Reflect

Tool Specification

for

Electricity North West

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Executive Summary

The Reflect tool aims to forecast electric vehicle (EV) charging demand from cars and vans in the Electricity North West Ltd (ENWL) licence area annually from 2020 to 2050. The tool will provide improved functionality compared to existing network forecasting tools used by ENWL by allowing uncertainty in the location of future EV charging demand to be analysed. This forecasting method will generate EV demand profiles which give the probability of a given EV charging load arising on a primary substation at half-hourly resolution.

The tool will consider 24 user archetypes, which are differentiated by being either: cars or vans; BEVs or PHEVs; commuters or non-commuters; parking off-street or on-street at home; and rural or urban home location. Charging behaviour will be differentiated across 12 charging archetypes, which follow the definitions of the user archetypes, however rural and urban located vehicles are assumed to have the same charging behaviour. Charging demand will be split across 5 charging location types: home; on-street residential; work; rapid en-route; and destination.

The current distribution of vehicles across user archetypes has been determined by collecting data on current battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) car and van ownership across the ENWL licence area. These have been further differentiated based on statistics and estimates of commuter numbers, off-street parking access, and rural or urban home location. Future user archetype vehicle numbers will be determined by combining the above information with EV uptake projections from Element Energy's Electric Car Consumer Choice model (ECCo). These datasets are described in detail in the Dataset Report produced for Lot 1 of this project. Additional parameters for EVs and charging behaviour will be provided by Element Energy based on previous studies. Charging start time profiles for each of the charging location types will also be provided and used to generate charging demand profiles.

The uncertainty in EV charging demand will be analysed by running several 'micro-scenarios' for each run of the tool. In each micro-scenario, the share of charging demand fulfilled at each charging location type will vary, with these shares being randomly sampled from user-defined probability distributions. The user will define probability distributions for the share of residential, work, and en-route charging demand for each charging archetype, meaning 36 probability distributions will be produced in total[1]. An Excel-based probability distribution generator will be provided to assist with the generation of these charging demand profiles. Each micro-scenario will have an associated probability, and the results from each micro-scenario will be combined to generate mean, upper quartile, and lower quartile charging demand profiles for each primary substation.

The tool will be coded in Python 3.7, using packages compatible with the Anaconda distribution. The user will provide inputs to the tool through an Excel control interface, which will produce CSV input files to be read by the tool. Outputs will be produced as CSV files in the same format as existing ENWL forecasting tools, to allow easy integration with business as usual processes. The maximum run time for the tool should be 24 hours to produce output primary substation demand profiles, and intermediate samples should be produced in 6 hours.

[1] The probability distribution for residential charging refers to home charging for charging archetypes with off-street home parking, and on-street residential charging for charging archetypes with on-street home parking. The share of destination charging is calculated as 1 - the sum of charging shares for the other charging location types.

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Glossary of terms

Vehicle types

EV	Electric vehicle
BEV	Battery electric vehicle
PHEV	Plug-in hybrid electric vehicle

Geographical areas

LSOA	Lower layer super output area, a Census statistical reporting area with a population between 1,000 people / 400 households and 3,000 people / 1,200 households
LA	Local authority
MSOA	Middle layer super output area, a Census statistical reporting area with a population between 5,000 people / 2,000 households and 15,000 people / 6,000 households
Primary substation area	The area that is assumed to be served by a single primary substation in this study. These areas are determined by considering the closest secondary substation to each point in the ENWL licence area

Commuting behaviour

Commuter	An individual who uses their vehicle to drive to and from their workplace. As the vehicle is kept at their workplace during the day it can use workplace charging
Non-commuter	An individual who does not use their vehicle for commuting. These individuals do not have access to workplace charging

Vehicle location

Rural	Vehicles that are registered in an MSOA classified as rural by the Office for National Statistics (ONS) are labelled as rural. These vehicles tend to have a higher average mileage than urban vehicles
Urban	Vehicles that are registered in an MSOA classified as urban by ONS are labelled as urban. These vehicles tend to have a lower average mileage than rural vehicles

Modelling archetypes

User archetypes	These represent the 24 different sets of EV users that will be modelled in the tool. User archetypes are differentiated by: car / van; BEV / PHEV; commuter / non-commuter; off street parking access; rural / urban location
Charging archetypes	These represent the 12 different sets of charging behaviour assumptions that will be modelled in the tool. Charging archetypes are differentiated by the same factors as user archetypes, except for rural / urban location, which is assumed to only affect average mileage of vehicles but not their charging behaviour
Charging location types	These represent the 5 different location types where EVCPs will be modelled in the tool. The location types are:
• Home	charging used at the driver's home. Available to drivers with off-street parking only
• On-street residential	charging used near the driver's home. Available to drivers with no access to off-street parking only
• Workplace	charging at office buildings and work sites. Available to commuters only
• Rapid en-route	charging used for a short rapid top-up during a journey. Available to BEVs only
• Destination	charging at a supermarket or recreational amenity (e.g. gyms)

Modelling runs

Scenario	A scenario is defined by the overarching parameters for a given tool run. These include the EV uptake scenario, the assumed power of different charging location types, and the locations where public charging is assumed to be installed
Micro-scenario	Each scenario is made up of a set of micro-scenarios. For each micro-scenario, probability distributions giving the share of charging at each location type for each charging archetype are randomly sampled to produce a set of charging shares

Other abbreviations

ENWL	Electricity North West Ltd
ECCo	Element Energy's Electric Car Consumer Choice model
Nomis	Government repository for labour market statistics
ONS	Office for National Statistics
TEMPro	Trip End Model Presentation Program
V2G	Vehicle-to-grid

1 Introduction

The Reflect tool is being developed for Electricity North West Ltd (ENWL) to aid in their network planning and load forecasting, and to allow ENWL to model uncertainties in the location of future EV charging demand. The tool will forecast electric vehicle (EV) charging demand annually from 2020 to 2050 and generate EV demand profiles which give the probability of an EV charging load arising on a primary substation at half-hourly resolution.

The tool will calculate charging demand for all battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) cars and vans registered in the ENWL licence area. Charging demand will be spread across five charging location types: home; residential on-street; work; destination; and rapid en-route charging.

Home and residential on-street demand will be modelled to occur at vehicles' registered locations. Some vehicles are registered to a depot so in this case the 'residential demand' will be allocated to the depot location. Charging demand will be forecast at primary substation level at half-hourly resolution for a summer and winter day each year.

