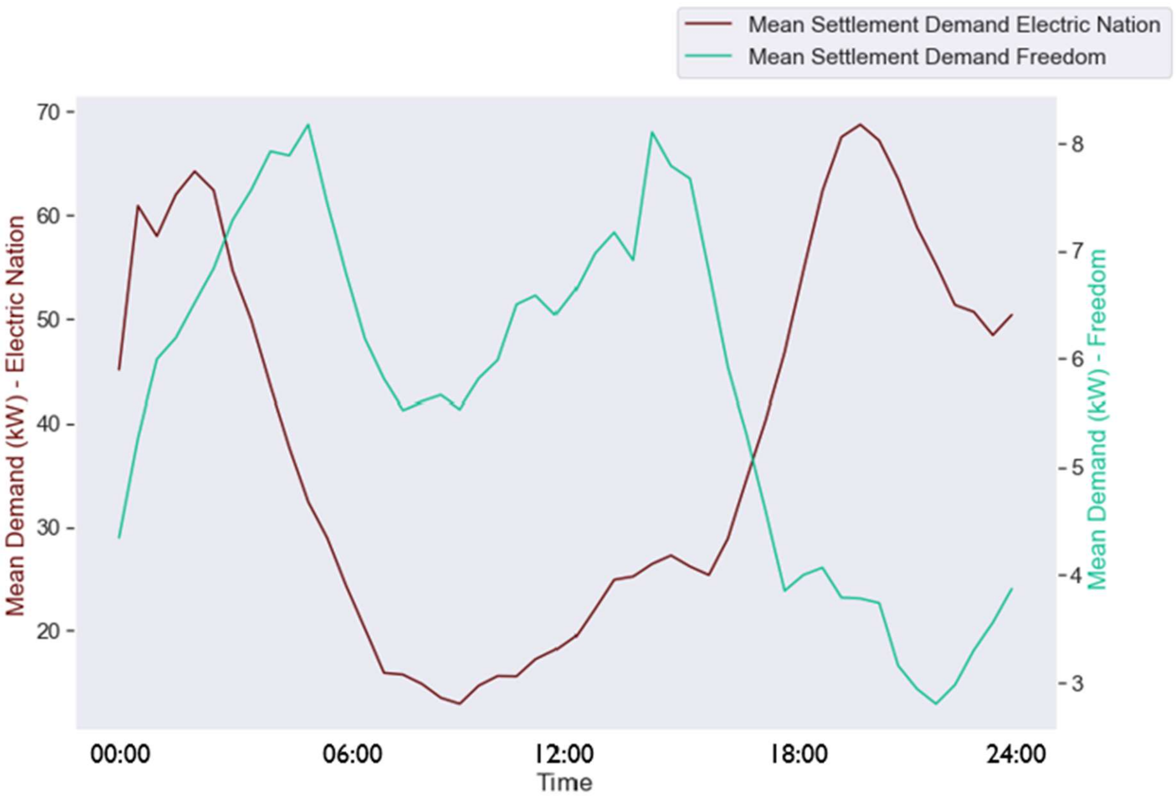


FIGURE 7: MEAN POWER DEMAND PER SETTLEMENT PERIOD

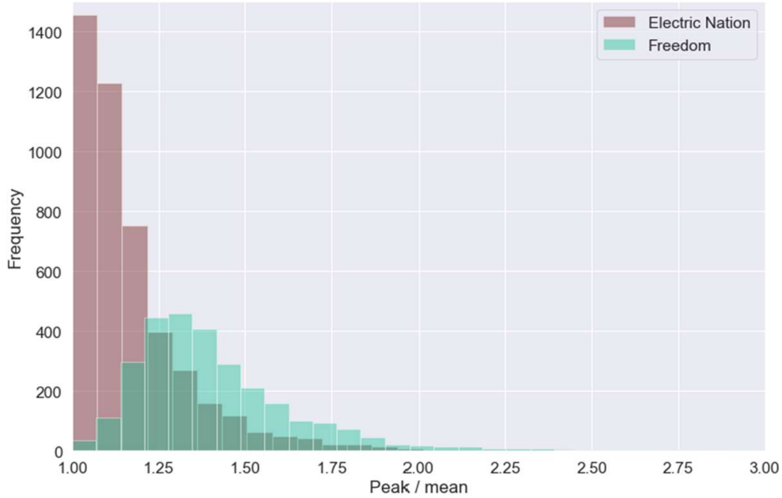


FIGURE 8: FREQUENCY DISTRIBUTIONS OF THE PEAK / MEAN RATIOS FOR ALL SETTLEMENT PERIODS (ALL DATA)

