NIA ENWL022

REFLECT Uncertainties around E-vehicle Charging to Optimise Network Forecasting (REFLECT) project

Closedown Report

A Network Innovation Allowance Project

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VERSION HISTORY

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REVIEW

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APPROVAL

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CONTENTS

GLOSSARY

ATLAS	Architecture of Tools for Load Scenarios (NIA project)
BEV	Battery Electric Vehicle
BSP	Bulk Supply Point
CBA	Cost Benefit Analysis
DFES	Distribution Future Electricity Scenarios
DfT	Department for Transport
ENWL	Electricity North West Ltd
EV	Electric Vehicle
GSP	Grid Supply Point
LA	Local Authority
MSOA	Middle Layer Super Output Area – Census statistical reporting area with population between 5 to 15 thousand people (2-6 thousand households)
NIA	Network Innovation Allowance
ONS	Office of National Statistics
PHEV	Plug-in Hybrid Electric Vehicle
ROCBA	Real Options Cost Benefit Analysis
V2G	Vehicle to Grid

1 EXECUTIVE SUMMARY

This document corresponds to the closedown report of the Reflect Uncertainties around E-vehicle Charging to Optimise Network Forecasting (REFLECT) project at Electricity North West Limited, funded under the Network Innovation Allowance (NIA) scheme.

1.1 Aim

Although planned developments to electrify bus fleets and taxis provide some certainty to distribution network planners on where ultra-fastchargers (i.e. >20kW up to 450kW) could be connected in the future, it is still uncertain when EVs will charge, where other ultra-fastchargers will appear to facilitate en-route charging and how much of the EV charging will take place at work/destination or at home/on street.

The aim of the REFLECT project was to:

- develop credible methodologies that introduce probabilistic assessments, use best available EV profile information (eg, from other NIA projects) and take into account traffic/travel information together with other local data to frame the uncertainties around the effects of the location and capacity of EV chargers;
- develop prototype tools that will implement the developed methodology for all BSP and primary substations (whole 132 to 33kV network) of our license area;
- provides specifications on how the uncertainties modelling in the developed methodology can be used to enhance decision making CBA processes.

1.2 Methodology

A key part of the methodology is the use of local data to frame local uncertainties around the location and capacity of charging. These datasets include information around the access to off-street parking, rural vs urban classification of EV registrations, volumes of vehicles commuting to work, data on travel patterns and potential locations for fast EV chargers including car parks beyond petrol and service stations.

All this local data is used to define the type and parameters of probability distributions that describe the likelihood of specific levels of EV charging per location/capacity type per primary substation feeding area. For example, an area with customers having high levels of access to off street parking has an associated probability distribution for home charging that exhibits high probability levels for overnight smart home charging. This is different from another area with limited access to off street parking, but with high traffic flows and high volumes of service stations that correspond to higher probabilities for en-route rapid charging.

The developed methodology has introduced the concept of micro-scenarios. These can be seen as variations around the core DFES scenarios taking into account the probabilistic analysis around the location and capacity of charging. Each micro-scenario has an associated probability assigned that expresses its likelihood to occur. Importantly, these probabilities can be used to inform risk assessments in decision making tools, such as the Real Options CBA developed under our Demand Scenarios NIA project.

The REFLECT methodology actually enhances the demand growth trends of the DFES scenario by showing how a user defined number of micro-scenarios with associated probabilities can exhibit different demand growth trends around the core scenario. These micro-scenario trends correspond to different levels of EV charging whilst all other demand components (eg, heat pumps, industrial demand etc) remain the same as the associated core DFES scenario.

1.3 Outcome

A prototype tool in Python platform has been delivered. The developed tool models the whole of our EHV network (all BSP and primary substations) and has a modular structure including:

- the probabilistic modelling module; and,
- the time-series EV profile module.

The probabilistic modelling module models the probability distributions of the different types of EV charging depending on the location / capacity, ie home; on-street residential; work; rapid en-route; and destination. Using the local data per primary substation feeding area, the probability distributions per EHV substation are defined. The module results are individual combinations of the EV charging share of the different types of EV charging (per location/capacity type), as well as the associated probability of each combination. The tool user has the option to either consider each of these combinations as a micro-scenario or further process them to define manually the micro-scenarios, eg using a K-means clustering to reduce the number of micro-scenarios.

