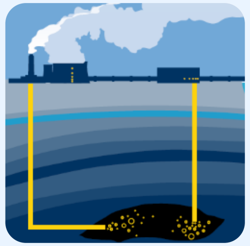


Transport for the North

Electric Vehicle Charging Infrastructure (EVCI) Model

Statement of Methodology

TRANSPORT FOR THE NORTH

elementenergy
an ERM Group company

wsp

This slide pack lays out the approach to Electric Vehicle Charging Infrastructure (EVCI) model development. The EVCI model main output will be the number of public charging points

Contents

- Working procedure for model development
- Scenarios and sensitivities that will be included in the model
- Detailed diagrams showing inputs, processing steps, and outputs for each modelling step
- Tables listing inputs to the model and outputs produced by the model
- Key assumptions used
- Risks and limitations arising from input data and processing steps
- Planned programme of work
- Baseline assessment of charging demand and EVCPs installed in 2018

Model in brief

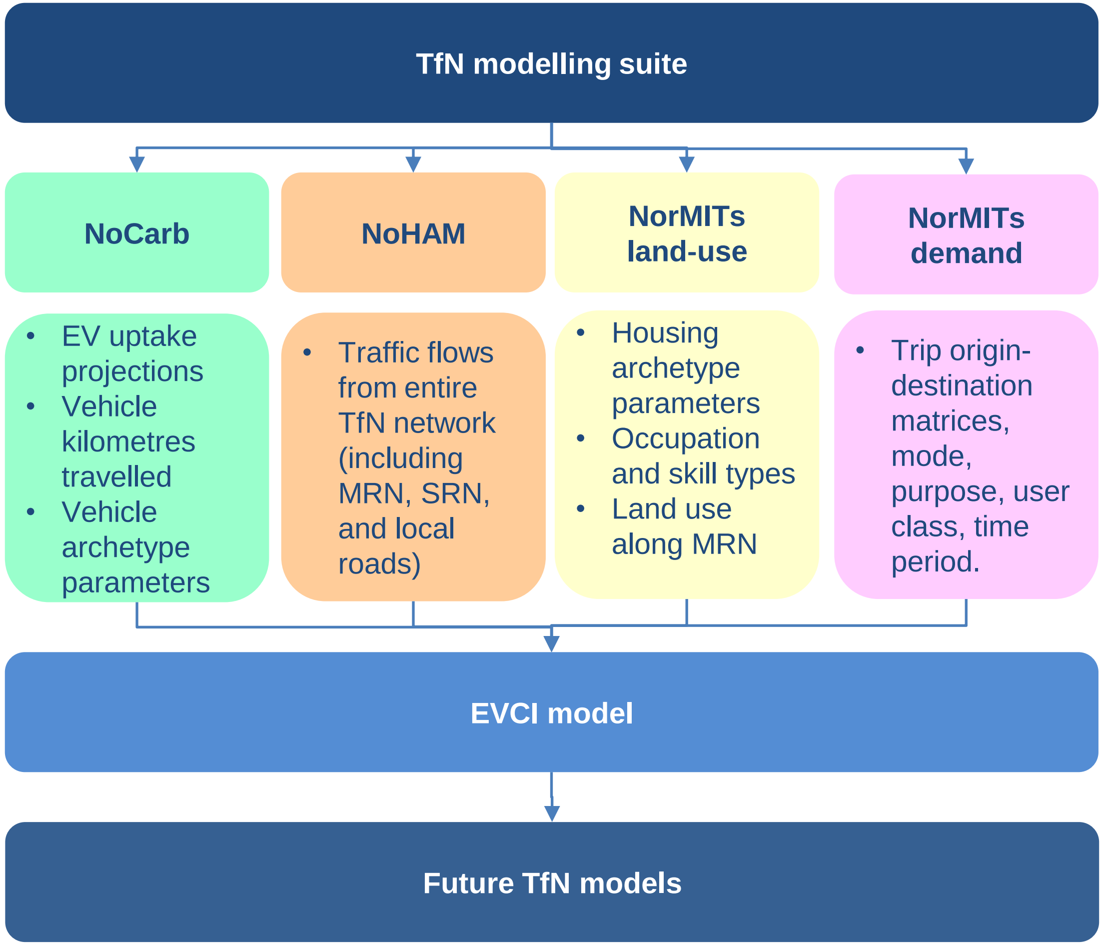
- The EVCI model will project charging infrastructure needs in the North of England, and estimate DNO reinforcement needed to support the EV charging network.
- The time horizon will be 2020-2050, in 5-year increments.
- It draws from several TfN models as inputs.
- TfN are the principal users of the model but Local Authorities, DNOs and other stakeholders also have access to model outputs.
- The model has been developed in Python and outputs are in csv/Excel files
- The overall objectives of TfN's EV charging infrastructure framework are to:
  - Support delivery of an integrated EV network
  - Improve outcomes for Electric Vehicles based on robust and data driven evidence
  - Future-proof EV infrastructure decision making
  - Provide a collective road map towards an effective, attractive and inclusive network

The EVCI model builds on TfN's current modelling suite and facilitate development of future TfN models

Short description of TfN modelling tools used

- NoCarb: a vehicle fleet model that produces a baseline estimate for surface transport emissions in the North and projects emissions into the future based on scenario inputs.
- NoHAM: model to forecast future year travel conditions on the highway network to assess the travel time benefits of proposed schemes.
- NorMITs land-use: a tool that creates current year residential base population estimates.
- NorMITs demand: a tool that provides travel market demand estimates

Integration of EVCI model with TfN modelling suite



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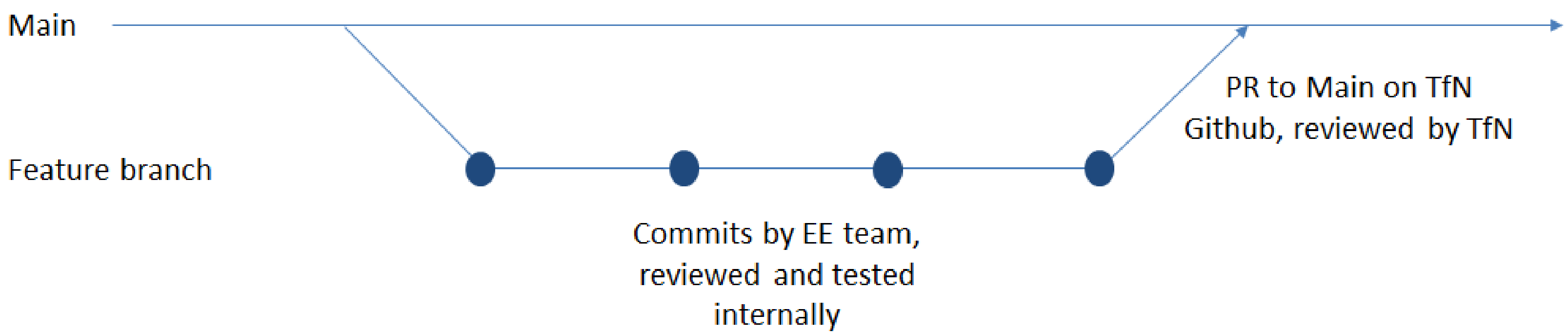
The EVCI model is built in Python, with extensive TfN collaboration throughout development

Coding language and style, code sharing procedure, and code QA

- The EVCI model is built in **Python**, following **TfN's coding standards**. The model is built in a highly **modular** fashion to allow easy integration with existing TfN models, and to future proof in case further extensions or integrations are needed.
- Model quality has been assured by implementing unit and integration **tests throughout development**, and through **code review** by both Element Energy and TfN.
- Code **readability** has been a priority during development, to ensure easy handover of the model to TfN.
- The code has been shared with TfN via the **TfN EVCI GitHub** repository. The process for this is outlined in the diagram below.



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The model is designed to integrate with existing TfN modelling using the TfN Future Travel Scenarios as input

Core Scenarios

TfN Future Travel Scenarios

(all scenarios exceed current UK Government projections for zero emission vehicle sales as a result of current petrol/diesel phase out targets)

- Just About Managing (3.4 million ZEV in 2030)
- Prioritised Places (3.7 million ZEV in 2030)
- Digitally Distributed (4 million ZEV in 2030)
- Urban Zero Carbon (4.6 million ZEV in 2030)

Inputs

- Each scenario represents a bundle of inputs relating to where people live, their trip distances and the proportion of trips by car
- These inputs can be changed using a single switch in the model to explore the different scenarios

Outputs

- Changes in charging demand and number of charge points across MSOAs for the 4 futures worlds described in TfN's Future Travel Scenarios.

Core Sensitivities

Core Sensitivities

- Where consumers will wish to charge in the future is currently uncertain. Scenarios will be used to explore these differences

Inputs

- **Baseline charging scenario** – this follows trends seen from charging trials to date
- **Home charging focused scenario** – Preference for residential (on/off street) charging increases at the expense of charging at destinations and rapid hubs
- **Public charging focused scenario** - Preference for destinations and rapid hub charging increases at the expense of residential (on/off street) charging

Outputs

- Changes in charging demand and number of charge points across MSOAs as a result of changes in charging behaviour and charging location preference.

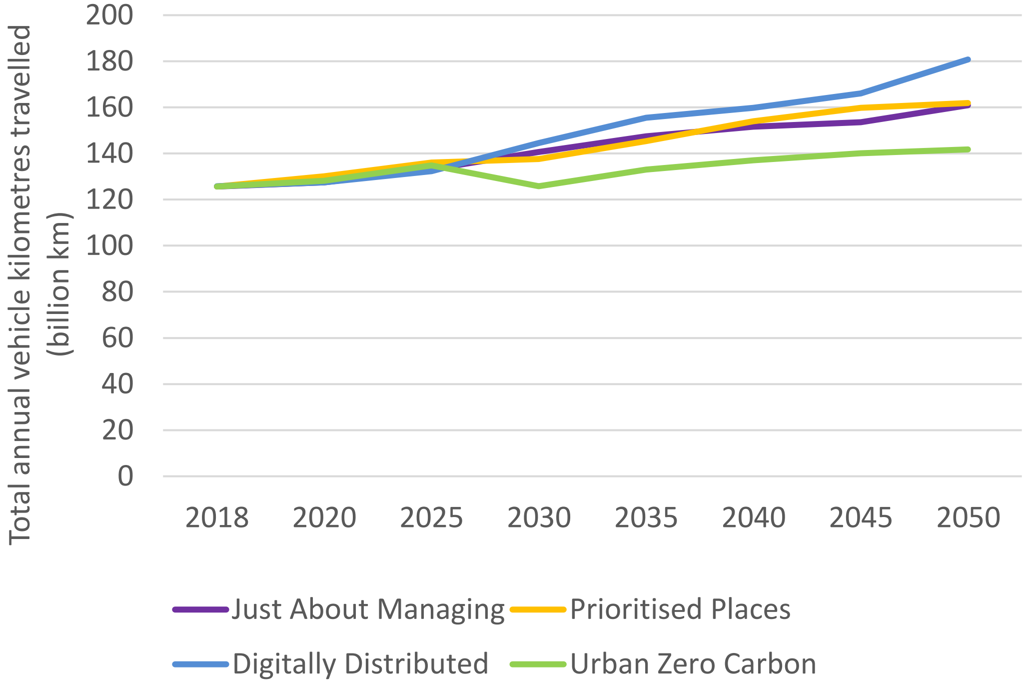
ZEV: Zero Emission Vehicle

Detailed information on TfN Future Travel Scenarios

Summary of main scenario attributes

Scenario	Key scenario assumptions
Just About Managing	• Retention of current transport behaviors assumed • Minor trend towards remote working • EV transition is market led, rather than by policy
Prioritised Places	• Political and economic shift to ensure no place is left behind, through bespoke local economic strategies and delivery • Greater economic equity across cities, towns and rural communities
Digitally Distributed	• Digital technologies assumed to become a strong transforming driver • Modal shifts assumed in everyday life, commuting and travel
Urban Zero Carbon	• Strong public attitude and government response to climate change assumed • Dramatic modal shifts and high levels of transport emission reduction

Vehicle kilometres travelled



- In addition to differing levels of EV uptake (outlined on previous slide), the four scenarios show different levels of vehicle kilometers travelled
- All scenarios use the same vehicle stock projections and assume demand reduction takes place through reduction in vehicle kilometers – in effect kilometers travelled per vehicle is reduced

Exploring EV fleet distribution approaches to understand EV uptake and charging demand

Core EV fleet projection (*applied in the July 2022 version of TfNs EVCI Framework*)

The EVCI model uses projected fleet and movement inputs in its charging calculations. The geographic distribution of the EV fleet determines how these vehicles fit into NoHAM's (TfN's highway model) flow and movement data. Consequently, changing the geographic distribution of EVs directly impacts charging demand.

Future fleet data is an input into EVCI from TfN's NoCarb model. The base fleet of 2018 is built from historic data of fleet composition. This fleet is split by vehicle type (car, LGV, HGV), fuel type and vehicle sub-segmentation.

Vehicles in this fleet are removed with time following a scrappage curve and new vehicles are injected in new sales/licensing based on the product of evolving tables of fleet size, fuel share, type share and sub-segmentation share. This creates a relatively even EV fleet distribution, with some characteristics built in from the baseline fleet.

Alternate income-based fleet projection (*for future collaboration and application*)

An alternative fleet distribution, based on SOC characteristics, has been created by analysis of DfT fleet licensing data and socioeconomic demographics (applying ONS UK Standard Occupational Classifications) within local authority regions.

This method assumes the purchasing and operation cost difference between electric and ICE cars and LGVs would result in different purchasing behavior in different socioeconomic demographics. A relationship between these was established using functional analysis between the two to create expected sales proportion weights for a model zone. To account for changing price parity over time, the relative strength of the weighting of these factors was adjusted based on future trends of electric-ICE cost comparisons.

The zonal fuel share is then adjusted according to these factors preserving the total number of EVs in the North but altering geographic location of the new sales injections.