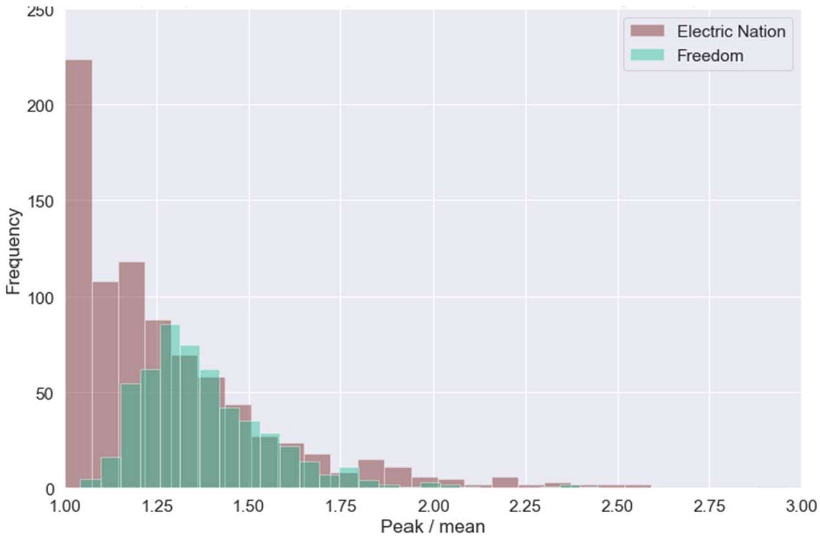


FIGURE 9: FREQUENCY DISTRIBUTIONS OF THE PEAK / MEAN RATIOS FOR THE MORNING DELIVERY PERIOD

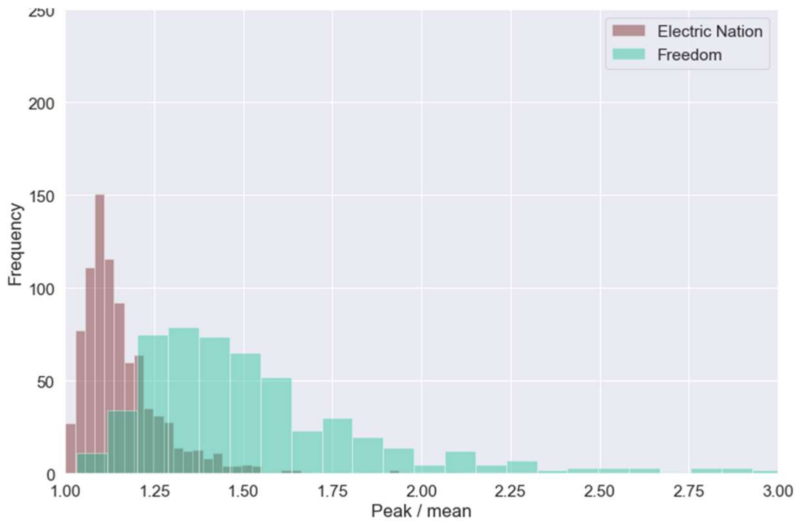


FIGURE 10: FREQUENCY DISTRIBUTIONS OF THE PEAK / MEAN RATIOS FOR THE EVENING DELIVERY PERIOD

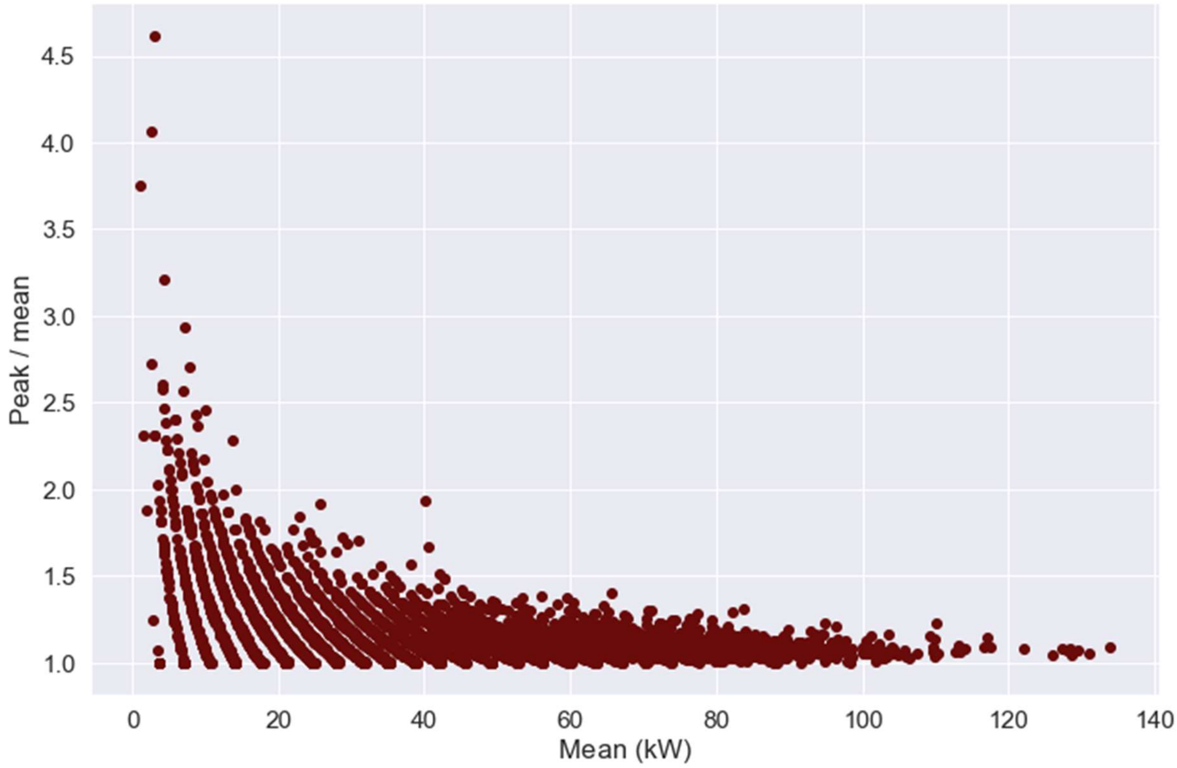


FIGURE 11: PEAK / MEAN AGAINST MEAN DEMAND – INCLUDES DATA FROM ALL SETTLEMENT PERIODS. DATASET: ELECTRIC NATION

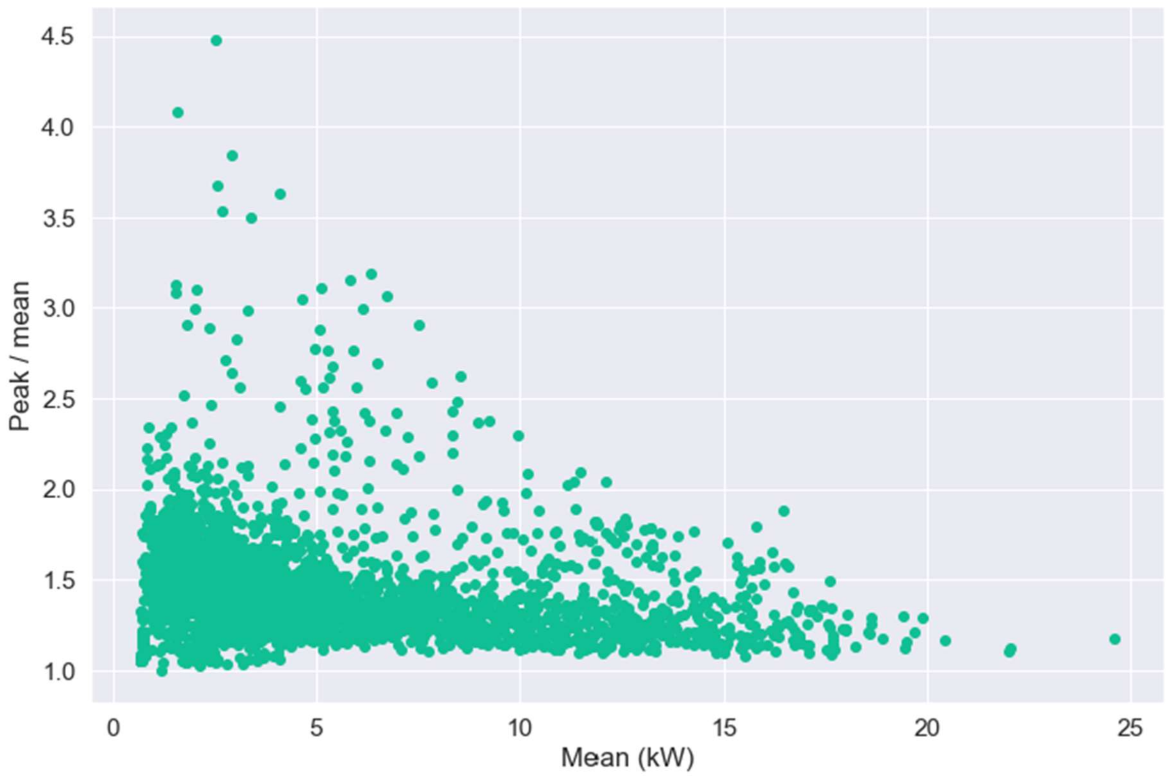


FIGURE 12: PEAK / MEAN AGAINST MEAN DEMAND – INCLUDES DATA FROM ALL SETTLEMENT PERIODS. DATASET: FREEDOM

Delivery Period	Dataset	Mean	Minimum	Maximum	Standard Deviation	P95
Morning	Freedom	1.39	1.04	2.99	0.22	1.76
	Electric Nation	1.29	1.00	4.62	0.34	1.88
Evening	Freedom	1.57	1.03	4.48	0.44	2.46
	Electric Nation	1.16	1.00	2.10	0.13	1.41
Whole Dataset	Freedom	1.43	1.00	4.48	0.30	1.91
	Electric Nation	1.18	1.00	4.62	0.21	1.54

TABLE 1: KEY METRICS FROM THE PEAK / MEAN FREQUENCY DISTRIBUTIONS

Key observations

The trends observed from these two datasets are generally quite different. In particular:

- Consumption profiles vary dramatically between the two datasets. Figure 7 shows a plot of the mean power demand (kW) per settlement period for the Electric Nation and Freedom datasets. The power demand for the Freedom dataset peaks at around 5 am and 2 pm, before the morning and evening electricity price peaks. This relationship is possibly seen because the heat pump systems in the Freedom project are optimised for least cost to customer: warming homes before peak energy price periods. In contrast, the Electric Nation dataset shows a demand peaks at 2 am, reaching a low from 8 am when most people are using their cars, and steeply increases from 4 pm to a peak around 8 pm as people plug in their cars when returning home from work.
- The peak/mean ratio varies during the day for both datasets – but the trends are not consistent with each other. This is shown in Figure 6. There are higher values during the evening for the Freedom dataset, whereas peak values for the Electric Nation dataset are during the morning. Overall the variation through the day is not particularly large with the highest and lowest settlement periods being within 0.5 of each other.
- The distributions of the peak/mean ratios shown for each delivery period and the whole day are very different. This is shown in Figure 8, Figure 9 and Figure 10 respectively. For the Freedom data these are characterised by Weibull distributions whereas it is exponentially decreasing for Electric Nation. The differences can be explained by: 1) the typical behaviour of the types of asset within each dataset. By their very nature, heat pump power consumption can vary a reasonable amount over short time frames. Electric vehicle chargers are likely to be on for longer periods of time and are more binary in their operation. This means that for electric vehicles the peak for many settlement periods, may well be the same as the mean. 2) the asset's control system will cause power consumption variability, for example the Freedom hybrid heat pumps under full optimisation will be quite variable, whereas with less stringent control, the power demand profiles may not vary significantly. *In the case of the Electric Nation trial, Everoze has assumed a constant charging rate from start to end of the 'transaction' at 3.6 kW or 7 kW (depended on the car battery charger rating). Typically, when plugging in an EV for charging, the power demand profile is relatively constant and flat until 80 % of the charge has been met, at this point the power demand decreases.*

In addition, an interesting outcome is the similarity in the graphs of peak/mean plotted against the mean for all settlement periods, shown in Figure 11 and Figure 12. These graphs both show there is a trend of increasing peak/mean ratio as consumption reduces. This is understandable as during a low consumption settlement period it requires less behaviour change to introduce a peak/mean ratio close to 2.0. This outcome is also demonstrated by the higher peak/mean ratio for the evening delivery period for the Freedom dataset, as observed in the values shown in Table 1 and the low evening demand in Figure 7.

4.1.2 Quantify the impact portfolio size has on half hourly averaging uncertainty

Everoze investigated the impact of portfolio size on the half hour averaging uncertainty, removing whole-assets from the portfolio and repeating the analysis from Section 4.1.1. Everoze reduced the population of both datasets to 25%, 50%, and 75% of the initial size and used a Monte-Carlo approach to produce 1000 different combinations of a 25% reduced dataset, a 50% reduced dataset and a 75% reduced dataset. Everoze calculated the mean of the 'peak / mean' ratios across all settlement periods, and plotted the 1000 mean values as a frequency distribution in Figure 13 for the Electric Nation dataset and in Figure 14 for the Freedom dataset. Table 2 provides the mean values taken from the distributions in each figure.