The time-series EV profile module combines the micro-scenario outputs from the probabilistic module, ie charging share per location/capacity type of EV charging, with EV profiles for the different types of charging and other modelling inputs/assumptions (eg, EV volume uptake trends per vehicle type and smart charging assumptions used in DFES etc) to produce a half-hourly EV demand forecasts. These half-hourly forecasts are produced per micro-scenario.

We have used the developed Python tool to carry out an analysis for all BSP and primary substations in our license area. The analysis has used 50 micro-scenarios and results are presented and discussed in this report. Results have revealed smaller or bigger differences across the different primary substation feeding areas that can be explained by the corresponding differences in their local characteristics.

Apart from the development and use of the Python tool, this report describes how the tool outputs can be used to enhance decision making CBA processes, such as our Real Options CBA tool developed in Demand Scenarios NIA project.

1.4 Key Learning – Future Work

Work in REFLECT project has led to a quantification of the min-to-max variation of EV charging demand using our Central Outlook from DFES 2020. This analysis has revealed which areas should have a different EV charging profile adopted that would reflect the “local reality” in EV charging. This learning has highlighted that we need to enhance our EV charging profiles in DFES. Therefore, we will use the profiles produced by the analysis using the REFLECT tool to update BSP and primary substation EV charging profiles (400+ profiles) in our DFES 2021 to enhance our demand forecasts that will be used to support our first Network Development Plan (NDP) in 2022.

Apart from the short-term implementation in our EHV network planning, REFLECT has importantly introduced a modelling framework that allows DNOs to use it in the future to model other critical uncertainties beyond EV charging to consider a) probabilities in planning and b) the use of micro-scenarios to enhance the use of scenarios in risk and cost assessments (eg, using our Real Options CBA tool).

2 PROJECT FUNDAMENTALS

Title	Reflect Uncertainties Around E-vehicle Charging To Optimise Network Forecasting
Project reference	NIA_ENWL022

Funding licensee(s)	Electricity North West Limited
Project start date	March 2019
Project duration	2 years
Nominated project contact(s)	Christos Kaloudas (innovation@enwl.co.uk)

3 PROJECT BACKGROUND

The forecasting of electric vehicle (EV) charging requires a better understanding not only on the future volumes of private and commercial EVs, but also on the location and capacity of the charging adopted. Although planned developments to electrify bus fleets and taxis provide some certainty to distribution network planners on where ultra-fastchargers (i.e. >20kW up to 450kW) could be connected in the future, it is still uncertain when EVs will charge, where other ultra-fastchargers will appear and how much of the EV charging will take place via slow and fast charging.

Understanding and modelling these uncertainties at a regional level (e.g. traffic flows affecting en route charging, home and depot parking space availabilities) is critical for Electricity North West, as these uncertainties need to be framed and reflected in the forecasting scenarios that are used for the strategic planning of the network.

A three-stage approach is proposed to produce prototype tools and associated methodologies that can be used by Electricity North West and other DNOs to reflect EV charging uncertainties in demand forecasts. The three stages can be summarized as follows:

Stage 1: Detailed scoping of requirements, plus identification of potential methods to incorporate probabilistic or other types of assessment within the business as usual scenarios;

Stage 2: Methodology development, including ability to use EV charging profiles produced from trials and analyses carried out by projects such as the NIA funded ‘Recharge the Future’ (UKPN) and the ‘CarConnect’ (WPD). Production of full prototype for the Grid and Primary network of Electricity North West (i.e. all GSPs, BSPs and primary substations);

Stage 3: Specifications for final tools for the Grid and Primary network, recommendations for future updates using additional data inputs (e.g. monitoring data for EV charging, development plans etc).