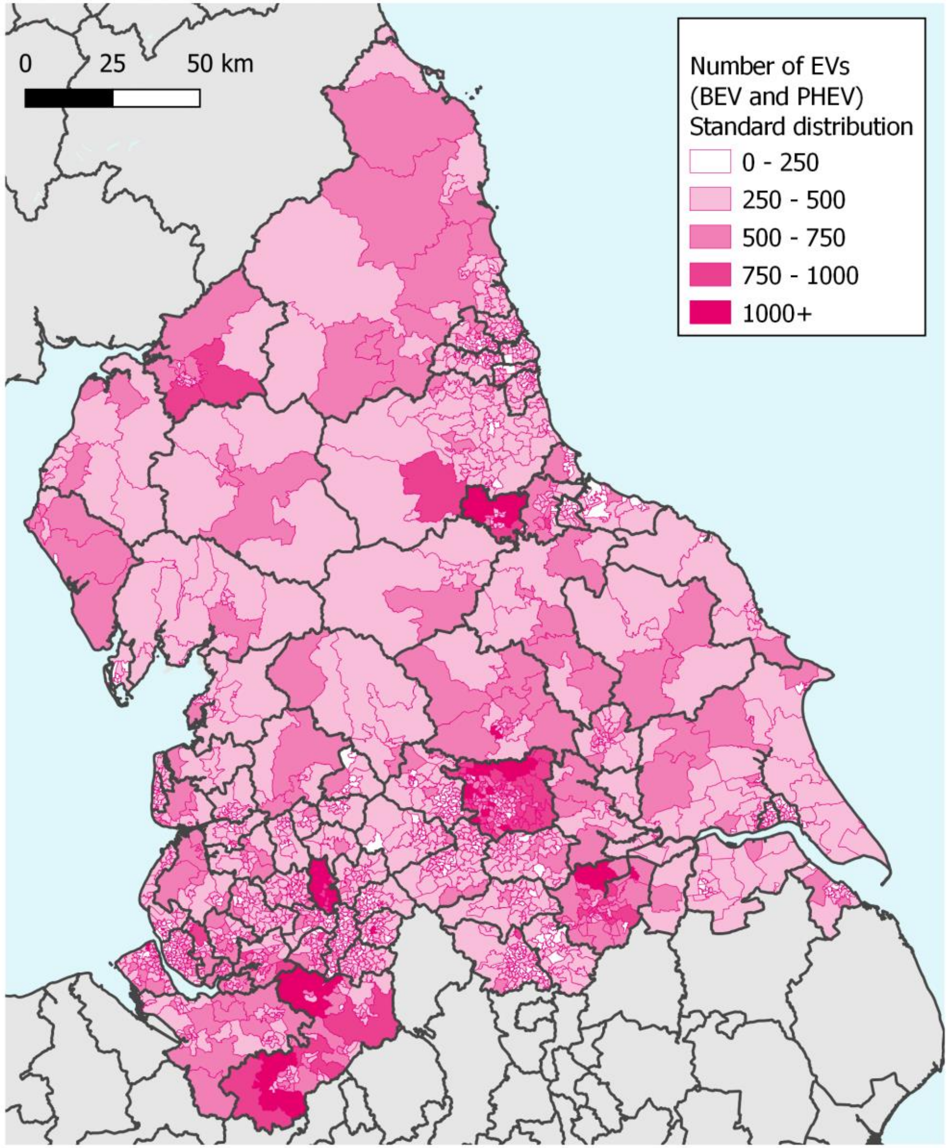
Comparison of fleet distribution approaches and what this can tell us

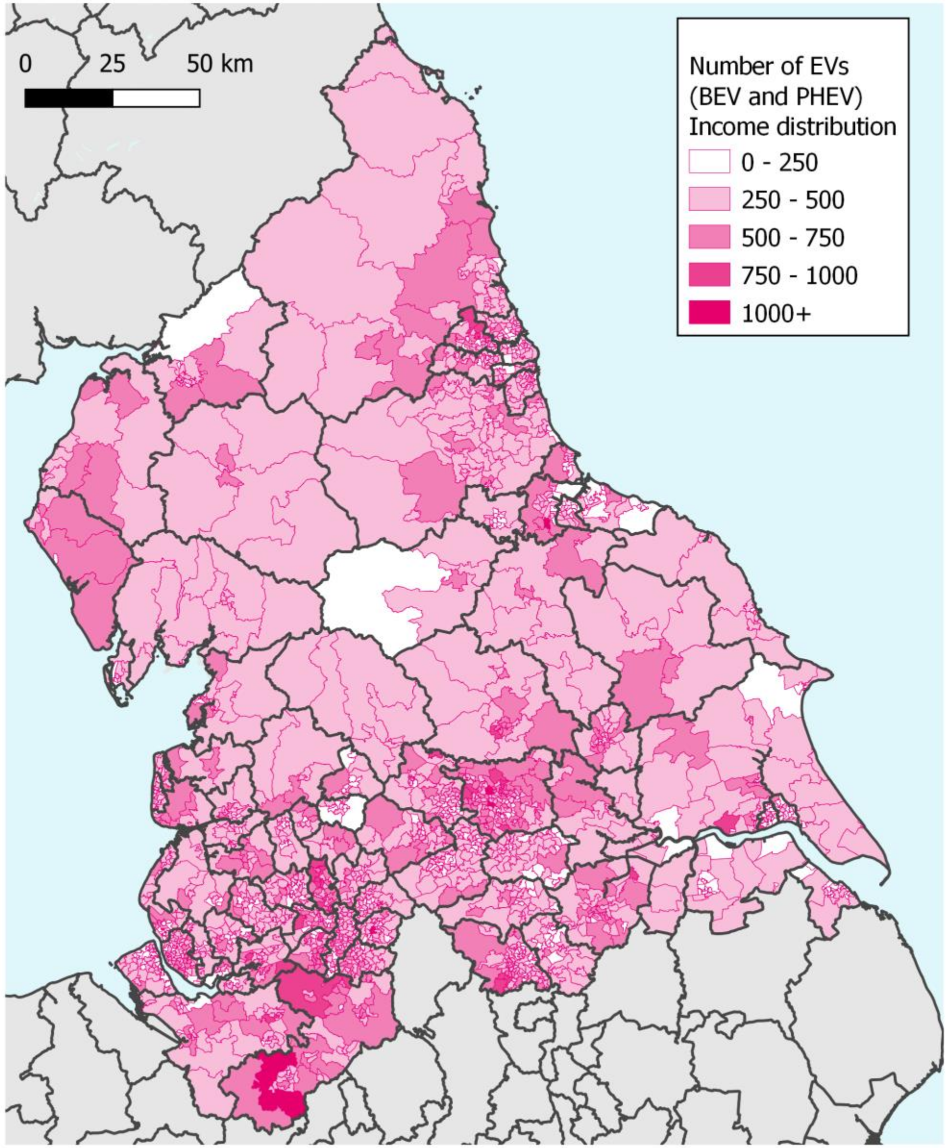
Displayed on the left is NoCarb's 'standard' distribution.

Displayed on the right is NoCarb's income distribution. Both images depict TfN's Digitally Distributed scenario in 2025.

While the same number of EVs appear in both, the latter shows a condensation of EVs into more affluent areas.

Additionally, there's a regional trend of 'migration' of EVs to the Northwest, and to a lesser extent Yorkshire and the Humber, from the Northeast.





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Overview of Task 2 - Development of EVCI Model

Description of high-level model structure

1. A 'Core' module, providing EV charge point numbers at MSOA level, with functionality to give indicative locations of charge points along the major road network (MRN).
2. A 'DNO impact' module, which will use EV charging demand and typical half hourly charging demand profiles to assess the potential impact of EV charging on the distribution network.

Model time horizon and future scenarios

- The model will produce outputs in 5 year increments, starting at 2020 and running to 2050 (i.e. 2020, 2025, 2030, 2035, 2040, 2045, 2050)
- In each model run, the user will select one of TfN's Future Travel Scenarios to provide projections of future travel attributes (e.g. EV stock, vehicle kilometres travelled, trips on the road network, etc)

Core module

1 Forecast EV charging demand from vehicles registered in each MSOA

2 Split EV charging demand by charging category

Home | On-street residential | Work | Destination | HGV depot — **Distributed at MSOA level**

Rapid en-route | HGV en-route — **Calculated for entire MRN**

3 Distribute EV charging demand for each charging category to the MSOA where it occurs

4 Calculate the number of EV charge points required in each MSOA for on-street and destination charging categories

5 Determine possible sites for rapid en-route charge points along the major road network

DNO Impact module

1-3 Determine half hourly EV charging demand profile for all charging categories per primary, for representative summer and winter days

4-6 Get overall peak for EV charging demand on primaries and secondaries and assess reinforcement costs for DNOs

Grid impact: Cumulative cost at primary level | Grid impact: Cumulative cost at secondary level

MSOA: middle layer super output area, used for reporting Census data. Each MSOA has a population between 5,000 and 15,000 and contains 2,000 – 6,000 households

High level Core Module diagram

Legend:

Note: Each scenario and year will be processed through the same pipeline to create the appropriate outputs

- Inputs changeable by modifying csv-s
- Scenario dependant input
- Passed processing data
- # Processing step
- Model output

Car population and energy demand parameters (annual mileage, fuel consumption etc.)

Vehicle archetype (car non-commuter, van commuter, etc.) and share of stock

1 Forecast EV charging demand from vehicles registered in each MSOA

Annual EV charging demand by vehicle archetype and MSOA, with all demand shown at the MSOA of registration

Charging behaviour (where, when and how often)

2 Split EV charging demand by charging category

Car and van charging categories:

HGV charging categories:

Home | On-street residential | Work | Destination

HGV depot

Distributed at MSOA level

Rapid en-route

HGV en-route

Calculated for entire MRN

Annual EV charging demand by vehicle archetype, charging category and MSOA, with all demand shown at the MSOA of registration

Origin-destination matrices

3 Apply seasonal variation factors and geographically distribute EV charging demand for each charging category to the MSOA where it occurs

Peak daily demand for rapid en-route charging of cars, vans and HGVs

Peak daily EV charging demand by vehicle archetype, charging category (excl. rapid en-route) and MSOA, with demand distributed to MSOA of charging

Power and utilisation (including trends over time and impact of daily and seasonal peaks) assumptions

4 Calculate the number of EV charge points required in each MSOA

EVCPs in each MSOA for on-street and destination charging categories

EV charging points required in each MSOA for on-street and destination charging categories

Data on land, travel patterns, access to off street parking etc. used to create filters for shortlist of sites

5 Determine possible sites for rapid charge points along the major road network

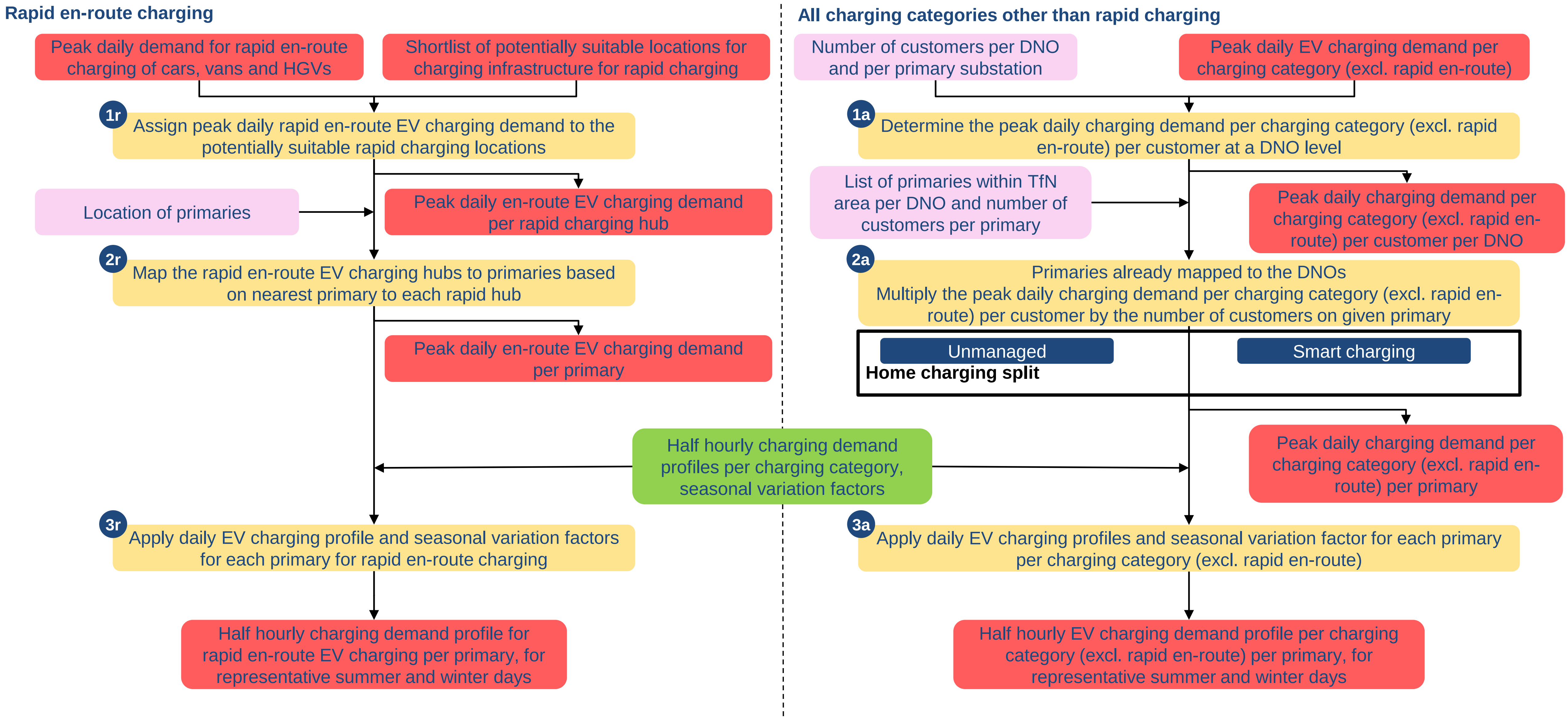
Shortlist of potentially suitable locations for rapid charging infrastructure

High level DNO Module diagram (1/2)

Legend:

Note: Each scenario and year will be processed through the same pipeline to create the appropriate outputs

- Inputs changeable by modifying csv-s
- Scenario dependant input
- Passed processing data
- # Processing step
- Model output



Note: On this diagram a customer refers to a specific network connection point, which is approximately a household

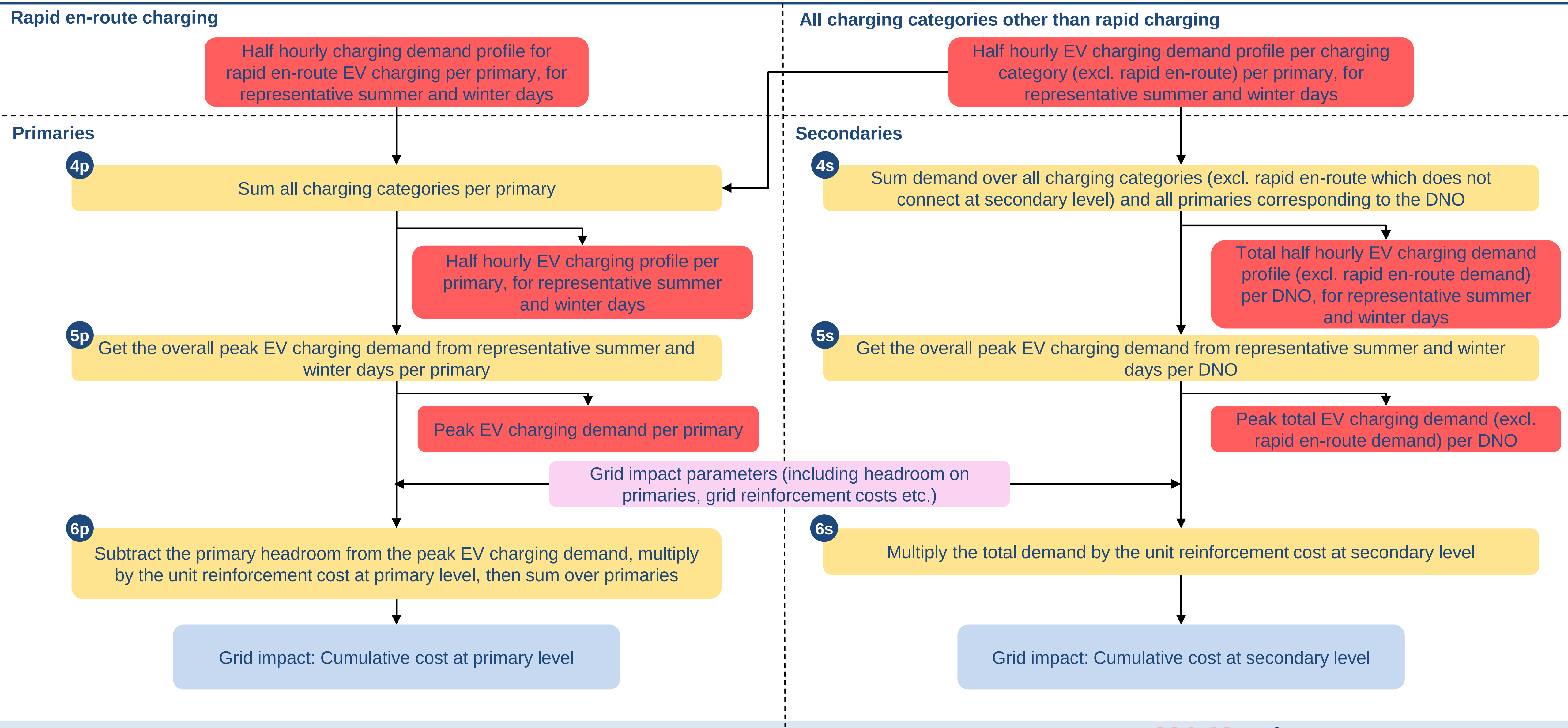
High level DNO Module diagram (2/2)