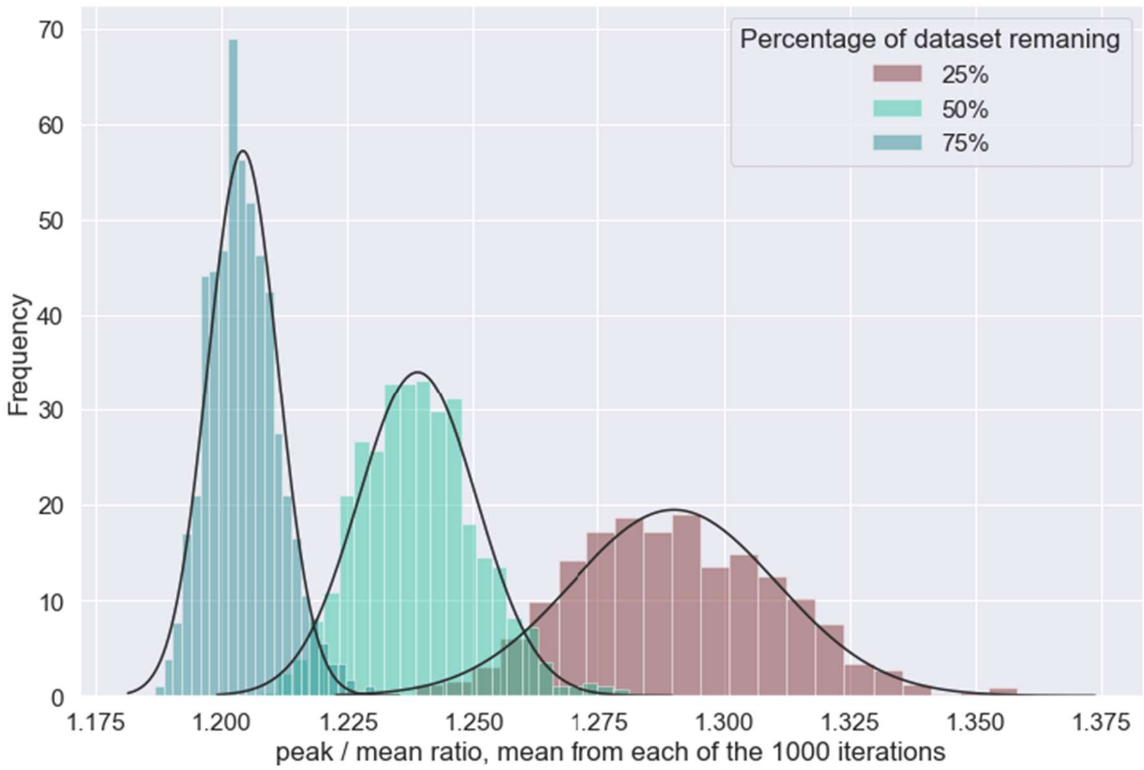


FIGURE 13: FREQUENCY DISTRIBUTIONS OF THE 'PEAK / MEAN' RATIO FOR THE REDUCED POPULATION ELECTRIC NATION DATASET

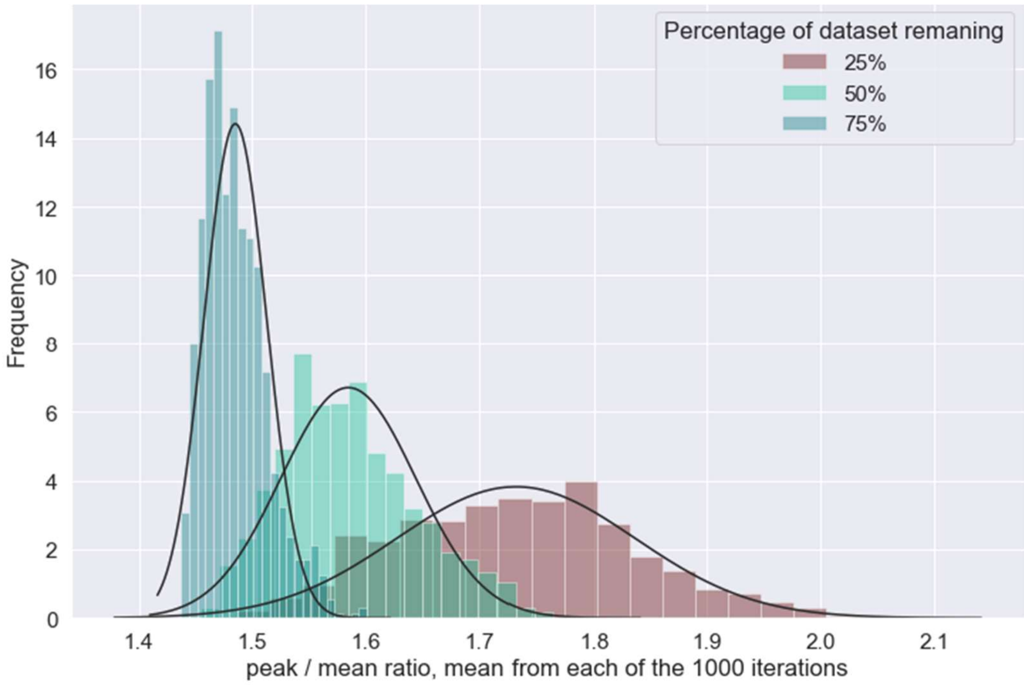


FIGURE 14: FREQUENCY DISTRIBUTIONS OF THE 'PEAK / MEAN' RATIO FOR THE REDUCED POPULATION FREEDOM DATASET

Dataset	25%	50%	75%	100%
Freedom	1.73	1.56	1.49	1.43
Electric Nation	1.29	1.24	1.20	1.18

TABLE 2: MEAN OF THE 'PEAK / MEAN' VALUES FOR THE 25 %, 50 % AND 75 % POPULATION SIZES

Everoze found that population size has a significant impact on the mean of the 'peak / mean' ratios. The spread of the mean peak / mean values increased considerably as population size reduced. When the datasets were reduced to 25% of their initial population size, Electric Nation displayed a mean 'peak / mean' ratio almost 10% higher than the entire dataset. For the Freedom dataset it was a 20% increase for the 25% dataset.

The variance of the means of the reduced dataset 'peak / mean' distributions for the Electric Nation dataset (Figure 13) were consistently smaller than for the Freedom dataset (Figure 14). This could be attributed to either 1) the population size of the initial dataset; the population size of the Electric Nation dataset was ~3 times greater than the Freedom dataset or 2) the type of assets (heat pump or EV).

To investigate the population size further when comparing the two dataset Everoze reduced the Electric Nation dataset (which had a starting population of 155 assets) down to the equivalent number of assets in the Freedom dataset for each of its reduced datasets. So a 100% case (49 assets), and also 75% (37), 50% (25), 25% (13) were considered. Everoze investigated the hypothesis that irrespective of asset type, the mean 'peak / mean' ratio is driven entirely by population size. Table 3 compares the mean values for the two datasets for at the same population size.

Dataset	Assets = 13	Assets = 25	Assets = 37	Assets = 49
Freedom	1.73	1.56	1.49	1.43
Electric Nation	1.34	1.31	1.29	1.27

TABLE 3: COMPARISON OF 'PEAK / MEAN' VALUES FOR THE TWO DATASETS

This was further explored by plotting the peak/mean as presented in Table 2 and Table 3 above against population size (Figure 15). A power law fit is applied and the trendlines are shown in the figure. The following observations are made:

The Electric Nation dataset shows a roughly linear trend across the population size, whereas the Freedom data shows a non-linear variation over the small population size considered in the analysis. The graph shows the trendlines for the peak/mean for both datasets converge for large population sizes. Based on these findings, Everoze hypothesises the following:

1. ***For sufficiently large populations (> 100 assets), the RUF's sensitivity on portfolio size is less pronounced and there is little variation across technology types.*** This suggests that there is reasonable grounds for taking a pragmatic approach when determining the DQF/DDF, such as considering a single common DQF value for populations above a certain size and not needing to distinguish this between technology types.
2. ***Variance in the RUF and therefore sensitivity to portfolio size, is only seen for small portfolios, and this sensitivity quickly diminishes for portfolios above a certain size.*** As smaller portfolios are unlikely to have a large impact on WPD's network constraint outcomes, if the aforementioned hypothesis of the variance in RUF being concentrated to small population portfolios only, a pragmatic and simplified approach may be considered where the same DQF/DDF as used for larger portfolios may also be used for small populations and avoid varying this for different population sizes and technology types.

Further analysis using additional datasets from Sustain-H will need to be performed to test these hypotheses, leading to firmer conclusions for design of the DDF.

Key observations:

1) Based on the available datasets, population size has a pronounced impact on the resolution UF and the magnitude of the impact is characteristic to the different technologies; however, this appears to be only for small portfolios and the sensitivity to population size and technology type is likely to be a non-driver for sufficiently large portfolios.
2) Heat pump portfolios display greater demand uncertainty compared to EV portfolios, and the uncertainty increases significantly as population size decreases. As noted above, the technology-specific characteristic appears to be diminished for large portfolios, and there is likely to be little difference in the demand uncertainty for the two datasets when considering large portfolios.

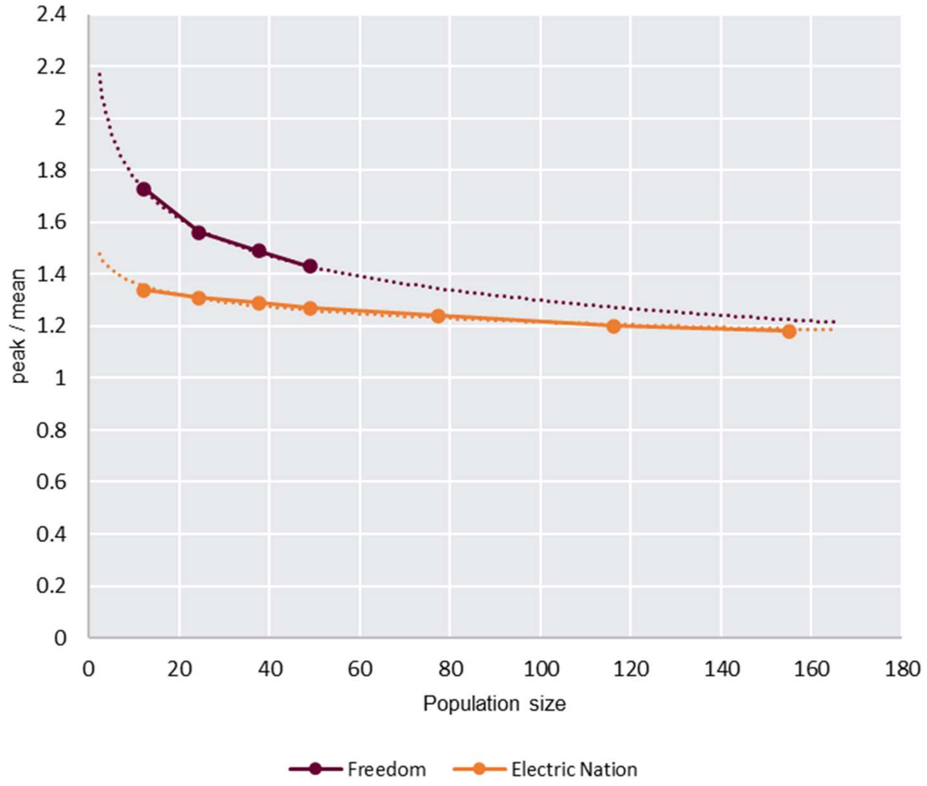


FIGURE 15: PEAK / MEAN VS POPULATION SIZE

4.1.3 Estimate value of RUFs

The RUFs are given in Table 4. Only the 'Whole Dataset' multipliers and standard deviations are used to calculate the DQF at this stage.

Delivery Period	Dataset	Multiplier	Standard Deviation
Morning	Freedom	1.39	0.22
	Electric Nation	1.29	0.34
Evening	Freedom	1.57	0.44
	Electric Nation	1.16	0.13
Whole Dataset	Freedom	1.43	0.30
	Electric Nation	1.18	0.21

TABLE 4: COMPONENTS OF THE RUFS

4.2 COMPLETENESS

The completeness analysis quantified the demand uncertainty introduced for different levels of incompleteness, when compared to a 100% complete dataset. Everoze removed whole-day assets randomly to reduce the 100% complete dataset, and calculated the ratio of the 100% complete whole-dataset power demand (kW) against the reduced dataset (kW) demand for the sampling period. As discussed in Section 3.2, only the Freedom dataset has been considered for the Completeness analysis.

Everoze randomly introduced null data, calculated the mean ratio of the 100% complete dataset demand (kW) against the reduced dataset demand (kW), and repeated this for 1000 or 10,000 iterations and plot the results from each iteration on a frequency distribution to capture the mean demand uncertainty and standard deviation for each distribution.

4.2.1 Quantify the 'completeness' of the dataset for the different portfolios considered

The initial data completeness of the Freedom dataset has already been discussed as part of the data pre-processing in the Section 3.2. While the dataset was reduced to a two month period for the analysis, this step also needed to consider the full trial dataset to provide more understanding of the dataset completeness and if there are any trends in the unavailability of data.