4 PROJECT SCOPE

The REFLECT project will improve the electricity demand forecasting for EV charging by reflecting the regional uncertainties around slow (<20 kW) and ultra-fast(up to 450kW) charging in the forecasting scenarios and consequential cost and risk assessments. The project aims to use EV charging profiles produced from trials and analysis carried out by projects such as the Recharge the Future and the CarConnect projects will enhance the scenario-based forecasting methodology to include probabilistic assessments. The developed methodologies will allow Cost Benefit Analysis (CBA) tools such as the Real-Options CBA (ROCBA) tool to reflect the uncertainties around slow and ultra-fast EV charging in risk and cost assessments.

5 OBJECTIVES

The REFLECT project will develop the forecasting methodologies to model the uncertainties around slow EV charging from the LV networks (e.g. home and destination charging) versus ultra-fast parking (e.g. at service stations).

This project supports the following primary objectives:

- develop methodologies and tools that consider regional characteristics to frame uncertainties around slow and ultra-fast charging;
- introduce the use of probabilistic assessments within the scenario-based forecasting approaches followed by DNOs;
- consideration of traffic flow data in modelling;

interoperability with EV charging profiles produced by analyses and trials from other UK and European projects (e.g. UKPN's Recharge the Future and WPD's CarConnect projects).

6 SUCCESS CRITERIA

The process will be successful if:

i. it delivers partial prototypes of load estimates that consider both slow and ultra-fast EV charging;
ii. it improves the currently followed scenario-based forecasting approach by considering via probabilities the likely effects of ultra-fast charging of EVs on future demand uptakes; and,
iii. it provides specifications on how the uncertainties modelling in the developed methodology can be used to enhance CBA processes.

7 PERFORMANCE COMPARED TO THE ORIGINAL PROJECT AIMS, OBJECTIVES AND SUCCESS CRITERIA

The REFLECT project has successfully delivered against its original aims, objectives and success criteria.

In relation to the first success criterion, the project has delivered a prototype tool developed by Element Energy in Python software platform that models EV charging across all Electricity North West primary substations (over 350). The EV charging is modelled across five location types:

i. home charging (slow charging);
ii. residential on-street (slow charging);
iii. work charging (slow & fast charging);
iv. destination charging (slow & fast charging); and,
v. rapid en route charging (very fast charging).

In relation to the second success criterion, the project has applied probabilistic modelling using probability distributions of the share of charging demand fulfilled by each charging location type for each user archetype. A set of 24 archetypes have been modelled depending on vehicle type (car/van), powertrain (plug-in or not; plug-ins not accessing rapid charging), commuter status, location (urban/rural) and access to off-street parking.

The probability distributions are associated not only with rapid charging, but with all other location types and have allowed us to frame the EV charging at local level, ie per primary substation feeding area.

In relation to the third success criterion, the project has introduced the concept of micro-scenarios, which are scenario variations with associated probabilities assigned. The micro-scenarios can be used similarly to any other scenarios as inputs to a CBA tool. The assignment of probabilities on every micro-scenario allows us to use them in the more sophisticated Real Options CBA (ROCBA) tool developed under our Demand Scenarios NIA project to produce cost and risk assessments to inform the decision-making process in load related investment under local EV charging uncertainties.

8 THE OUTCOME OF THE PROJECT

8.1 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.

8.2 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).

8.3 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).

8.4 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.

