1 The Outcome Of The Project

1.1 Summary of outcomes

The REFLECT project has developed credible methodologies and associated prototype tools for the probabilistic long-term forecasting of EV charging active power demand that can frame local EV charging uncertainties across the whole EHV network of Electricity North West.

The following works on regional data requirements, methodologies and modelling tools have been disseminated and are publicly available on the projects website (online: www.enwl.co.uk/reflect):

i. the Dataset report (see section 8.2) that describes what local data and associated granularity required to frame local uncertainties in the various types of EV charging; and,
ii. the Tool Specification report (see section 8.3) that describes the methodology and associated tools developed that use the local data as inputs and apply probabilistic analysis to model EV charging per primary substation.

Both reports have been delivered by Element Energy and have considered modelling recommendations provided by Electricity North West, especially around the introduction of the concept of micro-scenarios and the focus of probabilistic analysis on the location type of EV charging (ie, home, public on street, work, destination and rapid en-route).

Following the development of the REFLECT methodology and prototype tools in Python, we used the tools with inputs from our Electricity North West DFES 2020. The analysis carried out has revealed that local characteristics can result in different EV profiles both for the average risk and extreme cases under uncertainty. Results are discussed in section 8.4 of this report.

In section 8.6 we present how the proposed use of micro-scenarios that have been introduced in the REFLECT project can be used in decision making tools such as our Real Options CBA (ROCBA) tool developed in Demand Scenarios NIA project. To do that, we require manual processing of intermediate results of the REFLECT methodology, which is described in section 8.5. In practice, the developed Python tool allows use an automatic or manual process for the selection of micro-scenarios, depending on the planning process associated with the EV charging forecasts.

Our REFLECT project has focused on uncertainties around EV charging, but at the same time the developed modelling framework using probabilistic analysis on top of the network planning scenarios (eg, DFES) can be used in the future to model other key forecasting building blocks. This is particularly useful for building blocks where the existing DFES scenario frameworks cannot capture all critical uncertainties. Therefore, as described in section 8.6 the REFLECT modelling approach can be applied in future works to:

a. enhance the use of scenarios in network planning to capture all critical uncertainties not currently framed by DFES scenarios; and,
b. consider probabilities and likelihood metrics in DFES scenarios used in network planning.

1.2 Regional Datasets

Regional datasets and projections have been produced by Element Energy to inform the modelling of EV charging on Electricity North West's EHV network. The datasets produced and their purpose in the modelling of EV charging demand can be summarised as follows:

- Car and van ownership / current EV uptake: used to inform modelling of EV uptake.
- Off-street parking access: used to determine the scale and location of domestic EV charging demand.
- Rural / urban classification: used to inform travel patterns of drivers, as rural drivers tend to drive higher daily distances than urban drivers.
- Vehicles commuting to work: used to identify where commuters live, as they have very different travel and charging behaviour to the rest of the population.
- Existing EV charging infrastructure: used to map existing charging demand to network assets and understand where future infrastructure may be installed.
- Points of interest (POI): these can be potential locations of EV charging such as hotels, supermarkets, petrol stations and service stations. Used to predict where future EV charging infrastructure will be installed.
- Travel patterns: share of personal car work and shopping trip ends. Used to determine the scale and location of work and public EV charging demand.

Apart from the above datasets, uptake projections for EV volumes (cars and vans) are also required as data inputs. The analysis in REFLECT project has considered the EV uptakes adopted in Electricity North West DFES 2020 that follows the Department for Transport (DfT) projections of vehicle stock, as well as an uptake with lower vehicles on the road.

The project's dataset report (file ID: *ENWL022 - Lot1 Dataset Report.pdf*) can be accessed from REFLECT website (online: www.enwl.co.uk/reflect).

1.3 Methodology and Tool Specifications

The developed REFLECT methodology uses the regional datasets described in section 8.2 to model EV charging down to per primary substation feeding area. To do that, 24 archetypes have been defined, which are differentiated by being either:

- cars or vans;
- battery electric vehicle (BEV) or plug-in hybrid electric vehicle (PHEV);
- commuters or non-commuters;
- parking off-street or on-street at home;
- rural or urban home location.

Charging behaviour is 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 is split across 5 charging location types: home; on-street residential; work; rapid en-route; and destination. For home charging a correlation between battery size of the vehicle and energy per charge is used to determine the energy per charge. For the other charging location types, the number of charging events per EV per day at each charging location type are based on analysis of data from WPD's Electric Nation project.