As an initial step Everoze produced two outputs from the analysis:

1. Percentage completeness of the datasets
2. Frequency distribution plot of the dataset availability for two sampling periods: a) full trial and b) the period used for the resolution and completeness analysis

Table 2 captures the percentage availability of the full trial period, and the two month High Availability Window from 1st March to 30th April 2018. It is clear there is a large difference in data availability and this is not surprising as these are trial data which improved in availability as the trial progressed.

Trial	Full-Trial Period	High Availability Window
Freedom	53.%	94.5%

TABLE 5: DATASET COMPLETENESS (NON-NULL DATA OVER SAMPLE PERIOD)

Figure 16 and Figure 17 display the frequency distribution plots for the full trial sample and High Availability Window respectively. Figure 16 does not show any particular trend in the unavailability of the data, while Figure 17 shows some possible tendency towards a reverse Weibull distribution for the much higher data availability case. Considering the following factors Everoze has concluded there is not sufficient evidence of a strong trend of unavailable data:

- The limited number of datasets for this analysis, only one;
- The reasonably random trend of unavailable data in the full-trial period;
- Where there is evidence of a possible trend, it is relatively weak and only defined by a two month period of data.

If Everoze had identified sufficient evidence of a trend, the null data would have been removed in the next steps of the analysis proportionally, to fit that trend. Based on the lack of a strong trend and evidence that assets are usually unavailable for an entire day within the Freedom dataset, Everoze has introduced null data to reduce the 100% complete dataset on a whole-asset day basis, until 98, 95, 90 or 80 % of the data remained.

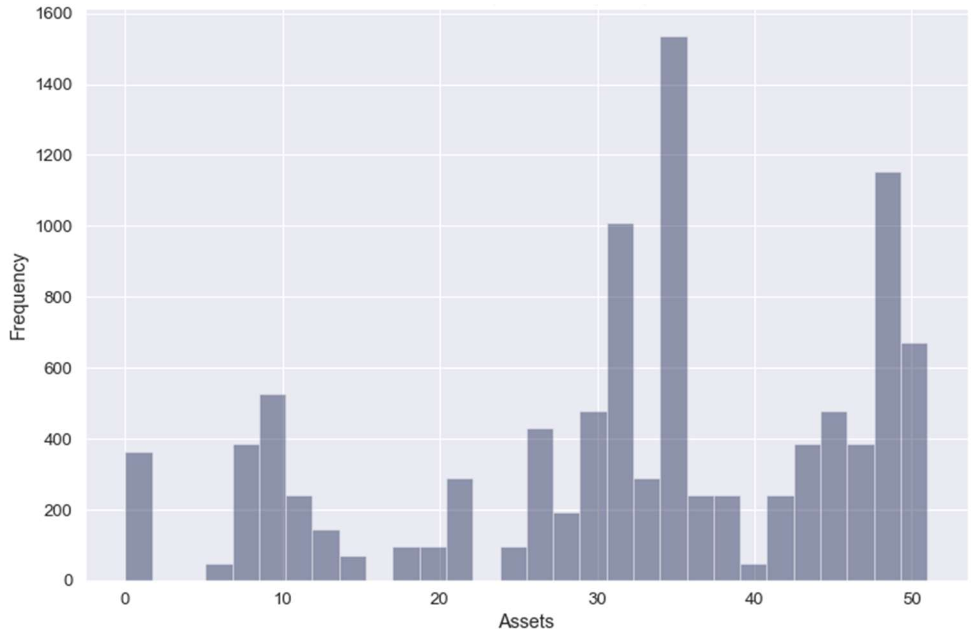


FIGURE 16: FREQUENCY DISTRIBUTION OF THE FREEDOM DATASET HALF-HOUR ASSET AVAILABILITY – FULL TRIAL PERIOD

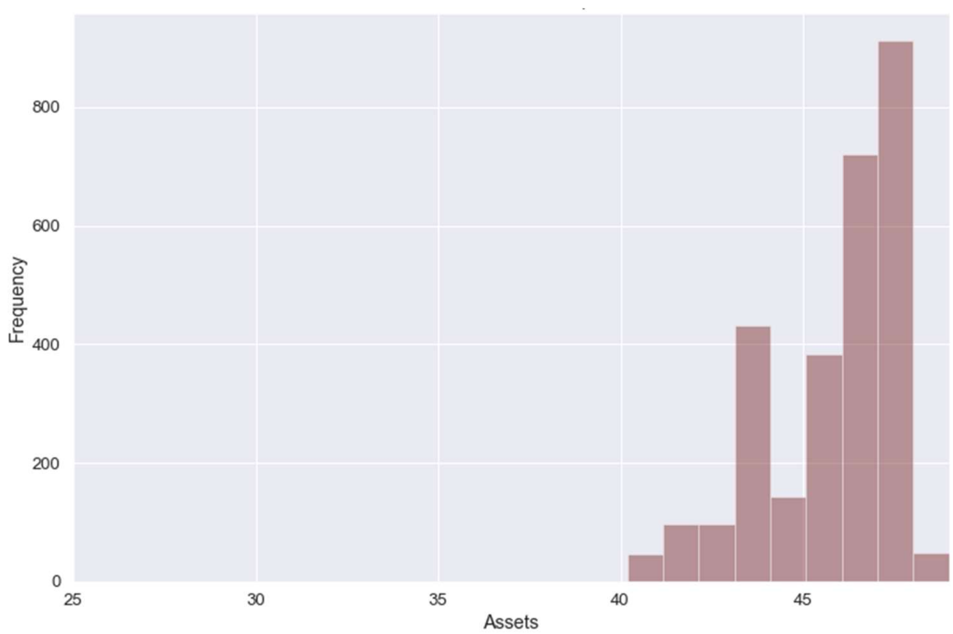


FIGURE 17: FREQUENCY DISTRIBUTION OF THE FREEDOM DATASET HALF-HOUR ASSET AVAILABILITY – SAMPLE SELECTED FOR ANALYSIS

4.2.2 For a fixed portfolio size, determine the impact 98, 95, 90 and 80 % portfolio data completeness has on measured demand uncertainty

Everoze has produced frequency distributions of the 1000 iterations of the 'Delta Demand' calculation (Equation 3) for the four different cases, as shown in Figure 18. Each iteration introduced null data randomly into the complete dataset, by removing whole-asset days, to reduce the dataset to the desired completeness percentage.

$$\text{Delta Demand} = \frac{100\ \%\ \text{complete dataset mean power demand (kW)}}{\text{x}\ \%\ \text{reduced dataset mean power demand (kW)}}$$

EQUATION 3

The reason for the range of different possible power demand levels for a given level of incompleteness, is due to the different power ratings of the individual assets, coupled with the assumption of no relationship between asset power rating and probability of data loss from that asset. This means that at one extreme, data incompleteness could occur solely in the assets of the lowest power rating, whilst at the other extreme, data incompleteness could occur in the assets solely in the assets of the largest power rating, and all variations in between. Therefore, the less complete the dataset, the wider the range of possible demand scenarios.

Each distribution appears to be normally distributed, therefore a normal distribution fit has been applied to each case and included in Figure 18. The key values that represent the normal distributions in are given in Table 6. For the 80% availability case Everoze also tested the outcome with 10,000 iterations with encouragingly similar results to the 1,000 iteration case, as shown in Table 6.

Based on the analysis of the Freedom dataset, the potential increase in true demand when compared to the demand calculated from an incomplete dataset, is shown numerically in Table 6 and graphically in terms of the mean, mean plus one standard deviation and the P95 level in Figure 19.

Completeness (%)	Iterations	Mean	Minimum	Maximum	Standard Deviation	P95
98	1000	1.0205	1.0100	1.0350	0.0032	1.0258
95	1000	1.0526	1.0388	1.0721	0.0053	1.0614
90	1000	1.1109	1.0899	1.1383	0.0077	1.1236
80	1000	1.2497	1.2141	1.3126	0.0131	1.2713
80	10,000	1.2503	1.2089	1.3089	0.0134	1.2723

TABLE 6: FREQUENCY DISTRIBUTION OUTPUTS FOR EACH COMPLETENESS CASE

Key observations:

1. As might be expected, the mean of each frequency distribution is approximately equal to the ratio: 100% divided by the reduced dataset completeness percentage (e.g. 100/80).
2. Demand uncertainty increases as the dataset becomes more incomplete, as reflected in the standard deviation values.
3. The increase in uncertainty as unavailability increases is reasonably linear.