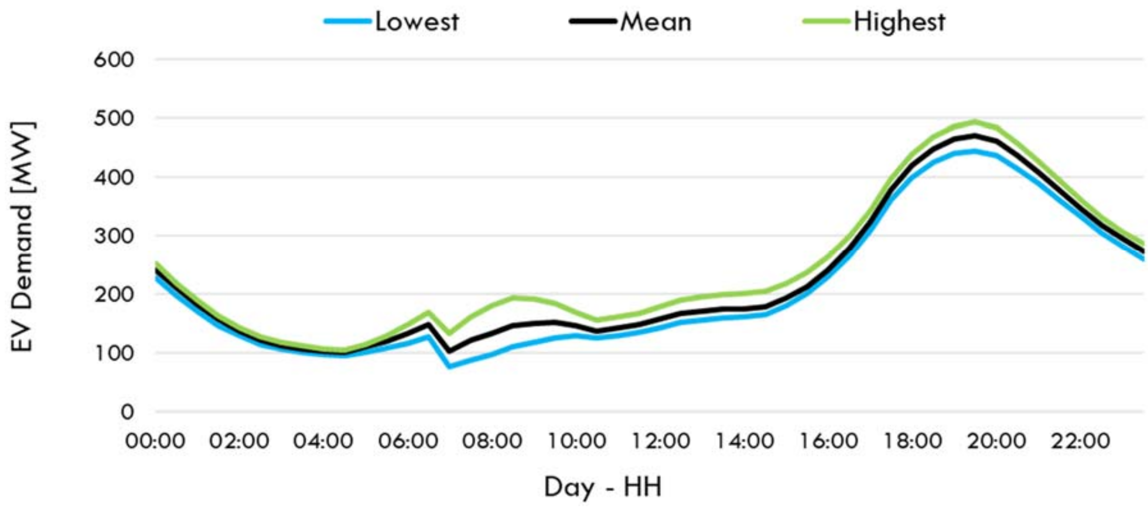

Fig. 1. Aggregated EV charging demand profile across all BSPs for a typical winter day in FY28. Results shown for the lowest, mean and highest EV charging demand profiles taking into account all 50 micro-scenarios.

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.

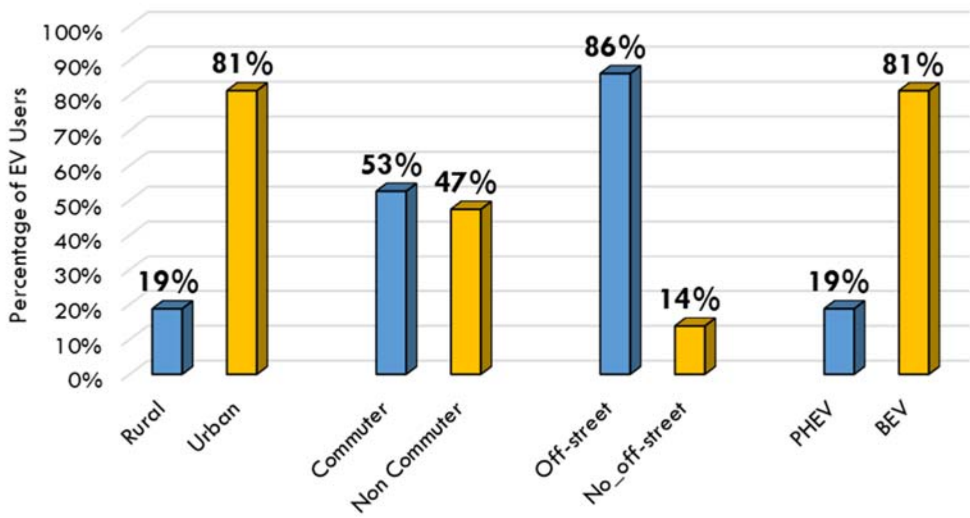

Fig. 2 EV user archetypes distribution for the whole ENWL license area.

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).