Legend:

Note: Each scenario and year will be processed through the same pipeline to create the appropriate outputs

Note: On this diagram a customer refers to a specific network connection point, which is approximately a household

- Inputs changeable by modifying csv-s
- Scenario dependant input
- Passed processing data
- # Processing step
- Model output



Contents

Model running and control overview

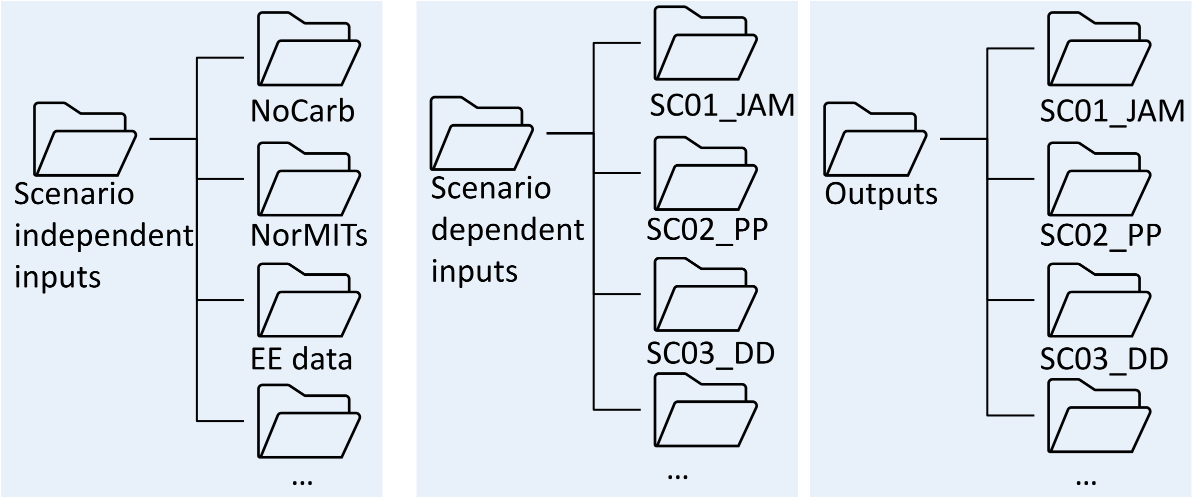
Batched running, to treat and construct scenarios flexibly

- We propose creating a master csv file to specify the locations of the different files needed for the different scenarios. The rows of the file would correspond to the scenarios and the columns to the required input file paths. The model would then automatically iterate through these predefined scenarios.

Scenario	NoCarb data sets	NorMITs data sets	…
Just about managing			
Prioritised places			
…			

Input and output structure

- Many inputs are from other models of the TfN's modelling framework. We propose to keep the output structure of these models for ease of use.
- Scenario dependent and scenario independent inputs will be stored in separate folders, as shown below.
- Output format will mimic the structure of the NorMITs and NoCarb models to provide current users of these models familiarity with the EVCI model.



Contents

Core Module Step 1 – Forecast EV charging demand from vehicles registered in each MSOA

Note: Each scenario and year treated separately through the same processing chain

I1.1 – NorMITs housing type and NS-Sec grouping by MSOA

Calculate share of vehicle owning households with off-street parking access by MSOA

I1.2 – Trip purpose share (incl. commuting)

I1.3 – Ownership share (private, company, shared, big haulier, small local HGV operator)

I1.4 – Electricity consumption (kWh / km)

I1.0 – NoCarb EV vkm and stock population by MSOA divided into archetypes by categorical variables: power train, car/van/HGV, rural/urban

Split by off/on street parking availability, trip purpose, ownership share and NS-Sec group for driver income split

Marginalise data set to remove irrelevant archetype variables: Ownership, driver income
Aggregate over different trip purposes keeping commuting/non-commuting split

Calculate annual charging demand per vehicle archetype (MWh)

O1.0/I2.0 – Annual EV charging demand by vehicle archetype and MSOA, with all demand shown at the MSOA of registration (MWh)

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

Note: Text in grey represents variables that are not strictly relevant to calculate the EVCP requirements and possible data complexity, which led to reduction based on run time

Core Module Step 2 – Split charging demand by charging category

Note: Each scenario and year treated separately through the same processing chain

O1.0/I2.0 – Annual EV charging demand by vehicle archetype and MSOA, with all demand shown at the MSOA of registration (MWh)

I2.1 – Charging behaviour assumptions for cars and vans.
Charging categories:
home; on-street residential; work; destination; and rapid en-route
(we will split the public charging share from ICCT between on-street residential and destination charging categories)

I2.2 – Charging behaviour assumptions for HGVs.
Charging categories:
depot charging and en-route charging
(we will split demand based on distribution of daily driving range across the year)

Split charging demand by charging category

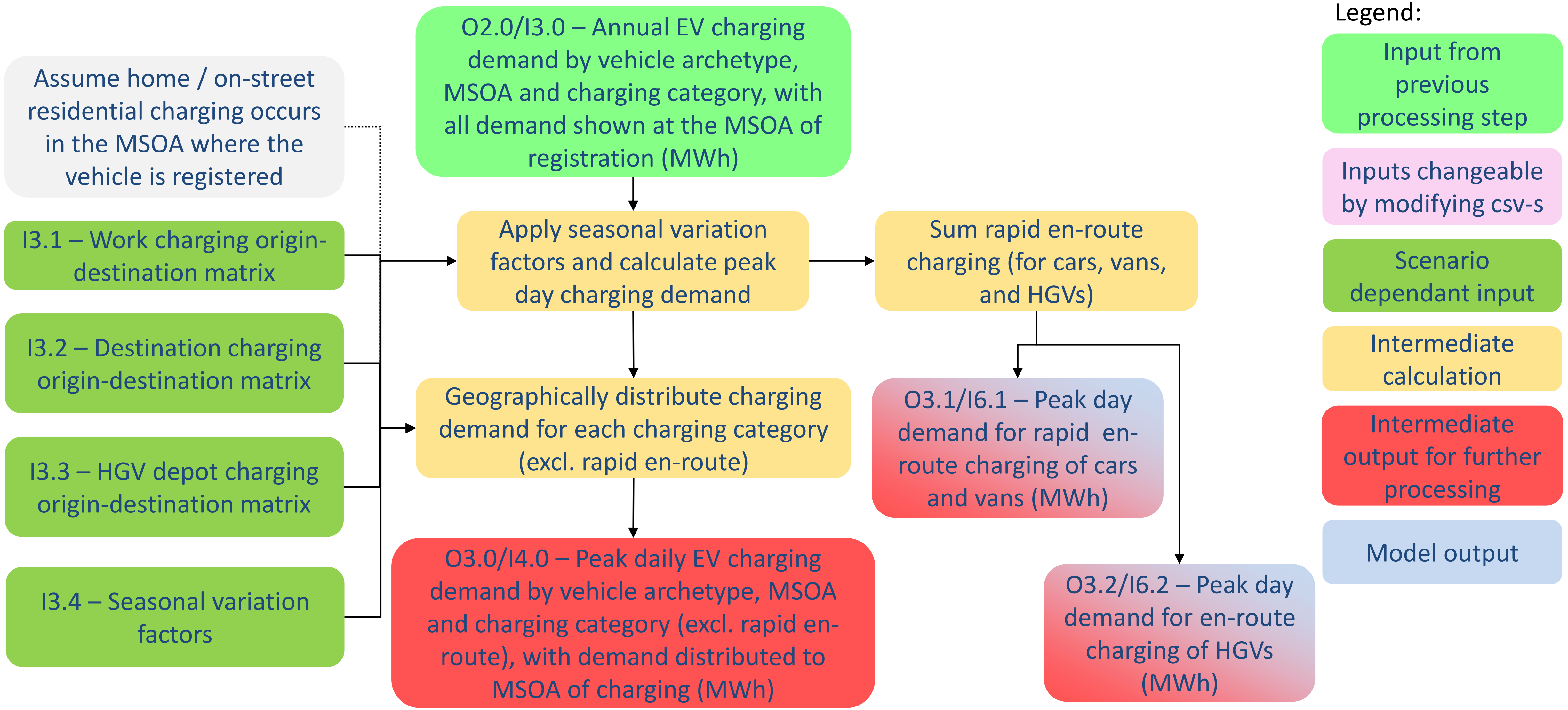
O2.0/I3.0 – Annual EV charging demand by vehicle archetype, MSOA and charging category, with all demand shown at the MSOA of registration (MWh)

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

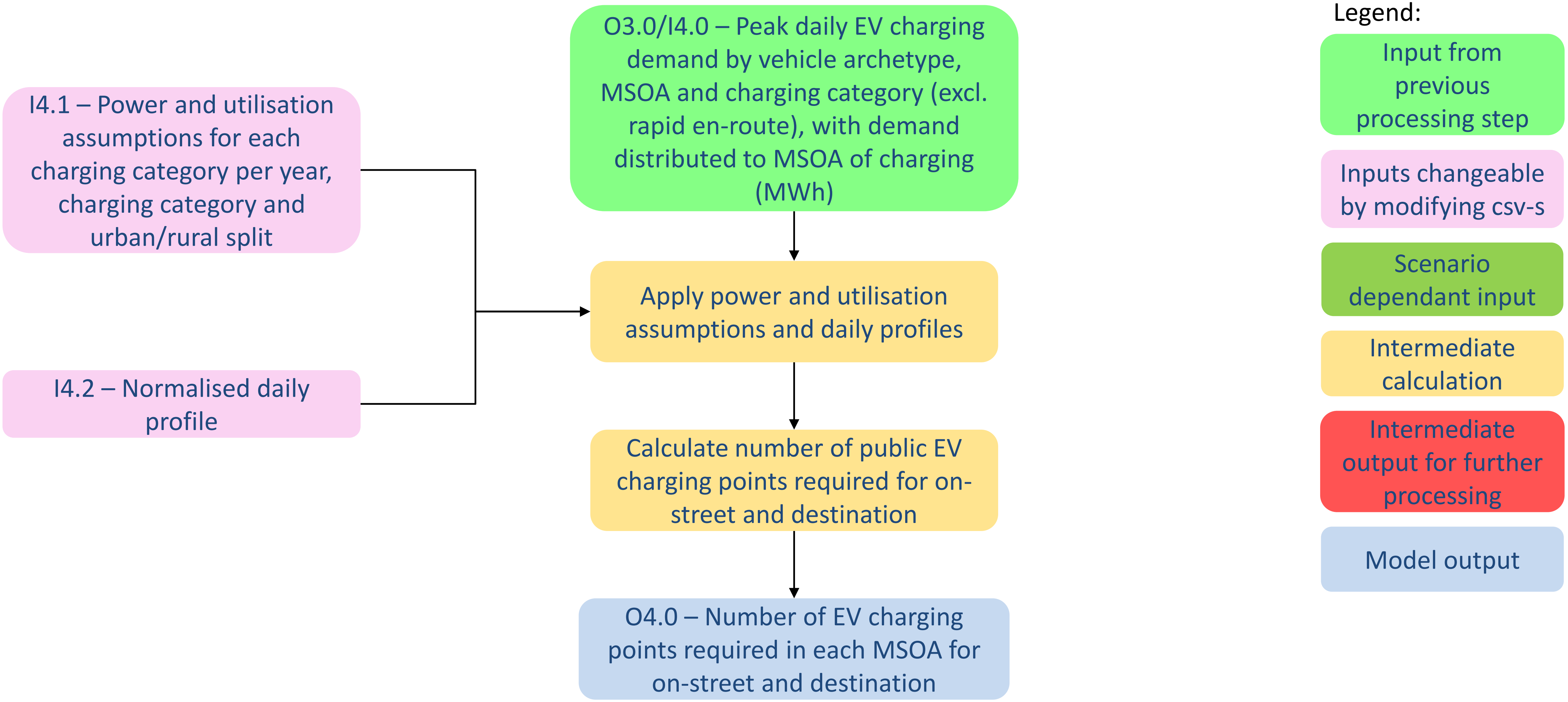
Core Module Step 3 – Geographically distribute charging demand for each charging category

Note: Each scenario and year treated separately through the same processing chain



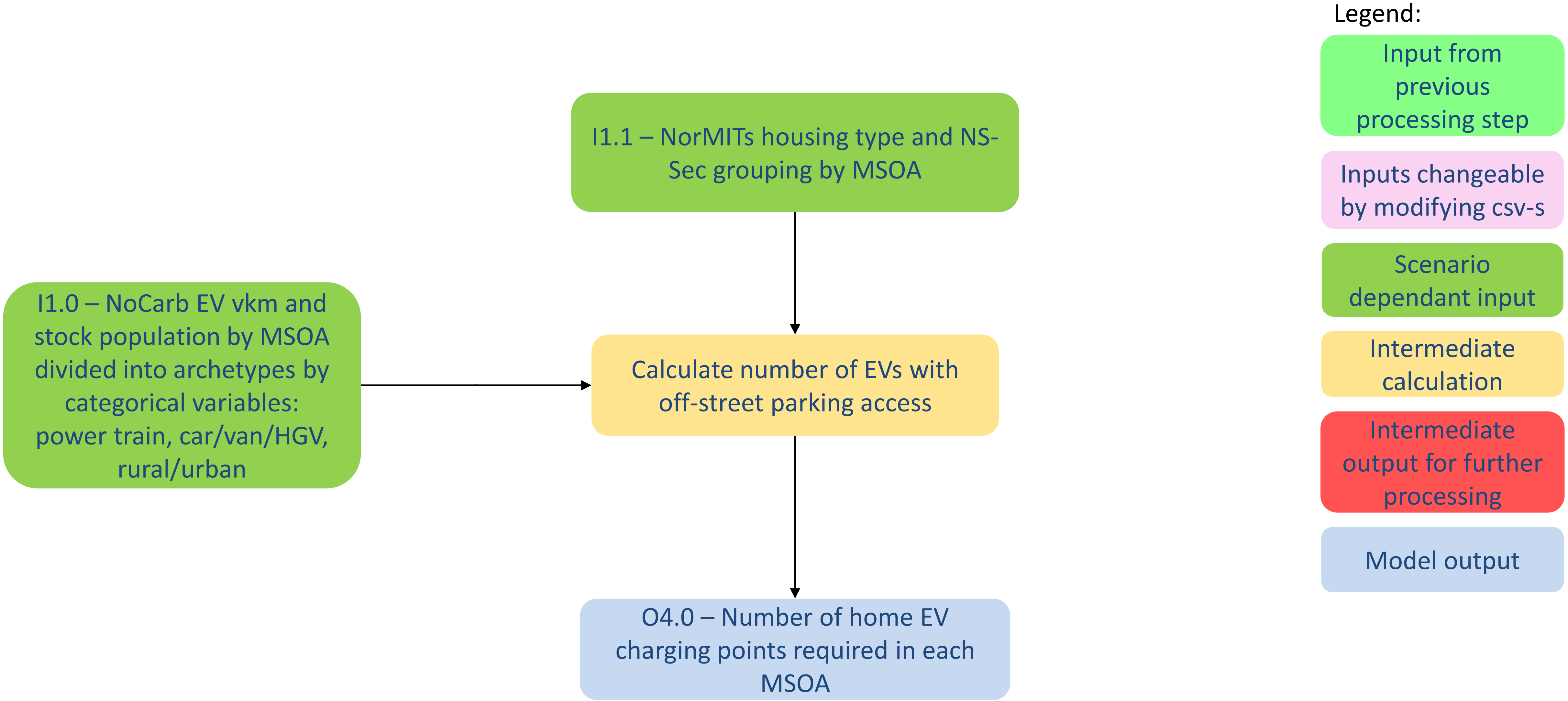
Core Module Step 4 – Calculate the number of public charge points required in each MSOA - All charging categories other than home charging