Outputs will be produced in separate CSV files for every year from 2020 to 2050. Three CSV files will be produced for each year and will include the mean, upper quartile, and lower quartile half-hourly demand profiles respectively for each primary substation and season (summer and winter only). An SQL database will also be produced containing the half-hourly demand profiles for each micro-scenario. A schematic diagram of tool inputs and outputs is shown in Figure 1.

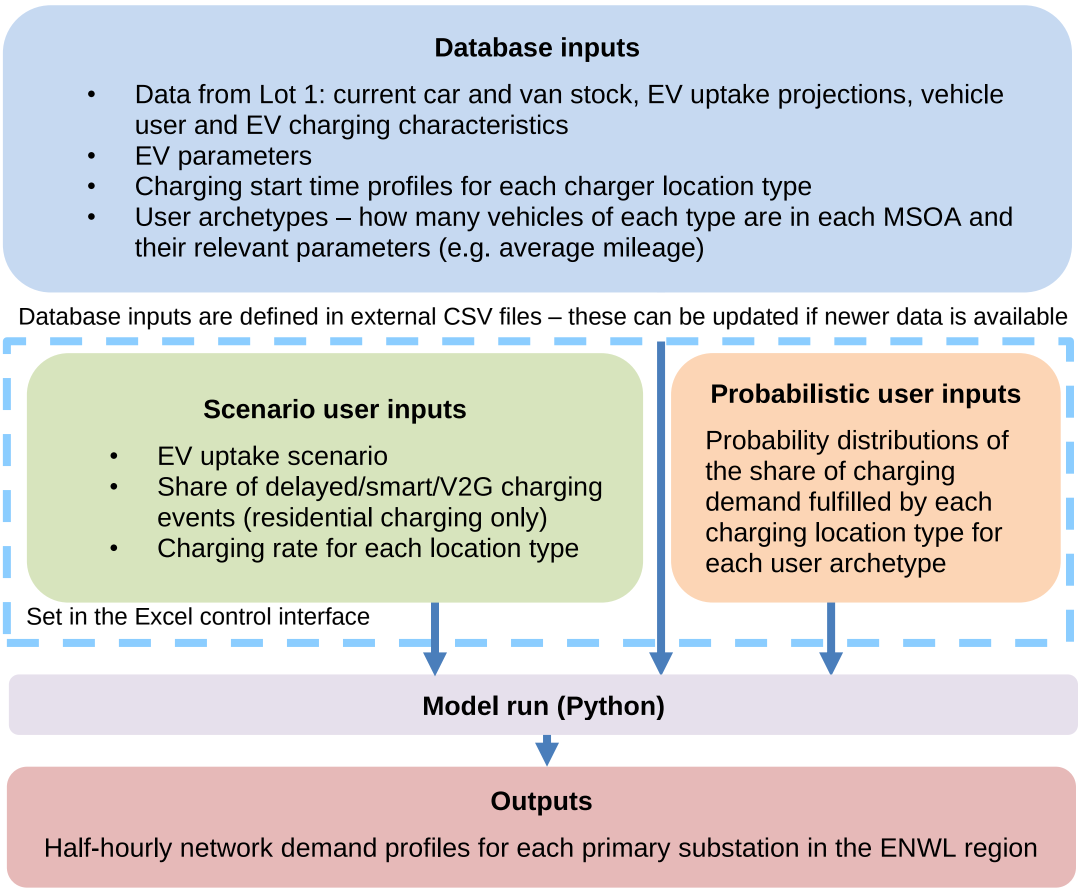


Figure 1. A schematic diagram showing the structure of tool inputs and outputs

2 Tool inputs

2.1 User archetypes

The Reflect tool will model 24 user archetypes. The attributes that define each user archetype are detailed below:

- **Vehicle:** Cars or vans.
- **Powertrain:** BEV or PHEV. PHEVs are assumed to not have access to rapid en-route charging as they cannot accept high charging rates.
- **Commuter status:** Commuter or non-commuter. Commuters have access to work charging. All vans are assumed to be non-commuter.
- **Location:** Rural or urban. Rural drivers are assumed to have a higher annual mileage than urban drivers.
- **Off-street parking access:** Access to off-street parking or no access to off-street parking. Vehicles with off-street parking access are assumed to charge at home for all their residential charging, while vehicles that are parked on-street must use on-street residential charging.

Several datasets and projections are used to determine the number of vehicles in user archetypes in each primary area and year modelled by the tool. The number of BEV and PHEV cars and vans in each year and MSOA are available from EV stock projections produced using Element Energy's Electric Car Consumer Choice model (ECCo). These projections are provided for several scenarios (Medium, High, Very High, Maximum BEV Uptake, Reduced Demand), and the user will select the EV uptake scenario to be used for each tool run.[2] EV uptake projections will be combined with datasets produced in Lot 1 of the Reflect project to determine the number of vehicles in each of the user archetypes – the datasets used are summarised in Table 1. The 24 user archetypes are detailed in Table 3.

Table 1. Datasets from Lot 1 used to determine vehicle numbers in user archetypes

Lot 1 dataset	Source used	Purpose of dataset
Vehicles commuting to work	Nomis data	Used to identify the number of vehicles in commuter user archetypes in each primary area
Rural/urban classification	ONS data	Used to determine the number of vehicles in urban and rural based user archetypes in primary areas
Off-street parking access	EE off-street parking model used to calculate access at OA level, aggregated to MSOA level	Used to determine the number of vehicles in user archetypes that park off-street in each primary area

2.2 EV parameters

Element Energy's Car and Van Cost and Performance model employs a bottom-us modelling approach to project how improvements in technology will affect EV parameters, and these will be used in the Reflect tool. The key parameters from this model for the Reflect tool are battery size, which affects how often vehicles charge, and electricity consumption, which is used to convert each user archetype's daily mileage into daily charging demand. These inputs are defined separately for EV cars and vans for each study year.

[2] Further details on EV uptake scenarios are available in the Reflect Lot 1 report

2.3 Charging demand distribution inputs

The method for distributing charging demand across the ENWL licence area depends on the charging location type being considered. Table 2 summarises the input datasets used to distribute charging demand to primary areas, and the methods that will be used to distribute charging demand for each charging location type are detailed below:

- **Residential charging** (home and on-street) will occur in the primary area in which the vehicle is registered.
- **Destination charging** will be summed for the whole licence area and distributed to each primary area based on the share of shopping trips ending in that primary area.
- **En-route charging** will be summed for the whole licence area and distributed to each primary area based on the number of fuel and service stations in that primary area.
- **Work charging** will be mapped from each primary area where commuting vehicles are registered, to the primary areas they commute to, based on the share of commuting trips originating in that primary area that end in each primary area.