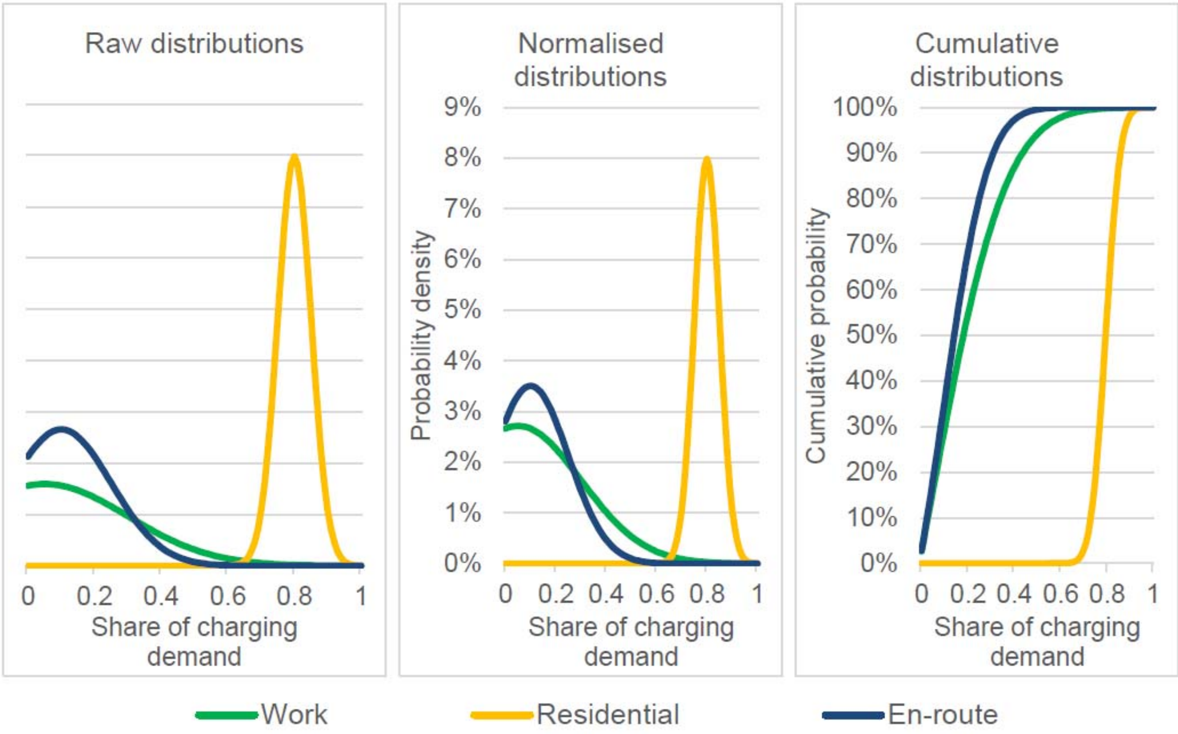

Fig. 3. Examples of raw user-defined probability distributions and generated normalised and cumulative probability distributions.

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.

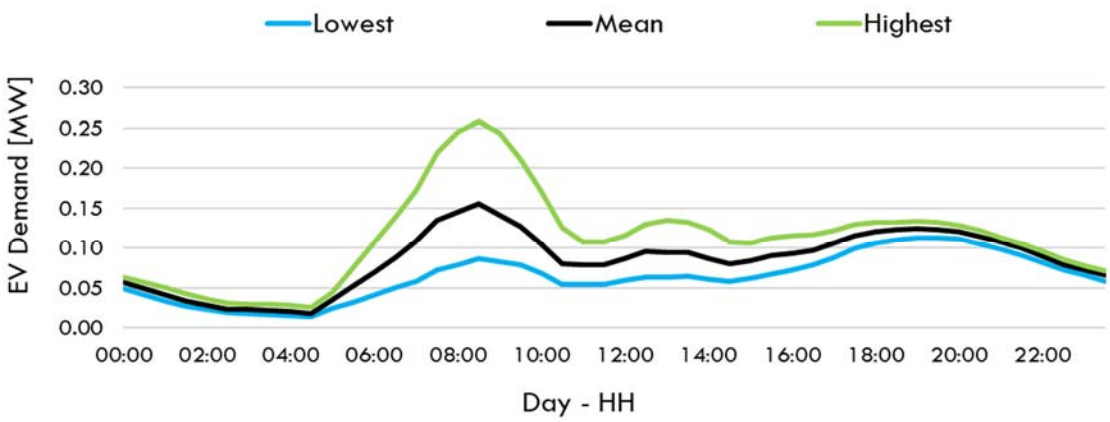

Fig. 4. EV charging demand profiles for Manchester University primary substation for a typical winter day in FY28. Results shown for the lowest, mean and highest EV charging demand profiles taking into account all 50 micro-scenarios.

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.