Note: Each scenario and year treated separately through the same processing chain



Core Module Step 4 – Calculate the number of public charge points required in each MSOA - Home charging

Note: Each scenario and year treated separately through the same processing chain



Core Module Step 5 - Determine possible sites for charge points along the major road network - Summary flowchart (1/2)

Forecasted En-route Charging Demand per MSOA of registration (Cars, Vans and HGV with BEV)

Forecasted Destination Charging Demand per MSOA of charging (Cars and vans)

Off-street Parking Share per MSOA

I1.0 – Forecasted EV uptake (Cars, Vans and HGV with BEV – 2020, 2025, 2030)

I5.3 – Observed Traffic Flow (AADT 2019)

I5.4 – Distance from MRN/SRN Road Network

I5.5 – Sites of 4+ existing DC Rapid Hubs

I5.6 – Distance from Motorway Junctions

I5.7 – Constraints: Flood Zone, Site of Special Scientific Interest, Area of Outstanding Natural Beauty, Green Belt

I5.8 – Forecast Traffic Flow (NoHAM Highway Reassignment Analysis) – 2025, 2030

I5.9 – Forecast Trip Length (NoHAM Highway Reassignment Analysis) – 2025, 2030

I5.0 – Land Use Data

I5.1 – Land Use Weights for each vehicle type

Identify clusters of land likely to feature parking and service stations and determine prospective en-route charging locations

I5.2 – Weights for each dataset

Apply filters to identify priority sites for further assessment, including a buffer around priority sites to promote broader geographic coverage

O5.0/I5.10 – Indexed demand rating for en-route charging by sites – for the 200 sites with highest demand (LDVs and HGVs – 2020, 2025, 2030)

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

Core Module Step 5 - Determine possible sites for charge points along the major road network - Summary flowchart (2/2)

I5.11 – NoHAM Model (SATURN files & node coordinates)
Choice of Year and Scenario

Filtered location constraints based on non-transport criteria

O5.1/I5.10 – Index highest flow volumes, aggregate TLD data by vehicle type and trip purpose

I5.12 – Link Selection choice of up to 200 sites. Manual/visual intervention

Selected link routine based on up to 200 sites

O5.2/I5.11 – Disaggregate Trip length distribution, travel distance by vehicle type and trip purpose by site

Apply further filters using the findings of the select link analysis accounting for average trip lengths, volume by trip purpose to refine and sort charging demand and importance across the 200 shortlisted sites

O5.3 – CSV outputs of all cells, and of top cells with Select Link Analysis applied. Cells have X and Y positions (eastings and northings in British National Grid)

O5.4 – GIS based spatial analysis identifying potentially suitable locations or specific sites for charging infrastructure on the MRN and SRN (catering to All Vehicles, LDV and HGV – 2020, 2025, 2030)

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

Contents

DNO Module Step 1r (Rapid en-route) – Map the charging demand to rapid hubs

Note: Each scenario and year treated separately through the same processing chain

Rapid en-route charging

O5.0/I6.0 – Shortlist of potentially suitable locations for charging infrastructure for rapid charging

O3.1/I6.1 – Peak daily demand for rapid en-route charging of cars and vans (MWh)

O3.2/I6.2 – Peak daily demand for en-route charging of HGVs (MWh)

Assign peak daily rapid en-route EV charging demand to the potentially suitable rapid charging locations

O6.0/I7.0 – Peak daily en-route EV charging demand per rapid charging hub (MWh)

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

Note: Depending on run times, the shortlist of potential suitable site location might be used as a static input, as we do not expect the site locations to change once they are established. (i.e.. Core Module Step 5 can be skipped in the processing chain if it has been run already.)

Note: EV charging demand assigned to rapid charging sites is a broad estimate, and not meant to represent commercial viability of the sites, therefore we would not recommend using this table as a model output

DNO Module Step 2r (Rapid en-route) – Map the charging demand to primaries

Note: Each scenario and year treated separately through the same processing chain

Rapid en-route charging

O6.0/I7.0 – Peak daily en-route EV charging demand per rapid charging hub (MWh)

I7.2 – Location of primaries

Map the rapid en-route EV charging hubs to primaries based on nearest primary to each rapid hub

O7.0/I8.0 – Peak daily en-route EV charging demand per primary (MWh)

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

DNO Module Step 3r (Rapid en-route) – Apply demand profile and seasonal variation factors

Note: Each scenario and year treated separately through the same processing chain

Rapid en-route charging

O7.0/I8.0 – Peak daily en-route EV charging demand per primary (MWh)

I8.2 – Half hourly charging demand profiles for rapid en-route charging

I8.3 – Seasonal variation factors for rapid en-route charging

Apply daily EV charging profile and seasonal variation factors for each primary for rapid en-route charging

O8.0/I9.0 – Half hourly charging demand profile for rapid en-route EV charging per primary, for representative summer and winter days

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

DNO Module Step 1a (All excl. rapid en-route) – Map the charging demand to DNOs

Note: Each scenario and year treated separately through the same processing chain

All charging categories other than rapid charging

O3.0/I4.0 – Peak daily EV charging demand by vehicle archetype, MSOA and charging category (excl. rapid en-route), with demand distributed to MSOA of charging (MWh)

Sum demand to determine total for the TfN region

I6.3 – Projected number of EVs per DNO and per primary substation

Determine the peak daily charging demand per charging category (excl. rapid en-route) at a DNO level

O6.1/I7.1 – Peak daily charging demand per charging category (excl. rapid en-route) per customer for each DNO

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

DNO Module Step 2a (All excl. rapid en-route) – Map the charging demand to primaries

Note: Each scenario and year treated separately through the same processing chain

All charging categories other than rapid charging

O6.1/I7.1 – Peak daily charging demand per charging category (excl. rapid en-route) per customer for each DNO

I6.3 – Projected number of EVs per DNO and per primary substation

Distribute demand over primaries corresponding to the DNOs and determine the peak daily charging demand per charging category (excl. rapid en-route) per primary

I7.2 – Unmanaged/smart home charging share

Split the home charging category into unmanaged and smart home charging

O7.1/I8.1 – Peak daily charging demand per charging category (excl. rapid en-route) at each primary

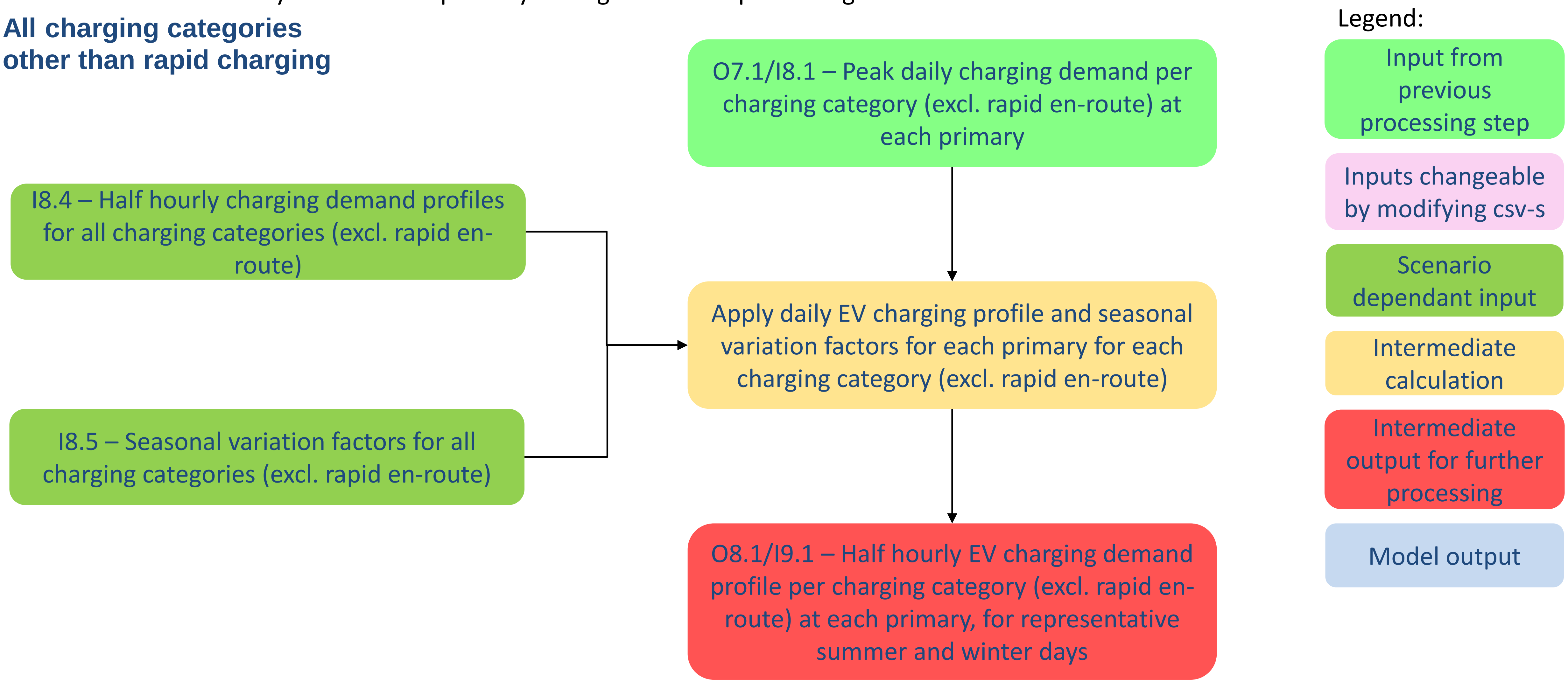
Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

DNO Module Step 3a (All excl. rapid en-route) – Apply demand profile and seasonal variation factors

Note: Each scenario and year treated separately through the same processing chain

All charging categories other than rapid charging



DNO Module Step 3, Step 4 – Linkage between different inputs and processing steps

Rapid en-route charging

O8.0/I9.0 – Half hourly charging demand profile for rapid en-route EV charging per primary, for representative summer and winter days

All charging categories other than rapid charging

O8.1/I9.1 – Half hourly EV charging demand profile per charging category (excl. rapid en-route) per primary, for representative summer and winter days

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

Primaries

Sum half hourly EV charging demand profiles for all charging categories per primary

Secondaries

Sum half hourly EV charging demand profiles over all charging categories (excl. rapid en-route) and all primaries corresponding to the DNO

DNO Module Step 4p (Primaries) – Sum EV charging demand profiles

Rapid en-route charging

O8.0/I9.0 – Half hourly charging demand profile for rapid en-route EV charging per primary, for representative summer and winter days

All charging categories other than rapid charging

O8.1/I9.1 – Half hourly EV charging demand profile per charging category (excl. rapid en-route) per primary, for representative summer and winter days

Primaries

Sum half hourly EV charging demand profiles for all charging categories per primary

O9.0/I10.0 – Total half hourly EV charging profile per primary, for representative summer and winter days

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

DNO Module Step 5p (Primaries) – Find the overall peak demand per primary

Note: Each scenario and year treated separately through the same processing chain

Primaries

O9.0/I10.0 – Half hourly EV charging profile per primary, for representative summer and winter days

↓

Get the overall peak EV charging demand from representative summer and winter days per primary

↓

O10.0/I11.0 – Overall peak EV charging demand per primary

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

DNO Module Step 6p (Primaries) – Apply grid impact parameters

Note: Each scenario and year treated separately through the same processing chain

Primaries

O10.0/I11.0 – Overall peak EV charging demand per primary

I11.2 – Headroom on primaries

I11.3 – Unit reinforcement cost per primary

Subtract the primary headroom from the peak EV charging demand, multiply by the unit reinforcement cost at primary level, then sum over primaries

O11.0 – Grid impact: Cumulative cost at primary level

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

Note: DNOs do not have long term projections for headroom values so values will be kept constant

DNO Module Step 4s (Secondaries) – Sum EV charging demand profiles

All charging categories other than rapid charging

O8.1/I9.1 – Half hourly EV charging demand profile per charging category (excl. rapid en-route) per primary, for representative summer and winter days

↓

Secondaries

Sum half hourly EV charging demand profiles over all charging categories (excl. rapid en-route) and all primaries (within the TfN region) corresponding to the DNO

↓

O9.1/I10.1 – Total half hourly EV charging demand profile (excl. rapid en-route demand) per DNO, for representative summer and winter days

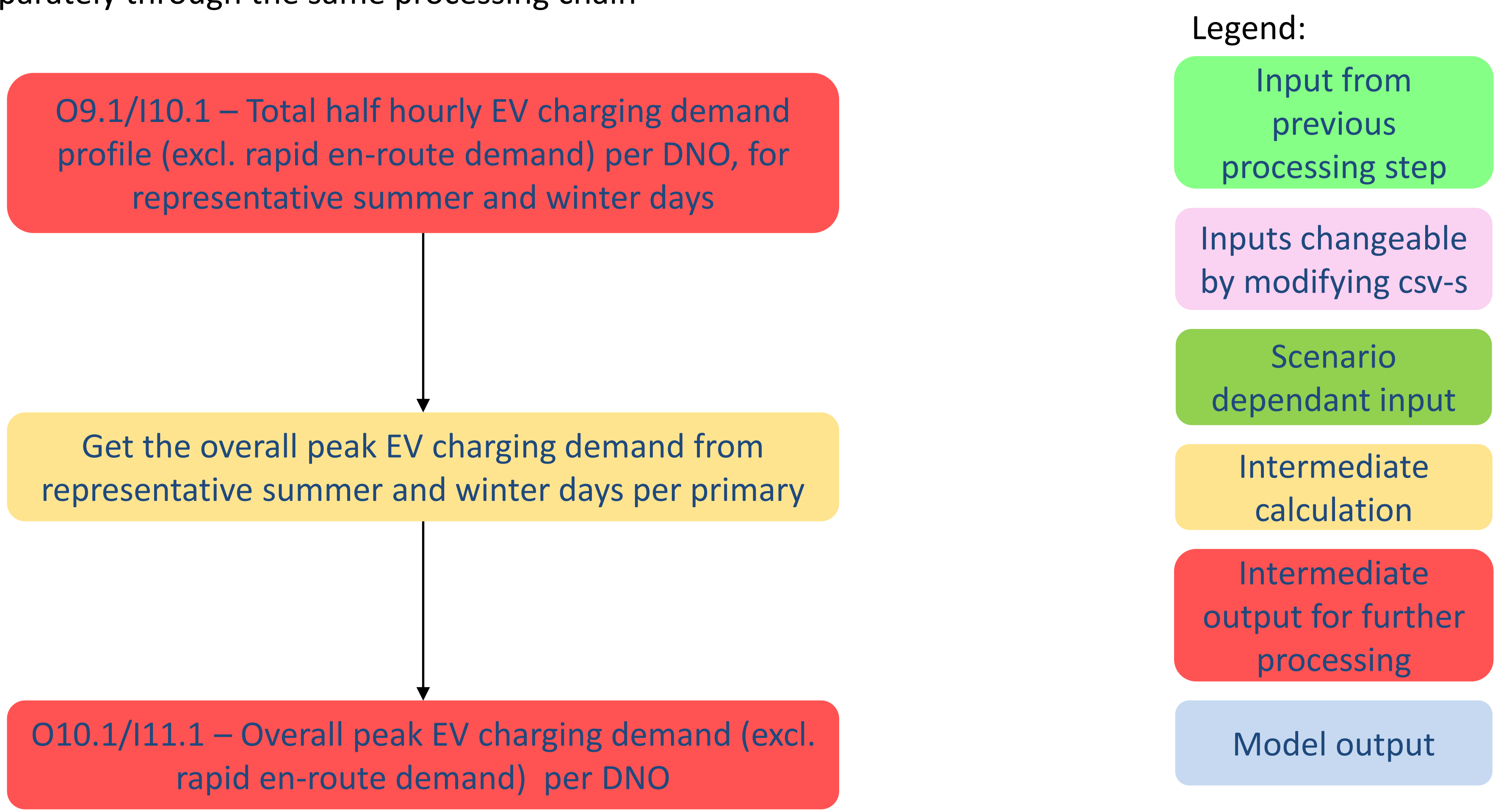
Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