Table 2. Datasets used to distribute charging demand to primary areas

Dataset	Sources used	Purpose of dataset
Share of personal car shopping trip ends	Trip End Model Presentation Program (TEMPro)	Distribute destination charging demand to primary areas
Petrol station and service station locations	OpenStreetMap, complemented by data received from LAs	Distribute en-route charging demand to primary areas
Commuting trips origin/destination matrix	Nomis	Distribute work charging demand from commuting vehicle origin to destination primary areas

2.4 Charging profile inputs

The starting point for generating charging profiles is charge start time profiles, which give the share of vehicles that plug in to an EVCP at half hourly resolution. Charge start time profiles are available from previous EV charging studies. It is important to note that these profiles are diversified, meaning they represent the behaviour of multiple EVs charging. Therefore the resulting ratio of average to peak demand will be lower than for a single EV as not all EVs will be charging at the same time, so demand is spread throughout the day.

A charging duration will then be applied to the charging start time profile to determine the share of vehicles that are charging at a given time. The resulting charging demand profile will be normalised to 1 kWh / day (to be combined with the daily kWh charging demand elsewhere in the tool). Charging duration will be calculated differently for home charging and other charging location types:

- **Home charging:** Users are assumed to only charge when their state of charge is low as they can guarantee access to the charge point. A correlation between kWh per charge and battery size will be used to determine the energy supplied per charging event. Dividing by the charger power gives the duration of a home charging event.
- **Other charging location types:** Users are assumed to charge once per day. Daily kWh demand at each site will be divided by user-defined charger power to determine the duration of a charging event for each user archetype at each charging location type.

For home charging, smart and vehicle-to-grid (V2G) charging profiles will also be provided. These profiles are taken from Element Energy's existing work for ENWL, in which smart and vehicle-to-grid charging profiles are included in the Element Energy Load Growth model provided to ENWL. The user will be able to set the share of home charging that is smart and V2G for each year of the tool run.

Table 3. The attributes of the 24 user archetypes that will be modelled in the Reflect tool

Vehicle	Powertrain	Commuter status	Location	Off-street parking access
Cars	BEV	Commuter	Rural	Access to off-street parking
				No access to off-street parking
			Urban	Access to off-street parking
				No access to off-street parking
		Non-commuter	Rural	Access to off-street parking
				No access to off-street parking
			Urban	Access to off-street parking
				No access to off-street parking
	PHEV	Commuter	Rural	Access to off-street parking
				No access to off-street parking
			Urban	Access to off-street parking
				No access to off-street parking
		Non-commuter	Rural	Access to off-street parking
				No access to off-street parking
			Urban	Access to off-street parking
				No access to off-street parking
Vans	BEV	Non-commuter	Rural	Access to off-street parking
				No access to off-street parking
			Urban	Access to off-street parking
				No access to off-street parking
	PHEV		Rural	Access to off-street parking
				No access to off-street parking
			Urban	Access to off-street parking
				No access to off-street parking

2.5 Probabilistic user inputs

The user will define probability distributions which will be randomly sampled to determine the share of each vehicle's charging demand that is fulfilled by each charging location type. Individual probability distributions will be defined for 12 charging archetypes – these are similar to the 24 user archetypes, however as rural/urban location is not predicted to have a significant effect on charging behaviour, this factor is excluded. The 12 charging archetypes are shown in Table 4 below.

Table 4. The attributes of the 12 charging archetypes that will be modelled in the Reflect tool

<table>
<tr><th>Vehicle</th><th>Powertrain</th><th>Commuter status</th><th>Off-street parking access</th></tr>
<tr><td rowspan="8">Car</td><td rowspan="4">BEV</td><td rowspan="2">Commuter</td><td>Access to off-street parking</td></tr>
<tr><td>No access to off-street parking</td></tr>
<tr><td rowspan="2">Non-commuter</td><td>Access to off-street parking</td></tr>
<tr><td>No access to off-street parking</td></tr>
<tr><td rowspan="4">PHEV</td><td rowspan="2">Commuter</td><td>Access to off-street parking</td></tr>
<tr><td>No access to off-street parking</td></tr>
<tr><td rowspan="2">Non-commuter</td><td>Access to off-street parking</td></tr>
<tr><td>No access to off-street parking</td></tr>
<tr><td rowspan="4">Van</td><td rowspan="2">BEV</td><td rowspan="4">Non-commuter</td><td>Access to off-street parking</td></tr>
<tr><td>No access to off-street parking</td></tr>
<tr><td rowspan="2">PHEV</td><td>Access to off-street parking</td></tr>
<tr><td>No access to off-street parking</td></tr>
</table>

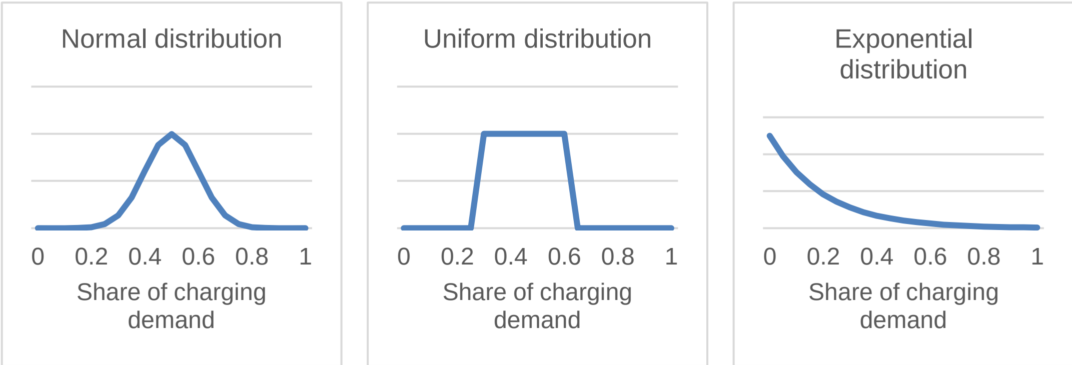
For each of the 12 charging archetypes, the user will provide 3 probability distributions:

- Share of residential charging
- Share of rapid en-route charging
- Share of workplace charging

A single run of the Reflect tool will consist of multiple micro-scenario runs. For each micro-scenario run, the probability distributions defined above will be randomly sampled to determine the share of charging demand that is fulfilled at each charging location type for each user archetype. Each micro-scenario will be assigned a probability based on the sampled values from the probability distributions; this process is described in more detail in Section 4.1. Once all micro-scenario runs in a tool run have been completed, their results will be aggregated to produce the final tool outputs.