The distribution of vehicles across user archetypes has been determined by collecting data on current BEV and PHEV car and van ownership across our 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.

The uncertainty in EV charging demand is 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 varies, with these shares being randomly sampled from pre-defined probability distributions. Probability distributions for the share of residential, work, and en-route charging demand for each charging archetype have been defined, meaning that 36 probability distributions have been produced in total.

The REFLECT methodology uses simple and reasonable at the same probability distributions for each charging location type. For example, the local percentage of access to off street parking has been used to define the mean value of a normal distribution (statistical distribution type) with standard deviation ±20% of the mean value for the off-street home charging. This modelling approach acknowledges the expected high correlation of availability of off-street parking with customers choosing to charge their EVs at home. On the contrary, for charging at work a uniform statistical distribution has been considered, recognising the higher uncertainties around employers providing EV charging at work. Future work can use insights from consumer choice to produce well informed and potentially more complex probability distributions.

The REFLECT tool is coded in Python 3.7 using packages compatible with the Anaconda distribution. The user can provide inputs to the tool through an Excel control interface, which produces CSV input files to be read by the tool. Outputs are produced as CSV files in the same format as existing Electricity North West forecasting tools, to allow easy integration with business as usual processes.

An Excel-based probability distribution generator has been produced to assist with the generation of the charging demand profile for each micro-scenario. Each micro-scenario has an associated probability, and the results from each micro-scenario are combined to generate mean/upper/lower quartile or user defined demand profiles for each primary substation.

More information on the REFLECT methodology and tools can be found in the project's tool specification report (file ID: *ENWL022 – Tool Specification Report.pdf*) can be accessed from REFLECT website (online: www.enwl.co.uk/reflect).

1.4 Analysis for Electricity North West's License Area

This section presents high level results using the REFLECT tool with EV volume uptakes from the Central Outlook and Consumer Transformation scenarios of ENWL DFES 2020. The two scenarios consider the same EV uptake trends. Analysis has been carried out across all BSP and primary substations in our license area.

To demonstrate how local characteristics can frame uncertainties in EV charging at local level, we present the comparison between the overall EV charging demand across all BSPs and the EV charging demand of a primary substation that exhibits different local characteristics from the average across our license area. Fig. 1 shows the EV charging profiles for the aggregated demand across all BSPs in our license area. Analysis has been carried out for 50 micro-scenarios, which can be considered as 50 variations in terms of half-hourly profiles around the half-hourly EV charging profiles of the Central Outlook scenario. Each micro-scenario has an assigned probability (see section 8.3) to indicate how likely it is for each variation to occur.

The three profiles presented in Fig. 1 are:

- **highest**: corresponds to the highest per half-hour EV charging demand across all micro-scenarios. The probability is different per half-hour and equal to the corresponding probability of the associated micro-scenario.
- **lowest**: corresponds to the lowest per half-hour EV charging demand across all micro-scenarios. The probability is different per half-hour and equal to the corresponding probability of the associated micro-scenario.
- **mean**: corresponds to the weighted average considering all micro-scenario profiles and the associated probability per micro-scenario.