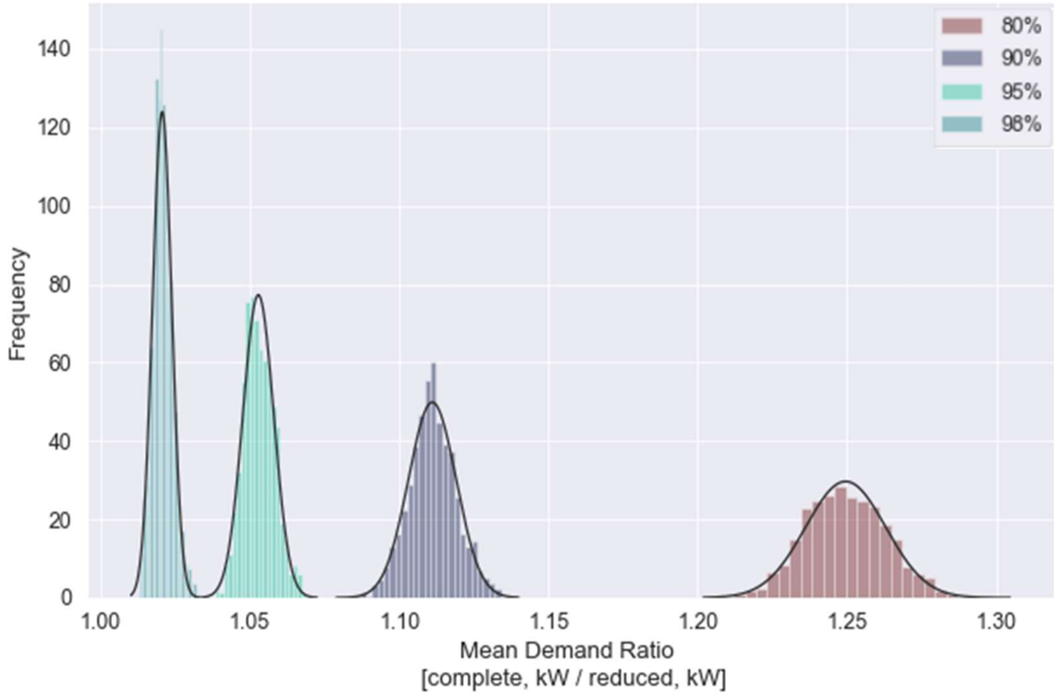


FIGURE 18: FREQUENCY DISTRIBUTIONS FOR EACH COMPLETENESS CASE FROM 1000 ITERATIONS

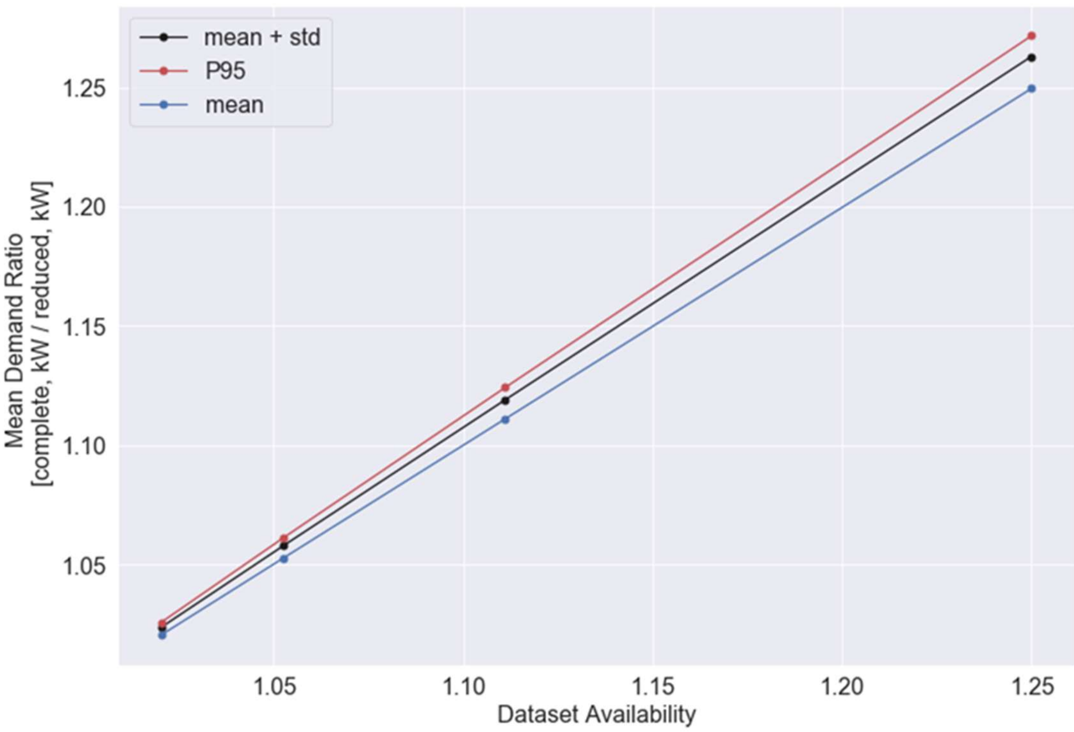


FIGURE 19: MEAN, MEAN PLUS ONE STANDARD DEVIATION, AND P95 VALUES FOR EACH COMPLETENESS CASE MODELLED.

4.2.3 Quantify the impact portfolio size has on measured demand uncertainty for the different completeness cases

Everoze investigated the impact portfolio size has on demand uncertainty for the 80% completeness case, by repeating the analysis from Section 4.2.1 on the Freedom dataset, using a 50% reduced population.

Everoze randomly removed 50% of the assets from the complete dataset, reducing the total number of assets from 49 to 24. The same process as described above in Section 4.2.2 was used to remove 20% of the remaining asset population using the same asset-day, reducing the completeness to 80%. This process was repeated for 100 iterations, and the mean of the 100% complete dataset demand (kW) / 80% complete dataset demand (kW) was calculated for each iteration. The mean of the 100 iterations equalled 1.25, which is the same as the mean calculated when the number of assets in the portfolio were 49. This demonstrates that portfolio size does not have a significant impact on the data completeness element of the demand uncertainty.

4.2.4 Estimate values of "CUFs"

Everoze has calculated the CUFs for each completeness case. The multiplier is taken as the ratio of 100 / % completeness and the standard deviations are taken from the mean demand ratio (complete (kW) / reduced (kW)) frequency distribution plots.

Completeness (%)	Multiplier	Standard deviation
98	100 / 98 = 1.0204	0.0032
95	100 / 95 = 1.0526	0.0053
90	100 / 90 = 1.1111	0.0077
80	100 / 80 = 1.2500	0.0134

TABLE 7: COMPONENTS OF THE CUFS

4.3 ACCURACY

4.3.1 Quantifying the uncertainty introduced to the metered data by metering accuracy

It is necessary to understand the uncertainty introduced to the metered data attributable to the accuracy of the half hourly smart meters (SMETS1 and SMETS2 meters) and the asset level meters used by participants for the Sustain-H trial. It is expected that the impact of Accuracy on data quality will be relatively small compared to data Resolution and Completeness. Everoze developed an approach to quantify the impact of Accuracy on the measured demand as outlined in Section 3.5. It has already been concluded that the multiplier for Accuracy is 1.0 as there is no expected bias in meter readings, only uncertainty from the meter accuracy. The meter accuracy as defined by the accuracy measurement given in the available published information (from datasheets and Sustain-H trial participant data) has been taken as the standard deviation for this work.

Electricity meters are classified into a particular 'class', which indicates the maximum permissible errors (MPE) of the electricity meter, based on IST (In Service Testing) test criteria. IST is a national sampling scheme based on the British Standard BS 6002-1:1993. Class A meters have an MPE of +/- 2%, Class B meters have an MPE of +/- 1 %, and Class C meters have an MPE of +/- 0.5 %. These values are based on the test requirements in Table 4 of BS EN 50470-3:2006 for tests of accuracy at reference conditions [5]. Table 8 lists 5 accuracy measurements from MPE complaint meters, the first three are listed as UK nationally approved electricity meters [6], and the last two have been provided by Sustain-H participants.

Electricity Meter	Description	Class	Accuracy
ES-12B	Residential single phase elements SMETS 2 compliant EM	A and B	+/- 1 and 2 %
Liberty 101 - secure	Residential; single phase elements SMETS 2 compliant EM	Class B	+/- 1%
Aclara 1-201+	Residential; single phase elements SMETS 2 compliant EM	Class C	+/- 0.20%
Confidential	Participant 1: Sustain-H Participant asset meter	Class B	+/- 1%
Confidential	Participant 2: Sustain-H Participant asset meter	Class B	+/- 1%

TABLE 8: METER ACCURACY INFORMATION

4.3.2 Calculation of the standard deviation of the accuracy measurements

Assuming that the asset metering accuracy for each asset in a portfolio is the same, the standard deviation component of the AUF can be calculated using the following equation:

$$\text{Accuracy UF Standard Deviation Component} = \frac{\text{Meter Accuracy for a single asset in Portfilio}}{\sqrt{\text{Number of assets in Portfolio}}}$$

EQUATION 4

Based on the 1% accuracy of the meters provided by Sustain-H participants, the standard deviation component of the AUF for the Freedom dataset (49 assets) is calculated to be **0.0014 (0.14%),** and for the Electric Nation dataset (155 assets), the standard deviation component is **0.0008 (0.08%).** Table 9 presents the accuracy values for portfolio sizes ranging from 1 to 250, calculated for +/- 1 % and +/- 2 % meter accuracy values.

Portfolio size	Standard Deviation [%] for 1 % accuracy	Standard Deviation [%] for 2 % accuracy
1	1.000	2.000
5	0.447	0.894
25	0.200	0.400
50	0.141	0.283
100	0.100	0.200
150	0.082	0.163
200	0.071	0.141
250	0.063	0.126

TABLE 9: AUFS FOR 1% AND 2% ACCURACY

Key observations:

- Measurement accuracy has minimal impact on the measured demand, for a sample size of 100 and 1 % metering accuracy, the standard deviation calculated is 0.1 %.
- Residential smart meters and asset meters are typically accurate to +/- 1 %.

4.4 COMBINED DATA QUALITY FACTOR

When deciding on an approach to combine the independent uncertainty factors into a single DQF, Everoze concluded the following:

1. DQFs have been calculated for the two datasets separately. This was decided based on the following:
    a. The completeness analysis was performed on the Freedom dataset only, and not the Electric Nation dataset for reasons described in Section 3.2. Therefore the CUF does not consider EV assets. Based on the range of outputs from the Resolution analysis, which varied for the different technologies, Everoze believe that the CUFs may also vary on a per-technology basis.
2. DQFs were calculated using data from all settlement periods, rather than for the two delivery periods. Results from the resolution analysis showed that there is some variation in peak/mean ratio throughout the day but there is no obvious trend for the morning or evening delivery periods. Therefore as there are limited datasets available for this work it is best to use the whole day values at this stage.
3. The DQFs calculated for the Electric Nation dataset combined the AUFs and RUFs only. Therefore the calculated DQF for EV assets is not finalised, and Everoze will update this value using Sustain-H data.

Table 10 presents the DQFs for the Electric Nation and Freedom datasets for both a central (P50) confidence level as well as a high (P95) confidence level. The root mean squared of the independent standard deviations calculated for the Freedom dataset varied marginally, from 0.3000 to 0.3003 as dataset completeness decreased. This is because the standard deviation component was dominated by the RUF standard deviation (0.300), which is a magnitude of 10 greater than those calculated from the completeness analysis, and a magnitude of 100 greater than those calculated from the accuracy analysis. The Multiplier component ranged from 1.43 to 1.79 for the Freedom dataset, and was fixed at 1.18 for the Electric Nation dataset.

Completeness (%)	Freedom		Electric Nation	
Confidence	**P50**	**P95**	**P50**	**P95**
100	1.43	1.92	1.18	1.53
98	1.46	1.95	-	-
95	1.51	2.00	-	-
90	1.59	2.08	-	-
80	1.79	2.28	-	-

TABLE 10: TABLE OF DQFS FOR ELECTRIC NATION AND FREEDOM DATASETS

Each DQF in Table 10 provides a factor to multiply to the measured half hour period to provide the likely actual peak demand during that half hour period. Factors have been provided for different levels of confidence to take into account the uncertainty. Therefore for the Freedom dataset, with 100% data completeness, the 1 minute peak demand in a half hour settlement period is 1.43 bigger than the value for the half hour for a 50% confidence level. If a higher confidence level is required, such as 95%, then the factor increases to 1.92. For the Electric Nation dataset the values are lower, providing a 50% confidence level factor of 1.18 and a 95% confidence level of 1.53.