In a particular micro-scenario, the user-defined probability distributions will be randomly sampled to determine the shares of residential, work, and en-route charging performed by each charging archetype. The share of destination charging will be calculated as 1 - (sum of other charging location type shares) for each charging archetype. Note that some charging location types will not be used by certain charging archetypes – for example non-commuters and vans will not use work charging, and PHEVs will not use rapid en-route charging. Excluding these distributions that do not need to be specified, the user will need to define 22 probability distributions in total.

A profile generator will be provided in the Reflect tool's Excel control interface. This will allow the user to define probability distributions by selecting one of several pre-defined distributions and providing input parameters. These pre-defined distributions are the normal distribution, uniform distribution, and exponential distribution, with user-defined parameters as shown in Figure 2. Alternatively, the user will be able to input distributions manually. A distribution will also be provided which always produces a charging share of 0 when sampled to represent unused charging types.



User-defined parameters:
Mean = 0.5
Standard deviation = 0.1

User-defined parameters:
Minimum = 0.3
Maximum = 0.6

User-defined parameters:
Mean = 0.2

Figure 2. Predefined probability distributions and user-defined parameters for each that will be set in the Excel control interface

2.6 MSOA to primary area mapping

User archetype vehicle numbers and datasets used to distribute work and destination charging demand are produced at MSOA resolution and must be mapped to primary area level before they can be used in the tool. MSOA boundaries are available from ONS. Primary area boundaries were determined by first creating a map where each region corresponds to the area closest to a given secondary substation, then aggregating these areas based on the primary substation that serves each secondary substation. The MSOA and primary area boundaries are shown in Figure 3 on the left and right respectively.

Inputs will be mapped from MSOA to primary area by distributing inputs from each MSOA to the primary areas it overlaps with, based on the share of the MSOA's area that overlaps with each primary area. Note that some MSOAs for which inputs were collected in Lot 1 only overlap partially or lie completely outside the ENWL licence area. In MSOAs where there is an area that does not overlap with any primary areas, the number of vehicles in that MSOA which are mapped to the ENWL licence area will be scaled down accordingly. Effectively, vehicles assumed to be registered in areas of MSOAs that do not overlap with any primary areas will be excluded from the tool.

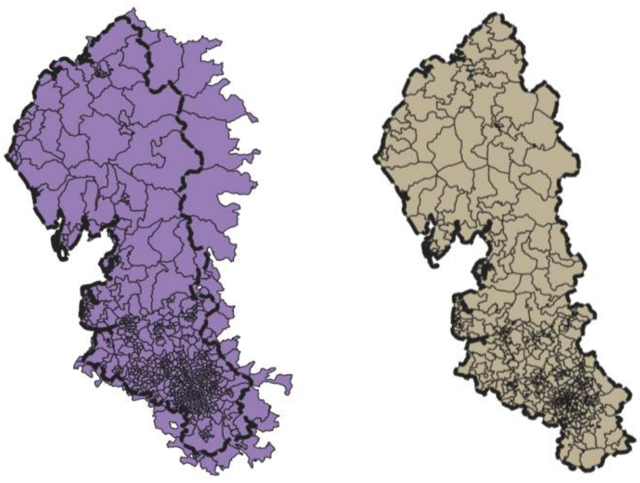


Figure 3. Maps showing how the ENWL licence area is split up into MSOAs (left) and primary areas (right)

2.7 Summary of inputs

The inputs to the Reflect tool are summarised in Table 5, along with where the input will be located. Inputs in the Excel control interface are expected to be changed by the user on a regular basis, so these will be made as easy to edit as possible. Other inputs will be provided in CSV files for easier integration into the tool, as the user is only expected to edit these inputs when performing an annual update to the tool.

Table 5. A summary of the inputs to the Reflect tool

Input name	Input location
EV uptake scenarios	Separate CSV files
Active EV uptake scenario	Excel control interface
Vehicles commuting to work	Separate CSV files
Rural/urban classification	Separate CSV files
Off-street parking access	Separate CSV files
Battery size	Separate CSV files
Electricity consumption	Separate CSV files
Share of personal car shopping trip ends	Separate CSV files
Petrol station and service station locations	Separate CSV files
Commuting trips origin/destination matrix	Separate CSV files
Home charging correlation between kWh per charge and battery size	Separate CSV files
Charging start time profiles	Separate CSV files
Smart and V2G charging profiles	Separate CSV files
Charger power	Excel control interface
Charging location type probability distributions	Excel control interface
MSOA to primary area mapping	Separate CSV files

3 Charging demand forecasting process

3.1 Allocation of charging demand to primary substations

The first step in the charging demand forecasting process is to determine the charging demand that vehicles registered in each primary area are responsible for, split by charging location type. This process will be performed for each user archetype in each primary area and is represented schematically in Figure 4.

Average daily mileage (in km) is multiplied by electricity consumption per km to determine the daily charging demand per EV. The daily charging demand is multiplied by the share of charging demand at each charging location type to calculate the daily charging demand per EV at each charging location type. This is then multiplied by the number of EVs in the active scenario to determine the total demand originating from vehicles registered in each primary area for each user archetype at each charging location type.