DNO Module Step 5s (Secondaries) – Find the overall peak demand per DNO

Note: Each scenario and year treated separately through the same processing chain

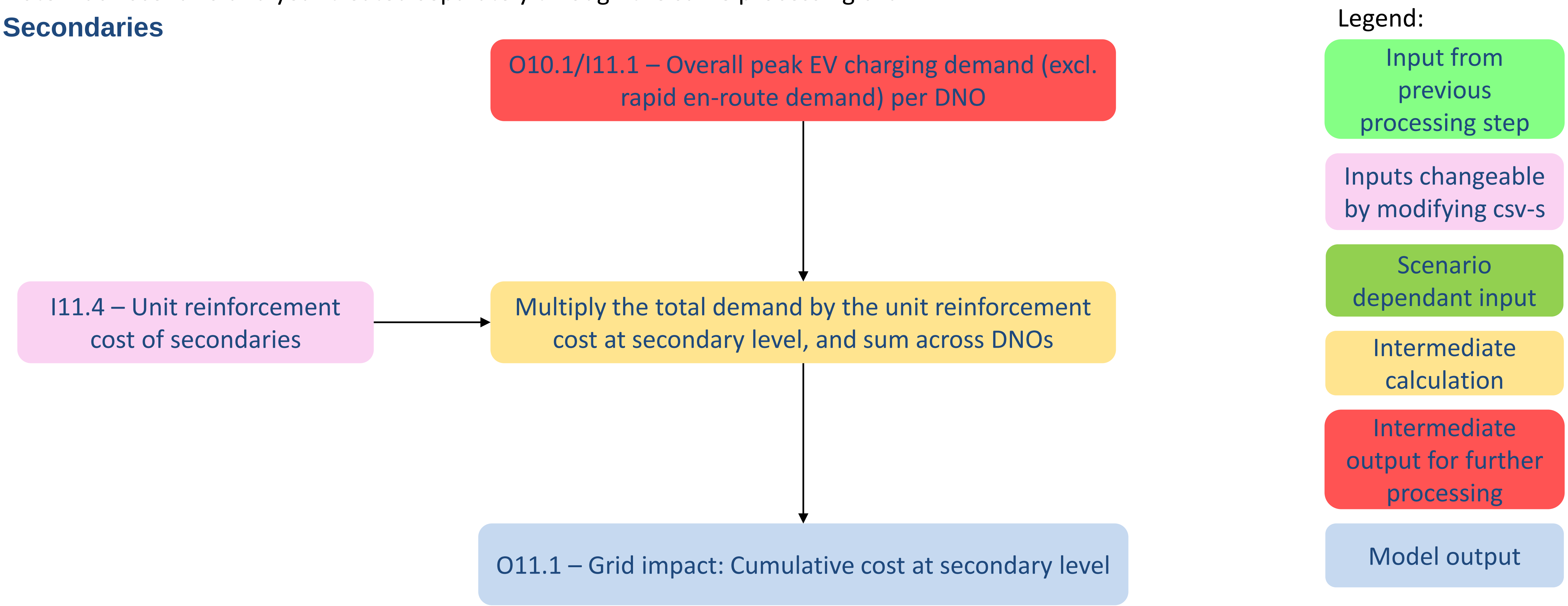
Secondaries



DNO Module Step 6s (Secondaries) – Apply grid impact parameters

Note: Each scenario and year treated separately through the same processing chain

Secondaries



Contents

En-route rapid shortlisting for the Strategic Road Network (SRN) and TfN defined Major Road Network (MRN)

What question is the task trying to answer: Which potential rapid charging sites along the SRN and TfN MRN are most likely to be needed to create a complete network.

TfN Northern Highways Assignment Model Data
NoHAM OD matrix data being used to understand trip origin destination and pathway. This will be used to understand the proportion of vehicles within the traffic flow which are completing long distance journeys (journeys greater than 130km for cars, 180km for vans and 280km for HGVs) and may need en-route charging

EE approach to en-route charging size
EVCI model identifies the public rapid charging demand. Analysis to size the demand from existing sites (following similar inputs as used for the RCF) can be compared to the EVCI output to identify the public charging gap

Mapping / sizing en-route charging need

Rapid charging module Step 1 – Identifying rapid charging demand distribution based on trip patterns across the TfN region

I20.0 – NoHam OD matrix for TfN Just About Managing future travel scenario in 2033 broken down by car, van and HGV

Traffic flows and journey length: Calculate the path (node series) taken by each vehicle from origin to destination. Calculate the distance travelled by each vehicle from the origin to each node along the route

I20.1 – Distribution of battery size and SOC when choosing to charge which when combined provides a probability curve of how likely a driver is to stop to charge at different distances along their journey

Charging probability: Once a vehicle has passed the minimum distance, assess the probability of the vehicle stopping to charge and the charging demand needed to reach the destination. Multiply the probability by charging demand to get the modelled demand at each point along the network

Transfer the charging demand from the NoHam road links to TfN definition of the line segments which make up the SRN + MRN

Proportion of EV: Calculate demand for each 5 year interval based on the DfT NRTP 22 Vehicle-led Decarbonisation Scenario for BEV uptake and traffic growth

O20.0 – Charging demand (kWh/year) and number of charge points for each road segment of the MRN, as defined by TfN, for 5 year intervals from 2025 to 2050, shown in the visualiser

Motorway Service Area demand: Calculate the number of vehicles assumed to stop on road segments within a 10km radius of each MSA

O20.1/I20.2 – Annual number of vehicles assumed to stop for each MSA

SOC = battery state of charge. CAS = Common analytical scenarios. MSA = Motorway Service Area

Rapid charging module Step 2 – Assess demand from the existing MSA network in order to calculate remaining whole network requirement

O20.1/I20.2 – Annual number of vehicles assumed to stop for each MSA

↓

I20.3 – BEV stock based on DfT NRTP 22 Vehicle-led Decarbonisation Scenario → Number of vehicles stopping multiplied by the proportion which are BEV in a given year

↓

I20.4 – Share of BEV which stop who choose to charge → Number of BEV stopping at the MSA multiplied by the share which stop to charge. Changes as a function of increasing battery sizes over time

↓

I20.5 – Charging energy gained per charging session → Number of BEV stopping to charge multiplied by the kWh gained in a charging session

↓

I20.6 – Traffic growth based on DfT NRTP 22 Core Scenario → Annual energy demand from charging multiplied by traffic growth between 2022 and each future year

↓

O20.2 – Annual charging demand for each MSA

Legend:

- Input from previous processing step
- Inputs changeable by modifying csv-s
- Scenario dependant input
- Intermediate calculation
- Intermediate output for further processing
- Model output

NRPT 22 = National Road Traffic Projections 2022. MSA = Motorway Service Area

Contents

Core Module (Step 1-4) data sources

Input data	Confidence in inputs over model time period	Recommended update frequency	Source
I1.0 – NoCarb EV vkm and stock population by MSOA	Long term (2050)	When TfN models updated	TfN NoCarb model
I1.1 – NorMITs housing type and NS Sec	Mid term (2040)	When TfN models updated	TfN NorMITs model
I1.2 – Trip purpose share (incl. commuting)	Mid term (2040)	When TfN models updated	TfN NorMITs model
I1.3 – Ownership share	Mid term (2040)	When TfN models updated	TfN NorMITs model
I1.4 – Electricity consumption (kWh / km)	Long term (2050)	Every 5 years	EE Electricity Consumption modelling
I2.1 – Charging behaviour assumptions for cars and vans	Short term (2030)	Annually	EV charging trials and EE database
I2.2 – Charging behaviour assumptions for HGVs	Short term (2030)	Annually	EV charging trials and EE database
I3.1 – Work charging origin-destination matrix	Mid term (2040)	When TfN models updated	TfN's NorMITs demand model
I3.2 – Destination charging origin-destination matrix	Mid term (2040)	When TfN models updated	TfN's NorMITs demand model
I3.3 – HGV depot charging origin-destination matrix	Mid term (2040)	When TfN models updated	TfN's NorMITs demand model
I3.4 – Seasonal variation factors	Short term (2030)	When TfN models updated	TfN visitor economy modelling
I4.1 – Power and utilisation assumptions for each charging category	Mid term (2040)	Every 5 years	ICCT method used as starting point, with improvements made by EE
I4.2 – Normalized daily profile	Short term (2030)	Review new EV charging data available annually	Various – from EE work on EV charging load forecasting for DNOs

The data provided by TfN may include data derived from: Department for Transport. (2022). *National Travel Survey, 2002-2021: Special Licence Access*. [data collection]. *11th Edition.* UK Data Service. SN: 7553, DOI: 10.5255/UKDA-SN-7553-11

Core Module (Step 5) data sources

Input data	Confidence in inputs over model time period	Recommended update frequency	Source
I5.0 – Land Use Data	Mid term (2040)	Annually	AddressBase Plus
I5.1 – Land Use Weights for each vehicle type	N/A	N/A	Set by WSP as part of analysis
I5.2 – Weights for each dataset	N/A	N/A	Set by WSP as part of analysis
I5.3 – Observed Traffic Flow	Short term (2030)	Annually (possibly waiting for 2022 data if 2021 data is affected by Covid-19)	DfT AADT Traffic Counts, 2019
I5.4 – Distance from MRN/SRN Road Network	N/A	N/A	Set by WSP as part of analysis
I5.5 – Sites of 4+ existing DC Rapid Hubs	Short term (2030)	Annually	National Charge Point Registry, Open Charge Map
I5.6 – Distance from Motorway Junctions	N/A	N/A	Set by WSP as part of analysis
I5.7 – Other planning constraints	Long term (2050)	Annually	Flood risk (DEFRA)
I5.8 – Forecast Traffic Flow	Mid term (2040)	When TfN models updated	TfN NoHAM Highway Reassignment Analysis
I5.9 – Forecast Trip Length	Mid term (2040)	When TfN models updated	TfN NoHAM model Highway Reassignment Analysis
I5.11 – NoHAM model	Mid term (2040)	When TfN models updated	TfN NoHAM model
I5.12 – Link selection	N/A	N/A	Set by WSP as part of analysis

The data provided by TfN may include data derived from: Department for Transport. (2022). *National Travel Survey, 2002-2021: Special Licence Access*. [data collection]. *11th Edition.* UK Data Service. SN: 7553, DOI: 10.5255/UKDA-SN-7553-11

DNO Module data sources

Input data	Confidence in inputs over model time period	Recommended update frequency	Source
I6.3 - Projected number of EVs per DNO and per primary substation	Short term (2050)	Annually when new DFES released	DNO Distribution Future Energy Scenarios (DFES)
I7.4 - Unmanaged/smart home charging share	Short term (2030)	Review available data annually	EE assumptions
I8.2, I8.4 - Half hourly charging demand profiles	Short term (2030)	Review available data annually	EV charging trials and EE database
I8.3, I8.5 - Seasonal variation factors	Short term (2030)	When TfN models updated	TfN visitor economy data
I11.2 - Headroom on primaries	Short term (2030)	Annually	DNOs, heatmaps and LTDS
I11.3 - Unit reinforcement cost per primary	Short term (2030)	Review available data annually	DNOs, ED2 Business plan
I11.4 - Unit reinforcement cost of secondaries	Short term (2030)	Review available data annually	DNOs, ED2 Business plan

The data provided by TfN may include data derived from: Department for Transport. (2022). *National Travel Survey, 2002-2021: Special Licence Access*. [data collection]. *11th Edition.* UK Data Service. SN: 7553, [DOI: 10.5255/UKDA-SN-7553-11](https://doi.org/10.5255/UKDA-SN-7553-11)

Model outputs

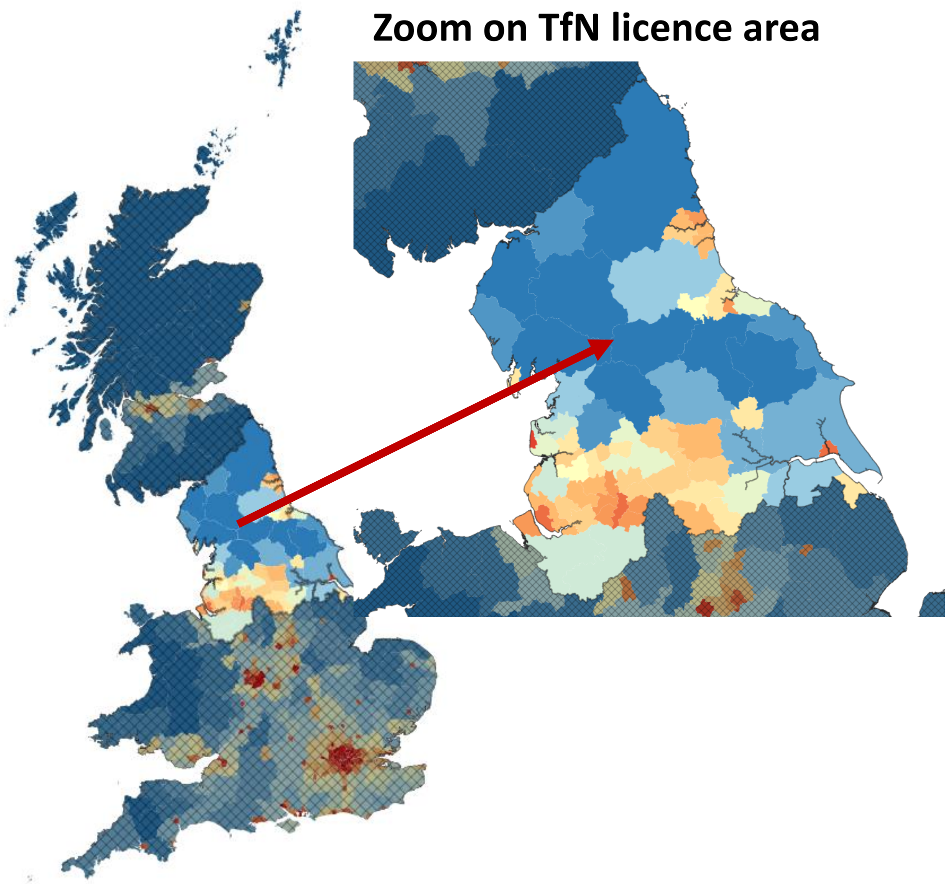
Output	Years of output	Confidence in outputs over model time period	Recommended update frequency for inputs	Description
O3.1/I6.1, O3.2/I6.2 – Peak day demand for rapid en-route charging	2020, 2025, …, 2050	Long term (2050)		Total peak day demand for rapid en-route charging of cars and vans (MWh) and total peak day demand for en-route charging of HGVs (MWh)
O4.0 – Number of EV charging points	2020, 2025, …, 2050	Mid term (2040)		Number of EV charging points required in each MSOA for on-street and destination charging
O5.3/O5.4 – CSV outputs and GIS based spatial analysis identifying potentially suitable locations or specific sites for charging infrastructure on the MRN and SRN	2025, 2030	Short term (2030)	Annually	CSV outputs and GIS based spatial output identifying potentially suitable locations or specific sites for charging infrastructure on the MRN and SRN (catering to BEV Cars, Vans and HGV - 2025, 2030)
O11.0, O11.1 – Grid impact	2020, 2025, …, 2050	Short term (2030)	Annually	Estimated cumulative cost of necessary network reinforcement to meet the EV charging peak demand at primary and secondary levels