5. CONCLUSIONS AND NEXT STEPS

Key conclusions:

1. **The limitations of available datasets pose a *substantial* challenge for reaching conclusions – emphasising the pressing need for WPD to gather more data in future**. Everoze's analysis was materially affected by the limitations of applying the Freedom and Electric Nation datasets to answer the available datasets. Most notably, key issues included the short duration of the datasets used and the Electric Nation dataset not being a minutely dataset. As such, Everoze strongly advocates seizing future opportunities to secure further domestic flexibility data, to maximise learning.

2. **Data resolution has the biggest impact on demand uncertainty, followed by Completeness, followed by Accuracy.** The standard deviation component of the Data Quality Factor is dominated by the Resolution Uncertainty Factor standard deviation (0.300), which is a magnitude of 10 greater than those calculated from the completeness analysis, and a magnitude of 100 greater than those calculated from the accuracy analysis. In short, lower resolution half-hourly data *substantially* reduces the confidence WPD can have in the ultimate peak demand compared to minutely resolution data. Meanwhile, completeness is of medium importance, and accuracy impacts are negligible.

3. **Results vary significantly by dataset – hinting at a possible need for a technology-specific approach to analysing data resolution:** Consumption profiles vary dramatically between the Freedom data (for heat pumps) and Electric Nation data (for electric vehicles); this applies both across the day and within individual half hour settlement periods. This has implications for the Resolution Uncertainty Factor, suggesting that it may be more appropriate to derive a separate resolution factor per technology. It is further possible that other assets (such as batteries) will show different behaviours again.

4. **For heat pumps at half-hourly resolution, the Data Quality Factor for a complete dataset was 1.43 for a 50% confidence level and 1.92 for a confidence level of 95%.** This means that we are 50% certain the peak demand recorded for a half-hourly metered heat pump portfolio is 1.43 times higher when assuming minutely resolution.

5. **For electric vehicles at half-hourly resolution, the Data Quality Factor for a complete dataset was 1.18 for a confidence level of 50% and 1.53 for a confidence level of 95%.** This means that we are 50% certain the peak demand recorded for a half-hourly metered electric vehicle is 1.18 times higher when assuming minutely resolution. The reason why the impact of resolution is lower for electric vehicles rather than heat pumps is the lower variability of electric vehicle charging requirements over a half hour period which may not vary at all, whereas heat pump demand is more variable.

6. **Analysis to date suggests that portfolio size strongly impacts the half-hourly resolution UF, and consequently the Data Quality Factor**. Everoze repeated the resolution analysis on reduced population samples for both the Electric Nation and Freedom datasets. The smaller population datasets yielded larger Resolution UFs. Interestingly, for a fixed portfolio size, different results were yielded for the two datasets, which indicates that technology type is also a driver of variation in the Data Quality Factor. The impact of portfolio size and technology type on the calculated Data Quality Factor (predominantly driven by the resolution UF), appears to diminish for large portfolios (> 100 assets). This convergence, or asymptotic behaviour, with increasingly large portfolios will have an impact in the design of the DQF/DDF where a simplified approach may be justified. These sensitivities are to be explored further and the hypotheses tested when more data from the Sustain-H trial is available.

7. **The linear impact of data incompleteness means that WPD can take a pragmatic approach.** In Everoze's analysis, demand uncertainty increased in a broadly linear fashion as the dataset became more incomplete. For instance, an 80% complete dataset led to a 125% increase in demand uncertainty when considering a 50% confidence level. As a result, there is potential for WPD to adopt a pragmatic approach here; for instance, for a 50% confidence level an 80% complete dataset might result in a multiplier of 1.25 within the Data Quality Factor, with corresponding impact on payment. Everoze also investigated the impact portfolio size has on demand uncertainty for an 80% incomplete dataset, and found the impact is independent of portfolio size.

5.1 CONCLUSIONS

Resolution

RECAP OF APPROACH: Everoze determined the 'peak/mean' ratio for both the Electric Nation and Freedom datasets, in order to understand the extent to which peak demand exceeds half hourly average demand.

- The 'typical' peak/mean ratio for resolution is around 1.2 to 1.6 – but generalisation depends on the required confidence level: It is difficult to derive a single value for a "typical" peak/mean ratio, however this value is likely to be in the range of 1.2 to 1.6. If WPD need more certainty, such as a confidence level of 95%, then values of 1.8 and above need to be considered. In addition, note that as consumption is reduced, which is the behaviour WPD want to motivate and reward consumers to do, peak/mean ratios increase.
- There is no trend for morning of evening delivery periods – suggesting that daily averages are appropriate: While there is some variation in peak/mean ratio throughout the day there is no obvious trend for the morning or evening delivery periods. Therefore as there are limited datasets available for this work it is most appropriate to use whole day averages at this stage.
- Population size does impact the peak/mean ratio of the dataset significantly. Analysis to date suggests the magnitude of the impact is characteristic to the different technologies, however for population sizes above 100, the peak/mean ratio converges to 1.2/1.3 irrespective of technology type.
- The distributions of the peak/mean ratios for the electric vehicle and heat pump datasets are very different – pointing to a need for a technology-specific approach to resolution factor. The Freedom data is characterised by Weibull distributions whereas it is exponentially decreasing for Electric Nation. The differences can be explained by the typical behaviour of the types of asset within each dataset. By their very nature, heat pump power consumption can vary a reasonable amount over short time frames. Whereas electric vehicle chargers are likely to be on for longer periods of time and are more binary in their operation. This means that for electric vehicles the peak for many settlement periods, may well be the same as the mean. The differences observed in the two datasets imply that it is better to derive a separate resolution factor per technology. In addition, other types of asset (such as domestic batteries) may show different behaviour again, as may the combinations of different assets. As such, it will be important to revisit these results with more data from the Sustain-H trial.

Completeness

RECAP OF APPROACH: The completeness analyses quantified the demand uncertainty introduced for different levels of incompleteness, when compared to a 100 % complete dataset. Everoze removed whole-day assets randomly to reduce the 100 % complete dataset to 98, 95, 90 or 80 % completeness, and calculated the ratio of the 100 % complete whole-dataset power demand (kW) against the reduced dataset (kW) demand. This was iterated using a Monte-Carlo approach 1000 or 10,000 times, and the mean from each iteration was plot on a frequency distribution to capture the mean demand uncertainty and standard deviation for each completeness distribution.

The unavailability of data within a dataset is randomly distributed. For the Freedom dataset it was also apparent that when an asset is unavailable it was for the whole day.

- Demand uncertainty increased in a broadly linear fashion as the dataset became more incomplete. As might be expected, the mean of each frequency distribution plotted using half hourly data from each settlement period, is approximately equal to the ratio: 100% divided by the reduced dataset completeness percentage (e.g. 100/80 or 1.25).

Accuracy

RECAP OF APPROACH: The meter accuracy as defined by the accuracy measurement given in the available published information (from datasheets and Sustain-H trial participant data) has been taken as the standard deviation for this work.

- Measurement accuracy has minimal impact on the measured demand. For a sample size of 100 and 1 % metering accuracy, the standard deviation calculated is 0.1%. Residential smart meters and asset meters are typically accurate to +/- 1 %.
- The multiplier for the Accuracy Uncertainty Factor should be 1: It has been concluded that the multiplier for Accuracy is 1.0 as there is no expected bias in meter readings, only uncertainty from the meter accuracy.

5.2 LIMITATIONS

1. Dataset limitations: The Electric Nation dataset had inherent limitations because the dataset was not 1-minute resolution, rather each row in the dataset captured a single 'charging event', which included a start and stop time, and car battery charging rate (kW). Using the available data, Everoze re-created the dataset to be of minutely resolution, which likely introduced uncertainty in the demand. This, coupled with the comparatively low percentage of data over the 3 month sampling period which was not 0 kW (approximately 5 %), meant that the dataset was unlikely to produce valid results for the completeness analysis. Consequently, the completeness UF was only calculated using the Freedom dataset. The Freedom dataset had much higher availability, however the sampling period considered capable of producing valid results was only 2 months' worth of data.

2. Absence of Completeness UF for Electric Nation dataset: Due to the above limitation, the DQF calculated for the Electric Nation dataset does not include a completeness UF. Everoze is likely to receive EV data from the Sustain-H trial, and so the DQF will be updated and include the completeness UF during the next stages of the Aggregated Datasets analyses.

3. Delivery period analysis trends lacking: Everoze found that, while there is some variation in peak/mean ratio throughout the day identified from the resolution analysis, there is no obvious trend for the morning or evening delivery periods. Therefore as there are limited datasets available for this work, Everoze assumed it was best to use the whole day averages when quantifying the UFs at this stage.

4. Battery assets missing: Whilst comparison has been made between the results from the Freedom and Electric Nation datasets, other types of asset (such as domestic batteries) may show different behaviour again. Also, all the combinations of different assets will likely show different behaviours.

5. Portfolio effects: The calculated UFs at this stage have not considered the impact portfolio size might have on the factors. However, the Electric Nation dataset has approximately 3x the number of assets compared to the Freedom dataset, so the DQFs are likely driven by sample size. For the next stages of the Aggregated Dataset analyses, sample size will be a key consideration. The best case scenario would be comparing datasets for different assets, but with the same availability and sample size, in order to derive technology-specific trends.

6. Flex actions within datasets: The Freedom assets experience multiple interventions during the trial duration, and these interventions (predominantly price signals) already introduce a 'flex action' which could drive uncertainty in the UF calculations. The Electric Nation assets also experienced interventions during the trial which limited the charging rate for groups of cars in localised areas, to reduce network constraint. However the magnitude of the reduction was not known. Therefore Everoze corrected these interventions so removed the 'flex action' and re-calculated the demand as if not managed.

5.3 NEXT STEPS

The proposed timelines for remaining scope items for the *Aggregated Datasets* workstream are outlined in the table below.