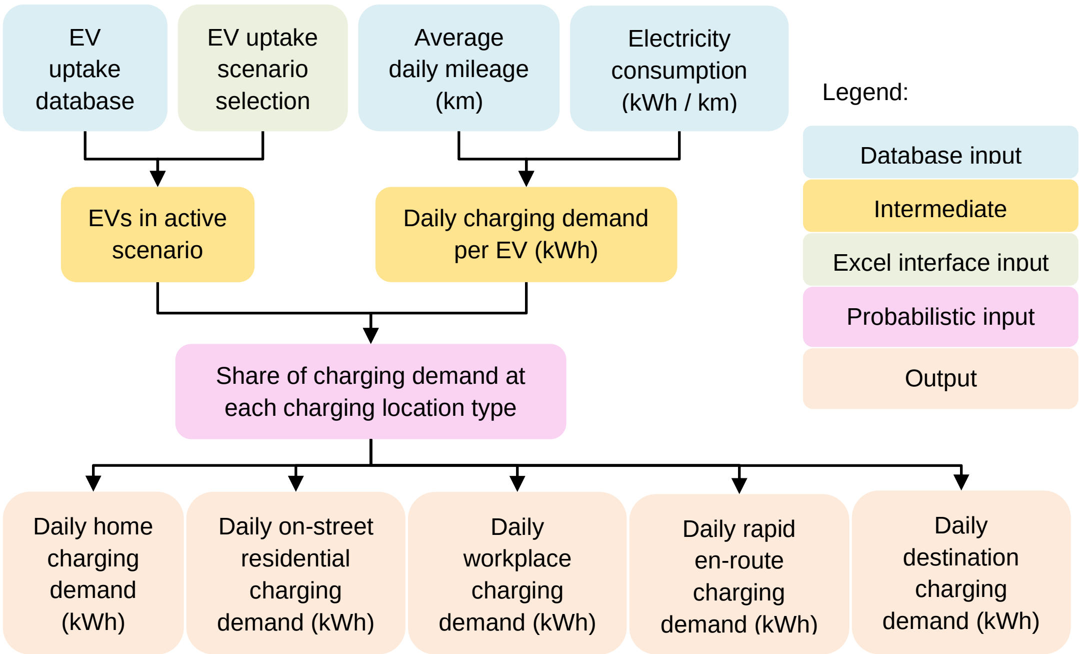


Figure 4. Process for determining the charging demand by location type for each user archetype for vehicles registered in a primary area

Charging demand from vehicles registered in each primary area will then be mapped to the primary substation where that charging is performed. The distribution method for each charging location type is described below, and datasets used to perform this mapping are discussed in Section 2.3.

- **Residential charging** (home and on-street) will occur on the primary substation corresponding to the primary area in which the vehicle is registered.
- **Destination charging** will be summed for the whole licence area and distributed to each primary substation based on the share of shopping trips that end in each substation's primary area.
- **En-route charging** will be summed for the whole licence area and distributed to each primary area based on the number of fuel and service stations in each substation's primary area.
- **Work charging** will be mapped from each primary area where commuting vehicles are registered, to the primary areas they commute to, based on the share of commuting trips originating in that primary area that end in each primary area.

3.2 Generation of charging profiles

Once the total charging demand for each charging location type and user archetype on each primary substation known, charging profiles will be generated to understand how demand will vary throughout the day. This process is shown schematically in Figure 5.

First, the energy per charge event will be determined. Two different approaches will be used depending on the charging location type being considered:

- **Home charging**: a correlation between battery size of the vehicle and energy per charge will be used to determine energy per charge.
- **All other charging location types**: the number of charging events per EV per day at each charging location type will be based on analysis of data from Western Power Distribution's Electric Nation project. Energy per charge is then calculated by dividing the daily charging demand per EV supplied at each charging location type divided by the relevant charges/day/EV figure:[3]
    - Destination: 0.038 charges/EV/day
    - En-route: 0.05 charges/EV/day
    - On-street residential: 0.28 charges/EV/day
    - Work: 0.39 charges/EV/day

Energy per charge is divided by the power of the charger to calculate the charging duration. This charging duration will be applied to the charge start time profile to generate a profile of share of vehicles currently charging, which will be normalised to produce a 1 kWh/day charging profile. This profile is multiplied by the total daily charging demand for the user archetype, charging location type, and primary substation being studied, to determine the overall charging demand profile. Total charging demand for all user archetypes and charging location types at each primary substation will be calculated by summing the charging profiles for each combination of user archetype and charging location type. Note that this approach will not be used for (residential) smart and vehicle-to-grid charging profiles, which will simply be inputted as normalised daily charging profiles.

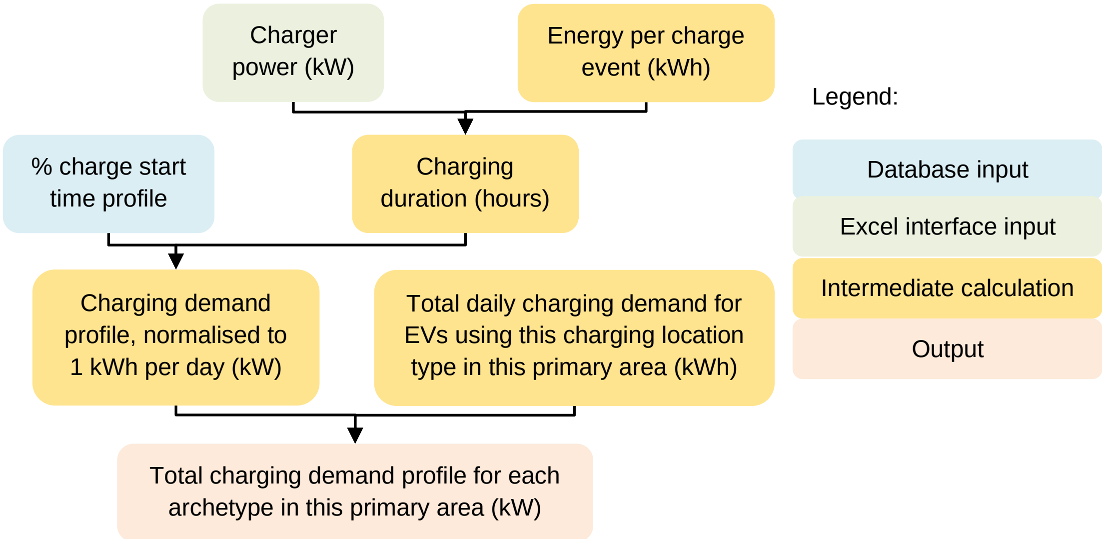


Figure 5. Process for generating charging demand profiles for a user archetype and charging location type combination at a primary substation

[3] Element Energy analysis of the interim Electric Nation dataset

4 Approach to probabilistic analysis

4.1 Sampling of probability distributions

The probabilistic approach to uncertainty in the location of future charging demand will require the user to define raw probability distributions for each charging archetype for work, residential (home or on-street depending on the charging archetype), and en-route charging. These raw distributions will be produced using the Reflect tool's profile generator or manually added by the user. Raw distributions will then be normalised to have a total probability of 100%. These normalised probability distributions will be used to generate cumulative probability distributions for use in the tool's calculations. Figure 6 shows example raw, normalised, and cumulative probability distributions for a single charging archetype.