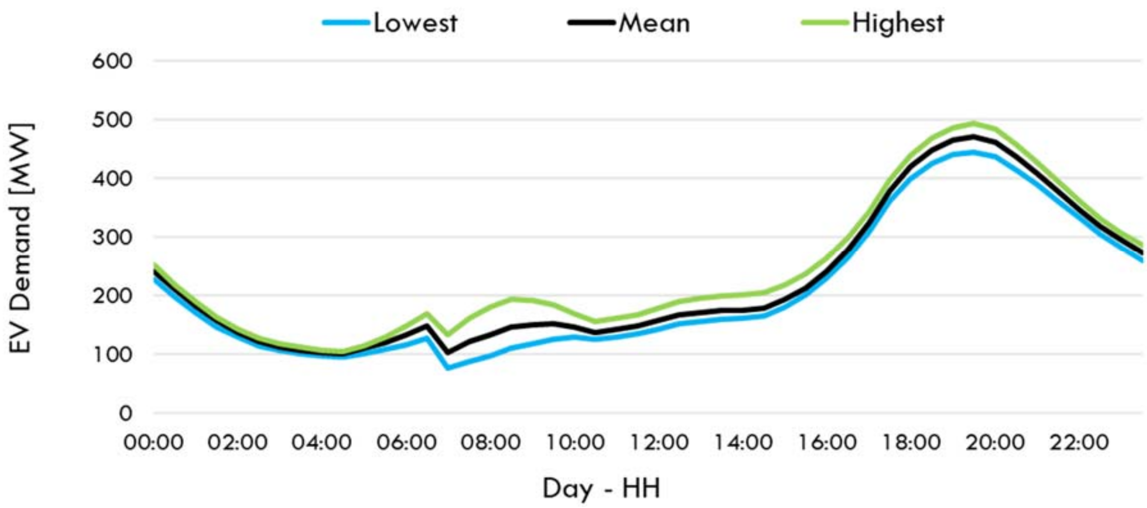

Fig. 1. Aggregated EV charging demand profile across all BSPs for a typical winter day in FY28. Results shown for the lowest, mean and highest EV charging demand profiles taking into account all 50 micro-scenarios.

What is evident in these three profiles is that a) the highest EV charging demand occurs in afternoon and evening hours and b) there is a relatively narrow range between the highest and lowest demand micro-scenarios. These can be explained by the associated EV user archetype data shown for the whole Electricity North West license area in Fig. 2. More specifically, the high percentage of access to off-street parking (86% of users) and the high percentage of commuters (53% of users) result in more charging away from working hours and a significant amount of overnight smart EV charging at home.

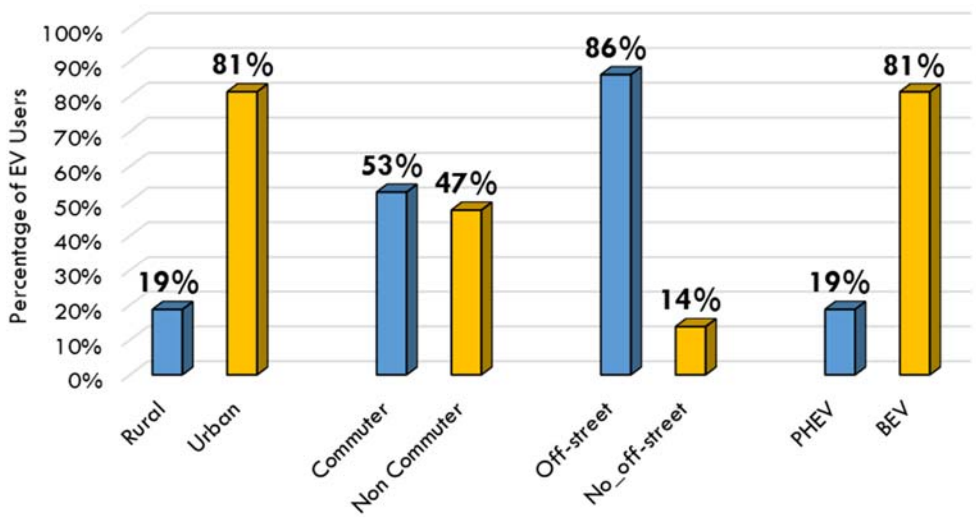

Fig. 2 EV user archetypes distribution for the whole ENWL license area.

From a modelling perspective, the narrow range between high and low demand in Fig. 1 and the peak demand for all three profiles being away from day time working hours is explained from the use of probability distributions for residential charging that consider higher certainties for users with access to off-street parking to charge their EVs at home. Fig. 3 shows how the raw probability distributions modelled for residential, work and en-route charging differ. In specific, it is evident that the normal distribution considered for residential charging has a high mean value (ie, statistical mean of a normal distribution) and low standard deviation. This is not the case for the other two types of charging recognising that there are higher uncertainties around when and where users will charge their EVs at work and/or en-route. For more information see section 8.3 and the Tool Specification report (online: www.enwl.co.uk/reflect).