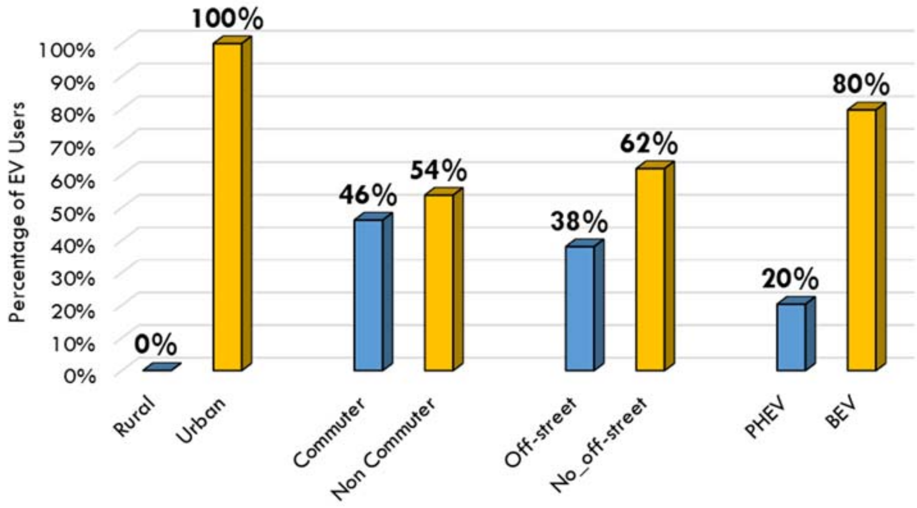

Fig. 5. Data for the EV user archetypes for the Manchester University primary substation feeding area.

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.

8.5 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.

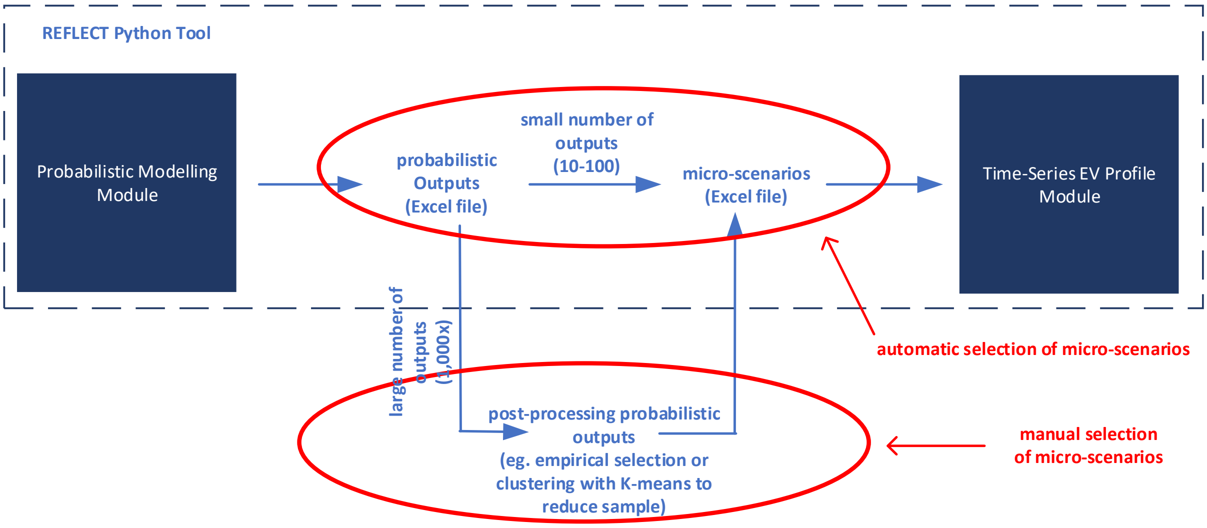

Fig. 6. Modular structure of the REFLECT Python tool that allows both automatic and manual definition of the micro-scenarios.

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.

8.6 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.

Use of REFLECT micro-scenarios in ROCBA

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.

Enhanced network planning using DFES with probabilistic analysis

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.