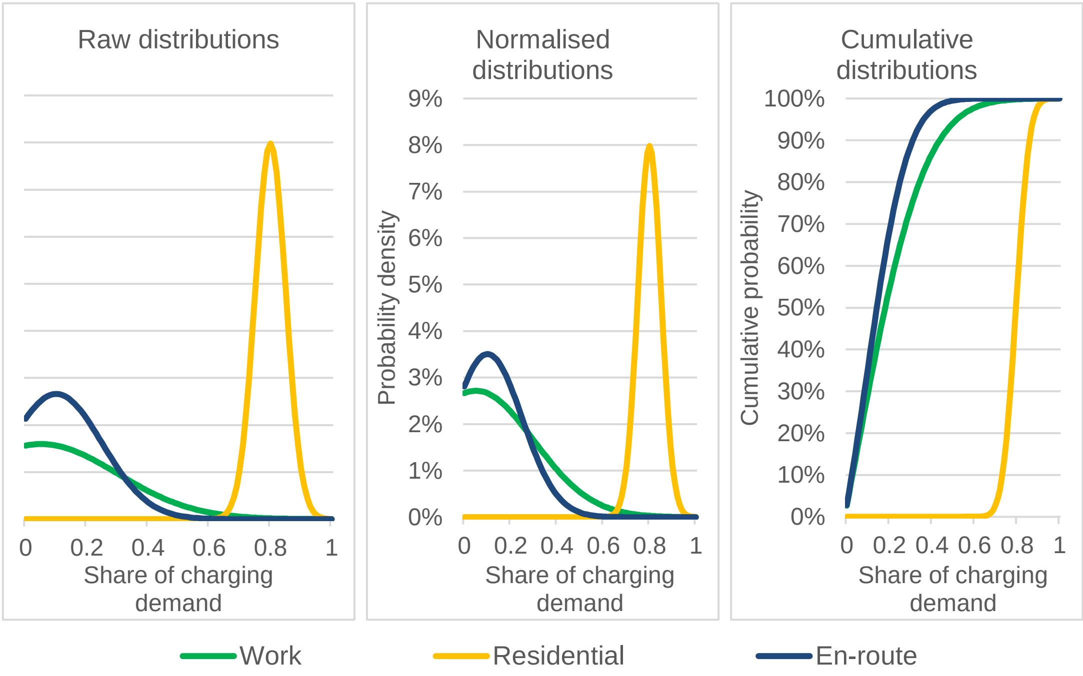


Figure 6. Examples of raw user-defined probability distributions, and generated normalised and cumulative probability distributions

These probability distributions will be sampled to produce inputs for each micro-scenario. For residential, work, and en-route charging respectively, a random number between 0% and 100% will be chosen, representing a particular cumulative probability. For each charging archetype, the charging demand share with this cumulative probability will be selected as an input for the micro-scenario. Figure 7 gives an example of this sampling for a single charging archetype:

- Work: 40% cumulative probability is randomly sampled, giving a charging share of 0.1.
- Residential: 10% cumulative probability is randomly sampled, giving a charging share of 0.7.
- En-route: 20% cumulative probability is randomly sampled, giving a charging share of 0.1.
- Destination charging is calculated as 1 - (sum of other charging types) – in this case the destination charging share is 0.1, i.e. 1 - (0.1 + 0.7 + 0.1) = 0.1.

Note that in this example, charging shares have been rounded to a resolution of 0.1 for clarity. In the tool, charging shares will be rounded to a resolution of 0.01, which gives ~1 million distinct micro-scenarios for a single charging archetype.

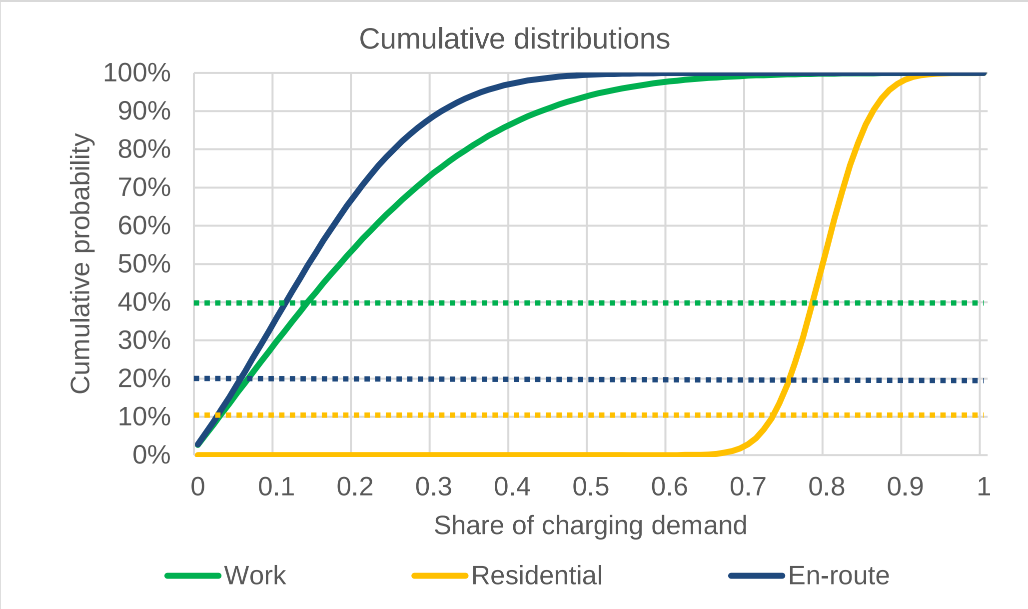


Figure 7. An example of the random sampling process for a single charging archetype

Sampling of distributions for each charging location type will be performed in a dependent way across all 12 charging archetypes. In each micro-scenario, 3 random numbers between 0% and 100% will be chosen, which will be used to sample the probability distributions for all 12 charging archetypes. Each of these random numbers will correspond to a particular charging location type – i.e. the first random number will be used to sample the residential charging distributions for each of the 12 charging archetypes, the second will be used to sample all the work charging distributions, and the third will be used to sample all the en-route charging distributions.