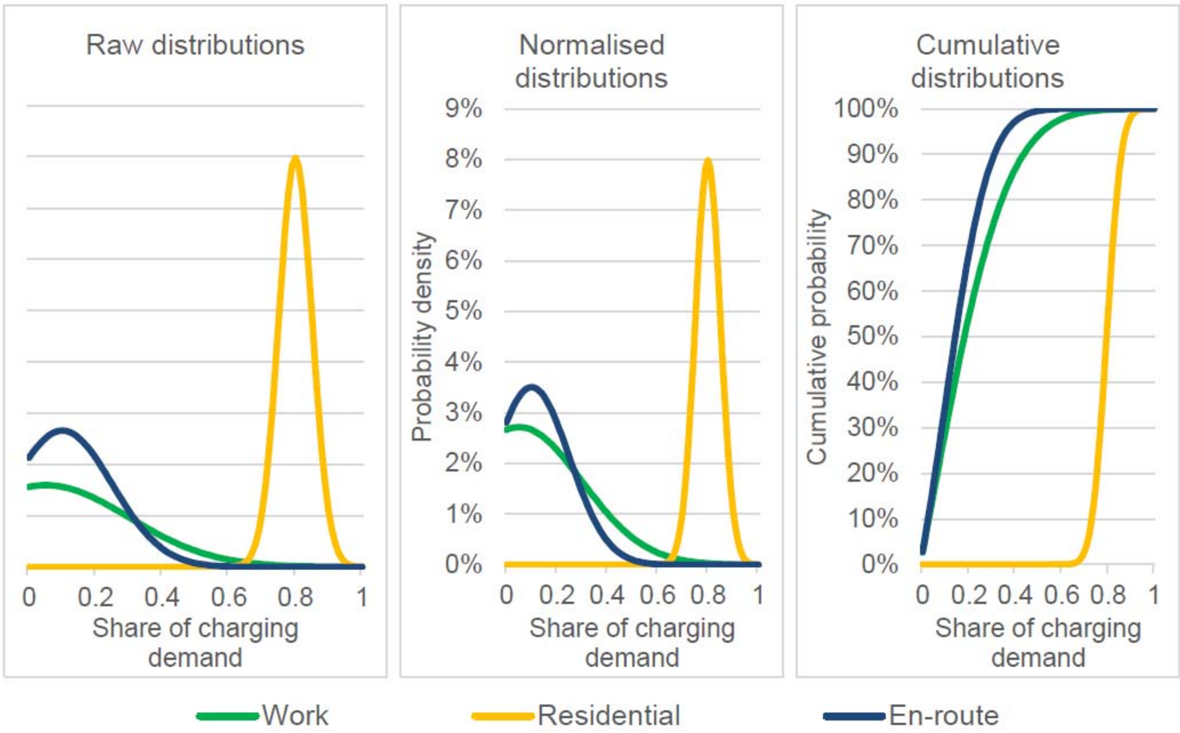

Fig. 3. Examples of raw user-defined probability distributions and generated normalised and cumulative probability distributions.

Unlike the profile characteristics for the EV charging across the whole of Electricity North West license area shown in Fig. 1, there are local EHV substations that exhibit very different EV charging profiles under uncertainty. Fig. 4 shows the corresponding profiles for the Manchester University primary substation. Unlike the EV charging profiles for the whole of Electricity North West license area, this primary substation exhibits a) peak demand in morning hours during working time and b) a wider range of peak demand between the micro-scenarios.

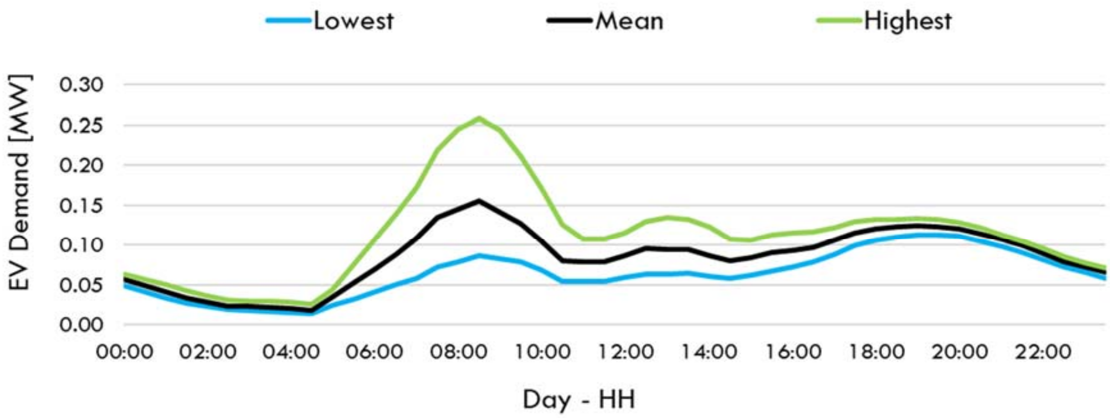

Fig. 4. EV charging demand profiles for Manchester University primary substation for a typical winter day in FY28. Results shown for the lowest, mean and highest EV charging demand profiles taking into account all 50 micro-scenarios.