- In addition to the above outputs, we will generate a high-level output file summarising key results for particular years of importance
- We will take views from the steering group on what a practical summary file would contain for their purposes (could be only short term results, aggregated at Local Authority level, for example)

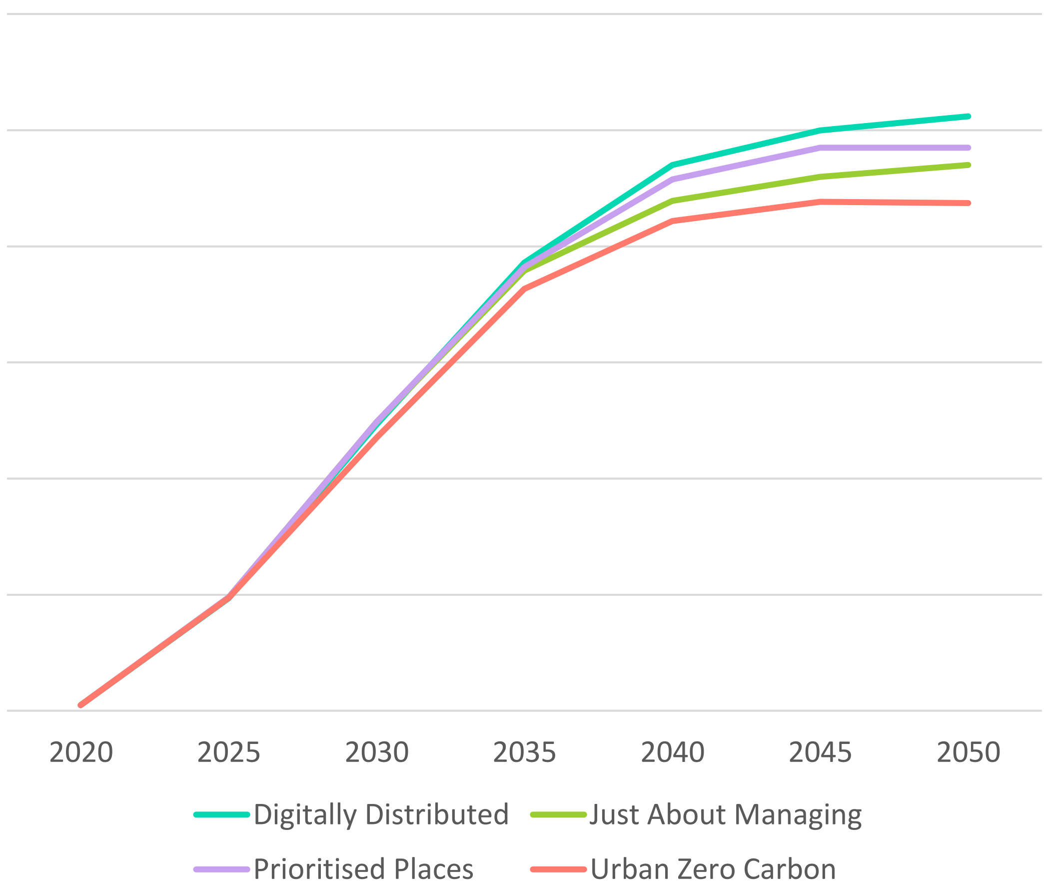
The data provided by TfN may include data derived from: Department for Transport. (2022). *National Travel Survey, 2002-2021: Special Licence Access*. [data collection]. *11th Edition.* UK Data Service. SN: 7553, DOI: 10.5255/UKDA-SN-7553-11

Example visualisations of results

Example heatmap of EV charging demand across GB



Example graph of EV charger needs in TfN licence area



Note as visualisations are indicative only, scales giving numbers of charge points or amount of charging demand have not been included

Contents

Charging behaviour assumptions have been based on those used in ICCT charging infrastructure reports, with some adaption (shown on the next slide)

Cars and Vans – ICCT values[1]

Power train	Commuting Status	Home Charging Availability	Home Charging	Work Charging	Public Charging (slow / fast)	DC Charging (rapid)
BEV	Commuter	Yes	70%	20%	5%	5%
		No	0%	45%	30%	25%
	Non Commuter	Yes	85%	0%	5%	10%
		No	0%	0%	40%	60%
PHEV	Commuter	Yes	65%	30%	5%	0%
		No	0%	65%	35%	0%
	Non Commuter	Yes	90%	0%	10%	0%
		No	0%	0%	100%	0%

- Typical charger power rates: home: 3-7 kW; on-street slow/fast: 7-22 kW; rapid en-route: 50-350 kW
- Exact assumptions around how charger power increases each year (from charge point power increases and higher charging rate acceptance from EVs) will be detailed in the statement of methodology

1: ICCT, 2020, https://theicct.org/sites/default/files/publications/UK-charging-gap-082020.pdf

Modelling Assumption – Charging Behaviour

Cars and Vans – proposed values for model baseline

Power train	Commuting Status	Home Charging Availability	Home Charging	On-street residential charging	Destination charging	Work Charging	En-route charging
BEV	Commuter	Yes	70%	0%	5%	20%	5%
		No	0%	35%	10%	45%	10%
	Non Commuter	Yes	85%	0%	5%	0%	10%
		No	0%	75%	15%	0%	10%
PHEV	Commuter	Yes	65%	0%	5%	30%	0%
		No	0%	30%	5%	65%	0%
	Non Commuter	Yes	90%	0%	10%	0%	0%
		No	0%	80%	20%	0%	0%

- As this will be a CSV file input into the model, the user can update the file as needed to test different futures of charging behaviour – for example if trend in working from home continues this could be tested with low work charging shares

Home and work charging % are in line with ICCT. Public charging split between on-street residential and destination. DC fast charging split between on-street residential and en-route

The effect of increasing the share of charging done at destinations was investigated through a sensitivity analysis

Charging behaviour assumptions – changes made in destination sensitivity analysis are in brackets

Powertrain	Commuting Status	Home Charging Availability	Home Charging	On-street residential charging	Destination charging	Work Charging	En-route charging
BEV	Commuter	Yes	70% (60%)	0%	5% (15%)	20%	5%
		No	0%	35% (30%)	10% (15%)	45%	10%
	Non Commuter	Yes	85% (70%)	0%	5% (20%)	0%	10%
		No	0%	75% (60%)	15% (30%)	0%	10%
PHEV	Commuter	Yes	65% (60%)	0%	5% (10%)	30%	0%
		No	0%	30% (25%)	5% (10%)	65%	0%
	Non Commuter	Yes	90% (75%)	0%	10% (25%)	0%	0%
		No	0%	80% (60%)	20% (40%)	0%	0%

- Values in red represent a decrease in charging demand share for home / on-street residential charging
- Values in green represent an increase in charging demand share for destination charging
- Note that despite the small absolute increase (5-10 percentage points for most archetypes) in destination charging demand, this is a large relative increase and leads to destination charging demand more than doublingin red represent a decrease in charging demand share for home / on-street residential charging

Modelling assumption – charging rates – for validation and discussion

Charging rates for each charging category (kW)

Charging category	2021	2025	2030	2035	2040	2045	2050
On-street residential	BEV: 8 kW, PHEV: 3.5 kW						
Destination	BEV: 8 kW, PHEV: 3.5 kW						
Workplace	BEV: 8 kW, PHEV: 3.5 kW						
Rapid en-route	35 kW	50 kW	65 kW	75 kW	100 kW	125 kW	150 kW

- Charging rates for slow/fast categories are taken from ICCT.
- Charging rates for rapid charging are taken from ICCT up to 2035. From 2040 onwards they have been assumed by EE.
- Note these charging rates represent the power being transferred to the vehicle, which is not always equal to the power of the charge point being used. Other factors, such as the maximum charging rate the vehicle can accept, influence the level of power that can be drawn from a charge point, and are taken into account in the above values.

Modelling assumption – utilisation – for validation and discussion

Utilisation for each charging category (hours / day)

Charging category	2025	2030	2035
On-street residential	4	5	6
Destination	4	6	7
Workplace		6 hours per weekday	
Rapid en-route	6	8	8

- Above values are taken from ICCT
- Note that these values are taken from equations derived by ICCT (shown below), which are dependent on level of EV uptake – we will use these equations in the EVCI model to calculate utilisation at each charging category

Public charging daily utilisation in hours	Average daily hours = 0.832 * LN (EV per million population) – 4.902
Fast charging daily utilisation in hours for metropolitan areas	Average daily hours = 0.650 * LN (BEV per million population) – 4.099
Fast charging daily utilisation in hours for nonmetropolitan areas	Average daily hours = 0.483 * LN (BEV per million population) – 3.021

Contents

Input-related risks (1/2)

Limitation	Risk (and mitigation strategy where appropriate)	Relevant step in model	Importance
Assumptions around charging behaviour are currently based on data from nascent market and modelled assumptions – as EVs become mass-market behavioural patterns may change	The charging network predicted may be different to the optimal network if behaviour patterns change. We will mitigate this by providing several charging behaviour scenarios	Core module, Step 2	High
The highest resolution of input data provided is at MSOA level	The model will not be able to capture LSOA level variations, even if they are large (for example in densely populated urban areas)	All steps	Medium
The processing pipeline will build on projections from TfN's modelling suite as well as projections from DNOs	Limitations of these models and data will propagate to the developed TfN EVCI model. Any unwanted or unpredicted behaviour of these models can change the results of the developed model	All steps	Medium
Detailed mapping of all destinations very challenging	New destinations arise over time or preferred charging destinations change over time. TfN's destination / trip purpose categories can be used to manage changing preferences and somewhat mitigate this risk	Core module, Step 3	Medium
Limitations around traffic flows applied for filtering sites	Limitations in using 2019 DfT AADT survey data to overcome short term more extreme influence of COVID on more recent traffic flows. Difficulties associated with mapping Saturn outputs for forecast future flows onto spatially accurate networks required for these assessments	Core module, Step 5	Medium

Input-related risks (2/2)

Limitation	Risk (and mitigation strategy where appropriate)	Relevant step in model	Importance
Land Use data used to identify suitable rapid hub locations is based on present day uses	Land Use data is based on present uses and would not account for changing land use or the potential for greenfield sites. Can be mitigated by updating TfN housing inputs, based on Ordnance Survey data	Core module, Step 5	Medium
Seasonal factors used in the DNO module will be based on historic data, and are dependent on weather conditions.	Future changes in weather patterns (more extreme weather, larger temperature swings etc.) will not be incorporated into these parameters	DNO module, Step 3	Low
While most inputs are defined at MSOA level, there are some overarching simplifications, with higher level data applied to some processing steps.	These simplifications may lead to underpredicting variation of charging demand across MSOAs. All of the key datasets in the TfN modelling suite are spatially disaggregated, and we will mitigate this risk by using inputs at MSOA level where possible.	Core module, all steps	Low
DNO module attributing charging demand to primary substations is based on customer numbers data from DNOs.	DNOs may be unable or unwilling to provide this piece of data (all other data types are available and/or have been received). If we are unable to acquire this data, we will make a minor change to the method to attribute charging demand based on primary locations rather than customer numbers	DNO module, all steps	Low

Processing-related risks (1/3)

Limitation	Risk (and mitigation strategy where appropriate)	Relevant step in model	Importance
The model provides projections rather than predictions.	Projections may differ from actual events and trends in the future. To mitigate this, multiple scenarios will be defined. It is also recommended to rerun the model whenever new data is available	All steps	High
Lack of differentiation between sites limiting scope to prioritise/rank	Risk that there is too little variation between sites using the filters applied to effectively filter down and identify the key most suitable sites. Will be mitigated by setting model parameters to ensure differentiation between sites	Core module, Step 5	High
The DNO module only determines EV charging demand peak rather than overall peak substation demand	The EV charging demand peak could be temporally misaligned with each substation's overall peak demand including other demand types. We are also not modelling the increase/decrease in demand over time from customer growth, energy efficiency, heat pumps, etc., nor are we conducting full power flow modelling. All of this is very resource intensive and outside of the scope of this project. Therefore, there is significant uncertainty in actual network impacts from EVs and hence the overall costs of the DNOs. Our high level analysis is sufficient to give an indication of likely network costs and how these vary between scenario, but should not be considered to give accurate calculations of network impacts for individual network assets	DNO module, all steps	Medium
Analysis of travel demands across different forecast horizons	Flows may rise or fall based on infrastructure and demand growth assumptions contained in the modelling. The top 200 sites for one year/scenario may not be the same sites for another year/scenario. This would potentially increase the number of sites and effort required for selected link analysis	Core module, Step 5	Medium

Processing-related risks (2/3)

Limitation	Risk (and mitigation strategy where appropriate)	Relevant step in model	Importance
Approach to identifying suitable sites will be indicative given the strategic level nature of the assessment	In practice there are many highly localised factors at play in influencing local charging demand and the suitability of a site. For example, the cost of the DNO connection has a significant bearing on the suitability of a site from a delivery perspective. Similarly, whilst potentially suitable host sites may be identified in proximity of the MRN, their accessibility and prominence to passing drivers will be variable	Core module, Step 5	Medium
Approach to filtering sites results in an uneven distribution of sites	A demand-led approach to filtering sites could result in an uneven distribution of sites, rather than the broader coverage of sites which was envisaged. To mitigate this a zone or weight based approach will be developed to ensure the potential sights are distributed across the region	Core module, Step 5	Medium
Long model processing and run times	Until the approach is further developed, model run times, process and structure are hard to predict. It may be that elements of the approach outlined could function as separate modules sitting outside of the core model, for example those associated with the Transport Model if inputs were not likely to vary between scenarios, and would otherwise add significantly to model run times / complexity	All steps	Medium
Defining a suitable site, and assumptions around charging infrastructure deployed	Risks associated with ensuring there is a clear definition of what is a 'suitable location or site', and to what extent this accounts for delivery, or demand only. Associated assumptions around the nature of the sites and charge point types (i.e. Rapid Charging hubs), where some may also be destinations in their own right. Will be mitigated by clearly defining what land use categories are considered from input data	Core module, step 5	Low

Processing-related risks (3/3)

Limitation	Risk (and mitigation strategy where appropriate)	Relevant step in model	Importance
Approach is likely to determine suitable areas or clusters of sites, as opposed to single optimal sites	It is likely that the site assessment process will identify suitable areas or clusters of sites, as opposed to singular or highly specific optimal sites. To mitigate this a zone or weight based approach will be developed to ensure the potential sights are distributed across the region	Core module, Step 5	Low
Strategic level representation of the local road network	Transport models primarily consider the core network, and whilst all trips are included within the model demand matrices, intrazonal trips are not assigned to network. Strategic and model zones are large so these represent the shorter distance demand "in the model" but not represented "on the network"	Core module, Step 5	Low
The vehicle archetypes the model uses are not exhaustive	Some variation lost in the data (e.g. from vehicles used for multiple purposes such as Uber, different car classes, etc.) and peaks for certain categories might be a slight under or over estimation. Will be mitigated by using as detailed archetyping as possible given available input data	All steps	Low
The charging categories defined might not be exhaustive as other charging technologies might emerge in the future.	Some charging points might become redundant if higher efficiency or higher power charging becomes available. To mitigate this, the model is made modular, with charging categories easily amendable if required	All steps	Low
Fixed cost flow simplification in transport modelling	Derivation of fixed cost flows will help to improve the usability of the model with respect to selected link interrogation, potentially expanding the analysis that can be conducted. It does however result in a simplification of routings and the resulting outputs may vary slightly from the original assignment	Core module, Step 5	Low

Translation to energy requirements - what isn't covered at this time, how might we cover it?