SCOPE ITEM	DELIVERED BY
1. Conduct Analysis outlined in Section 3 of this Report	30/09/2021
2. Form recommendations	31/10/2021

As it currently stands, the timescale of interim deliverables for scope item 1 are as follows:

INTERIM DELIVERABLES FOR SCOPE ITEM 1	DELIVERED BY
Conduct analysis on the two pre-trial datasets: Electric Nation and Freedom (This report)	31/10/2020
Collect Sustain-H trial participant data on a monthly basis throughout the trial duration.	31/07/2021
Pre-process the first datasets received from each participant the month following retrieval. This is to allow time for assessment of the data format so any subsequent data requests could be made, if necessary, before any further data are received.	31/07/2021
Conduct analysis on received trial datasets, as outlined in Section 3 of this Report.	31/09/2021

The longlist for possible next steps includes the following:

- Refine Completeness analysis: Calculate Completeness Uncertainty Factors using electric vehicle data, and update the Completeness Uncertainty Factors for heat pumps.
- Refine Resolution analysis: Update the Resolution Uncertainty Factors using electric vehicle and heat pump data.
- Probe portfolio effects: Calculate the Completeness Uncertainty Factors and Resolution Uncertainty Factors RUFs for different portfolio sizes.
- Update Data Quality Factor: Update and the Data Quality Factor using the results points 1 to 3 on a per technology basis.
- Explore batteries: If possible, calculate Data Quality Factor for domestic battery portfolios.
- Explore delivery periods: Probe whether the Data Quality Factor should be specific to delivery periods.
- Conclude on technology agnosticism: Compare the results from items 1 to 4 listed above for the independent UFs for each technology type, and consider whether a technology-agnostic DQF is plausible based on the updated results.
- Form recommendations: Tease out the implications for future WPD DSO service procurement.

Everoze proposes to prioritise remaining analysis based on:

- Data availability in Sustain-H: This is expected to be dominated by electric vehicles. Heat pump data is expected to be negligibly low.
- Materiality of impact: Everoze will focus on factors demonstrated to be of material significance to data quality. This will ensure that the remaining budget is well targeted.

In particular, Everoze proposes to conduct the following steps in the final stage of analysis:

1. Refine Resolution analysis: Update the Resolution Uncertainty Factors using electric vehicle data, which is expected to be plentiful from the Sustain-H trial.
2. Probe portfolio effects: Calculate the Completeness Uncertainty Factors and Resolution Uncertainty Factors for different portfolio sizes.
3. Update Data Quality Factor: Update and the Data Quality Factor using the above, with a focus on delivering a Table of Data Derating Tables which can be of pragmatic use to WPD.
4. Form recommendations: Tease out the implications for future WPD DSO service procurement.

6. REFERENCES

[1] Everoze, WESTERN002-AD-R-01-B, "FutureFlex: Supplier Trial – Data Review", Revision B, 29th May 2020

[2] Everoze, WESTERN002-AD-R-02-B, "Aggregated Datasets - Methodology", Revision B, 10th September 2020

[3] Passiv Systems "Freedom: Trial Data Description", September 2020

[4] Western Power Distribution, Electric Nation, "Electric Nation Customer Trial - CrowdCharge Transaction Data", 24th October 2019

[5] GOV UK, Office for Product Safety & Standards, "In-Service Testing (IST) Handbook", February 2020.

[6] GOV UK, "Schedule 4: UK nationally approved electricity meters", January 2020.

[7] PassivSystems, FREEDOM, "FREEDOM Trial Data", 18th April 2018

7. APPENDIX 1: PRE-PROCESSING

7.1 FREEDOM DATA

7.1.1 Pre-processing

Freedom Data Format Summary

Asset meter data from the Freedom trial was provided in minutely and half hourly format for each asset as independent data files. Three types of heat pumps were included in the Freedom trial: MasterTherm, Samsung and Dakin heat pumps. The minutely trial data description document [7] included the following columns:

- *heat pump power consumption*: measurements of instantaneous electrical power consumption in kW
- *heat pump reactive power consumption*: measurements of instantaneous (electrical) reactive power in kW
- *heat meter overall power*: measurements of instantaneous heat pump heat production in kW
- *heat pump heating control*: on/off events sent to MasterTherm/Samsung heat pumps (not used for Daikin)
- *1minute timestamps*

The half hourly power consumption data files were more extensive, providing information on the occurrence and types of faults present in the data. The Freedom trial datasheet indicated that **it is essential that the main data set (30 min resolution) is cross-referenced with the 1 minutely dataset to exclude fault periods.**

Freedom Pre-Processing:

1. Loaded file data paths to Python Pandas**.**
2. Read the 30 min resolution files and identified any errors when opening files. Only error was due to one 30 min dataframe which was empty and couldn't be opened. Removed the asset file, which reduced the sample by 1 (to 74)
3. Filtered through the opened 30 min res files to find which have 'System Faults'. Found that all remaining 30 min res files contain System Faults. Also found some datasets contained System Faults 100 % of the time. Removed files (assets) which were 100 % incomplete (64 / 75 of the 30 min data files remain).
4. Cross referenced the 1 min timestamps against the 30 min timestamps**.** This was done to identify when the 1 minute data (which did not have a column to indicate faults present) fell within a System Fault period in the 30 min dataset. Within the 30 min dataset, [7] had removed all data in the rows (including the timestamp) during fault periods. Therefore, if the 30 min timestamp from the 1 min datafile was also present in the 30 min datafile, then there was not a system fault. If the timestamp was not present in the 30 min datafile, then the 1-minute data electricity demand (kW) fell within a fault period, and these data points were converted to 'null'.
5. Calculated the % completeness of the 1 minute dataframe for each asset. Identified any files < 100 % complete following step 4.
6. For the 1 min processed data files, extracted the heat pump power consumption (kW), home ID and 1 minute timestamp.
7. Combined the files from step 6 into a single file, indexed by timestamp, 1 column per asset to create a portfolio of electricity demand data (kW)
8. Plot the availability of the datafile from step 7 against the 'date' to determine the time periods when the dataset was most available (i.e. low % of null datapoints and high participants). Found lots of Null data points during the start of the trial. Best data availability is from 1st Mar to 30th April.
9. Re-sampled the dataset to only include time stamps from 1st Mar to 30th Apr. Checked the availability of assets during this period, and removed any assets if the asset availability was < 50 %. This reduced the sample size to 49 assets. Saved the file ready to upload for the completeness and resolution analysis.

7.2 ELECTRIC NATION DATA

7.2.1 Pre-Processing

Electric Nation Data Format Summary
Each 'transaction' i.e. charging event is provided as a single row in the Electric Nation data file. The columns provide information on the start charging (ActiveCharging_Start) and end charging (EndCharge) time, and the total electrical demand during the charging event (Consumed kWh). Therefore the energy consumed during the charging period is a minutely average. Ideally, the data would be minutely 'actual' power consumption rather than an average demand during charging period.

Electric Nation Data Pre-Processing
Data pre-processing was undertaken in 8 stages:

1. Removed data points whereby the consumed kWh was greater than 100 kWh. This is a result of inaccuracies in the data. The largest battery capacity participating in the project was 100 kWh, therefore any charging events greater than this were an anomaly.
    a. Events where the ConsumedkWh < 0.5 were kept in despite the total charge being marginal, because this indicated that the car was plugged in and available for DSO services even if the car was charged.
2. Removed any data where Participant ID = Null. In these instances, the participant could not be linked to a charger which is required to quantify the total number of participants charging on any one date.
3. Removed instances where ActiveCharging_Start = Null. This was caused due to internet connectivity issues.
4. Removed instances when EndCharge = Null. This was always the case if ActiveCharging_Start = Null because the EndCharge time could not be approximated. Additionally this was caused if the internet was down during the end of the charging period.
5. Checked CrowdCharge note (incorrectly calculated EndCharge). CrowdCharge noted that there are instances when the EndCharge time was not calculated correctly in the datasheet. EndCharge was estimated (by CrowdCharge analysts) as the time when charging ended based on the meter value data (looking for sustained reductions in the current being drawn in the absence of demand management). Some of these calculations were inaccurate because the total consumed kWh over the charging duration was greater than technically possible given the charger capacity. For example, for a single transaction using a 7kW charger, if ActiveCharging_Start was 17:00 and EndCharge was 18:30, but 21kWh of energy was transferred then it's likely that EndCharge is inaccurate (because it isn't possible to add 21kWh in 1.5 hours using a 7kW charger).
    a. Everoze performed the following to check if the 'Charge time' was too short:
        i. ChargeTime = EndCharge – ActiveCharging_Start
        ii. ChargingRate = ConsumedkWh/ChargeTime
        iii. If ChargingRate>Battery Rating, then the end charging time is incorrect.
        iv. There are 379 transactions where this was the case, which is 0.53% of the data.

    To overcome this error, the EndCharge time was re-calculated for the rows where the above formula was true by the following:
        v. NewChargeDuration = ConsumedkWh/CarkW(rating of the participant's vehicle, either 3.6 kW of 7 kW which is provided per row).
        vi. NewEndCharge = ActiveChargingStart + NewChargeDuration

    Assumption: that the rate of charge was constant at 7kWh or 3.6 kWh throughout the charging period.
6. Corrected for those with managed charging, by re-calculating the charging duration as if not managed by assuming a constant charging rate equal to the maximum battery rating, because information was not available on the level of demand management during the trial / the total energy demand per minute when managed.

    The participants with chargers rated 3.6kW (16 A), who's chargers were controlled, control when the cars where charging regularly (because of their dual-fuel tariff) were rarely managed. Whereas those with 7 kW chargers (32A) and who used their car to charge during peaks times are more often than not managed. Any events where a start and end charge time cannot be determined due to an absence of meter values were not managed. Trials 1,2 were managed in some instances and the Trial 3 transactions were effectively 'managed' because of the CrowdCharge algorithm used alongside the ToU tariff, therefore there are no T3 Managed columns.

7. Removed any assets where the charging duration was longer than battery charging capabilities, e.g. 21 kW of charge was transferred in 1 minute (which was not possible because the chargers were rated at 3.6 or 7 kW). 3771 transactions were removed.
8. Set up the 'transaction' data remaining following step 7 into a aggregated1-minute timeseries portfilio, Everoze assumed a constant charging rate for each minute, for each charging event (asset). The charging rates were either 3.6 kW or 7 kW. Set all null data as 0kW (e.g. when the car was plugged in and not charging) and saved the file ready to upload for the resolution analysis.

Table 11 captures the number (and percentage) of transactions removed from the input Electric Nation data file during pre-processing stages 1 to 7. Stages 5 and 6 are not included because data was not removed from the input file, instead the EndCharge times were corrected and replaced.