This dependent sampling process ensures that utilisation of charging location types is consistent across all charging archetypes in a given micro-scenario – for example, if a random number of 95% is generated for work charging, this means that all charging archetypes will have a work charging share equal to the 95th percentile of their cumulative distribution (i.e. a relatively high level of work charging). It is likely that charging behaviour is correlated across user archetypes (e.g. a micro-scenario with relatively high levels of en-route charging for one user archetype should also have relatively high en-route charging for the other 11 charging archetypes), and this dependent sampling process effectively assumes a fixed correlation for each charging location type. If this correlation is accurate, this will increase the accuracy of the results, however if it is not, this will introduce inaccuracies into the tool outputs.

4.2 Probability calculation methodology

Charging shares at different charging location types are assumed to be independent, so the overall probability of a micro-scenario occurring will be calculated as follows:

$$
\begin{aligned}
&P(Micro\ scenario) = \\
&P(Residential\ charging\ share) \\
&\times\ P(Work\ charging\ share) \\
&\times P(En\ route\ charging\ share)
\end{aligned}
$$

P(Residential charging share) refers to the probability of the sampled residential charging shares for each of the charging archetypes being sampled simultaneously. Similarly, P(Work charging share) and P(En-route charging share) refer to the probabilities of the sampled work and en-route charging shares for each of the charging archetypes being sampled simultaneously.

As the probability distributions for a given charging location type will be sampled dependently, P(Residential charging share) cannot simply be calculated as the product of the probabilities of the sampled charging share being obtained for each of the charging archetypes. A worked example of the dependent probability calculation for work charging is demonstrated below for a simplified case of 3 charging archetypes – the process is identical for residential and en-route charging.

For a given charging location type, choosing a random cumulative probability will give a corresponding charging demand share for each charging archetype. In this example, the randomly selected cumulative probability is 68%. This corresponds to a micro-scenario where charging archetypes 1, 2, and 3 have a work charging share of 0.1, 0.3, and 0.1 respectively (rounded to 1 decimal place), as shown in Figure 8.

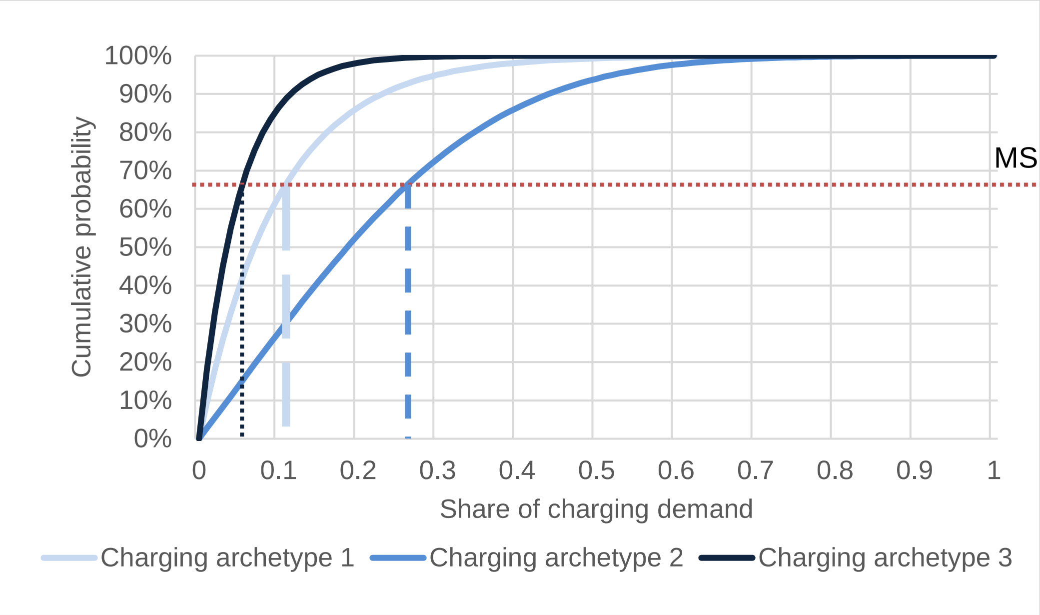


Figure 8. A plot showing the first step of micro-scenario (MS) probability calculation; determining the charging shares for each charging archetype in the micro-scenario

Each micro-scenario can be defined as a region on the cumulative probability line where the charging shares for each charging archetype round to a certain set of values; in the example being considered, the micro-scenario corresponds to the region of the cumulative probability line where the work charging shares for charging archetypes 1, 2, and 3 round to 0.1, 0.3, and 0.1 respectively. In the tool, the resolution of charging shares will be 0.01 rather than 0.1, however a broader resolution has been used in this example for simplicity.

As each micro-scenario corresponds to a region on the cumulative probability line, the width of this region (or the height of the region when cumulative probability is plotted on the y axis as in Figure 8 – we will use the blanket term "width" to describe this) is equal to the probability of the micro-scenario. The process for finding the probability of the micro-scenario is shown in Figure 9. In this example, the lower bound of the micro-scenario region on the cumulative probability line is 64% and the upper bound is 80%, meaning the probability of the micro-scenario is 16%, the width of this region of the cumulative probability line.