Limitation	Future options
The total impact of electrification on the grid over the coming decades will be driven by a combination of electrification of transport and heating. To accurately cost the impact, projections for both transport and heat are needed.	As this study focuses mostly on transport and not these wider DNO considerations, the relative difference rather than the absolute values are the main output. For total grid investment, refer to each DNO DEFES and or specific site data please contact the relevant DNO.
The key area that needs improving is how we map charging demand to the correct assets on the distribution network. The model does not currently have a definitive mapping from MSOAs to distribution network assets. The data we currently have on headroom is only available for primary substations, and this data is not normally collected at secondary substation level.	Non-rapid charging demand could be mapped to primary substations based on the MSOA where that demand occurs, rather than summed and distributed across the region (would require DNOs to provide a mapping from MSOAs). DNOs could incorporate EV load growth into their load models – would require engagement with DNOs to understand how outputs need to be adapted for integration into their models.
The grid costs are very dependent on the existing available headroom on grid assets. DNOs do not have data on the headroom on an asset by asset (to secondary substation level) basis limiting the level of detail possible. Our current workaround is to use the predicted share of EVs at each to determine the share of demand that is allocated to each of the substations.	Indication of headroom on secondary substations could be included to improve forecasting of reinforcement needs, however DNOs do not have data on the headroom at an asset by asset (to secondary substation level) basis.
Costs are for reinforcing network assets and distribution infrastructure, i.e. transformers and cables/power lines. They do not include generation capacity. Costs may be lower as we assume EV demand takes up available headroom, then costs are incurred when headroom is exceeded.	Reinforcement costs per MW could be refined as more reinforcement cost data becomes available.
Results do not include the impact on the extra high voltage or transmission network.	Continued engagement with the energy sector to manage risks and identify potential avenues to tackle limitations.
Headroom, capacity is correct as of today, but this is a constantly changing value meaning headroom may not be available in the future when the EVCP are installed, resulting in additional costs.	

Summary of approach for determining reinforcement costs on primary and secondary substations

Primary substations (typically 10-50 MW)

- Both rapid and non-rapid peak daily charging demand are distributed to primary substations.
- Rapid charging demand is assigned from hubs identified in core module step 5 to the closest primary substation.
- Non-rapid charging demand is aggregated for the whole region, then distributed to individual primary substations based on the projected number of EVs on each.
- Hourly charging profiles are applied to daily demand to calculate additional load at hourly resolution.
- Peak hourly load is compared to headroom on each primary substation. If headroom is exceeded, additional load above headroom is included in reinforcement needs.
- A reinforcement cost of £400,000 / MW increase above firm capacity is assumed for all primary substations.

Secondary substations (typically 25-500 kW)

- Only non-rapid peak daily charging demand is assumed to occur on secondary substations, as the power requirements of most rapid hubs are too large to connect to secondary substations.
- Non-rapid charging demand is aggregated for the whole region, then distributed to each DNO based on the total number of projected EVs on each.
- Hourly charging profiles are applied to daily demand to calculate additional non-rapid load at hourly resolution for each DNO.
- Peak non-rapid hourly load is calculated for each DNO. As headroom estimates are not available for secondary substations, this load is assumed to entirely contribute to reinforcement needs.
- A reinforcement cost of £50,000 / MW increase in peak load is assumed for all secondary substations.

Notes:

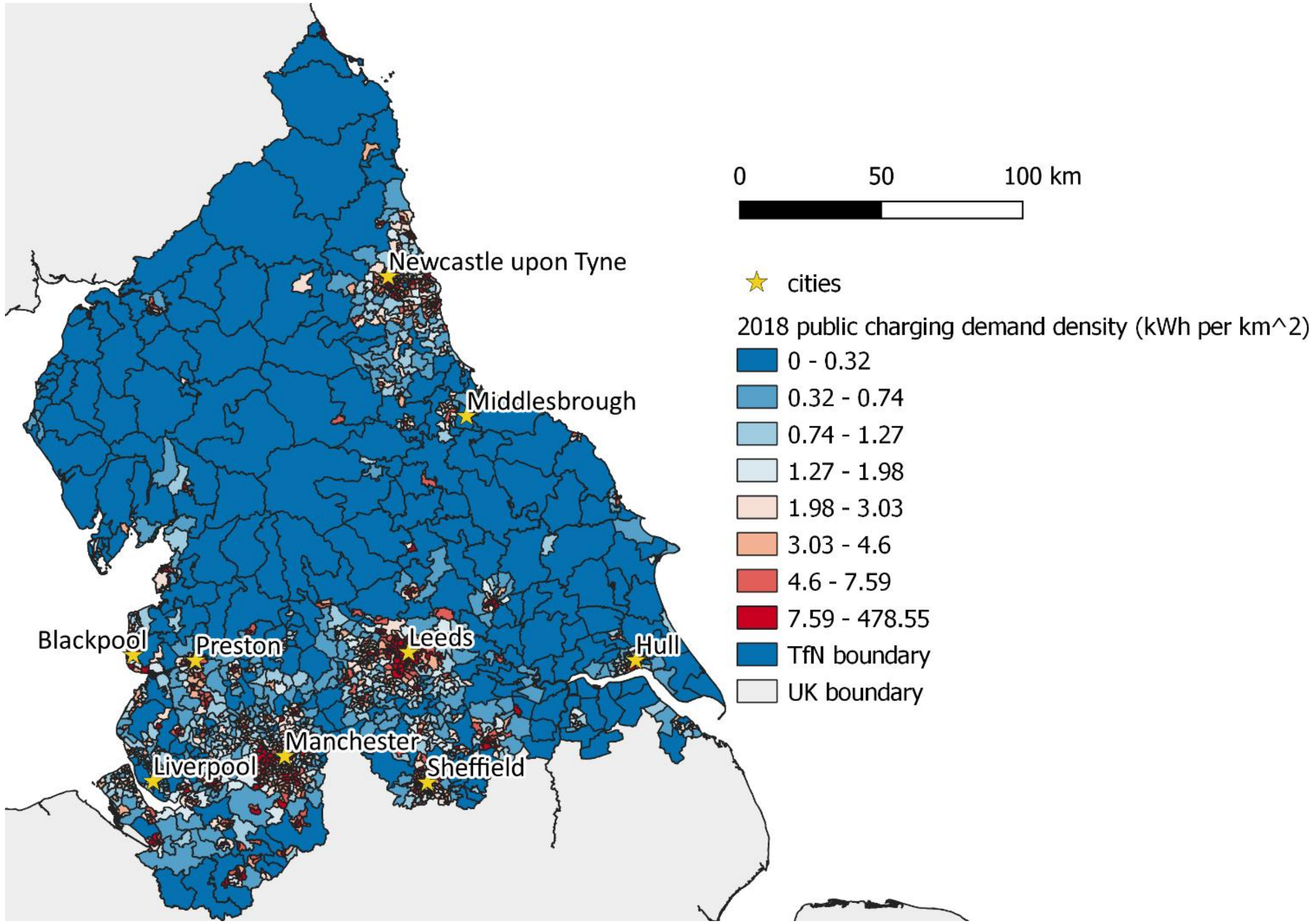
- Assessment of reinforcement costs includes **all charging demand** modelled in the EVCI model. This includes public slow/fast charging (public residential and destination charging, presented in core module results), as well as home, workplace, HGV depot, and rapid en-route charging.
- This work does not assess the impact of increased electricity demand from other low carbon technologies, such as heat pumps.
- Reinforcement costs are based on publicly available data from the three DNOs' Statement of methodology and connection charges, as well as other sources including their draft business plans. The cost of a connection can vary significantly depending on the specific circumstances - the data we have taken gives an indication of typical expected costs.

Contents

Public charging demand in 2018 was highest from vehicles registered in residential areas

Public charging demand in 2018

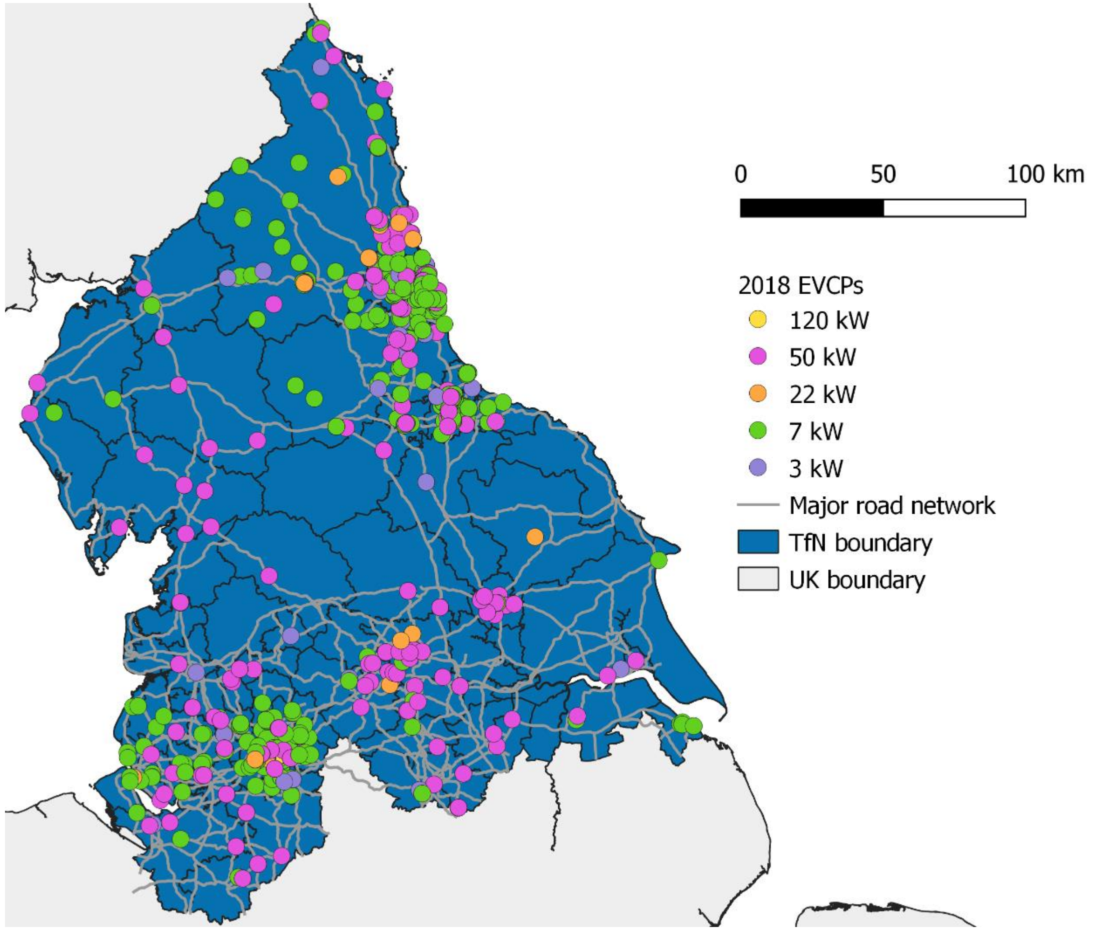
- From data provided from TfN's NoCarb model, the public charging demand of all EVs in the TfN region was predicted to be 25,800 kWh
- The map opposite shows the density of public charging demand from vehicles registered in each MSOA
- The highest density of charging demand is seen in urban areas, following the historic trends of EV uptake and provision of EVCPs



A total of 1,100 charge points were deployed in the TfN region in 2018

Charge points deployed in 2018

- The map opposite shows data from the National Chargepoint Registry for charge points registered up to 2018 in the TfN region
- A total of 1,100 points were installed: 866 slow/fast (3 – 22 kW) and 234 rapid (50+ kW)
- The majority of charge points are clustered around the urban centres of Manchester, Liverpool and Newcastle
- Rapid charge points are distributed across the major road network, but significant lengths of major roads still exist without rapid charge point provision



Note the data from the National Chargepoint Registry may not be complete, and may include incorrect or outdated data

Contents

Accepted values of Categorical Variables

Categorical Variable	Accepted values
Vehicle type	Car, Van, HGV
Power train	BEV, PHEV
Commuting/non-commuting (Trip purpose)	Commuting, Non-commuting
Ownership	Private, Company, Shared, Big haulier, Small local HGV operator
Driver income	Low, High
Rural/urban	Rural, Urban
Charging categories for cars and vans	Home, On-street residential, Work, Destination, Rapid en-route
Charging categories for HGVs	HGV depot, HGV en-route
Home charging	Unmanaged, Smart charging

Vehicle archetype parameters: Vehicle type, Power train, Commuting/non-commuting, Ownership, Driver income, Rural/urban

Note: While these are the default accepted values for the categorical variables, these can be modified by updating model constants.

Note: The variables in blue are not strictly necessary to calculate the EVCP requirements. Whether or not these are kept will depend on processing times and data availability. To be discussed and decided by TfN during model development.

Core module step 1 to 4 - Calculate the number of public charge points required in each MSOA

Core Module Step 1 – Forecast EV charging demand from vehicles registered in each MSOA, Provisional column structure of inputs and interim outputs

Input, Interim output, Model output	Columns
I1.0 – NoCarb EV vkm and stock population by MSOA	Scenario, Year, MSOA, Vehicle type, Power train, Vehicle stock, Chainage
I1.1 – NorMITs housing type and NS Sec	Scenario, Year, MSOA, Area type (rural/urban classification), Property type (to estimate Parking status), NS-Sec index (to estimate Driver income), Number of cars, Number of URPN-s
I1.2 – Trip purpose share (incl. commuting)	Variables to merge on, Trip purpose (incl. Commuting status), Share
I1.3 – Ownership share	Variables to merge on, Ownership, Share
I1.4 – Electricity consumption (kWh / km)	Vehicle type, Power train, Electricity consumption
O1.0/I2.0 – Annual EV charging demand by vehicle archetype at the MSOA of registration	Scenario, Year, MSOA, Vehicle type, Power train, Parking status, Trip purpose (incl. Commuting status), Annual demand, Rural/Urban, Driver income, Ownership

Note: The input data columns are only indications of the target columns necessary for the model run. We recognize that the data might be provided to us in multiple data sets, each containing a few target variables that need to be aggregated to arrive at the target input. However, we expect the pre-processing steps that are needed to be straight forward and not to add a large overhead to the development. (e.g. Certain inputs will be provided on a NoHAM zone basis, with a NoHAM to MSOA mapping included and the mapping done as a pre-processing step).

Note: The column names might differ in the model inputs and outputs based on the data set names or better representative names. These names were selected to reflect what the columns would contain. The possibly modified names should be self-explanatory.

Note: The variables in blue are not strictly necessary to calculate the EVCP requirements. Whether or not these are kept will depend on processing times and data availability. To be discussed and decided by TfN during model development.

Core Module Step 2 – Split charging demand by charging category, Provisional column structure of inputs and interim outputs

Input, Interim output, Model output	Columns
I2.1 – Charging behaviour assumptions for cars and vans.	Vehicle type, Power train, Parking status, Commuting status, Charging category, Share of demand
I2.2 – Charging behaviour assumptions for HGVs.	Vehicle type, Power train, Parking status, Commuting status, Charging category, Share of demand
O2.0/I3.0 – Annual EV charging demand by vehicle archetype and charging category at the MSOA of registration	Scenario, Year, MSOA, Vehicle type, Power train, Parking status, Trip purpose (incl. Commuting status), Charging category, Annual demand, Rural/Urban, Driver income, Ownership

Note: The input data columns are only indications of the target columns necessary for the model run. We recognize that the data might be provided to us in multiple data sets, each containing a few target variables that need to be aggregated to arrive at the target input. However, we expect the pre-processing steps that are needed to be straight forward and not to add a large overhead to the development. (e.g. Certain inputs will be provided on a NoHAM zone basis, with a NoHAM to MSOA mapping included and the mapping done as a pre-processing step).