This behaviour can be explained from the local EV user characteristics in the associated primary substation feeding area. As shown in Fig. 5, Manchester University primary substation supplies an urban area with very limited access to off-street parking and relatively lower commuters compared to the Electricity North West area average. In addition to this, this area has higher trip origins and ends for work and shopping travels than the Electricity North West license area average (see section 8.3 on regional datasets). These mean that more EVs are expected to consider EV charging at work and destination, where higher uncertainties have been modelled using “flatter” probability distributions that model the uncertainties for employers and commercial entities to provide EV charging at work, shops etc.

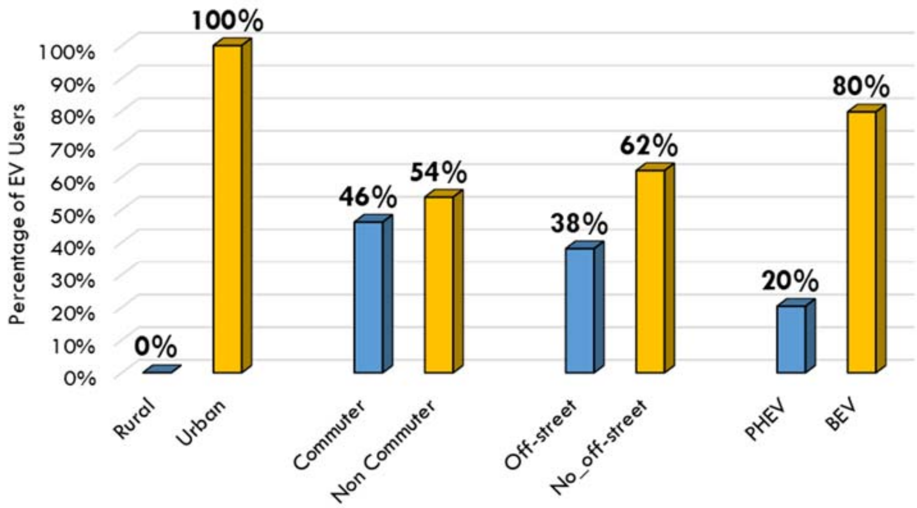

Fig. 5. Data for the EV user archetypes for the Manchester University primary substation feeding area.

To sum up, the developed Python tool has been used to analyse the whole of our EHV network. Results are presented in this report for 50 micro-scenarios around our Central Outlook EV uptake scenario from Electricity North West DFES 2020. To assess the highest and lowest EV charging profiles using all micro-scenarios and define an envelope for the range of EV charging profiles, we have modified the original prototype tool produced by

Element Energy that considered upper/lower quartile and not the actual envelope (see Tool Specification report).

Our analysis has revealed that local characteristics data can define both the time of peak EV charging and the range of min-to-max demand per half-hour. Importantly the tool can be used to do this on each and every BSP and primary substation to support distribution network planning, as well as for wider areas or for the whole of our license area to inform transmission network planning from a whole system perspective.

1.5 Automatic and Manual Selection of Micro-scenarios

The analysis presented in section 8.4 using 50 micro-scenarios has a significant computational cost of 15-20 hours on a personal computer. This is due to the fact that the developed REFLECT tool in Python combines a) a probabilistic analysis to model the share of EV charging per charging location with b) a half-hourly analysis that models all 24 archetypes (see section 8.3). The process followed in section 8.4 is shown in in Fig. 6 within the dashed lined box of the REFLECT Python tool. Specifically the probabilistic modelling module of the model was used to produce the 50 probabilistic outputs, ie combinations of the shares of EV charging demand between different types of location of charging (work, en-route etc). Each of the probabilistic outputs with a corresponding probability to occur was then considered as a micro-scenario and modelled together with all other local data and charging data (ie, 24 modelling archetypes) to produce the half-hourly EV charging profiles of that micro-scenario for each EHV substation.