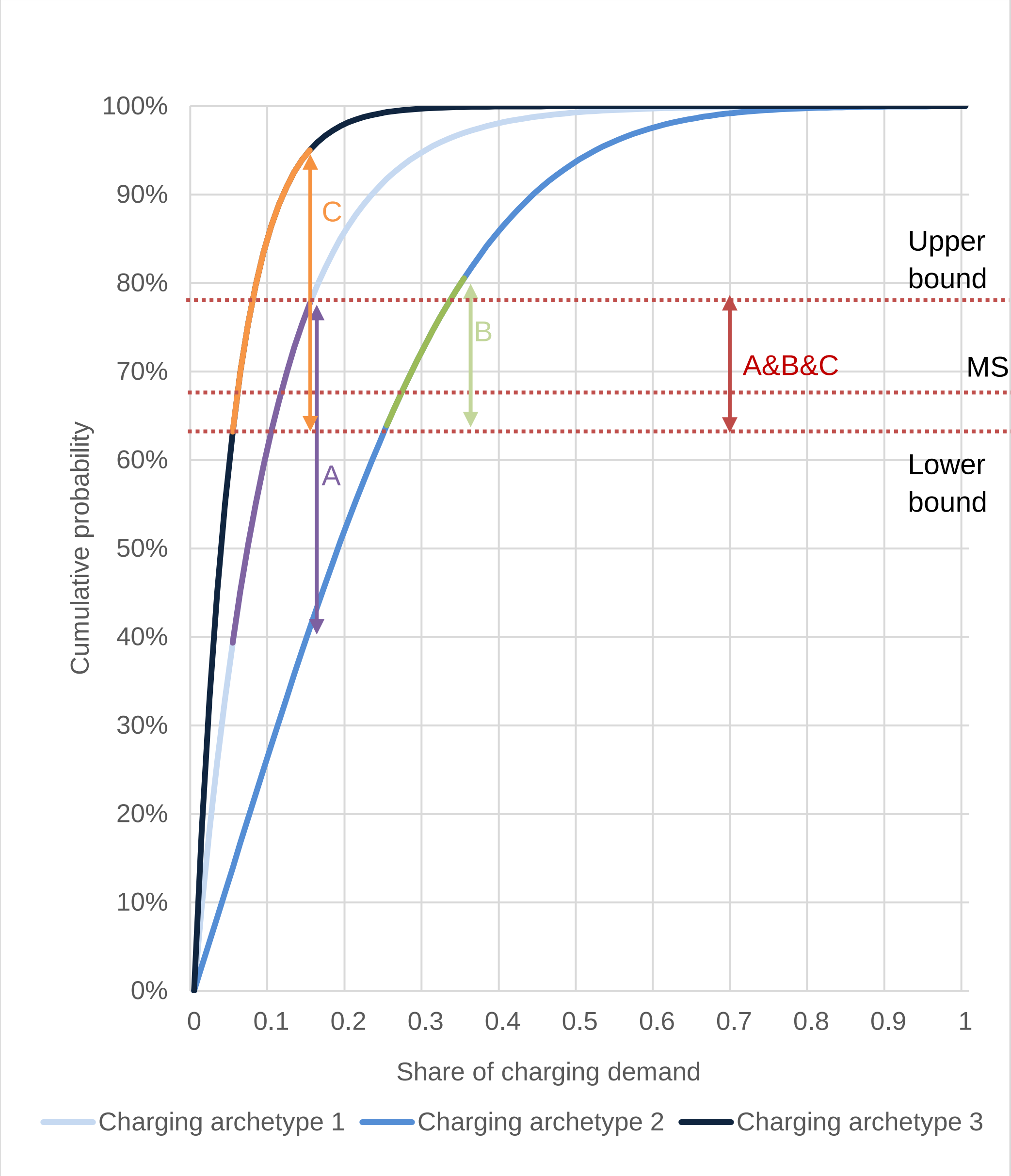


Figure 9. A plot showing how the probability of a micro-scenario (MS) is determined. A represents the region of cumulative probability where charging archetype 1's work charging share rounds to 0.1; B represents the region of cumulative probability where charging archetype 2's work charging share rounds to 0.3; C represents the region of cumulative probability where charging archetype 3's work charging share rounds to 0.1. The region A&B&C is the intersection of these three regions, whose width corresponds to the probability of the micro-scenario

4.3 Limitations to this approach

As the probability distributions for the 3 charging location types will be sampled independently, in some cases, the sampled shares for each of the charging location types may sum to a number that is greater than 1. The resulting sample would be invalid and would not be included in the analysis. Probabilities of valid micro-scenarios will be scaled up based on the ratio of invalid to valid micro-scenarios to account for this. However, care must be taken when defining probability distributions to minimise the number of invalid samples that are produced. For transparency in the sampling process, invalid samples will be shown to the user.

As there will be 3 independently calculated charging location type shares (the destination charging share is calculated as 1 - sum of other charging location type shares so is not independent), each with 101 possible values (0 to 1 in 0.01 steps), there will be over 1 million (101^3) possible micro-scenarios. Running this many micro-scenarios would require a prohibitive amount of time and storage space, so a lower number of samples will be taken which are well distributed throughout the sample space.

It is important to note that the probability of a given micro-scenario does not necessarily correspond to the probability of a given demand profile – this is because several micro-scenarios could lead to very similar levels of demand. Therefore it is recommended that statistics calculated for the set of micro-scenarios run in the model, i.e. the mean and upper/lower quartile demand, are used to assess the expected demand and uncertainty in this prediction.

5 Implementation of the tool

5.1 Tool platform

The tool will be coded in Python 3.7, using packages compatible with the Anaconda distribution. The user will provide inputs to the tool through an Excel control interface, which will produce CSV input files to be read by the tool – this interface is discussed further in Section 5.2.

As requested by ENWL, the targeted maximum run time for the tool will be 24 hours to produce output primary substation demand profiles, and intermediate samples should be produced in 6 hours.

5.2 User interface

The user will interact with the tool via an Excel spreadsheet interface. This will allow the user to set inputs, generate probability distributions, and randomly sample these distributions to generate a set of micro-scenarios. The tool will produce mean, upper and lower quartile demand profiles by aggregating results from all micro-scenarios (including those that were sampled but not selected by the user). The user will also be able to select a set of micro-scenarios whose results will be outputted in CSV files.

5.3 Outputs

For micro-scenarios that the user chooses to run, a single half-hourly demand profile will be produced for each year, season, primary substation combination – 22,444 profiles per micro scenario (31 years * 2 seasons (summer and winter only) * 362 primary substations). The user will be able to name each scenario run and results for each run will be saved in a separate folder for ease of future access.

To keep the output file size at an acceptable level and for easy data access, profiles for each micro-scenario run will be saved to an SQL database. Test runs suggest each micro-scenario takes up ~130 MB of disk space, so a tool run with 100 micro-scenarios will take up ~13 GB of disk space – therefore care must be taken when producing several scenario runs with a large number of micro-scenarios, as this may lead to disk space issues.

Results from all micro-scenarios will be combined to produce a mean, upper quartile, and lower quartile demand profile for each year, season, primary substation combination – 67,332 profiles in total (31 years * 2 seasons (summer and winter only) * 362 primary substations * 3 probability levels (mean, upper quartile, lower quartile). As these profiles are only produced for each scenario run, disk space is much less of an issue; therefore these profiles will be produced in CSV format for easy integration with the EELG model's existing outputs. Three CSV files will be produced for each year and season and will include the mean, upper quartile, and lower quartile demand profiles respectively for all substations being modelled. CSV files in the same format will also be produced for any micro-scenarios selected by the user. It is important to note that this CSV is not suitable for a large number of micro-scenarios due to the large amount of disk space that would be required.