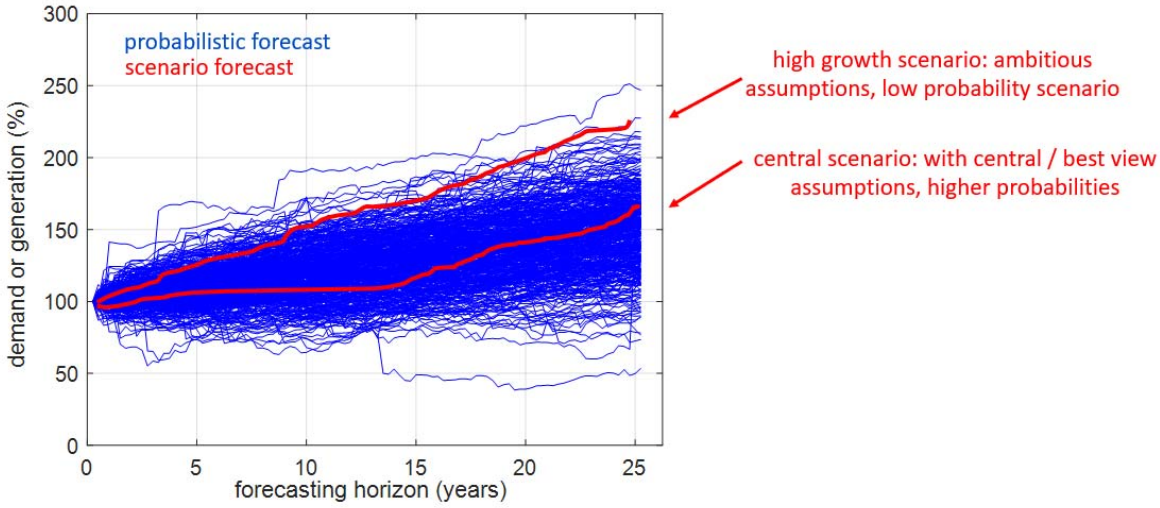

Fig. 7. High level overview of long-term demand and generation forecasts produced by scenario based and probabilistic modelling approaches.

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).

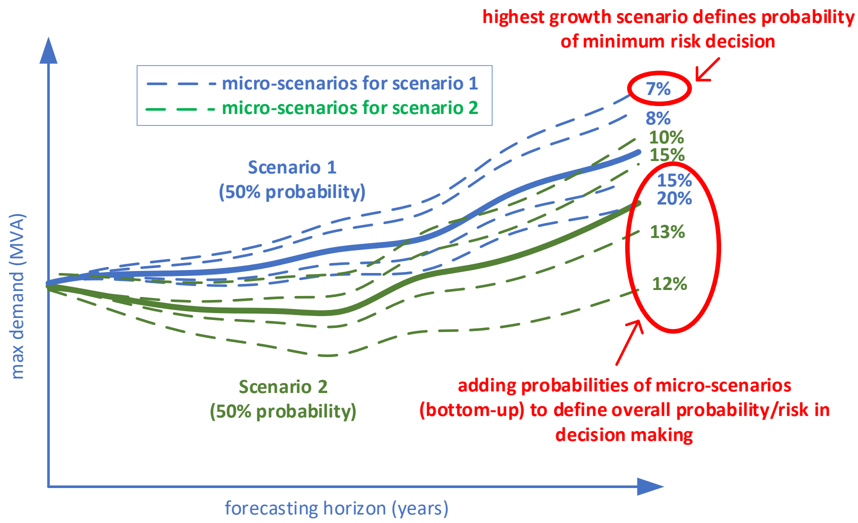

Fig. 8. Extending the micro-scenario concept of REFLECT project beyond EV charging to model key forecasting uncertainties not captured by existing scenario frameworks.

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.

9 REQUIRED MODIFICATIONS TO THE PLANNED APPROACH DURING THE COURSE OF THE PROJECT

Extensions to scope

Initial scope was to carry out probabilistic analysis of EV charging based on the different location types of charging, ie home, work, rapid en route and destination. A fifth type was added, ie on-street residential, as this type could have a significant share of EV charging for areas where customers do not have access to off street home parking.

Initial scope was also to utilise travel flow data of vehicles to assess the levels of EV charging. The developed methodology has used instead local data of starting and destination locations of commuting and shopping trips. For the en route charging the developed methodology considers the volumes of service and fuel stations per primary substation feeding area to frame associate EV charging uncertainties.

The initial registration document mentioned we would use EV charging profiles from NIA projects, such as UKPN's Recharge the Future and WPD's CarConnect. We have eventually used profiles processed by Element Energy from a study for the ESO that included over 8 million real life charging events. We have also used data from WPD's Electric Nation project to model volumes of charging events per EV per day at each charging location type (for all location types apart from home).