Note: The column names might differ in the model inputs and outputs based on the data set names or better representative names. These names were selected to reflect what the columns would contain. The possibly modified names should be self-explanatory.

Note: The variables in blue are not strictly necessary to calculate the EVCP requirements. Whether or not these are kept will depend on processing times and data availability. To be discussed and decided by TfN during model development.

Core Module Step 3 – Description of how the demand is distributed for different charging categories

Vehicle type	Charging category	Distribution mechanism
Cars, Vans	Home / on-street residential	Assumed to occur in the MSOA where the vehicle is registered.
	Work	Distributed based on the origin-destination matrix of commuting trips from TfN's NorMITs demand model.
	Destination	Distributed based on the origin-destination matrix of relevant trip types from TfN's NorMITs demand model. This will likely include shopping and leisure trips, but relevant trip types will be agreed with TfN during the development based on data availability.
	Rapid en-route	Summed for the whole MRN and distributed to specific sites in Step 5.
HGV	Depot	Distributed using EE's GB database of depot locations and fleet sizes.
	Rapid en-route	Summed for the whole MRN and distributed to specific sites in Step 5.

Core Module Step 3 – Geographically distribute charging demand for each charging category, Provisional column structure of inputs, interim outputs and model outputs

Input, Interim output, Model output	Columns
I3.1 – Work charging origin-destination matrix	Scenario, Year, Vehicle type (Car, Van), Charging category (Work), MSOA of origin, MSOA of destination, Trip frequency
I3.2 – Destination charging origin-destination matrix	Scenario, Year, Vehicle type (Car, Van), Charging category (Destination), MSOA of origin, MSOA of destination, Trip frequency
I3.3 – HGV depot charging origin-destination matrix	Scenario, Year, Vehicle type (HGV), Charging category (HGV depot), MSOA of origin, MSOA of destination, Trip frequency
O3.0/I4.0– Annual EV charging demand by vehicle archetype and charging category at the MSOA of charging	Scenario, Year, MSOA, Vehicle type, Power train, Parking status, Trip purpose (incl. Commuting status), Charging category (excl. en-route), Annual demand, Rural/Urban, Driver income, Ownership
O3.1/I6.1, O3.2/I6.2 – Annual demand for rapid en-route charging	Scenario, Year, Vehicle type, Charging category (only en-route), Annual demand

Note: The input data columns are only indications of the target columns necessary for the model run. We recognize that the data might be provided to us in multiple data sets, each containing a few target variables that need to be aggregated to arrive at the target input. However, we expect the pre-processing steps that are needed to be straight forward and not to add a large overhead to the development. (e.g. Certain inputs will be provided on a NoHAM zone basis, with a NoHAM to MSOA mapping included and the mapping done as a pre-processing step).

Note: The column names might differ in the model inputs and outputs based on the data set names or better representative names. These names were selected to reflect what the columns would contain. The possibly modified names should be self-explanatory.

Note: The variables in blue are not strictly necessary to calculate the EVCP requirements. Whether or not these are kept will depend on processing times and data availability. To be discussed and decided by TfN during model development.

Core Module Step 4 – Calculate the number of public charge points required in each MSOA, Provisional column structure of inputs, interim outputs and model outputs

Input, Interim output, Model output	Columns
I4.1 – Power assumptions for each charging category	Year, Vehicle type, Power train, Charging category (on-street and destination), Apparent power
I4.1 – Utilisation assumptions for each charging category	Year, Charging category (on-street and destination), Utilization rate
I4.2 – Normalized seasonal variation profile	TBC – TfN summer holiday modelling
I4.3 – Normalized daily profile	TBD - Vehicle type, Power train, Commuting status, Charging category (on-street and destination), Hour, Share of stock charging
O4.0 – Number of EV charging points required in each MSOA for on-street and destination charging	Scenario, Year, MSOA, Charging category (on-street and destination), EVCPs required

Note: The input data columns are only indications of the target columns necessary for the model run. We recognize that the data might be provided to us in multiple data sets, each containing a few target variables that need to be aggregated to arrive at the target input. However, we expect the pre-processing steps that are needed to be straight forward and not to add a large overhead to the development. (e.g. Certain inputs will be provided on a NoHAM zone basis, with a NoHAM to MSOA mapping included and the mapping done as a pre-processing step).

Note: The column names might differ in the model inputs and outputs based on the data set names or better representative names. These names were selected to reflect what the columns would contain. The possibly modified names should be self-explanatory.

Note: The variables in blue are not strictly necessary to calculate the EVCP requirements. Whether or not these are kept will depend on processing times and data availability. To be discussed and decided by TfN during model development.

Core Module Step 5 (1/2) - Determine possible sites for charge points along the MRN, Detailed description of the process

In order to translate the MSOA level forecast demand for EV charging into the identification of specific enroute rapid charging sites on the MRN, a series of filters and further supplementary analysis will be applied to the outputs generated from Tasks 2.1 and 2.3.

Site Filtering Approach	
Land Use – Prospective enroute charging locations and sites of charging demand	The first step will be to identify prospective sites around the MRN and SRN, using land use data to identify clusters of land uses likely to feature parking, and so potentially suitable for intermediate or destination charging, i.e. service stations, retail, food/drink retail. Differential weightings will be applied to land uses and agreed with TfN.
Sites will be filtered based on key localised determinants of charging demand to identify specific areas of higher demand:	
Traffic flow volumes on the MRN	Using DfT AADT Counts for 2019, to avoid potentially unrepresentative COVID impacts on more recent data
Distance from the MRN	Testing a range of sensitivities, but likely to range from between 500m to 1km
Forecast MWh demand per MSOA	As a further indicator of localised EV charging demand, though recognising the proportion likely to charge on the MRN may be low
Local reliance on on-street parking	As a further indicator of localised EV charging demand, but also recognising the proportion likely to charge on the MRN may be low
Major delivery depots in the local area	Informed by the emerging TfN freight model

Core Module Step 5 (1/2) - Determine possible sites for charge points along the MRN, Detailed description of the process

Potential supply side barriers and delivery constraints will also be considered. A further filtering mechanism will be developed to promote a broader geographic coverage of site across the MRN. Upon applying the series of spatial filters identified, it will be necessary to sensitivity test the weightings applied to each, in order to effectively filter down the number of prospective sites.

Site Filtering Approach	
Planning restrictions	Conservation areas, flood risk areas
Existing Charging Hubs	Existing DC Rapid Hubs, derived from a synthesised and cleaned version of the National Charge Point Registry and Open Charge Map datasets. Parameters to be defined through sensitivity testing, with existing hubs of 2-4+ DC chargers likely to be included.
Geographic spread and spatial coverage	Buffering around sites with the highest demand rating A further filtering mechanism will be developed to promote a broader geographic coverage of site across the MRN than may otherwise occur, through applying buffers around the sites with the highest demand rating in a given area.
Sensitivity testing to filter the number of prospective sites	Sensitivity test the weightings applied to each, in order to effectively filter down the number of prospective sites to no more than 200 focus areas across the MRN, to ensure the next step is practicable

The methodology will be prototyped in Excel before being implemented in Python. Code will be written in a modular fashion in line with TfN's coding standards and will be pushed to TfN's GitHub regularly during development.

Core Module Step 5 (2/2) - Determine possible sites for charge points along the MRN, Detailed description of the process

The next step is to assess which of these areas carry the greater **number of vehicles making long distance journeys**, and would **cover a given distance into their journey**.

A reassignment approach will be adopted using SATURN reassignment functionality. Steps taken include

- calculate Vkm by vehicle type/trip purpose
- Save in assignment data field using original route choices.
- Highest resultant links will either be from greater distance or higher trip totals (or both).
- Average trip length also calculable
- Seeking MRN links with highest flow and longest trip length.

To expedite the **detailed analysis of EV charging sites** we propose

- a “fixed cost” version of the model could be utilised, where travel times are informed by an original simulation assignment,
- Approximation of original flows allowing **interrogation of assignments** via **selected link** procedures.

Both the above routines would be programmed in python.

We will conduct disaggregate analysis on

- Analysis of **Trip length distribution** by distance bin
- **volume by trip purpose** and
- **speed of journey** will be possible.

Based on this further filters will be applied to refine an assessment of charging demand across the 200 shortlisted sites

Sense checking will be undertaking reviewing a sample of locations identified using desk based checks against Google Street View, and where appropriate the weightings assigned to the different metrics will be adjusted accordingly.

Output of this process will be **GIS based spatial analysis identifying potentially suitable locations** or specific sites for charging infrastructure on the MRN and SRN (catering for BEVs, LDV and HGV and scenarios for 2025 and 2030), to produce spatial and temporal mapping outputs.

DNO Module Steps 1 to 6

DNO Module Step 1r, 2r, 3r – Calculate charging demand profiles for rapid en-route per primary, Provisional column structure of inputs and interim outputs

Input, Interim output, Model output	Columns
O5.0/I6.0 – Shortlist of potentially suitable locations for charging infrastructure for rapid charging	Scenario, Year, Site rank, EVCP site location, Hub size
O6.0/I7.0 – Annual en-route EV charging demand per rapid charging hub (MWh)	Scenario, Year, EVCP site location, Charging category (car/van and HGV en-route), Annual demand
I7.2 – Location of primaries	DNO, Primary ID, Primary location
O7.0/I8.0 – Annual en-route EV charging demand per primary (MWh)	Scenario, Year, DNO, Primary ID, Primary location, Charging category (car/van and HGV en-route), Annual demand
I8.2 – Half hourly charging demand profiles for rapid en-route charging	Scenario, Year, Charging category (car/van and HGV en-route), Normalized daily profile
I8.3 – Seasonal variation factors for rapid en-route charging	Scenario, Year, Charging category (car/van and HGV en-route), Seasonal variation factor
O8.0/I9.0 – Half hourly charging demand profile for rapid en-route EV charging per primary, for representative summer and winter days	Scenario, Year, DNO, Primary ID, Primary location, Charging category (car/van and HGV en-route), Season, Daily profile

Note: The input data columns are only indications of the target columns necessary for the model run. We recognize that the data might be provided to us in multiple data sets, each containing a few target variables that need to be aggregated to arrive at the target input. However, we expect the pre-processing steps that are needed to be straight forward and not to add a large overhead to the development.

Note: The column names might differ in the model inputs and outputs based on the data set names or better representative names. These names were selected to reflect what the columns would contain. The possibly modified names should be self-explanatory.

DNO Module Step 1a, 2a, 3a – Calculate charging demand profiles per charging category per primary, Provisional column structure of inputs, interim outputs

Input, Interim output, Model output	Columns
I6.3 – DNO and MSOA boundaries, for MSOA to DNO mapping	MSOA, DNO
I6.4 – Number of customers per DNO and per primary substation	DNO, Number of primaries, Average number of customers per primary
O6.1/I7.1 – Annual charging demand per charging category (excl. rapid en-route) per customer for each DNO	Scenario, Year, DNO, Charging category (excl. en-route), Annual demand per customer per primary
I7.3 – List of primaries per DNO, Number of customers per primary	DNO, Primary ID, Primary location, Number of customer on primary
I7.4 – Unmanaged/smart home charging share	Charging category (unmanaged/smart home), Share
O7.1/I8.1 – Annual charging demand per charging category (excl. rapid en-route) at each primary	Scenario, Year, DNO, Primary ID, Primary location, Charging category (excl. en-route), Annual demand
I8.4 – Half hourly charging demand profiles for all charging categories (excl. rapid en-route)	Scenario, Year, Charging category (excl. en-route), Normalized daily profile
I8.5 – Seasonal variation factors for all charging categories (excl. rapid en-route)	Scenario, Year, Charging category (excl. en-route), Seasonal variation factor
O8.1/I9.1 – Half hourly EV charging demand profile per charging category (excl. rapid en-route) at each primary, for representative summer and winter days	Scenario, Year, DNO, Primary ID, Primary location, Charging category (excl. en-route), Season, Daily profile

Note: The input data columns are only indications of the target columns necessary for the model run. We recognize that the data might be provided to us in multiple data sets, each containing a few target variables that need to be aggregated to arrive at the target input. However, we expect the pre-processing steps that are needed to be straight forward and not to add a large overhead to the development.

Note: The column names might differ in the model inputs and outputs based on the data set names or better representative names. These names were selected to reflect what the columns would contain. The possibly modified names should be self-explanatory.

DNO Module Step 4p, 5p, 6p – Assess grid impact on primaries, Provisional column structure of inputs, interim outputs and model outputs

Input, Interim output, Model output	Columns
O9.0/I10.0 – Total half hourly EV charging profile per primary, for representative summer and winter days	Scenario, Year, DNO, Primary ID, Primary location, Season, Daily profile
O10.0/I11.0 - Overall peak EV charging demand per primary	Scenario, Year, DNO, Primary ID, Primary location, Peak EV charging demand
I11.2 – Headroom on primaries	DNO, Average headroom on primaries
I11.3 – Unit reinforcement cost per primary	DNO, Average unit reinforcement cost on primaries
O11.0 – Grid impact: Cumulative cost at primary level	DNO, Cumulative reinforcement cost at primary level

Note: The input data columns are only indications of the target columns necessary for the model run. We recognize that the data might be provided to us in multiple data sets, each containing a few target variables that need to be aggregated to arrive at the target input. However, we expect the pre-processing steps that are needed to be straight forward and not to add a large overhead to the development.

Note: The column names might differ in the model inputs and outputs based on the data set names or better representative names. These names were selected to reflect what the columns would contain. The possibly modified names should be self-explanatory.

DNO Module Step 4s, 5s, 6s – Assess grid impact on primaries, Provisional column structure of inputs, interim outputs and model outputs

Input, Interim output, Model output	Columns
O9.1/I10.1 –Total half hourly EV charging demand profile (excl. rapid en-route demand) per DNO, for representative summer and winter days	Scenario, Year, DNO, Season, Daily profile
O10.1/I11.1 – Overall peak EV charging demand (excl. rapid en-route demand) per DNO	Scenario, Year, DNO, Peak EV charging demand
I11.4 – Unit reinforcement cost of secondaries	DNO, Average unit reinforcement cost on secondaries
O11.1 – Grid impact: Cumulative cost at secondary level	DNO, Cumulative reinforcement cost at secondary level

Note: The input data columns are only indications of the target columns necessary for the model run. We recognize that the data might be provided to us in multiple data sets, each containing a few target variables that need to be aggregated to arrive at the target input. However, we expect the pre-processing steps that are needed to be straight forward and not to add a large overhead to the development.

Note: The column names might differ in the model inputs and outputs based on the data set names or better representative names. These names were selected to reflect what the columns would contain. The possibly modified names should be self-explanatory.

Appendix

Reference Studies

- EV Charging Behaviour Study, National Grid, Element Energy (2019)
- Quantifying the electric vehicle charging infrastructure gap in the United Kingdom, ICCT (2020)
- DfT Vehicle Licensing Statistics - Table VEH0132a Ultra low emission vehicles (ULEVs) 1 licensed at the end of the quarter by upper and lower tier local authority 2, United Kingdom from 2011 Q4
- The CCC - Sixth Carbon Budget (2020)
- Society of Motor Manufacturers and Traders (SMMT) - SMMT new car market and parc outlook to 2035 by powertrain type (2021)
- Deloitte – 'Hurry up and wait'(2020)
- Alternative Fuels Infrastructure Directive (AFID) (2014)
- Competition & Markets Authority (CMA) (2021) - Policy Exchange, Forecasts from CCC, Transport & Environment, Delta-EE and ICCT - all 2020.