Stage	Transactions Removed from Input File	Cumulative % Removed
1	21	0.03
2	3899	5.47
3	19707	27.65
4	20855	29.26
7	24626	34.60

TABLE 11: ELECTRIC NATION DATA PRE-PROCESSING: TRANSACTIONS REMOVED DURING EACH STAGE LISTED IN SECTION 7.2

7.2.2 Results from pre-processing

Factors which influenced the decision to use the Electric Nation (CrowdCharge) dataset included:

1. 65.4 % of the initial dataset (71,264 transaction) remained after correcting for the null data, meaning the data remaining was still substantive.
2. There were three trials conducted as part of the Electric Nation project. Trial 1 featured minimal interventions, meaning that the 'trial' data is close to a 'real-world' scenario and therefore the impact of trial interventions on the UF calculations are low if using Trial 1 data.
3. The Resolution UF calculations, can be performed on the data remaining. The results might be slightly inaccurate because the trial data is not 'real-world', however, the UFs (and subsequently DQF) will be updated following retrieval of Sustain-H trial datasets.

8. APPENDIX 2: UPDATED METHODOLOGY

8.1 RESOLUTION

8.1.1 Determine the variance of the data at 1-minutely intervals and when averaged into half hourly intervals for a portfolio.

Following pre-processing, it was found that the Electric Nation data could be analysed at a 1-minute resolution (with some pre-processing assumptions, as described in Section 7.2.2). The Freedom data was also made available at 30-minute and 1-minute resolution, provided by PassivSystems. Therefore Everoze computed the Resolution analysis using both Electric Nation and Freedom datasets.

It is currently unclear whether, or how much, Sustain-H trial data may be available on a minutely basis. Depending on data provision, Everoze will update the RUFs using Sustain-H trial data using this approach.

Analysis steps which have been conducted by Everoze on the third party datasets are presented below:

Step 1: For a fixed population size within a defined period (maximising the size and period of the dataset as appropriate), Everoze summed the minutely portfolio electricity demand. Everoze produced an output of the net portfolio demand (in kW) for each minute over the sampling period. The population size over the selected sampling duration was fixed for both datasets.

Step 2: Everoze quantified how the ratio of peak-1-minute / 30-minute mean varies for each HH settlement period (48 in total), for the dataset as a whole, and also for each Delivery Period in the Sustain-H trial. The following steps were taken to analyse the (peak-1-minute/30-minute mean):

a. Everoze calculated the mean (30-min) demand for each HH period within the time frame considered[1].
b. For each 30-min interval across the timeframe considered, Everoze calculated the (1-min peak / 30-min mean) ratio.
c. For each half hourly settlement period (48 in total), the frequency distribution of the (peak-1-minute/30-minute mean) ratios was derived using the output from b, to produce 48 frequency distributions. Everoze found that the frequency distributions varied considerably across neighbouring settlement periods. Therefore, Everoze combined the peak/mean ratios for the morning Delivery Period, evening Delivery Period and for the whole dataset, and re-plot the frequency distributions to detect dataset trends.
d. For each of the frequency distributions created from step 2.c, Everoze derived the following values and wrote the values in a look up table:
    1. Mean (peak-1-minute/30-minute mean) ratio;
    2. Maximum;
    3. Minimum; and
    4. Standard Deviation.
    5. P95 exceedance cases.

Step 3: Everoze extracted the "multiplier" (in this case the Mean (peak-1-minute/30-minute mean) ratio) and corresponding standard deviations from the whole dataset frequency distribution for the DQF calculation**.**

[1] Implicit assumption: for fixed population size, the variance in completeness of the dataset is small so that there is nedligible noise within the results. Using a dataset close to 100% completeness will improve the validity of this assumption.

8.1.2 Quantify the impact portfolio size has on half hourly averaging uncertainty

Step 1: Everoze randomly selected a sub-group of the data population from those analysed in Section 8.1.1 to create reduced population sizes (e.g. reduced 100 participants to 25 and 50 for further analysis).

Step 2: Repeat Steps 1 to 3 from Section 8.1.1 on the different population sizes to assess how the results vary.

8.1.3 Estimate value of "RUFs"

Through analysis of the findings in the analysis described above, Everoze estimated the value of "RUFs" for each dataset for the morning Delivery Period, evening Delivery Period and whole dataset.

8.2 COMPLETENESS

8.2.1 Quantify the 'completeness' of the dataset for the different portfolios considered

Step 1: Everoze quantified the percentage completeness for the 1-minute dataset.

Step 2: Everoze created a 30 minute availability datasets from the 1-minute asset meter dataset. Half hour availability was calculated for each asset, by counting the number of non-null minutes within each half hour. If > 25 % of the minutes were null values for each asset, the availability for that asset-half hour was marked as '0'. All other half hour periods were marked as 1. Using this output, Everoze quantified the number of assets operating for each half hour period.

Step 3: Everoze plot the output from Step 2, the dataset availability, as a frequency distribution across the fixed period.

Step 4: Everoze visually interpreted the output from Step 3 with the intention of fitting a simple mathematical distribution to the probability distribution (e.g. a Weibull curve). After review of the plots, Everoze decided that the distribution did not conform to a typical distribution. This had directly implications on the Method for introducing null values to artificially introduce incompleteness into the dataset.

8.2.2 For a fixed portfolio size, determine the impact 98, 95, 90 and 80 % portfolio data completeness has on measured demand uncertainty

Potential invalid datapoints in a HH metered dataset (for example) may take the following forms:

1. An obviously invalid value (e.g. outside conceivable range)
2. Null value
3. Zero value (could or could not be valid)
4. A realistic value which may not capture the full duration of that time period (e.g. only 15 minutes of data in a 30 minute period)

In order to estimate the impact of Completeness on uncertainty, it is necessary to artificially introduce "incompleteness" into a complete dataset and quantify the difference in measured demand for varying levels of completeness. This requires the starting dataset to be 100% complete before introducing null (or back filled) values randomly. When aggregated over a portfolio, this could have the effect of artificially lowering the portfolio metered value for the affected periods, where the 'real' portfolio demand would be higher than this metered value.

Everoze conducted the completeness analysis using only the Freedom dataset. This decision was made due to reasons described in Section 3.2.

Steps 2 to 6 set out steps Everoze carried out to quantify the percentage uncertainty for different completeness and population size scenarios. Steps 2 to 6 introduced incompleteness as null values.

Step 1: Everoze set up the starting dataset to be 100 % complete so that random incompleteness can be introduced artificially. The completeness was introduced using the following approach, in order of priority:

a. Take the average for asset with identified invalid data across the same hour of either weekday or weekend across the duration of the dataset.

b. If the data available to perform the averaging process in item 1 is < 75%, then: Everoze took a through day average for that asset [split between weekdays and weekends]

c. If the data available to perform the averaging process in item 2 is <75%, then Everoze took an average across all assets for that time of day.

Step 2: For a fixed population size, Everoze summed the 30 minute average electricity demand for each 30 minute interval across the timeframe considered. The output would be the total demand for each 30 minute interval.

Step 3: Everoze randomly introduce an average completeness (e.g. 98%) into the dataset by allocating 2% of electricity demand readings as null values. In the previous deliverable, it was noted that the null values would be allocated using a skewed-normal (Weibull) distribution which had been derived from, and checked against, appropriate data. However, upon the analysis described in section 1, the distribution of the data did not followed a skewed-normal distribution, or any other distribution. Therefore, rather than applying a distribution to the data, whole-day assets were removed from the dataset, to reduce the overall availability to the desired completeness percentage e.g. to 98%.

Step 4: Everoze calculated the mean electricity demand (kW) output from step 2, and the mean electricity demand (kW) output from step 3. Everoze then divided the two to give a demand difference for the dataset as a whole (the numerator was always 100% complete 30-minute demand, therefore by dividing the 100 % complete 30 minute demand by the 98 % complete 30-minute demand, the ratio was than 1, or equal to 1, depending on the random allocation of incompleteness in the data).

Step 5: Everoze repeated Steps 3 to 4 for 1000 iterations, for different cases of random introduction of incompleteness, in the form of a Monte Carlo analysis. 10,000 iterations were performed for the 80 % completeness case for comparison.

Step 6: Everoze created frequency distributions from Step 5 and captured the following:

1. Mean;
2. Maximum;
3. Minimum; and
4. Standard Deviation.
5. P95

Step 7: Everoze extracted the "multiplier" (100 / incompleteness (e.g. 98)) and corresponding standard deviations for each of the frequency distributions from Step 6 for the DQF calculation**.**

8.2.3 Quantify the impact portfolio size has on measured demand uncertainty for the different completeness cases

Everoze investigated the impact portfolio size has on demand uncertainty for the 80% completeness case, by repeating the analysis from Section 4.2.1 on the Freedom dataset, using a 50 % reduced population.

To approach this, Everoze randomly removed 50 % of the assets from the complete dataset, reducing the total number of assets from 49 to 24. Next, 20 % of the 'whole-day' assets from the remaining asset population were removed, reducing the completeness to 80 %. This process was repeated for 100 iterations, and the mean of the 100 % complete dataset demand (kW) / 80 % complete dataset demand (kW) was calculated for each iteration.

8.2.4 Estimate values of "CUFs"

Through analysis of the findings in the analysis described above, Everoze estimated the "CUFs" for the Freedom dataset.

8.3 ACCURACY

There are three key parts to the analysis:

- Quantify the 'Accuracy' of different meter types;
- Calculate the standard deviation of this uncertainty; and
- Estimating "AUFs" for the Data Quality Factor equation.

These are each described below.

8.3.1 Quantify the uncertainty introduced to the metered data attributable to the metering accuracy of half hourly smart meters (SMETS1 and SMETS2 meters) and the asset level meters used by participants for the trial.

Everoze reviewed metering standards for residential electricity meters, and retrieved accuracy meter measurements from two Sustain-H participants, to determine appropriate parameters for metering accuracy.

Everoze undertook a broad sensitivity analysis to examine the consequences of varying meter accuracy on overall Data Quality for varying portfolio sizes.

8.3.2 Calculate the standard deviation of the accuracy measurements

The standard deviation of the combined accuracy measurements were assessed based on available information.

8.3.3 Estimate the values of "AUFs"

Through analysis of the findings in the assessment described above, Everoze defined the range of "AUFs" for a two accuracy meter values, and a range of portfolio sizes.