10 PROJECT COSTS

Item	Category	Estimated costs (£k)	Final costs £k (rounded)	Variance
1	Research & Development	£192,500	£74,000	£118,500
	Total			

As the project developed the estimated costs were much lower than the project was registered for (£192,500). The research and development aspect was outsourced to Element Energy and their quotation for the work was significantly less than anticipated.

11 LESSONS LEARNT FOR FUTURE PROJECTS

The REFLECT project has so far demonstrated that it is feasible, but challenging at the same time for a DNO to:

- carry out probabilistic analysis of half-hourly EV charging using a numbers of micro-scenarios that is significantly higher than the numbers of scenarios in DFES;
- embed such an approach with the overall demand forecasts in DFES.

Practical limitations have been identified around the computational cost of the end-to-end process to:

a. produce as a first step large number of probabilistic outputs, ie combinations of different shares per location type of EV charging; and,
b. then as a second step model the half-hourly EV charging profile at the associated substation feeding area for each EHV substation.

Following a modular structure in developing the Python tool, ie using a probabilistic modelling and a time-series profile modules, has allowed us overcome these issues.

Big data analyses, especially when they combine probabilistic modelling with time-series profiles of a large number of archetypes, revealed that special concern should be taken in modelling to deal with issues not only around computational cost, but also memory limitations.

12 PLANNED IMPLEMENTATION, RECOMMENDATIONS OR NEXT STEPS

Work in REFLECT project has led to a quantification of the min-to-max variation of EV charging demand from our Central Outlook from DFES 2020. Analysis has been carried out for all BSP and primary substations using the developed prototype tools in Python. Results have revealed that EV charging uncertainties are more significant for areas with high potential for destination and at work charging. Insights from our analysis will be shared with local stakeholders in the EV section of our next DFES 2021.

Additionally, the mean profiles produced for all BSP and primary substations in our license area will be normalised (400+ profiles) and they will be used in our DFES 2021 forecasts to enhance our demand forecasts and support our first Network Development Plan (NDP) in 2022.

Apart from the short-term business as usual benefits in our 132kV and EHV network planning, REFLECT has importantly introduced a modelling framework that allows DNOs use it to model critical uncertainties beyond EV charging to consider a) probabilities in planning and b) the use of micro-scenarios to enhance the use of scenarios in risk and cost assessments (eg, using our Real Options CBA tool).

13 DATA ACCESS & QUALITY DETAILS

Electricity North West's Innovation Data Sharing Policy can be found on our website at

https://www.enwl.co.uk/innovation/our-approach/our-innovation-data-sharing-policy/

The local data collected as part of the REFLECT project are described in Lot 1 dataset report that can be accessed online at: www.enwl.co.uk/reflect

Data on the EV volume uptakes are already publicly available per EHV substation and can be accessed from our DFES workbook, online available at: www.enwl.co.uk/dfes

The changes in methodology introduced by REFLECT were around how the raw data was processed and combined to project future demand levels. Thus there has been no available monthly data to share during the project.

The volumes of processed data in the project are large. Therefore, any requests for data sharing will be assessed on a case-by-case basis against the customer interest.

14 FOREGROUND IPR

Not applicable.

15 FACILITATE REPLICATION

Information about the REFLECT project was shared extensively outside Electricity North West on our website and through presentations.

This dissemination activity enables other organisations to assess how they could use the REFLECT approach to load scenarios for themselves. The audiences have been other DNOs, National Grid, relevant consultancies and also academics and similar network companies internationally. Further information on the principles of REFLECT to allow DNOs or others to replicate the developed techniques is shared as part of this closedown report.

REFLECT was presented at Energy Networks Innovation Conference (ENIC) 2020. Project video was produced to accompany the conference presentation and discussion.

REFLECT was also presented to all other DNOs and Ofgem during an Overarching Working Group (OAWG) in 2020 that focused on probabilistic modelling used in forecasting and decision making.

All project reports and factsheets can be found on the REFLECT project website (online: www.enwl.co.uk/reflect).

16 STANDARDS DOCUMENTS

Not applicable.

17 OTHER COMMENTS

None.