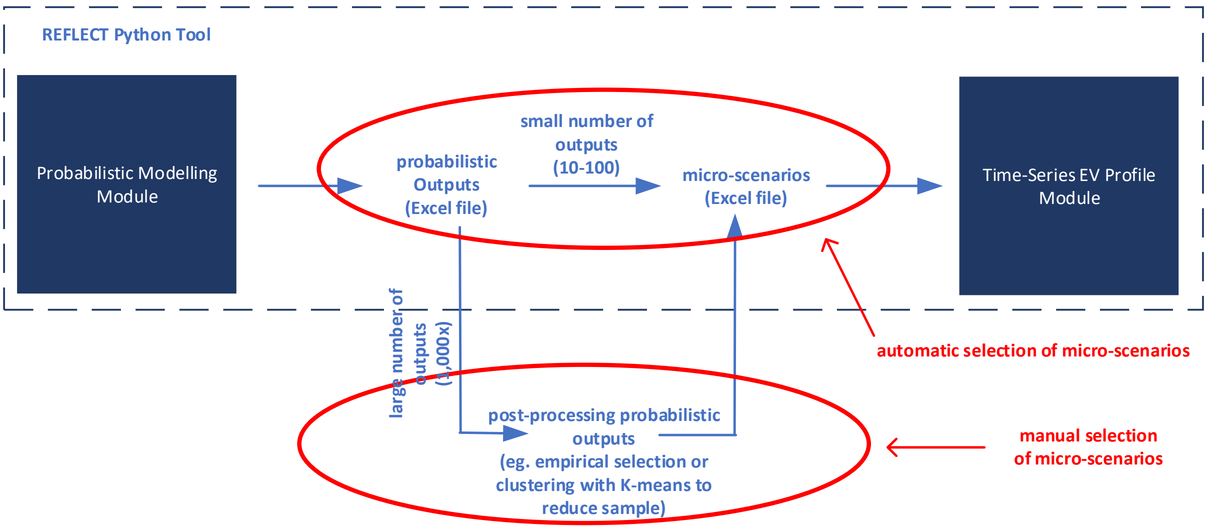

Fig. 6. Modular structure of the REFLECT Python tool that allows both automatic and manual definition of the micro-scenarios.

The analysis to produce EV profiles for every EHV substation in Electricity North West license area described in section 8.4 has involved an automatic process to select micro-scenarios as shown at the upper part of Fig. 6. Even though an automatic process can provide up to 50-100 variations/micro-scenarios around a core DFES planning scenario, each micro-scenario corresponds to a probabilistic output and therefore there is a relatively low probability that a more extreme micro-scenario could not be identified. At the same time, even though the analysis in section 8.4 is sufficient to produce the envelope of min-to-max EV charging per EHV substation, the number of micro-scenarios could be required to be relatively low (eg, no more than 10) when used in decision making tools such as our ROCBA tool that has been developed under our Demand Scenarios NIA project.

To cater for the above, a manual processing of the probabilistic outputs is required as shown in Fig. 6 to:

- allow the selection of a single micro-scenario out of a very large sample of probabilistic outputs (ie, in the order of thousands); and,
- allow the production of a small number of micro-scenarios using the clustering of a large sample of probabilistic outputs, eg using a robust K-means approach on the shares of charging between the different location types per substation feeding area.

To facilitate this manual selection of micro-scenarios we have requested Element Energy to have an intermediate output Excel file that contains all probabilistic outputs. The model can in this case run to produce the probabilistic modelling module outputs and then stops. A manual processing of the outputs can then take place and the tool user can then define in the same Excel file format the micro-scenario settings to run the time-series EV profile module that produces the EV charging profile per micro-scenario and per substation.

1.6 Building on the REFLECT Methodology to Enhance Decision Making in Network Planning

There are two key areas that the developed REFLECT methodology can enhance decision making in network planning:

i. enhance CBA analysis tools that consider multiple scenarios, such as the Real Options CBA (ROCBA) tool developed by the Demand Scenarios NIA project; and,
ii. introduce a new modelling framework for DFES/FES with the introduction of micro-scenarios and the use of probabilities in scenarios and network planning risk and cost assessments.

<u>Use of REFLECT micro-scenarios in ROCBA</u>

Our ROCBA tool was developed in our Demand Scenarios NIA project and can use multiple scenarios to inform network planning decisions between traditional network reinforcement and flexible service options. Even though DNOs currently do not assign probabilities on each DFES scenario used in network planning, ROCBA allows the use of scenarios with assigned probabilities in risk and cost assessments.

However, the ROCBA tool requires scenario inputs to model demand growth rather than any other probabilistic form of input, eg a large sample of Monte Carlo combinations or a decision tree with a large number of combinations. Our REFLECT approach overcomes this limitation with the introduction of micro-scenarios, which are similar to the scenarios which can be used to produce a half-hourly EV charging profile. This profile can be superposed on the forecasted demand profile for the examined scenario to define the per year peak true demand required as an input in the ROCBA tool.

As described in the previous section, the REFLECT tool can produce a large sample of probabilistic outputs that will allow a manual selection of the micro-scenarios. The proposed approach to produce the micro-scenarios used in ROCBA tool is to consider the clustering of a limited number of micro-scenarios, ie no more than 5-10 per scenario, from a sample of over a thousand probabilistic outputs. More specifically, using a K-means clustering the probabilities assigned to each probabilistic output will be aggregated to assess the overall probability of every micro-scenario.

Following this approach the ROCBA tool can use micro-scenarios where EV charging model allows us to:

- consider a large sample of probabilistic outputs / combinations of EV charging per location type without significant computational cost;
- use this large sample to produce a small number of micro-scenarios that can be used as demand growth inputs in ROCBA with associated probabilities calculated directly from the sample.
- produce micro-scenarios around each DFES scenario to effectively enhance a decision-making approach that uses a complete DFES set of scenarios with additional uncertainty modelling for EV charging per substation feeding area.

<u>Enhanced network planning using DFES with probabilistic analysis</u>

Forecasting scenarios are traditionally produced and published in the whole system FES world (ie, set of FES and DFES covering the whole of GB) to inform transmission and distribution system and network planning. These established forecasting approaches consider a large number of components / building blocks that would make it very challenging to be modelled using a probabilistic modelling approach.

Even though EV charging uncertainties are critical in network planning decisions within the running decade, as more EVs are registered we can improve our understanding on local EV charging using the available monitoring data (eg, from smart meter data and LV measurements). However, the developed modelling framework in REFLECT can be used in the future to use probabilistic assessments to model uncertainties around other demand or generation components that cannot be framed using the DFES scenarios.

As shown in Fig. 7 in terms of a high level demonstration with dummy trends, a probabilistic forecast would consider all possible combinations of the settings of building blocks, resulting in a large number of forecasting trends for demand (and/or generation) covering the whole spectrum of future outcomes. Such an approach would have a very high computational cost. Using a scenario forecast would account for a limited number of combinations of building block assumptions. A proper selection of building block assumptions as we follow in our ATLAS forecasting methodology would allow the production of a higher probability central scenario (best view) with average/central risk in planning and lower probability scenarios that could cover the min-to-max future range of demand.

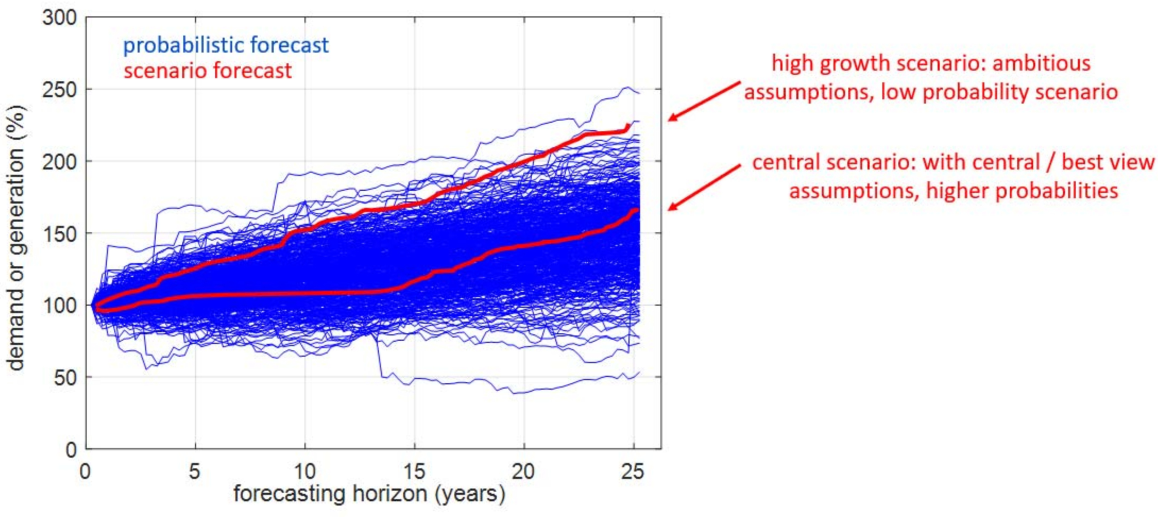

Fig. 7. High level overview of long-term demand and generation forecasts produced by scenario based and probabilistic modelling approaches.

However, scenarios cannot always capture future uncertainties around demand growth. Our REFLECT project has focused on the local uncertainties around EV charging that cannot be captured with existing scenarios, given that DFES across all GB DNOs currently focus on EV uptake trends rather than how uncertain it will be for the different types of charging to occur from one local area to another. The concept of micro-scenarios with assigned probabilities that has been introduced in REFLECT project can be in future adopted in other types of key uncertainties that cannot be currently framed using scenarios.

Fig. 8 shows an example of the use of the REFLECT type micro-scenarios in decision making for network planning. A set of micro-scenarios are considered here in terms of peak demand. For example, each micro-scenario trend could be produced by first summating the Central Outlook scenario demand profiles (without EV charging) and the EV charging profiles from each micro-scenario presented in section 8.3. Next the peak demand from every year could be extracted and presented as a micro-scenario peak demand trend around the core scenario (Central Outlook in this case).

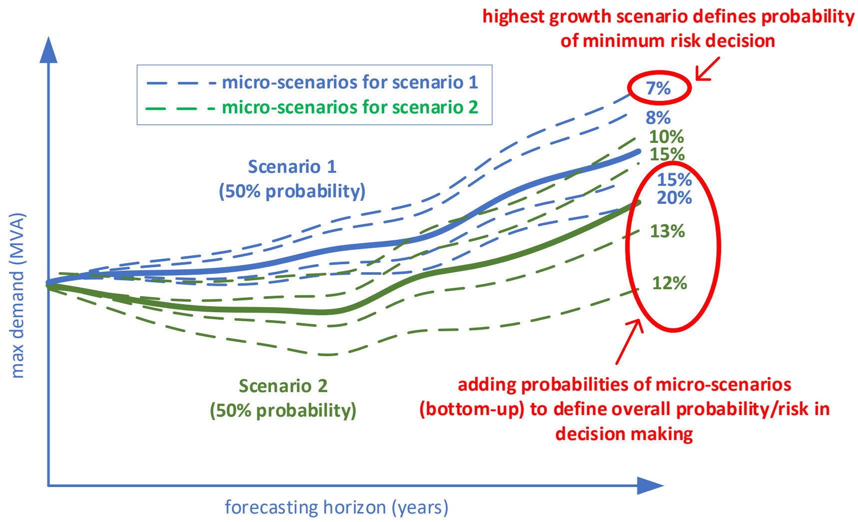

Fig. 8. Extending the micro-scenario concept of REFLECT project beyond EV charging to model key forecasting uncertainties not captured by existing scenario frameworks.

As shown in Fig. 8, this approach can be extended to more than one scenario. In such a holistic approach with a full set of scenarios and a number of micro-scenarios around every scenario, a set of micro-scenarios can be used to define a peak demand trend with an associated overall probability. For example, the four circled micro-scenarios in Fig. 8 can be used to define:

- a per year peak demand as the maximum per year peak demand value of these micro-scenarios; and,
- an overall probability that demand cannot extend this per year peak demand value. This probability can be assessed as the aggregated probabilities of all associated micro-scenarios.

It should be highlighted that it is the role of the decision-making methodology (eg, ROCBA) to inform an optimal planning approach in terms of minimising both the risks and costs of planned interventions. However, the concept of micro-scenarios can enhance the current role of scenarios in decision making. This can be easily understood from the example of Fig. 8 if our aim was to minimise network risks in planning. With the use of the two scenarios without any micro-scenario, the minimum risk approach where network capacity will not be exceeded in the future would require the use of scenario 1 peak demand trend. However, the micro-scenario analysis demonstrates that at least two micro-scenarios with associated probabilities of 7 and 8% exhibit higher demand growth than scenario 1. Therefore, there is an overall 15% risk in this example that future demand exceeds network capacity if the micro-scenarios are neglected and network planning is informed purely by the two scenarios.

To sum up, our REFLECT project has introduced a wider framework of enhancing the use of scenarios in decision making with the introduction of micro-scenarios with probabilistic modelling on top of the scenarios. In the REFLECT project we have applied the developed methodology to produce micro-scenarios and frame uncertainties around EV charging for the whole of our EHV network. However, the developed methodology with the use of micro-scenarios can be applied to other key factors that can have a significant impact on demand growth, but current scenario frameworks cannot properly capture the associated uncertainties.